Essays on the Weather Derivatives Market

by

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For my parents, Robert and Pamela. This work is made possible by your love, nurturing and guidance over the years. For my wife, Alyssa. This work is made possible by your love and unrelenting positivity. For my siblings, Julianne and Jimmy. This work is made possible by your unconditional love and support.

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ABSTRACT

Essays on the Weather Derivatives Market

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This dissertation consists of two essays examining the functioning and effects of a recent financial innovation: the weather derivatives market. The modern weather derivatives market originated in the late 1990s and allows participants to share non-catastrophic weather risks. The structure and development of the market provide a relatively clean empirical setting to study and better understand financial markets.

The first essay examines how financial sector stress affects asset prices in the weather derivatives market. The structure of the market allows price movements due to financial sector stress to be disentangled from price movements due to fundamentals. Estimated risk premiums, which are small and statistically indistinguishable from zero on average, are 31% per year during the 2008-09 financial crisis. Contracts with greater margin requirements and idiosyncratic risk experience larger increases in risk premiums. Open interest falls by 40%. The results provide evidence that adverse shocks to the capital of financial institutions lead to increased hedging costs for end users and less risk sharing in the economy.

The second essay examines how the introduction of weather derivatives affect

a government stakeholder: the National Weather Service. More broadly, the essay examines the ability of markets to discipline government agencies. The Chicago Mercantile Exchange has introduced several temperature related derivative contracts on different U.S. cities in a staggered fashion since 1999. The payoffs of these contracts depend on the temperature levels at a specific weather station in the underlying city. We show that the introduction of these contracts improves the accuracy of temperature measurement by the dedicated weather station of the National Weather Services (NWS) in that city. We argue that temperature-based financial markets generate additional scrutiny of the temperature data measured by the NWS, which in turn motivates the agency to minimize measurement errors. Consistent with this idea, stations with higher economic interests in weather derivatives see greater improvement in measurement accuracy. Our results indicate that the visibility and scrutiny generated by financial markets can improve the efficiency of government agencies even in the absence of explicit incentive contracts.

CHAPTER I

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

1.1 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. Estimated weather risk premiums, which are small and statistically indistinguishable from zero on average, rise to over 30% per year during the 2008-09 financial crisis. Contracts with greater margin requirements and idiosyncratic risk experience larger increases in risk premiums. These results support the notion that adverse shocks to the capital of financial institutions lead to increased hedging costs for end users and less risk-sharing in the economy.

1.2 Introduction

A recent theoretical literature argues that adverse shocks to financial sector capital can affect asset prices. After an adverse capital shock, asset prices may fall below their fundamental values if the positions of financial institutions are limited by their capital constraints.[1] However, it is difficult to measure the effect of financial sector stress on asset prices in most market settings. The difficulty arises because asset fundamentals are likely to change 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 risk premiums in the Chicago Mercantile Exchange's (CME) monthly temperature futures market.

The monthly temperature futures market allows end users to hedge monthly temperature risks. Energy and utility companies are the predominant end users. The typical trade is for utilities to sell the local temperature future to minimize their exposure to mild temperature outcomes and, thus, low energy sales. Financial institutions satisfy this asymmetric hedging demand by going long the futures contract and bearing this mild temperature risk. Financial sector stress likely affects the willingness and ability of financial institutions to bear risk in this market, but it should not affect the weather. To measure the effect of financial sector stress on asset prices, I compare expected returns of going long temperature futures (i.e, risk premiums) during a period of financial sector stress (the 2008-09 financial crisis) to expected returns in normal times. This test properly identifies 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 qualities of temperature futures ensure that asset fundamentals (payoffs and risks) are not systematically mis-estimated during the financial stress period. First, contract payoffs are based on local temperature outcomes, which are exogenous to

[1] See Aiyagari and Gertler (1999), Gromb and Vayanos (2002), Fostel and Geanokoplos (2008), Brunnermeier and Pedersen (2009), Adrian and Shin (2010) and Garleanu and Pedersen (2011) 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 will depend on the aggregate wealth of the financial sector. For a review of the literature, see Duffie (2010).

