Financial Sector Stress and Asset Prices: Evidence from the Weather Derivatives Market

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August 6, 2015

ABSTRACT

I examine the impact of financial sector stress on asset prices in a novel setting: the Chicago Mercantile Exchange's weather derivatives market. The structure of the market allows me to disentangle price movements due to financial sector stress from price movements due to fundamentals. In normal times, contracts are priced near their actuarially fair value. During the recent financial crisis, contract prices one-month before maturity fall by 2.2%. This discount is equivalent to an annualized weather risk premium of 26%. Contract prices decline with increases in the TED spread and the VIX and the declines are greatest for high margin and high total risk contracts. Examining end users, I find the risk-sharing benefits of the weather derivatives market decrease during the crisis. The results provide causal evidence of the importance of financial sector stress in the pricing of financial contracts and its effect on risk sharing in the economy.

Keywords: financial sector stress, weather derivatives, margin, idiosyncratic risk.

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A recent theoretical literature argues that adverse shocks to financial sector capital and increases in funding constraints can affect asset prices. After an adverse shock, asset prices may fall below their fundamental values if financial institutions are capital constrained.[1] However, it is difficult to measure the effect of financial sector stress on asset prices in most markets. The difficulty arises because asset fundamentals shift during periods of financial sector stress, which can lead to biased estimates of the effect of stress. In this paper, I estimate the causal effect of financial sector stress on asset prices by exploiting a novel setting in which fundamental values are unlikely to be systematically mis-estimated. Specifically, I examine the impact of financial sector stress on contract prices in the Chicago Mercantile Exchange's (CME's) weather derivatives market.

The weather derivatives market ties contract values to location-specific weather outcomes. I focus on the monthly temperature futures market, which allows end users to hedge monthly temperature risks. Energy and utility companies are the predominant end users. The typical trade is for utilities to short the local temperature future to minimize their exposure to mild temperature outcomes (i.e., temperatures near 65°F) and, thus, low energy sales. Financial institutions satisfy this asymmetric hedging demand by going long the futures contract and bearing this mild temperature risk.

Prices should fall with increases in financial sector stress if financial institutions become less willing to bear mild temperature risk. I estimate the price impact of financial sector stress by comparing the price of a contract during periods of financial sector stress to the price of the same contract in normal times. These tests properly identify the causal effect of financial sector stress on asset prices because any error in measuring the fundamental value of the futures contract is uncorrelated with the financial sector stress period.

Four features of temperature futures ensure that asset fundamentals (payoffs and risks) are not systematically mis-estimated during the financial stress periods. First, contract payoffs are based on local temperature outcomes, which are exogenous to financial sector stress. Thus, the adverse shock to the financial sector does not affect the distribution of contracts' payoffs. Second, contract payoffs are largely idiosyncratic. This rules out the possibility that changes in the price

[1] See Adrian and Shin (2010), Aiyagari and Gertler (1999), Brunnermeier and Pedersen (2009), Fostel and Geanakoplos (2008), Garleanu and Pedersen (2011), and Gromb and Vayanos (2002) for models on how asset prices may be sensitive to margin and debt constraints. He and Krishnamurthy (2012, 2013) examine the effect of equity constraints on asset prices and find that asset prices depend on the aggregate wealth of the financial sector. For a review of the literature, see Duffie (2010).

of systematic risk are driving the change in prices. Third, I can control for changes in temperature expectations with temperature forecasts. Fourth, there is no counterparty risk because trades clear on an exchange. These four features allow me to clearly identify the causal effect of financial sector stress on asset prices in a manner that no other empirical setting allows.

Contracts in the monthly temperature futures market vary by location, month, and temperature index. Unlike most markets, market expectations can be observed in the form of temperature forecasts. Although temperature forecasts are imperfect, it is unlikely that there is any bias in the forecasts that would affect my results. I estimate the market expected index on a contract by combining near-term (12 day) expectations from temperature forecasts with longer-term temperature expectations from simulating future temperature paths using an optimized model of daily temperature. I use the calculated expected index to control for changes in time-varying market expectations in formal tests.

I employ multiple proxies for financial sector stress. The first proxy is the spread between the three-month Eurodollar deposit rates and the three-month Treasury bill rate (the TED spread). Increases in the TED spread should capture increases in funding constraints for financial institutions in the weather derivatives market as unsecured borrowing becomes relatively more costly compared to risk-free Treasury bonds. The spread increases significantly in crisis periods (Brunnermeier (2009)). The second proxy is changes in the implied volatility of S&P 500 Index options (the VIX). Adrian and Shin (2010) argue that increases in the VIX will decrease the willingness of financial institutions to take on risks and Cheng, Kirilenko, and Xiong (2014) show that financial institutions decreased their long positions in commodities markets when the VIX increased during the recent financial crisis. The third proxy is a dummy variable for the period of the financial crisis starting after the collapse of Lehman Brothers in September 2008 and ending in December 2009.

Comparing the forecast-implied expected index to contemporaneous contract price, I find that contracts are priced near their actuarially fair value on average. The difference between the logarithm of contract prices and the logarithm of forecasted payoffs is small and statistically insignificant. This is consistent with idiosyncratic risk not being priced during periods of financial sector stability. Examining contract prices during the recent financial crisis from September 2008 to December 2009, I find that prices one-month before maturity fall by 2.2%. This is equivalent to an increase in the annualized risk premium of 26%. Similarly, I find contract prices are significantly negatively correlated with both the TED spread and changes in the VIX. A one standard deviation increase in the TED spread (VIX) leads to a decrease in contract prices of 1.79% (1.45%) on average. In sum, contracts are typically priced near their actuarially fair value, but during periods of financial sector stress, they are lower than this value. This is consistent with financial institutions decreasing their supply of capital to the weather derivatives market during periods of financial sector stress.

There are two main reasons why financial institutions may decrease their supply of capital to the weather derivatives market during periods of financial sector stress. First, capital is necessary to meet margin requirements in the market. Without sufficient capital, financial institutions will be unable to meet these requirements. Brunnermeier and Pedersen (2009) and Garleanu and Pedersen (2011) predict that when capital constraints bind, the spread between an asset's fundamental value and market price is increasing in the contract's margin requirement.[2] Second, monthly temperature futures have significant amounts of total risk that financial institutions may be unwilling to take on during a period of stress. When financial institutions' capital levels are low, increasing the risk on their balance sheet will significantly increase the probability they will have to raise costly new capital in the future.[3] To limit their risk exposure, financial institutions will supply less capital to markets with more unhedgeable risk (Froot and Stein (1998); Garleanu, Pedersen, and Poteshman (2009)).

Motivated by these theories, I examine the differential impact of stress on higher margin contracts and contracts with more total risk. By early 2008, the CME had introduced temperature contracts on 18 U.S. locations geographically dispersed throughout the country. Each location-month-index has a different amount of total underlying risk (coefficient of variation of contract payoffs) and the CME has location-index-specific margin requirements. I run difference-in-difference regressions, where a financial sector stress proxy is interacted with the contract's margin requirement or total risk or both. Consistent with theory, I find that higher margin and higher total risk contracts

[2] Modeling a market equilibrium with constrained traders, Brunnermeier and Pedersen (2009) show that higher margin contracts experience a greater decline in market liquidity, defined as the difference between market and fundamental values, after an adverse capital shock. Garleanu and Pedersen (2011) predict that a security's expected excess return is increasing in the interaction between the contract's margin requirement and the shadow cost of funding.

[3] There are many reasons why financial institutions in the weather derivatives market may be capital constrained. Financial institutions could suffer from an asymmetric information problem (Myers and Majluf (1984); Stein (1998)), debt-overhang (Myers (1977)) or a moral hazard problem (Holmstrom and Tirole (1997)). In addition, the costs of searching for capital are likely to be high considering most individual investors and financial professionals are unfamiliar with the market and, as a recent financial innovation, may have appeared unsafe to investors seeking safety during the recent crisis (Caballero and Krishnamurthy (2008); Gennaioli, Shleifer and Vishny (2012)).

experience the largest price declines during periods of financial sector stress. When the TED spread increases by 1%, a one standard deviation increase in the margin requirement is associated with an additional 2.8% decrease in contract price. Of similar magnitude, I find a one standard deviation increase in total risk leads to a 4.25% decline in price. This evidence supports the theory that adverse capital shocks and increased funding constraints have a significant effect on asset prices, especially on prices of high-margin and high-risk contracts.

A decrease in contract prices alone does not imply that the supply of financial capital to the weather derivatives market decreases during periods of financial sector stress. Contract prices may also decrease if hedging demand increases and the supply of capital is not perfectly elastic in the short-run.[4] If hedging demand is driving the decrease in prices, greater quantities of risk would be hedged during the crisis. However, this is not the case. The notional value of the weather derivatives market *decreased* by over 50% from \$32 billion to \$15 billion during the crisis. Similarly, open interest in the monthly futures market fell by 40% between the third and fourth quarter of 2008. In describing the collapse of the market, the Weather Risk Management Association's President, Martin Malinow, said "It's just mirroring what's going on in the greater financial markets. We are surviving from the same pool of capital. We've had a financial storm over the past year that's destroyed trillions of dollars of capital."[5] The dramatic decline in notional value and open interest rules out the alternative that an increase in hedging demand is driving the decrease in prices.[6]

Documenting the effect of financial sector stress on asset prices is important for understanding the risks that hedgers and investors face, the way those risks are priced, and how risks are shared in the economy. Pérez-González and Yun (2013, henceforth PGY) find that after the introduction of weather derivative contracts in 1997, firms most exposed to temperature risks were more likely to use weather derivatives, experience an increase in firm value, invest more, and increase their leverage. If prices fall and risk premiums rise because of financial sector stress, the costs to use these contracts and to obtain these benefits increase. As a result, there will be less risk-sharing than in a perfect market.

[4]Keynes (1930) and Hicks (1939) first proposed this argument to explain risk premiums in the commodities market. Garleanu, Pedersen, and Poteshman (2009) document a demand effect in the options market, by showing that option prices increase as constrained market makers respond to positive demand shocks.

[5]"Survey: Weather Risk Market Value Plunges 53%." *Claims Journal*, June 2009 `http://www.claimsjournal.com/news/national/2009/06/03/101075.htm`.

[6]Another alternative is that hedging demand declined. If this is the case, prices would be unchanged or fall during the crisis, not increase.

I test for the effect the decline in risk-sharing has on end users in the weather derivatives market in two ways. First, I examine the exposure of energy utilities to weather shocks during the crisis (2008:Q4 through 2009) compared to pre-weather derivative introduction (1977-1996) and post-weather derivative introduction outside of the financial crisis period (1997-2012 excluding the crisis period). Confirming PGY, I find that firms are less exposed to mild temperature risks post-weather derivative introduction. During the recent crisis, this improvement disappears. Utilities are just as exposed to mild temperature shocks as in the pre-weather derivative introduction period (pre-1997). Second, I examine the relative change in valuation, investment and financing of firms highly exposed to temperature risks compared to firms less exposed in the three different periods. Similar to PGY, I find that firms highly exposed to weather risks experienced increased firm valuation, investment, and leverage, and decreased cash levels after weather derivative introduction. During the crisis, the investment and leverage benefits dissipate as firms became more exposed to temperature risk. The benefits decrease by at least one-third for investment and two-thirds for leverage. The relative valuation and cash levels remain similar during the crisis compared to the post-weather derivative introduction period. In sum, end users most exposed to weather risk invest less and decrease their leverage during the financial crisis when weather derivative hedging becomes more expensive.

Researchers have documented the effects of adverse capital shocks on market outcomes in the currency, convertible bond, lending, life insurance and other markets.[7] Examining commodity markets, Cheng, Kirilenko, and Xiong (2014) find that an increase in the VIX index leads to lower commodity prices and a "convective" flow of risk from financial institutions to hedgers. Relatedly, Acharya, Lochstoer, and Ramadorai (2013) and Etula (2013) find that risk premiums in commodity markets increase when broker-dealer risk-bearing capacity decreases. Due to the nature of commodity markets, these studies cannot cleanly separate price movements due to fundamentals

[7]Examining the currency markets, Brunnermeier, Nagel, and Pedersen (2008) show that the funding constraints of speculators can lead to currency crash risk and this can help explain the "forward risk premium puzzle." Chava and Purnanandam (2011), Paravisini (2008), Paravisini et al. (2011), and Iyer et al. (2013) find evidence that adverse shocks to bank capital affect lending and other real outcomes. Mitchell, Pedersen, and Pulvino (2007) find price effects of slow-moving capital in the convertible bond market and merger spreads. Mitchell and Pulvino (2011) find substantial price differences in similar assets during the recent financial crisis. Examining the relationship between expected returns and margin requirements, Garleanu and Pedersen (2011) find a significant positive relationship between the CDS-bond basis and the TED spread. Examining the life insurance market, Koijen and Yogo (2015) find significant shadow costs of financial frictions for life insurers during the financial crisis by exploiting variation in required reserves. Additionally, Adrian, Etula, and Muir (2013) find that a factor based on the leverage of financial intermediaries can be used to explain a large portion of the variation in the cross-section of expected returns.

from price movements due to financial sector stress. Additionally, these studies do not examine the real effects of the increase in hedging costs.

The most closely related empirical evidence to the results in this paper is on the increase in catastrophe insurance risk premiums after adverse shocks to insurers and reinsurers capital (see Born and Viscusi (2006), Froot and O'Connell (1999), and Zanjani (2002)) The effect of financial sector stress on prices in the weather derivatives market is similar, but the markets differ from each other in three important ways. First, the main risk bearers in the catastrophe insurance market are reinsurers and insurers, while hedge funds, investment banks, energy trading desks, commodity traders, and monoline weather traders all participate in the CME weather derivatives market. Second, the contracts examined in this paper are exchange traded on the CME, so the market should be relatively more competitive and liquid than the catastrophe insurance market as the barriers to entry are lower and intermediaries provide more depth. Third, estimating risk premiums in the catastrophe insurance market is more difficult than in the temperature futures markets. Catastrophes are less predictable than temperature outcomes, which makes controlling for fundamentals a difficult task. Beyond examining a market with different characteristics, the results in this paper differ from the previous literature by providing clean evidence (i.e., fundamentals are uncorrelated with financial sector stress) of: (1) financial sector stress spillovers across markets, (2) the differential impact of financial sector stress on more "capital-intensive" and riskier contracts in a centrally-cleared exchange market, and (3) how financial sector stress affects firm-level outcomes through the channel of increased risk exposure of end users.

Overall, the results show that financial sector stress can have a large impact on the prices of financial assets. If the effects documented in the weather derivatives market are similar in other markets, the impact of financial crises on risk-sharing and capital flows in the economy are substantial. Hedgers and other insurance purchasers may be exposed to dramatically more risk during financial crises than in a world with perfect markets.

The rest of the paper proceeds as follows. In Section I, I describe the weather derivatives market, the main players and the main hedging strategy by energy companies. In Section II, I discuss the data. In Section III, I present the research design and empirical results. Concluding remarks are given in Section IV.

I. Weather Derivatives Market and Hedging Tactics

Almost all business is subject to weather risks. Dutton (2002) estimates that over $3 trillion of the U.S. GDP is associated with weather-sensitive industries. Although the importance of weather in affecting business outcomes has been understood for millenniums, the first modern-day weather derivative contract was written in 1996. The contract obligated Aquila Energy to sell Consolidated Edison electric power at a discount if August temperatures were cooler than expected (Everitt and Melnick (2008)). Subsequently, corporations, especially energy companies, began to hedge risks tied to non-catastrophic weather outcomes (e.g., temperature, frost, snowfall, and rainfall) using various tactics depending on their risk exposure. The entire weather derivatives market grew from a notional value below $2 billion in 1998 to $32 billion in 2008 (Weather Risk Management Association (2002, 2011)).

In 1999, the CME introduced standardized monthly temperature contracts on 10 locations in the U.S. Exchange-traded contracts were not immediately popular. The market grew in the over-the counter (OTC) market, where Enron was a main player and market maker. When Enron collapsed in 2001, end users and financial intermediaries became more aware of counterparty risk in the OTC market and shifted trading to the CME. The CME has periodically added contracts on 14 locations throughout the United States and expanded into Canada, Europe, Japan, and Australia. Contracts are based on temperature outcomes over seasonal, monthly or weekly time periods and multiple temperature indices. As of 2015, there are 47 locations around the world with temperature-based weather contracts traded on the CME.

I focus on the U.S. monthly temperature futures. In 2005, temperature contracts accounted for over 95% of the entire weather derivatives market and 50% of the temperature contracts were monthly degree day futures (Weather Risk Management Association Survey (2006)). Contracts on U.S. locations have been introduced in five waves: 1999, 2000, 2003, 2005, and 2008. In Table I, I document the 24 U.S. locations with temperature-based weather derivatives traded on the CME. The introduction of contracts is correlated with proxies for hedging demand, such as a city's population (energy usage) and the region's crop production.

Although the CME temperature futures market has seen tremendous growth, it is relatively illiquid. Bid-ask spreads are large and many deals are conducted off exchange and submitted as block trades. Markets typically open in the 1-3 weeks before the contract month (the median market is opened 39 days before maturity) and participants rarely change their positions. After a market is initially opened, open interest does not change on 85% of trading days.[8] Open interest decreases on less than 5% of trading days. The market's illiquidity is likely to amplify financial institutions' unwillingness to take on additional risk and lead to larger price distortions, as predicted by Garleanu and Pedersen (2007).[9]

A. *Contract Structure*

The payoffs of the standard temperature derivative contracts traded on the CME are based on either a heating degree day (HDD) index or cooling degree day (CDD) index for a specific location and time duration. The monthly indices are calculated as follows:

$$HDD_{im} = \sum_{t=1}^{T_m} \max\{65 - Temp_{it}, 0\}, \tag{1}$$

$$CDD_{im} = \sum_{t=1}^{T_m} \max\{Temp_{it} - 65, 0\}, \tag{2}$$

where HDD_{im} (CDD_{im}) is the HDD (CDD) index for location i and month m, T_m is the number of days in month m, and $Temp_{it}$ is the average temperature of location i on day t. The average temperature is the arithmetic mean of the maximum and minimum temperatures recorded during the day. The contract payoffs are $\$20 * HDD_{im}$ and $\$20 * CDD_{im}$. The indices received their names due to their relationship with energy usage. When the HDD (CDD) index is high, temperatures are cold (hot) and consumers need more energy to heat (cool) their homes and buildings.

B. *Main Players 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.

[8] Calculated for 2006-2012 for the monthly temperature futures market.

[9] Although the market is illiquid, it appears to be relatively efficient. Similar to Roll (1984), Chincarini (2011) finds that prices in the temperature market can improve temperature predictions beyond National Weather Service forecasts.

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.[10] 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 (PGY). Every state in the U.S. has purchased gas adjustments (PGA) for natural gas utilities (American Gas Association (2007)). PGA 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 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."[11] 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 81% 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

[10] 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.

[11] "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/`.

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 (WNA), adjust rates in response to weather-driven 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.[12] In 2009, natural gas utilities in 36 states had non-volumetric rate designs and electric utilities in only nine states had decoupling mechanisms.[13] 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

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

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

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 Section II.C, I show that 91% of energy utilities have revenues positively correlated with HDDs, while only 64% 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)). The Weather Risk Management Association documents that hedge funds, investment banks, insurance/reinsurance companies, monoline weather trading desks, and energy trading desks all play an active role in the exchange market. 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 the analysis of prices.

II. Data Description

A. Data for Temperature Future Analysis

End-of-day price, open interest, and margin data for the CME monthly temperature futures was provided by the CME.[14] To eliminate concerns about cross-country differences, I only analyze contracts on U.S. locations. Due to a lack of trading pre-crisis, I eliminate the six U.S. locations that were introduced in 2008, leaving 18 U.S. locations. I focus my analysis on HDD contracts since the direction of risk exposure of end users is nearly universal (see discussion in Section I.B). The data covers monthly contracts from the first month traded, October 1999, to February 2012. The temperature and forecast data were obtained from MDA Information Systems, Inc. MDA is the provider of official temperatures used to settle CME temperature contracts. Data for the TED spread were obtained from the Federal Reserve Bank of St. Louis and VIX data was obtained from Bloomberg.

In Figure 1, I plot the average price and open interest of February HDD contracts by location. Prices and open interest are greater for locations with more extreme temperature and more economic interest, respectively. Minneapolis, with the coldest February temperatures, has the highest average price. New York City, with the largest population, has the highest open interest.

Margin and total risk are the main cross-sectional variables of interest in the difference-in-difference regressions. I proxy for total risk with the contract's coefficient of variation, which is calculated as follows: $\frac{\sigma_{index}}{\mu_{index}}$, where σ_{index} and μ_{index} are the standard deviation and mean, respectively, of the degree day index for the specific location and month. The mean and standard deviation are calculated over the years 1974 to 2011. The coefficient of variation closely approximates the standard deviation of contract returns over the life of the contract and is equivalent to the standard deviation of contract returns if the contract price is always equal to the historical mean.[15]

[14] The CME does not provide margin data pre-2008. For dates before 2008, I use the margin requirement in 2008. This assumption should be reasonable. Margin is highly persistent in the weather derivatives market. The median number of margin changes between 2008 and 2011 was one. There were zero margin changes between June 2008 and June 2010. Relative margin is especially persistent. Margins are usually changed for the majority of contracts within a short period of time and the relative rank of margin requirements is very similar. The Spearman rank correlation between the 2008 margin requirements and the 2011 margin requirements is 0.84. This persistence minimizes concerns that margin changes are driving the results. Additionally, the results are robust to using July 2008 margin requirements throughout the entire sample.

[15] Further motivation for using the coefficient of variation comes from Hirshleifer (1988). He shows that the risk premium on a commodity should be increasing in its coefficient of variation if there is a fixed cost to participating in the market.

In Panel A of Table II, I present summary statistics for contract open interest, maintenance margin requirements, and the historical coefficient of variation of the contract index. Contracts are defined along location, index, month, and year dimensions. The sample is limited to the 644 HDD contracts that were open at least 31 days before maturity. Open interest is the maximum open interest achieved at least 31 days before maturity.[16]

The mean open interest over the entire period is 214 per contract. There is a lot of variation in open interest, with a 10th percentile of 12 and a 90th percentile of 515. The margin requirements are right skewed. The mean maintenance margin requirement is 5.38%, while the median is 4.8%. There is significant variation in margin requirements with a standard deviation of 1.63 and a range of 2.7% to 10%. The coefficient of variation is also right skewed, with a mean of 0.22 and a median of 0.20. The coefficient of variation ranges from 0.11 to 0.97, with a standard deviation of 0.10. Although margins are set based on price volatility, the correlation between margin and coefficient of variation is only 0.47. The relatively low correlation is due to margins being set at the location-index level, while the coefficient of variation is calculated at the location-index-month level. Additionally, margins are set based on daily price volatility, while the coefficient of variation is estimated for the monthly index.

B. Price, Expected Index, and Expected Return Variables

In the main price analysis, I examine the price of contracts approximately one-month before contract maturity. Specifically, I take the average end-of-day price across all trading days between thirty-seven and thirty-one days before contract maturity ($Price$).[17] The maturity date is the last day of a contract's specified month. Thirty-seven to thirty-one days before maturity was chosen due to the trade-off between the increase in open interest as the contract month approaches and the amount of temperature information (realized or forecasted temperatures) embedded in prices.

To control for temperature expectations, I estimate an expected degree day index. I combine temperature forecasts from MDA Federal, Inc. with simulated temperature paths from a model for the average daily temperature process for each location. The temperature is modeled as a discrete-time AR(1) process following Bellini (2005), Dornier and Querel (2000), and Ritter,

[16]The open interest 31 days before maturity is typically about one-half of the maximum open interest achieved during the trading period.

[17]Results are robust to using the price 31 days before maturity.

MuBhoff and Odening (2010). The model captures seasonality in the mean and standard deviation of daily temperatures. I use maximum likelihood estimation to estimate the parameters for each location separately. I estimate the model using temperature realizations from January 1, 1999 to January 31, 2012. In Appendix A, I detail the temperature process, the likelihood estimation and give the parameter estimates for each location. The parameter estimates align with the observed temperatures in each location. In Figure 2, I plot the average temperature versus the estimated mean temperature by day of the year for the four most populated cities. The model estimates appear to capture the mean temperature dynamics fairly well.

After the temperature process has been estimated, I calculate the expected index (payoff) using the forecasted daily temperatures for the first 12 days allowing for forecast error, and simulating the remaining days using the estimated model for each location. The AR(1) simulation has a starting value equal to the temperature forecast on the last day of forecasts plus random forecast error. I simulate 1,000 temperature paths for each contract. From the forecasted and simulated temperatures, I apply the HDD temperature formulas to calculate the payoff of the contract for each path. The expected index is the average of the sum of the forecasted degree days from month start to month end. I use the average of the expected index over the trading days from thirty-seven to thirty-one days before maturity as the expected index value ($E[Index]$).

Panel B of Table II presents summary statistics for contract prices, the expected index and realized index ($Index$), as well as return variables. The estimated expected index is very similar to the contract price. The average price is \$13,341 and the average expected index value is \$13,479. Their difference is statistically significant at the 1% level. This difference is most likely due to a few extreme expected index estimates. The median expected index is actually lower than the median price. Taking the logarithm of price and expected index, the average difference is 0.0033 and is insignificant. In other words, contracts are priced near their actuarially fair value on average. All tests use the logarithm of price and logarithm of the expected index to eliminate concerns about outliers.

The estimated expected index captures the variation in contract prices very well. The correlation between the logarithm of contract price and the logarithm of the expected index is 0.98. Regressing the logarithm of price on the logarithm of the expected index with fixed effects, the expected index has a within R-squared of 0.46. For comparison, the correlation between the logarithm of contract price and the logarithm of the realized index is 0.96 and the within R-squared is only 0.08. There are very few settings in which the fundamental value of a financial contract can be as precisely estimated.

The average contract price is slightly above the average realized index. This difference is statistically significant at the 1% level. This is consistent with the results of Dorfleitner and Wimmer (2010), who show that weather derivative market participants did not fully adjust contract prices for a warming trend in temperature during their sample period. The fact that the average forecasted expected index is higher than the realized index, as well, is evidence that temperature forecasts did not fully adjust for the upward trend in temperatures during the sample period. This bias in prices should not affect the results as long as it is uncorrelated with proxies of financial sector stress.

In addition to the price analysis, I also examine the effect of financial sector stress on returns. I use three different return measures: the expected return, the expected return on margin, and the realized return. The expected return is calculated as follows: $\frac{E[Index]-Price}{Price}$. The expected return on margin adjusts for the amount of capital invested by multiplying the expected return by the inverse of the margin requirement: $\frac{E[Index]-Price}{Price} \times \frac{1}{\%Margin}$. The realized return is calculated as follows: $\frac{Index-Price}{Price}$. I do not discount for the risk-free rate since securities (e.g., Treasury bills) can be used to meet margin requirements.

The return variables are presented in percentage terms, are approximately monthly, and are winsorized at the 1% level to reduce the impact of outliers on the analysis. The mean expected return for the entire sample is 0.51%, which is not significantly different from 0. The median expected return for the entire sample is 1.03%. Examining the realized returns, the mean realized return is -1.89% and is statistically significant. The negative realized return is most likely due to market participants not fully adjusting for the warming trend in temperature. The negative returns are concentrated in the low open interest (<300) contracts. High open interest HDD contracts have a positive mean return.

Why do financial institutions participate in the market if expected returns are near zero on average (and realized returns are negative on average)? Even if expected returns are zero, financial institutions experience a diversification benefit from investing in weather derivatives. I find there is negative systematic risk exposure in going long a weather derivative contract. In Appendix B, I present the results of CAPM regressions of excess returns to going long HDD futures on excess market returns. I calculate an alpha and a beta for each weather derivative location in the sample. I find a positive and significant average alpha of 4.72 and a negative and significant average beta of -0.48. An equally-weighted portfolio of HDD contracts has a statistically significant alpha of 5.268 and a beta of -0.557. Even if prices are consistently too high in the market, this should not bias my examination of relative changes in expected returns during periods of financial sector stress.

C. Data for End-User Analysis

For the end-user analysis, 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.[18] There are 264 firms in the sample. Summary statistics on firm financials and matching quarterly degree days are presented in Panel A of Table III. All firm variables are winsorized at the 1% level to minimize the effect of outliers.

I calculate a firm's weather risk exposure following 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. The coefficient on the degree days measure is the firm's degree day beta (HDD beta, CDD beta or energy degree day (EDD) 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 or cold temperature shocks. Energy degree days are the sum of HDDs and CDDs during the quarter. EDD beta captures the direction of risk exposure, but not the level. To estimate the level and direction of exposure, I multiply the firm's EDD beta by the standard deviation of quarterly energy degree days ($\beta_{EDD} \times \sigma_{EDD}$). For some analyses, I use absolute weather-induced volatility, which is calculated as: $|\beta_{EDD}| \times \sigma_{EDD}$. This measure captures the portion of a firm's revenue volatility due to temperature fluctuations.

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

Panel B of Table III provides summary statistics for the measures of temperature risk exposure. Eighty-one percent of firms have positive energy degree day exposure. The number is highly skewed; the mean is 0.022 and the median is 0.008. Mild temperature risk is much more prevalent in the winter months (i.e., for HDDs than CDDs). Ninety-one percent of utilities have a positive HDD beta, while only 64% 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 want to short CDD contracts. This is the motivation for focusing on HDD contracts in the price analysis.

III. Empirical Design and Analysis

A. Research Design

My main hypothesis is that a loss of financial sector capital and increases in funding constraints (i.e., financial sector stress) cause financial institutions to decrease their supply of capital to the weather derivatives market leading to lower contract prices (i.e., higher hedging costs for end users) and lower open interest. To test this hypothesis, the ideal empirical design would include a comparison of contract prices during periods of financial sector stress and the prices that would exist if the financial sector were not stressed. However, since this counterfactual does not exist, I compare prices during financial sector stress to prices when the sector is not under stress. The identifying assumption is that the fundamental values of the contracts are not systematically misestimated during periods of financial sector stress. This seems reasonable for three reasons: (1) the temperature processes are relatively stationary over time and are unaffected by financial sector stress, (2) variation in market expectations is captured fairly well by temperature forecasts, and (3) there is no counterparty risk since contracts clear on the exchange.

The following is the regression specification used in the main test:

$$log(Price_{imdy}) = \alpha_{imd} + \beta \cdot Stress_{ym} + \psi_X \cdot X_{imdy} + \epsilon_{imdy}, \tag{3}$$

where $Stress_{ym}$ is one of three indicators of financial sectors stress and α_{imd} is the contract fixed effect for the contract on location i, month m, and index d. The contract fixed effects capture the time-invariant component of contract prices of which there is significant heterogeneity. X_{imdy}

consists of the three control variables: the contract-specific margin requirement, the logarithm of the expected index payoff, and the logarithm of the previous month's index value on the same location. The temperature-related variables control for the change in price due to a change in temperature expectations, while the margin requirement controls for the change in price due to a change in margin requirement. I use this regression to analyze the annual variation in prices for the same contract defined along the location, index, and month dimensions. For example, the price of the 2009 New York City February HDD contract will be compared to the price of the New York City February HDD contract in the years 2000-2008 and 2010-2012. β provides the coefficient estimate of interest. In the main hypothesis, I posit that $\beta < 0$ (i.e., prices decrease during periods of financial sector stress).

The three indicators of financial sector stress used are: (1) TED, the spread between the three-month Eurodollar deposit rates and three-month Treasury bill rate (the TED spread) thirty-one days before contract maturity, (2) ΔVIX, the monthly change in the implied volatility of S&P 500 Index options (the VIX) in the month preceding the contract month, and (3) $FinancialCrisis$, an indicator variable equal to 1 during the recent financial crisis. The TED spread and the change in VIX capture funding constraints for financial institutions. The financial crisis period used is October 2008 to December 2009. The bankruptcy filing by Lehman Brothers in mid-September 2008 played a major role in the systemic crisis in the global financial system (Brunnermeier (2009)). October 2008 contracts should be the first impacted by Lehman's collapse because I examine prices one-month before contract maturity. The VIX spiked in September 2008 and did not return to its pre-crisis level until late 2009. The S&P 500 plummeted around the Lehman Brothers bankruptcy, reached its nadir in March 2009, and slowly grew throughout 2009. An end date of December 2009 should capture the majority of the crisis. The results are slightly stronger if a shorter time period is used.

After controlling for contract fixed effects and the expected index value, any variation in contract prices should be due to unobserved movements in market expectations of temperatures, changes in the market structure or shifts in the contract supply, and demand curves. The identifying assumption in the main test is that the remaining variation in prices due to unobserved changes in market expectations or market structure is uncorrelated with the financial crisis. The validity of this assumption is critical to the interpretation of the results, so I will briefly discuss each of the potential sources of bias.

I observe a decrease in contract prices during the financial crisis. For this to be due to a bias in estimated expectations, market expectations must have been systematically more *mild* than forecasted temperatures during periods of financial sector stress. This is highly unlikely. Additionally, realized temperatures were significantly more extreme in the HDD months. This is inconsistent with unusually mild temperature forecasts driving the results. Lastly, when realized temperatures are included as controls, there is no change in the statistical or economic significance of the estimates.

Another concern is that I use 2008 margin requirements as a proxy for margin requirements pre-2008, which may lead to bias in the estimation. The CME chooses margin levels to cover approximately 99% of price moves during a trading day. The volatility of the underlying temperature is relatively stable over time; therefore, it is unlikely that margins varied significantly in the pre-2008 period. It is especially unlikely that unobserved margin changes are correlated with financial sector stress, considering that margin requirements did not change during the financial crisis.

To further analyze the role of financial sector stress in affecting asset prices, I conduct difference-in-difference tests examining the differential impact of financial sector stress on contracts with different margin requirements and total risk. I present the empirical strategy with the contract's margin requirement as the cross-sectional variable of interest, but the same method is used in the total risk regressions. The regression is specified as:

$$log(Price_{imdy}) = \alpha_{imd} + \beta \cdot Stress_{ym} + \lambda \cdot Margin_{imdy} + \gamma \cdot Stress_{ym} \cdot Margin_{imdy} + \psi_X \cdot X_{imdy} + \epsilon_{imdy}. \tag{4}$$

The stress variable, $Stress_{ym}$, controls for the average change in price due to financial sector stress and any mis-measurement of the expected index correlated with stress that is constant across contracts.[19] $Margin_{imdy}$ controls for any change in price due to a change in the margin requirement for a contract. γ will capture the differential change in price of high versus low margin contracts during periods of financial sector stress. Only if the mis-measurement of the expected index was systematically different for high-margin contracts during the financial crisis would the regression

[19] In unreported tests, I include time (year-month) fixed effects in the VIX and TED spread regressions. This has no impact on the economic or statistical significance of the results.

be misidentified. If increased funding constraints lead to a decrease in prices, then γ should be less than 0, as financial institutions should be less willing to take more "capital-intensive" positions during a period of stress.

B. Price Results

I estimate the impact of financial sector stress on contract prices in the weather derivatives market by estimating Equation 3. Results of the main test are reported in Table IV. In columns (1)-(3), the financial sector stress proxy is the *Financial Crisis* dummy, the TED spread, and the monthly change in the VIX, respectively. I cluster standard errors at the year-month level in all regressions. The coefficient estimates are negative for all three stress proxies, with the TED spread and the change in the VIX significant at the 1% level and the financial crisis dummy significant at the 10% level. During the financial crisis, contract prices one-month before maturity decreased by 2.18% per month, or a 26% annualized discount, on average. A 100 bps increase in the TED spread decreases prices by 2.54%. Similarly, an increase in the VIX of 10% is associated with a 1.89% decrease in contract prices. These results support the hypothesis that financial sector stress has a meaningful impact on prices in the weather derivatives market.

The effect of financial sector stress on prices is economically quite large. The average dollar decrease in contract price during the financial crisis is 7.5% of the average contract notional value and the percentage decline is about 41% of the average HDD contract margin requirement.[20] The notional value of the CME weather derivatives market in 2009 was $15.1 billion. If the effect in other weather derivative markets was similar to the effect in the monthly futures market, the direct increase in hedging costs during the financial crisis is approximately $1.13 billion. This estimate does not consider the indirect costs due to the lower quantity of risk being shared in the market.

The TED spread is the strongest predictor of price movements both in terms of statistical significance of the coefficient and the improvement in the within R-squared. This is likely because the TED spread measures the funding costs of financial institutions directly, while changes in the VIX and the *Financial Crisis* dummy are indirect measures of funding costs. Additionally, the TED spread measure needs fewer assumptions than the other two measures. For example, it is not

[20] The average dollar decrease in price is calculated as: $-0.0281 \times \overline{Price} = \$375$. The notional value is calculated as two times the historical standard deviation of the monthly degree day index. The average notional value per contract is $5,000.

clear what is the optimal time interval over which to calculate VIX changes (i.e., monthly, weekly, daily, etc.) or the exact timing of the financial crisis. Therefore, it is not surprising that the TED spread best captures price movements due to financial sector stress.

Examining the control variables, prices are highly correlated with the expected index value and the past month's index. A regression including only the two temperature-related variables has a within R-squared of 47% and an overall R-squared of 95.1% (see Appendix C for results). The controls for temperature expectations do a good job of explaining price movements due to market expectations. Further, the results are robust to controlling for realized temperatures, not controlling for past month temperatures, and not controlling for market expectations at all (see Appendix C). It is highly unlikely that unobserved changes in market expectations (i.e., not accounted for by the control variables) are driving the results.

Changes in the margin requirement are unrelated to contract prices. The coefficient on margin is close to zero and insignificant in all regression specifications in Table IV. Small changes in margin requirements for the same contract do not seem to matter for contract pricing. This is consistent with financial institutions being insensitive to margin requirements when their capital constraints do not bind (Garleanu and Pedersen (2011)).

To further investigate whether capital constraints are affecting contract prices, I examine the cross-sectional impact of financial sector stress on contracts with different levels of margin and total risk. All else equal, if a financial institution is capital constrained, its required return on a position is increasing in the shadow cost of capital and the position's margin requirement (Garleanu and Pedersen (2011)). If an adverse shock to financial sector capital and increased funding constraints are driving the decrease in prices, greater price discounts should be seen in contracts with higher margin requirements. Additionally, positions in the weather derivatives market cannot be perfectly hedged as the underlying is not tradable. This leaves financial institutions exposed to the idiosyncratic risk of the contract. An increase in idiosyncratic risk increases the likelihood of having to raise costly external capital and the amount of capital financial institutions must have available to cover price movements. This amount is likely beyond the margin requirement for longer-term positions. As funding constraints increase, financial institutions should be less willing to take on contracts with greater idiosyncratic risk.

To test for the impact of financial sector stress on contracts with different margin requirements, I estimate Equation 4. If margin is priced when funding constraints tighten, then the interaction between the proxies of financial sector stress and margin should be negatively related to prices. The results are reported in Table V. Consistent with financial sector stress differentially impacting markets with greater margin requirements, the coefficients on the interaction term are negative and significant across all specifications. The TED spread and *Financial Crisis* dummy are significant at the 1% level. The coefficient on the *Financial Crisis* dummy and margin interaction term is -0.0266, which corresponds to a 2.66% greater price discount with an increase in the margin requirement of 1% during the financial crisis. For a Las Vegas HDD contract with a margin requirement of 5.4%, the regression implies a decrease in the contract price of 2.2% during the crisis. For the higher margin Dallas HDD contract with an 8% margin, the estimated price discount would be 9.1%. High margin contracts experience a much greater discount during periods of financial sector stress.

The results for total risk are presented in Table VI. The regression specification is similar to Equation 4. The evidence shows that total risk is priced as well. The coefficients are negative and significant at the 1% level for all regression specifications. These results indicate that more volatile contracts experienced relatively greater discounts during the financial crisis. Economically, a one standard deviation increase in a contract's coefficient of variation is associated with a decrease in price of approximately 8% during the financial crisis. For a Cincinnati April HDD contract, which has a coefficient of variation of 0.21, the coefficient estimates imply a price discount of 1.3% during the crisis. For a higher risk Atlanta February HDD with a coefficient of variation of 0.25, the coefficients imply a price discount of 4.6%. Similarly, the coefficients from the TED spread regression imply that an increase in the TED spread of 1% leads to a decrease in price of 4.0% for the Atlanta February HDD contract. Based on these estimates, a contract in the top 75% of the total risk distribution experiences a discount in price with an increase in the TED spread of 1%. These results support the notion that financial institutions become effectively more averse to total risk during periods of financial sector stress.

Margin requirements are based off market conditions, mainly price volatility. If margin requirements are just proxies for idiosyncratic risk or vice versa, then the results presented above may be redundant and it would be difficult to disentangle the decrease in prices due to margin from the decrease due to total risk. Beneficial for this study, margins are not a linear function of total risk. The correlation between margin requirements and coefficients of variation is 0.47. The two are not perfectly correlated for two reasons: (1) margins are set at the location-index level, while contract risks are at the contract level, and (2) margin requirements are clustered at certain numbers (e.g., 4 and 7), even though risks are not identical across locations with the same margin.

To determine whether margin and contract risk have unique effects, I run difference-in-difference regressions including a three-way interaction between margin, total risk, and the financial crisis dummy. If both margin requirements and contract risk are drivers of the price discount during financial sector stress, then we should see a negative and significant coefficient on the three-way interaction.

Results are reported in Table VII. Examining the regressions without the triple interaction term, contract risk remains negative and significant across all specifications. Margin has mixed results. Consistent with margin *and* total risk affecting prices, the coefficient on the triple interaction is negative and significant in all regressions. Contracts with both high risk and high margin requirements are most affected by financial sector stress, although total risk appears to have a greater effect than margin requirements. This could be due to total risk better estimating the capital necessary to cover long-term positions in the market. In sum, it appears that both margin levels and contract risk appear to matter to stressed financial institutions.

C. Notional Value and Open Interest

The previous results show that contract prices decrease during periods of financial sector stress. These results are consistent with a shift in the supply curve of capital, but they are also consistent with an increase in hedging demand. If hedging demand is driving the decrease in contract prices, then the open interest and the notional value of contracts should increase during the financial crisis. If a decrease in the supply of capital is driving the decrease in prices, then these quantities should decrease during periods of financial sector stress.

In Figure 3, I plot total open interest in the monthly temperature futures market by quarter. Open interest grew rapidly from introduction in 1999 until the fourth quarter of 2008, then fell by nearly 40% with the start of the financial crisis. The decrease in open interest is consistent with a decrease in the supply of financial institution capital, not an increase in end user hedging demand during the crisis. At the contract level, of the 136 contracts (defined at the location, month, and index) that traded in the 12 months pre-crisis, 65 contracts experienced a decline in open interest of at least 66% during the first 12 months after the Lehman Brothers bankruptcy. Thirty-six contracts collapsed completely (zero open interest), and only 33 experienced an increase in open interest. Surprisingly, there were 46 contracts with zero open interest in the 12 months pre-crisis (October 2007 to September 2008) that traded during the crisis.[21]

The CME monthly temperature futures market did not fully recover after the crisis during the sample period. One concern may be that activity migrated to the OTC and seasonal futures market during and after the crisis. In other words, activity just shifted across markets and the quantity of risk shared did not change. However, this is not the case. The notional value of the entire weather derivatives market decreased dramatically during the financial crisis. The April 2007 to March 2008 notional value was $32B, the 2008-2009 value was $15B, and the 2009-2010 value was $10B (Weather Risk Management Association (2011)).[22] The 50% decline in notional value between 2007-2008 and 2008-2009 is remarkable and contradicts an increase in hedging demand driving the decrease in prices. The entire weather derivatives market did not completely rebound after the crisis, but the notional value increased by 20% to $12B in 2010-2011 (Weather Risk Management Association (2011)). Diagnosing the lack of renewed interest in the market is beyond the scope of this paper, but one possible explanation is participants are unwilling to make a market due to an increase in the risk of another common liquidity shock (Fernando, Herring, and Subrahmanyam (2008)). In sum, the decrease in prices during the financial crisis was not driven by increased hedging demand; instead, it was driven by a decrease in the supply of financial capital to the market.

D. Impact on End Users

In this section, I examine how the decrease in the supply of risk-bearing capital during periods of financial sector stress affects end users. PGY examine the effect of weather derivative introduction on energy utilities. They find that after weather derivative introduction, (1) energy utilities that use weather derivatives are less exposed to weather shocks, and (2) firms most exposed to weather

[21] In the crisis, April and October both saw a dramatic increase in the number of contracts traded (14 in each month). The cause of this increase is unclear. It could be due to investors hedging seasonal contract positions after the onset of the crisis. Post-crisis there were very few contracts traded in these months.

[22] The Weather Risk Management Association surveys market participants and the CME each April about weather derivative activities over the previous calendar year. WRMA computes a market-wide notional value across all weather derivative contracts, both OTC and exchange-traded.

risk pre-derivative introduction are more likely to use weather derivatives and experience greater valuation, increase investment and leverage, and decrease cash holdings. Their analysis ends in 2008. I extend their sample period through the first quarter of 2012 and examine firm outcomes in the financial crisis. My main hypothesis is that the decrease in risk-sharing in the weather derivatives market during the crisis exposed firms to greater amounts of weather risk and this impacts firm valuation, investment, and financing decisions of firms. In other words, PGY showed the benefits enjoyed by end users from the introduction of weather derivatives when financial markets are functioning properly and I examine the decline in these benefits during a period of financial sector stress.

I run two sets of tests. First, I compare the exposure of energy utilities to mild weather shocks during the financial crisis (2008:Q4 to 2009:Q4) to their exposure in two other time periods: pre-weather derivative introduction (before 1997) and post-weather derivative introduction outside of the crisis (1997-2008:Q3 and 2010-2012). Second, I examine the relative change in valuation, investment, leverage, and cash holdings of firms highly exposed to temperature risk versus firms less exposed to temperature risk during the crisis.

If hedging temperature risk becomes more costly during the financial crisis, then there should be a decline in end user hedging. This will increase end users' sensitivity to mild temperature shocks. To test this, I run regressions of the form:

$$\begin{aligned} Y_{it} &= \lambda \times WeatherShock_{it} + \gamma \times WeatherShock_{it} \times PostIntro_t \\ &+ \beta \times WeatherShock_{it} \times FinancialCrisis_t + \alpha_i + q_t + \delta \times X_{i,t-1} + \epsilon_{it}, \end{aligned} \tag{5}$$

where Y_{it} is either the logarithm of net income or net income-to-assets, $WeatherShock_{it}$ is a mild temperature shock, $PostIntro_t$ is a dummy variable equal to 1 in the years 1997-2012 excluding the crisis period, $FinancialCrisis_t$ is a dummy variable equal to 1 in the crisis period (4th quarter of 2008 through 2009), α_i is a firm fixed effect, q_t is a year-quarter time fixed effect, $X_{i,t-1}$ are control variables (lagged operating return on assets and lagged logarithm of total assets), and ϵ_{it} is the error term. A mild temperature shock is defined as a quarterly energy degree days realization in the bottom 20% of realizations measured at the firm level. The lower the EDD, the more mild the temperatures during the period and the lower the energy demand. The coefficient λ captures the average effect of a mild temperature shock on net income pre-1997, γ captures the relative sensitivity of firm revenue or net income to weather shocks post-derivative introduction compared to pre-1997, while β captures the relative sensitivity during the crisis period compared to pre-1997. The difference between β and γ captures the effect of the collapse of the weather derivatives market. If there is no effect, I would expect $\beta = \gamma$. I perform Wald tests to test for a difference in coefficients.

Regression results are presented in Table VIII. The regressions presented in columns (1) and (3) include all firms. The regressions presented in columns (2) and (4) include only firms in the top 25% of mild temperature risk exposure ($\beta_{EDD} \times \sigma_{EDD}$) measured in the pre-derivative introduction period. The dependent variable in columns (1) and (2) is the logarithm of net income and in columns (3) and (4) is the ratio of net income to assets. Consistent with PGY, the effect of a mild temperature shock is negative and significant at the 1% level in the pre-1997 period for three of the four specifications. The coefficient is negative, but not significant for the logarithm of net income when all firms are included. The effects are economically significant with an average decline in net income of 3.72% for the firms with greater exposure to mild temperatures. After weather derivative introduction, this sensitivity decreases. For highly exposed firms, the introduction of weather derivatives nearly eliminates the sensitivity of net income to mild temperature in normal times.

During the financial crisis, firm weather risk exposure increases. Firms are just as as exposed or more exposed to temperature shocks as in the period before weather derivative introduction. Firms most sensitive to mild temperature are especially affected by the crisis. A Wald test for the difference in coefficient between the post-introduction and financial crisis period is significant at the 1% (10%) level for the net income to assets and the logarithm of net income regressions, respectively. In sum, the revenue or income smoothing benefits from weather derivatives are not realized during periods of financial sector stress. This is consistent with there being less weather risk sharing during the crisis.

PGY find that firms most exposed to temperature risks (measured by absolute weather induced volatility) experienced a large positive impact from the introduction of weather derivatives in the years 1997 to 2008. I examine whether the relative increase in valuation, investment, and leverage, as well as the decrease in cash experienced by these firms declined in magnitude during the crisis. I run difference-in-difference tests following a similar methodology as PGY. The first difference is across firms: the difference between firms highly exposed to weather risk versus firms less exposed. The less exposed firms are less likely to hedge (PGY). They serve as controls for firms that are more likely to hedge their weather risk. The second difference is over time. I compare firm-level outcomes during the crisis to firm-level outcomes in two other states of the world: (1) the period pre-weather derivative introduction (1977-1996) and (2) the period post-weather derivative introduction outside of the financial crisis (1997-2008:Q3, 2010-2012).

Specifically, I run the following regression:

$$Y_{it} = \gamma \times HighRisk_i \times PostIntro_t + \beta \times HighRisk_i \times FinancialCrisis_t + \alpha_i + q_t + e_{it}, \qquad (6)$$

where Y_{it} is the firm-level outcome for firm i in period t, $HighRisk_i$ is a dummy variable equal to 1 if firm i is in the top 25% of firms most exposed to temperature risks ($|\beta_{EDD}| \times \sigma_{EDD}$), $PostIntro_t$ is a dummy variable equal to 1 if weather derivatives are in existence (i.e., 1 for all years 1997 or later), $FinancialCrisis_t$ is a dummy variable equal to 1 during the crisis period (fourth quarter of 2008 through 2009), α_i is a firm fixed-effect, q_t is a year-quarter time fixed effect, and e_{it} is the error term.

The five dependent variables examined are related to investment (CAPEX/assets), financing (book leverage to assets, net debt to assets, and cash to assets), and valuation (market-to-book ratio). γ captures the improvement in firm outcomes due to the existence of weather derivatives outside of the crisis period and β captures the improvement in firm outcomes due to the existence of weather derivatives inside the crisis period. The difference between β and γ captures the relative effect of the collapse in the weather derivatives market. The identifying assumption is that the financial crisis period and post-introduction period are uncorrelated with other unobserved factors that may differentially affect firm outcomes for high exposure versus low exposure firms.

Results are presented in Table IX. Consistent with PGY, firms most exposed to weather risk increase investment and leverage, hold less cash, and experience significantly higher valuation after weather derivative introduction. The results are economically significant. The relative increase in the market-to-book ratio is almost 6%, the relative increase in capital expenditures is nearly 65% of one standard deviation, the increase in leverage is 3.84% for book leverage to assets and 4.7% for net debt to assets, and cash to assets declines by approximately 48% of one standard deviation.

Most of the positive effects of weather derivative markets are diminished during the financial crisis. High-risk firms have lower relative investment during the crisis than in the rest of the post-introduction period. The coefficient is approximately 40% smaller in magnitude. The difference between the post-introduction coefficient and financial crisis coefficient is significant at the 3% level. The leverage benefit is significantly lower during the crisis for the high-risk firms with coefficients of 0.0117 and 0.178 for both book leverage to assets and net debt to assets. These coefficients are less than one-third of the post-introduction coefficients. The difference in coefficients is significant at the 1% level in both specifications. Similarly, the relative decrease in cash holdings shrinks during the crisis. The coefficient during the crisis is just two-thirds of the post-introduction coefficient, although the difference is not significant. The relative difference in the market-to-book ratio actually increases slightly during the crisis, although the coefficient is insignificant with a p-value of 0.7519. The decline in weather risk-sharing does not seem to impact the market-to-book ratio over the relatively short crisis period.

Overall, these results are consistent with financial sector stress affecting firm-level outcomes through the hedging channel. A majority of the benefits experienced by firms most exposed to temperature risk after weather derivatives market introduction diminish during the financial crisis as hedging costs increase.

E. Robustness

E.1. Expected Return, Expected Return on Margin, and Realized Return

In the preceding analysis, I examined contract prices controlling for fundamentals using the estimated expected index. As an alternative test for the effect of financial sector stress, I examine contract returns as the dependent variable. The three return measures I examine are the estimated expected return, the estimated expected return on margin, and realized return. All three return measures will have significantly more noise than the true expected return. For example, the standard deviation of monthly realized returns is 16.7% (see Table II). This additional noise will decrease the power of the tests.

I focus on the TED spread as the measure of financial sector stress since it has the greatest predictive power for movements in contract prices in the preceding regressions.[23] I regress the return variables on the TED spread, as well as its interaction with margin and total risk. I control for contract fixed effects since expected returns likely differ across contracts.[24]

I present the regression results in Table X. All three return measures are significantly positively related to the TED spread. The coefficient on the TED spread in the expected return, expected return on margin, and realized returns regression are significant at the 5%, 10%, and 1% levels, respectively. The realized return regression coefficient implies a 4.16% increase in realized monthly returns with a 1% increase in the TED spread. The expected return regression coefficient implies a 1.61% increase in the expected return. For the expected return on margin regression, the coefficient implies an increase of 25.02%. The capital necessary to cover price movements over one-month is somewhere between the required maintenance margin and the contract price. Therefore, the expected return on margin considered here will likely overstate the expected return on capital necessary to meet obligations, while the expected return results will likely understate the true expected return on capital. These results further support the hypothesis that financial institutions become effectively more risk averse during periods of financial sector stress, which leads to lower prices and higher expected returns.

Examining the interaction terms, Table X shows that all three return measures are increasing in margin and total risk during periods of high TED spreads. The coefficients are statistically significant in the regressions with either expected return measure as the dependent variable. Surprisingly, margin appears to matter even in the expected return on margin regression. This implies that expected returns are increasing non-linearly in margin. This could be due to an additional illiquidity premium. For example, if fewer investors buy higher margin contracts, it will likely be more costly for financial institutions to reverse their position in the future. This will amplify the effects of margin during periods of financial sector stress.

[23]The results using the change in the VIX or the financial crisis dummy are presented in Appendix C. The results are similar in magnitude, although not as statistically significant in some specifications.

[24]Expected returns may vary across contracts with different risk profiles, margin requirements, hedging demand, and possibly other sources of heterogeneity.

E.2. Systematic Risk

A maintained assumption throughout the previous tests is that there is zero systematic risk in the weather derivatives market. This assumption is in line with the prevailing sentiment among market participants. The Weather Risk Management Association website[25] states "weather essentially is uncorrelated with secular or systemic risk in general financial markets and provides an opportunity for diversification for traders." Unlike stocks, whose discount rates and cash flows are driven by changes in the economy, it is not obvious how or in what direction temperature outcomes in Cincinnati, for example, would be correlated with the return on the market. Supporting this view, Cao and Wei (1999) implement a Lucas (1978) equilibrium model with temperature as a fundamental variable and find little evidence that temperature risks should be priced.

Although realized returns are noisy and the return data is a relatively short time series, I attempt to measure the amount of systematic risk in the market. Ideally, tests for systematic risk would be conducted at the individual contract level because risks will differ across the location, month, and degree index dimensions. Contract-level regressions are not feasible with only 13 years of data (i.e., 13 observations per contract). Instead, I run CAPM regressions at the market level. Regressions are 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. Returns are calculated using "physical" returns. 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.[26] Financial institutions enjoy

[25] `http://www.wrma.org`

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

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.

One may be concerned that an increase in the price of systematic risk is driving the relationship between financial sector stress and contract prices. This is not the case. If the price of systematic risk increased during the crisis, prices would increase on average because the position of financial institutions has negative systematic risk. If anything, not adjusting for systematic risk will bias the regressions against identifying a decrease in contract prices. As further evidence that contract prices are not being driven by systematic risk, in Appendix B, I control for a location's beta in the difference-in-difference regressions. I find that the coefficients on margin and total risk are basically unchanged and still highly significant. An increase in the price of systematic risk cannot explain the decrease in contract prices during periods of financial sector stress.

For my tests to be properly identified, the model estimated expected index must not be systematically biased during the financial crisis. This bias may manifest if market forecasted temperatures or the temperature model are systematically biased during periods of financial sector stress. To explain the observed results, bias in the forecasted temperatures would have to be correlated with the proxies for financial sector stress and the bias would have to be larger for high-margin and riskier contracts. This assumption is impossible to test without even more precise knowledge of the market's forecasted temperatures. As a check of robustness, I can control for market expectations using the realized index. This regression gives the market a lookahead bias. Results are presented in Appendix C and are unaffected by controlling for the realized index. The results are not driven by bias in the estimated expected index.

IV. Conclusion

During periods of financial sector stress, financial institutions' capital constraints may bind. This will limit their supply of capital to various markets and affect market equilibrium prices and quantities. I examine the effect of financial sector stress on prices in a novel setting: the CME's weather derivatives market. The structure of the market allows me to disentangle price movements due to financial sector stress from price movements due to fundamentals.

During the recent financial crisis, contract prices in the weather derivatives market one-month from maturity decreased by over 2% and notional value declined by 50%. Prices are significantly negatively correlated with measures of financial institutions' funding constraints (the TED spread and changes in the VIX). Higher margin contracts and contracts with more total risk experience a greater decline in prices during periods of financial sector stress as financial institutions are less willing to supply capital to these capital-intensive markets. The results show that the cost for end users to hedge weather risk increased and there is less risk sharing during periods of financial sector stress.

Examining end users, I find that the exposure of end users to temperature shocks increased during the financial crisis, which is consistent with the decline in risk sharing during the crisis. Additionally, I find that the relative increase in investment and leverage experienced by weather sensitive end users after weather derivative introduction diminished during the crisis. Although I examine a relatively small and youthful market, the effects documented could exist in other markets where risks cannot be perfectly hedged. The results give insight into the risks investors and hedgers face, the importance of financial sector capital in the pricing of contracts, and how risks are shared in the economy.

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Table I
Contract Locations and Introduction Dates

This table presents information on contract locations and introduction dates. Introduction Year is the year the location was introduced. City is the closest city to the underlying weather station.

Introduction Year	**City**
1999	Atlanta
	Chicago
	Cincinnati
	New York City
2000	Dallas
	Des Moines
	Las Vegas
	Philadelphia
	Portland
	Tucson
2003	Boston
	Houston
	Kansas City
	Minneapolis
	Sacramento
2005	Baltimore
	Detroit
	Salt Lake City
2008	Colorado Springs
	Jacksonville
	Little Rock
	Los Angeles
	Raleigh-Durham
	Washington D.C.

Table II
Summary Statistics for Monthly Weather Derivatives

This table presents summary statistics for the monthly weather derivatives. Panel A presents open interest, margin requirements, and coefficient of variation statistics. *Open Interest* is the maximum contract open interest in the period at least 31 days before maturity. *Margin Requirement* is the speculator maintenance margin requirement, while *Coefficient of Variation* is the coefficient of variation ($\frac{\sigma_{DD}}{\mu_{DD}}$) of the historical temperature degree index over the years 1974-2011. Panel B presents contract prices and returns for HDD contracts. *Price* is the average contract price one-month before maturity, *E[Index]* is the forecasted index payoff, *Index* is the realized index, *Expected Return* ($E[r]$) is the estimated expected return to going long the future, *Realized Return* (r) is the realized return to going long the future, and *Expected Return on Margin* ($E[r \times \frac{1}{m}]$) is the expected return on margin to going long the future. I present the number of observations (N), mean (Mean), standard deviation (Std. Dev.), 10th percentile (10th), median (Median), and 90th percentile (90th). Each observation is a location-index-month-year. For the premium and return variables, t-tests of mean equal to 0 are conducted.

Panel A: Contract Characteristics						
Variables	**N**	**Mean**	**Std. Dev.**	**10th**	**Median**	**90th**
Open Interest	644	214	360	12	100	515
Margin Requirement	644	5.38	1.63	4.00	4.80	8.00
Coefficient of Variation	644	0.22	0.10	0.14	0.20	0.31
Panel B: Prices and Returns						
Variables	**N**	**Mean**	**Std. Dev.**	**10th**	**Median**	**90th**
Price	644	13,341	6,822	4,964	12,914	22,560
E[Index]	644	13,479	7,040	4,643	12,886	23,228
Index	644	13,151	7,148	4,460	12,365	23,190
Expected Return ($E[r]$)	644	0.51	10.84	-11.38	1.03	11.91
Realized Return (r)	644	-1.89***	16.75	-23.00	-1.64	17.65
Expected Return on Margin ($E[r \times \frac{1}{m}]$)	644	10.76	202.86	-222.42	19.21	223.48

*** p<0.01 ** p<0.05 * p<0.1

Table III
Summary Statistics for End Users

This table presents summary statistics for energy utilities (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, revenue, and net income are in thousands of March 2008 dollars (adjusted using the Consumer Price Index). *Operating Income/Assets* is the ratio of operating income before depreciation to total assets. *M-B Ratio* is the market-to-book ratio calculated: (book value of total assets + market value of equity - book value of common equity - book value of deferred taxes)/(book value of total assets). *CAPEX/Assets* is the ratio of capital expenditures to total assets. *Book Lev./Assets* is the ratio of long-term debt plus debt in current liabilities to total assets. *Net Debt/Assets* is the ratio of long-term debt plus debt in current liabilities minus cash and short-term investments to total assets. *Cash/Assets* is the ratio of cash to total assets. *Net Income/Assets* is the ratio of net income to total assets. *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. *HDD (CDD, EDD) Beta* is the the coefficient from a regression of revenue-to-assets on heating (cooling, energy) degree days (in ten-thousands) controlling for the logarithm of total assets. *Abs. Value of EDD Beta* is the absolute value of EDD Beta. *EDD Standard Deviation* is the standard deviation of quarterly energy degree days (in ten-thousands). *Mild Temperature Exposure* is the product of EDD beta and EDD standard deviation. *Absolute Weather Induced Volatility* is the product of the absolute value of EDD beta and EDD standard deviation. 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	31,564	6,215	8,248	392	3,042	16,603
Revenue	31,564	632	761	58	331	1,674
Net Income	31,564	54.71	83.37	-0.25	26.87	154.30
Operating Income/Assets	31,564	0.030	0.015	0.014	0.028	0.047
M-B Ratio	18,585	1.012	0.146	0.854	0.989	1.200
CAPEX/Assets	8,057	0.017	0.011	0.007	0.014	0.028
Book Lev./Assets	31,564	0.371	0.081	0.275	0.369	0.469
Net Debt/Assets	31,564	0.359	0.084	0.255	0.359	0.461
Cash/Assets	31,564	0.012	0.018	0.001	0.005	0.033
Net Income/Assets	31,564	0.010	0.009	-0.000	0.009	0.020
Heating Degree Days	31,564	1,311	1,178	42	923	3,076
Cooling Degree Days	31,564	263	380	0	83	797
Energy Degree Days	31,564	1,574	965	608	1,157	3,078

Panel B: Firm Weather Exposure Information						
Variables	**N**	**Mean**	**Std. Dev.**	**10th**	**Median**	**90th**
HDD Beta (β_i^{HDD})	264	0.296	0.398	-0.006	0.137	0.863
CDD Beta (β_i^{CDD})	264	-1.673	6.993	-3.530	0.173	0.537
EDD Beta (β_i^{EDD})	264	0.263	0.410	-0.039	0.109	0.851
Abs. Value of EDD Beta ($\lvert\beta_i^{EDD}\rvert$)	264	0.308	0.377	0.013	0.131	0.851
EDD Standard Deviation	264	0.087	0.034	0.031	0.097	0.123
Mild Temperature Exposure $\beta_{EDD} \times \sigma_{EDD}$	264	0.022	0.033	-0.003	0.008	0.085
Absolute Weather Induced Volatility $\lvert\beta_{EDD}\rvert \times \sigma_{EDD}$	264	0.024	0.031	0.001	0.010	0.085

Table IV
The Effect of Financial Sector Stress on Contract Prices

This table presents the results of an examination of the effect of financial sector stress on contract prices in the weather derivatives market. 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. 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. *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)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*
Financial Crisis	-0.0218*		
	(0.0127)		
TED		-0.0254***	
		(0.0052)	
Δ *VIX*			-0.0019***
			(0.0005)
Log(E[Index])	0.4800***	0.4701***	0.4701***
	(0.0624)	(0.0617)	(0.0659)
Log($Index_{m-1}$)	0.0279**	0.0271**	0.0297**
	(0.0135)	(0.0120)	(0.0129)
Margin	-0.0046	-0.0060	-0.0048
	(0.0056)	(0.0056)	(0.0059)
Observations	644	644	644
Contract FEs	Yes	Yes	Yes
R^2	0.4822	0.5106	0.4966

Table V
The Effect of Margin on Contract Prices During Periods of Financial Sector Stress

This table presents the results of an examination of the effect of margin requirements on contract price during periods of financial sector stress. 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 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 (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 * $p < 0.1$.

VARIABLES	(1) *Log(Price)*	(2) *Log(Price)*	(3) *Log(Price)*
Financial Crisis	0.1217***		
	(0.0376)		
*Financial Crisis*Margin*	-0.0266***		
	(0.0087)		
TED		0.0671***	
		(0.0176)	
*TED*Margin*		-0.0174***	
		(0.0040)	
Δ *VIX*			-0.0018***
			(0.0004)
Δ *VIX*Margin*			-0.0001**
			(0.0001)
Margin	-0.0017	0.0024	-0.0006
	(0.0053)	(0.0057)	(0.0061)
Observations	644	644	644
Contract FEs	Yes	Yes	Yes
R^2	0.5184	0.5549	0.5081

Table VI
The Effect of Total Risk on Contract Prices During Periods of Financial Sector Stress

This table reports the results of an examination of the effect of total risk on contract price during periods of financial sector stress. 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. *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 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 * $p < 0.1$.

	(1)	(2)	(3)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*
Financial Crisis	0.1634***		
	(0.0305)		
*Financial Crisis*CV*	-0.8365***		
	(0.1518)		
TED		0.0704***	
		(0.0129)	
*TED*CV*		-0.4418***	
		(0.0646)	
Δ *VIX*			-0.0016***
			(0.0004)
Δ *VIX*CV*			-0.0044***
			(0.0015)
Margin	-0.0018	-0.0041	-0.0030
	(0.0043)	(0.0048)	(0.0055)
Observations	644	644	644
Contract FEs	Yes	Yes	Yes
R^2	0.5917	0.6090	0.5179

Table VII
The Effect of Margin and Total Risk on Contract Prices During Periods of Financial Sector Stress

This table reports the results of an examination of the effect of margin and total risk on contract price during periods of financial sector stress. 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. *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 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*	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*
Stress	0.1444***	-0.2611***	0.0782***	-0.0699*	-0.0011***	0.0012
	(0.0295)	(0.0823)	(0.0166)	(0.0364)	(0.0004)	(0.0010)
*Stress*Margin*	0.0069	0.0699***	-0.0025	0.0212***	0.0006**	0.0005*
	(0.0075)	(0.0156)	(0.0030)	(0.0067)	(0.0003)	(0.0003)
*Stress*CV*	-0.9186***	0.9818**	-0.4155***	0.2728	-0.0189**	-0.0156*
	(0.2019)	(0.3924)	(0.0684)	(0.1900)	(0.0078)	(0.0083)
*Stress*Margin*CV*		-0.2766***		-0.1022***		-0.0021**
		(0.0590)		(0.0313)		(0.0010)
Margin	-0.0022	-0.0041	-0.0029	-0.0036	-0.0164**	-0.0132*
	(0.0043)	(0.0045)	(0.0052)	(0.0054)	(0.0074)	(0.0076)
Observations	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5931	0.6187	0.6096	0.6217	0.5345	0.5494

Table VIII
End User Exposure to Weather Shocks and the Financial Crisis

This table reports the results of an examination of the exposure of firm net income to temperature shocks pre-weather derivative introdution, post-introduction, and during the financial crisis. The dependent variables are the logarithm of quarterly net income (columns 1 and 2) and the quarterly net income to assets ratio (columns 3 and 4). *Weather Shock* is an indicator variable equal to one if the quarterly energy degree days are in the lowest 20% for each firm-quarter. *Post-Intro* is an indicator variable equal to one if the year is 1997 (the weather derivative introduction year) or later. *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). In columns 2 & 4, only firms with *Mild Temperature Exposure* ($\beta_{EDD} \times \sigma_{EDD}$) in the top 25% of firms are included (labeled "High Exposure"). Temperature exposure is calculated in the years pre-1997.All regressions include firm fixed effects, year-quarter fixed effects, and control for lagged operating income to assets and lagged logarithm of assets (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 * $p < 0.1$.

	(1)	(2)	(3)	(4)
VARIABLES	*Ln Net Income*	*Ln Net Income*	*Net Income/Assets*	*Net Income/Assets*
Weather Shock	-0.0057	-0.0372***	-0.0016***	-0.0055***
	(0.0085)	(0.0096)	(0.0003)	(0.0007)
*Weather Shock*Post-Intro*	-0.0173	0.0324*	0.0009***	0.0048***
	(0.0227)	(0.0172)	(0.0003)	(0.0008)
*Weather Shock*Financial Crisis*	-0.0454	-0.0465	0.0003	0.0000
	(0.0998)	(0.0451)	(0.0008)	(0.0017)
Wald Test p-value	0.7672	0.0874	0.4374	0.0064
Observations	31,052	7,162	31,052	7,162
Firms	All	High Exposure	All	High Exposure
Firm FEs	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes
R^2	0.0308	0.1163	0.1005	0.2904

Table IX
Weather Exposure Effect on Value, Investment, and Financing of End Users During the Crisis

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 year-quarter is during the financial crisis time period (Q4 2008 to Q4 2009). All regressions include firm fixed effects and 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) *CAPEX/ Assets*	(2) *Book Leverage/ Assets*	(3) *Net Debt/ Assets*	(4) *Cash/ Assets*	(5) *M-B Ratio*
*High Risk*Post-Intro.*	0.0071***	0.0384***	0.0470***	-0.0087***	0.0580***
	(0.0021)	(0.0099)	(0.0104)	(0.0015)	(0.0220)
*High Risk*Financial Crisis*	0.0043*	0.0117	0.0178	-0.0059**	0.0649**
	(0.0026)	(0.0135)	(0.0149)	(0.0029)	(0.0269)
Wald Test p-value	0.0281	0.0083	0.0080	0.2340	0.7519
Observations	8,057	31,564	31,564	31,564	18,585
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.1323	0.1894	0.1902	0.0387	0.3515

Table X
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 contemporaneous TED spread (*TED*). *Margin* is the contract-specific margin requirement. *CV* is the coefficient of variation of the contract's index (calculated over the years 1974-2011). 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
TED	1.6144**	-5.6939**	-7.0709***	25.0240*	-71.7173	-91.8701***	4.1595***	3.1263	0.9078
	(0.7081)	(2.4646)	(1.6140)	(13.0129)	(45.3564)	(31.7133)	(1.2750)	(4.1262)	(3.7066)
*TED*Margin*		1.3768***			18.2251**			0.1947	
		(0.4976)			(7.7374)			(0.8708)	
*TED*CV*			40.0822***			539.4590***			15.0065
			(7.7690)			(132.7783)			(17.0126)
Margin	-0.0905	-0.7531	-0.2474	-5.6186	-14.3895	-7.7302	-0.0961	-0.1898	-0.1548
	(0.5928)	(0.6859)	(0.5291)	(13.4746)	(13.9216)	(12.8051)	(1.1726)	(1.3117)	(1.1736)
Observations	644	644	644	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0208	0.0574	0.1280	0.0173	0.0380	0.0798	0.0305	0.0307	0.0338

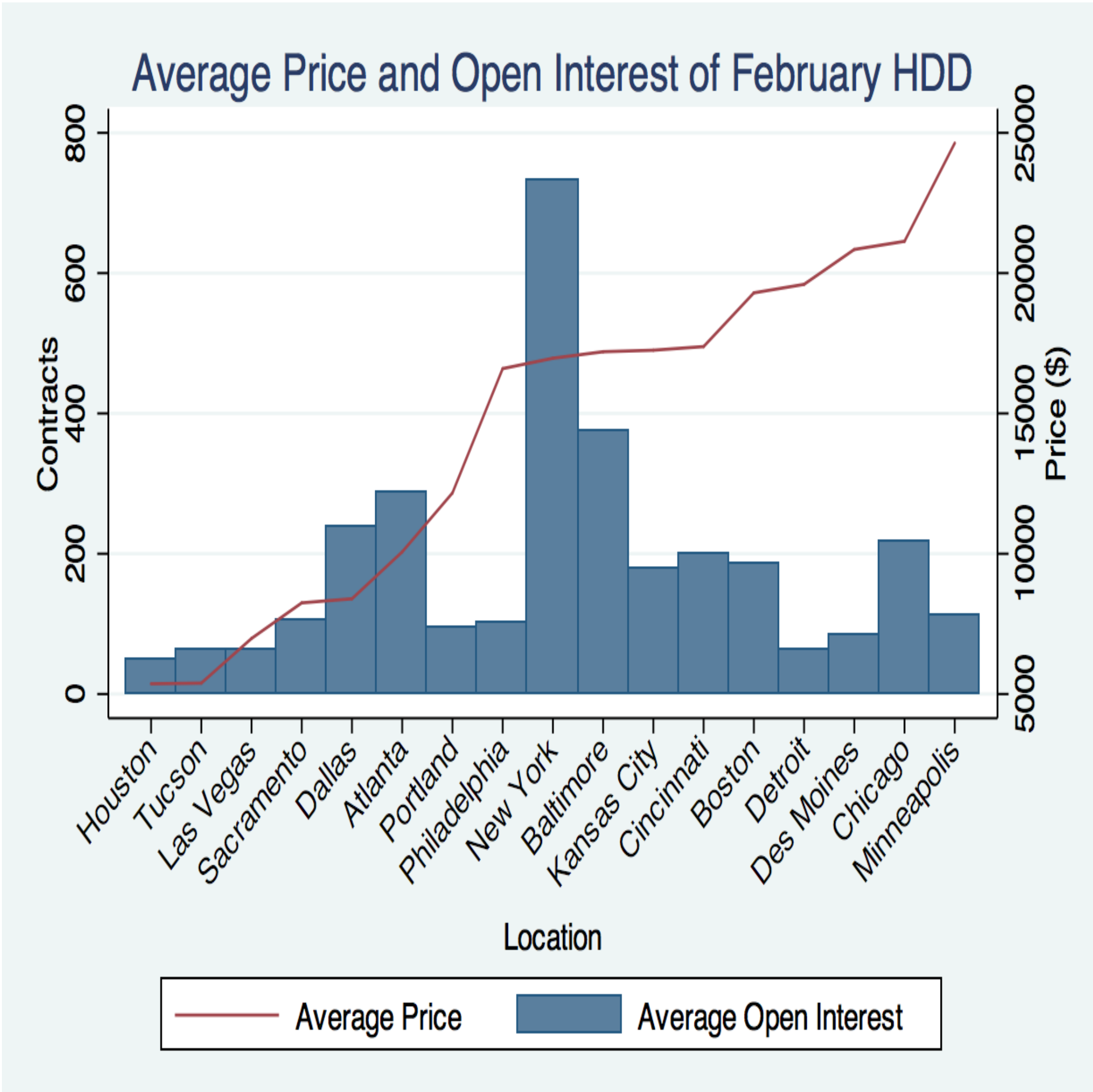

Figure 1. Average Price and Open Interest for February HDD Contracts. This figure shows the average price and open interest for February HDD contracts from 2000 to 2011.

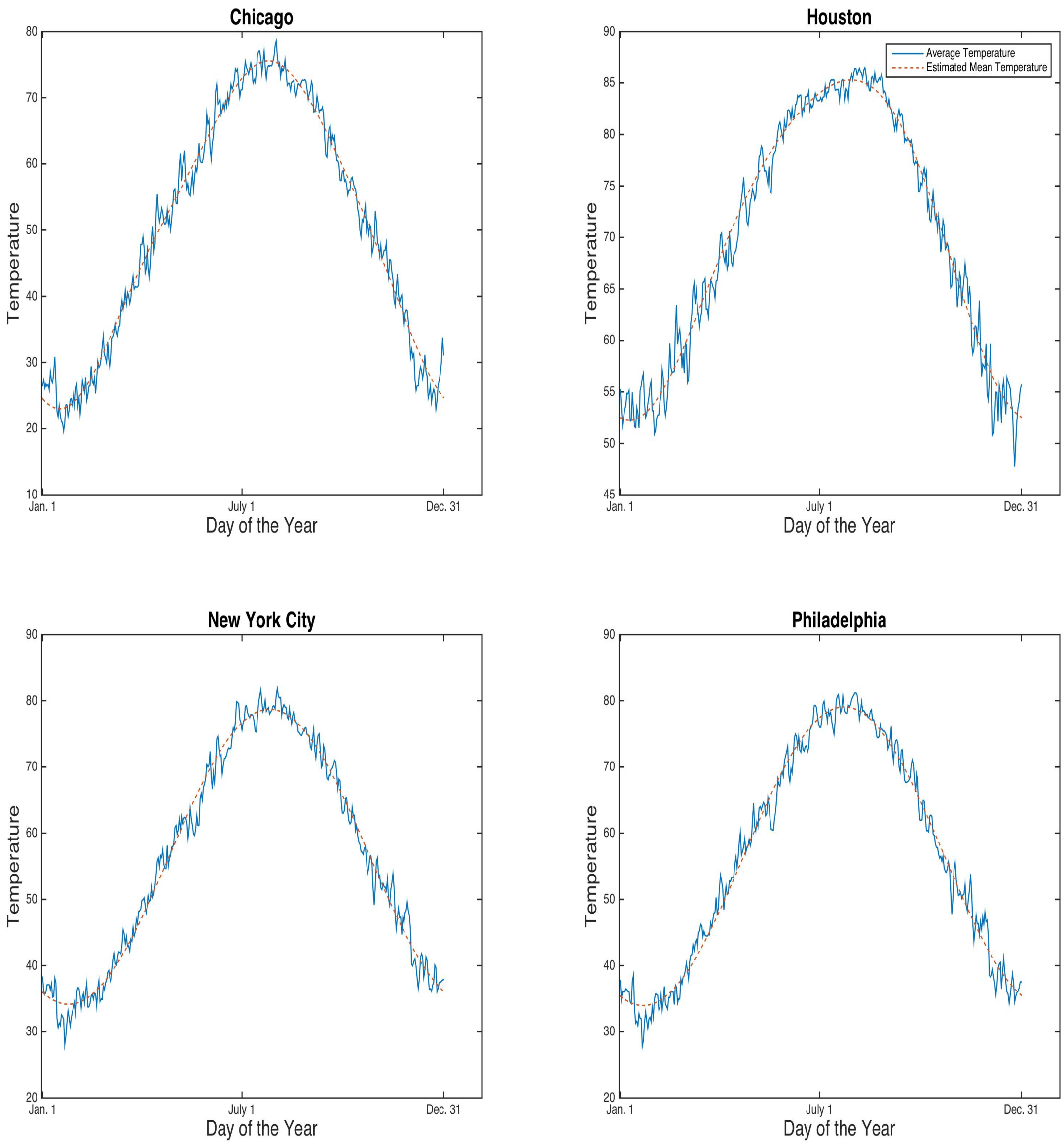

Figure 2. Estimated Mean Temperature vs. Average Temperature. I plot the estimated mean temperature (θ_t) and the average temperature for each day of the year for Chicago, Houston, New York City, and Philadelphia. The parameters of the mean temperature process are estimated separately for each city. The average temperature is calculated over the period from January 1, 1999 to January 31, 2012. 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 $\sigma(t) = \gamma_0 + \sum_{q=1}^{Q} \gamma_p \sin(\frac{2\pi}{365} qt + \psi_p)$.

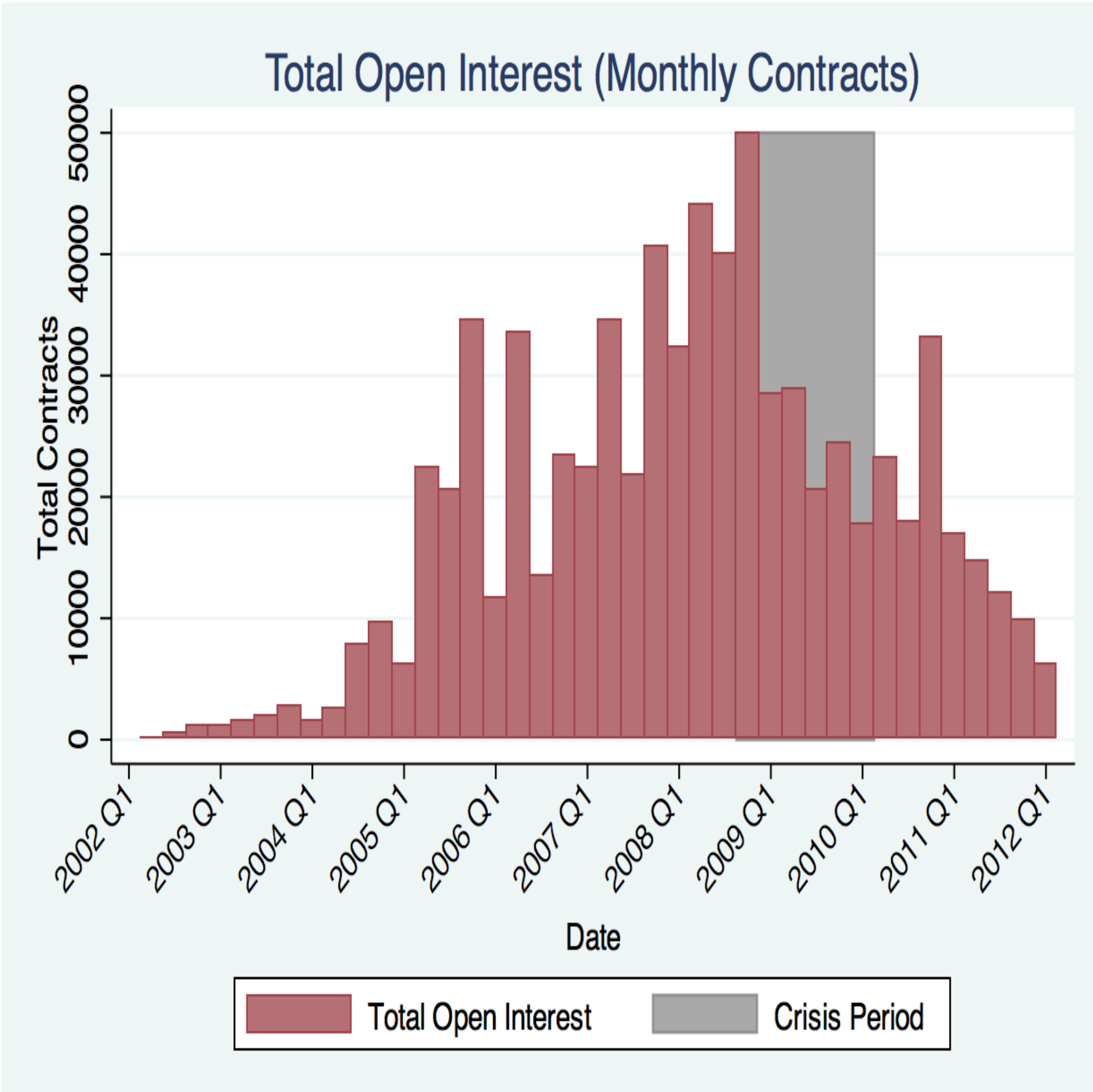

Figure 3. Monthly Open Interest. This figure shows the total open interest (maximum open interest during trading period summed across contracts) by contract year-month.

Appendix

Appendix A. Estimating Expected Index Values

I calculate the expected index value for each contract by combining temperature forecasts from MDA Federal, Inc., with simulated temperatures from a temperature model. I calculate a forecasted index value on each trading day with open interest between 37 and 31 days from contract maturity. I take the average across the days as the expected index value (i.e., one expected index value for each contract). Thirty-seven to 31 days was chosen as a trade-off between the number of contracts with open interest and the amount of information in prices. This also allows for returns to be described as approximately monthly. For simplicity, I present the forecasted index value calculation for a contract 32 days from maturity below.

MDA provides temperature forecasts for 12 days (including the day of). I use the MDA forecasted temperature from day T-32 to day T-21 and then simulate 1,000 temperature paths over the next 21 days until contract maturity (T-20 to T) using an estimated temperature process (Ritter, MuBhoff, and Odening (2010)). I allow for error in the forecasted temperature by adding random error to the forecasted temperatures in each simulation. The distribution of forecast error is the 12-by-12 variance-covariance matrix of error between realized and forecasted temperatures estimated during the sample period for each location separately. For each simulation, I randomly draw a vector of forecast errors from the estimated distribution and add it to the forecasts.

To estimate the average daily temperature process for each location, I follow Bellini (2005) and Dornier and Querel (2000). The temperature process for each location is a generalized Ornstein-Uhlenbeck process:

$$dT(t) = \frac{d\theta(t)}{dt} + e^{-\kappa}[\theta(t) - T(t)]dt + \sigma(t)dW(t), \tag{A1}$$

where $T(t)$ is the temperature on day t, $\theta(t)$ is the moving average, κ is the mean reversion parameter, $\sigma(t)$ is the standard deviation of temperature on day t, and $W(t)$ is a Brownian motion. Dornier and Querel (2000) show that $\frac{d\theta(t)}{dt}$ is necessary for the model to tend towards the historical mean.[27] The mean and standard deviation of temperature vary with the day of the year:

$$\text{Mean Temperature} = \theta(t) = \beta_0 + \delta t + \sum_{p=1}^{P} \beta_p \sin(\frac{2\pi}{365} pt + \phi_p), \tag{A2}$$

$$\text{Std. Dev. of Temperature} = \sigma(t) = \gamma_0 + \sum_{q=1}^{Q} \gamma_p \sin(\frac{2\pi}{365} qt + \psi_p), \tag{A3}$$

where β_0 (γ_0) captures the average expected (standard variation of) temperature of a location during the year, P (Q) is the number of sinusoidal functions, β_p (γ_q) governs the magnitude of the seasonal movements, and ϕ_p (ψ_q) is the phase parameter, which shifts the seasonal variation so the peak and trough of the sinusoidal curve align with the peak and trough of temperature (standard deviation of temperature) during the year. δt captures any long-run trend in temperature such as global warming. P or Q equal to 1 captures annual seasonality, P or Q equal to 2 captures semi-annual seasonality, etc. By allowing for $P > 1$ and $Q > 1$, I allow for seasonality at shorter than annual frequencies.

Bellini (2005) shows that the continuous process in equation A1 can be represented in discrete-time as an AR(1) process:

$$T(t) = \rho T(t-1) - \rho\theta(t-1) + \theta(t) + s(t)\epsilon(t), \tag{A4}$$

where $\rho = e^{-\kappa}$, $\epsilon(t)$ is distributed $N(0,1)$ and $s(t)$ is:

$$s^2(t) = \int_{t-1}^{t} e^{-2\kappa(t-u)}\sigma^2(u)du. \tag{A5}$$

I use maximum likelihood estimation to determine the parameters for each location separately. I estimate the model using temperature realizations from January 1, 1999 to January 31, 2012. I estimate a maximum likelihood function, where the conditional likelihood of each temperature observation is:

$$f(T(t)|T(t-1), \Theta) = (2\pi\sigma^2(t))^{-\frac{1}{2}} e^{-\frac{1}{2\sigma^2(t)}(T(t)-\theta(t)-\rho(T(t-1)-\theta(t-1)))^2}. \tag{A6}$$

[27] The equation for $\frac{d\theta(t)}{dt}$ is: $\frac{d\theta(t)}{dt} = \delta + \sum_{p=1}^{P} \frac{2\pi}{365} p\beta_p \cos(\frac{2\pi}{365} pt + \phi_p)$.

The maximum log-likelihood function is:

$$\begin{aligned} \ln L(\Theta|\{T\}_{t=2}^{N}) = -\frac{N-1}{2}\ln 2\pi - \frac{1}{2}\sum_{t=2}^{N}\ln \sigma^2(t) \\ -\frac{1}{2}\sum_{t=2}^{N}\frac{1}{\sigma^2(t)}(T(t)-\theta(t)-\rho(T(t-1)-\theta(t-1)))^2. \end{aligned} \tag{A7}$$

I maximize the likelihood for each city separately. I maximize the log-likelihood function for P={1,2,3,4} and Q={1,2,3,4}. To choose the optimal P and Q, I step through the P-Q grid by calculating the likelihood of the model with an additional P and the likelihood of the model with an additional Q and step towards the function with the greatest improvement. A step is only taken if the LR-test statistic between the alternative and null models has a p-value less than or equal to 10%. I limit P and Q to a maximum of 4 for ease of calculation and simplification. This should not affect the results presented in the main body text.

The resulting parameter estimates are presented in Table XI. 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.[28]

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,

$$E[HDDPayoff] = \frac{1}{1,000} \sum_{s=1}^{1,000} \sum_{t=\text{1st Day of Month}}^{T-21} \max(0, 65-(Temp_{forecast,t}+\epsilon_s)) + \sum_{t=T-20}^{T} \max(0, 65-Temp_{s,t}), \tag{A8}$$

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.

[28] My estimates for the optimal P and Q vary slightly from Bellini's (2005) estimates. She estimates parameters for four cities: Chicago, Philadelphia, Portland, and Tucson. Her estimated P and Q were (2,3) for Chicago, (1,3) for Philadelphia, (2,3) for Portland, and (5,3) for Tucson. The discrepancies are most likely due to estimating over different sample periods and different criteria for increasing P and Q.

Table XI
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 B. Systematic Risk Results

In Table XII, 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 calculated $R_{it} = \frac{Payoff_{it}}{E[Payoff_{it}]} - 1$, where $Payoff_{it}$ is the realized degree index value and $E[Payoff_{it}]$ is the expected index. The return is for going long an HDD contract. 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 XIII, 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.

Table XII
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: $R_{it} = \frac{Payoff_{it}}{E[Payoff_{it}]} - 1$, where $Payoff_{it}$ is the realized degree index value and $E[Payoff_{it}]$ 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 XIII
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 C. Additional Results

In this section, I provide results from 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 sector stress dummy, *Financial Crisis*, as the proxies for financial sector stress. Table XIV presents the results using Δ *VIX*. Table XV 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.

In Table XVI, 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 return 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.

Table XIV
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 XV
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 XVI
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