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 of systematic risk are driving the change in risk premiums. Third, changes in expected payoffs due to random temperature variation can be controlled for by modeling and estimating a temperature process for each contract. 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. In Figure A.1, I plot the logarithm of contract prices for contracts on three different locations which settle based on June temperature realizations. For each location, I plot the average price (32 days before maturity) and the average payoff at maturity over the years 2000-2012. I also plot the price (32 days before maturity) during the crisis period. The average price and payoff of each contract are nearly identical, consistent with the contracts being priced near their actuarially fair value. In contrast, the price during the crisis is far below the average price and payoff of each contract. This figure illustrates the relatively low prices on weather derivative contracts during the crisis.

[Figure A.1 Here]

Figure A.1 does not control for market expectations of contract payoffs. In the main empirical tests, I control for market temperature expectations by modeling a daily temperature process for each location and calculating a model simulated expected payoff. With the expected payoff and market price, I calculate the expected return from going long the futures contract, i.e. the weather risk premium.

To formally test for the effect of financial sector stress on risk premiums, I compare the risk premium for a contract pre- and post-crisis to the risk premium for the same contract during the 2008-09 financial crisis. The average risk premium across all contracts over the entire period is less than 2% per year and is statistically insignificant. This is consistent with idiosyncratic risk not being priced during normal times. During the financial crisis, estimated average risk premiums rise to a statistically significant 30% per year. In sum, contracts are typically priced near their actuarially fair value, but during the crisis, contract prices are consistently below this value. This is consistent with financial institutions decreasing their supply of capital to the weather derivatives market during a period of financial sector stress.

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) find that after the introduction of weather derivative contracts, 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 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. Further if the effect of financial sector stress documented in this market is present in other markets, financial crises may cause large dislocations in prices and significantly lower amounts of risk-sharing in the economy.

There are two main reasons why financial institutions may decrease their supply of capital to the weather derivatives market after an adverse shock to their capital. First, capital is necessary to meet margin requirements in the market. Without sufficient capital, financial institutions will be unable to meet these requirements. 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. 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.[2] To limit their risk exposure, financial institutions will supply less capital to markets with more total risk (Froot and Stein 1998).

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 United States, on 12 different months and 2 different indices. 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 the financial crisis dummy variable is interacted with the contract's margin requirement or total risk or both. I find a one standard deviation increase in margin increases risk premiums by about 76% per year in the financial crisis. Of similar magnitude, I find a one standard deviation increase in total risk increases risk premiums by about 80% per year. In addition, contracts with both high margin and high coefficient of variation are the most impacted by financial sector stress. This evidence supports the notion that adverse capital shocks to financial institutions have a significant effect on asset prices, especially on prices of high-margin and high-risk contracts.

An increase in risk premiums alone does not imply that the supply of financial capital to the weather derivatives market decreased during the financial crisis. Risk premiums may also increase if hedging demand increases and the supply of capital

[2]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 flying to safety during the crisis (Caballero and Krishnamurthy 2008; Gennaioli, Shleifer and Vishny 2012).

is not perfectly elastic in the short-run.[3] If hedging demand is driving the increase in risk premiums, we would expect greater quantities of risk to be hedged during the crisis. This is not the case. The notional value of the entire 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 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."[4] Further supporting a decrease in capital supply, I find that markets for high-margin contracts and riskier contracts were significantly more likely to collapse, i.e. have zero open interest, during the crisis. The dramatic decline in notional value and open interest rules out the alternative that an increase in hedging demand is driving the increase in risk premiums.[5]

The existing literature has documented the effects of adverse capital shocks on market outcomes in the commodities, currency exchange, convertible bond, lending and other markets.[6] Additionally, Adrian, Etula and Muir (2013) find that a factor based on the leverage of financial intermediaries can explain a large portion of the

[3]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.

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

[5]Another alternative is that hedging demand declined. If this is the case, we would expect risk premiums to be unchanged or fall during the crisis, not increase.

[6]Cheng, Kirilenko and Xiong (2013) find that an increase in the VIX index leads to lower commodity prices and a "convective" flow of risk from financial institutions to hedgers. 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 2008 financial crisis.

variation in the cross-section of expected returns. I extend these results by providing clean evidence of the large impact that capital constraints can have on asset prices and that idiosyncratic risk and margin requirements are priced during periods of financial sector stress. The most closely related empirical evidence is on the increase in catastrophe insurance risk premiums after adverse shocks to insurers and reinsurers capital (Froot and O'Connell 1999).[7] 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 players 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 catastrophe insurance literature by providing evidence of price spillovers across markets and the differential impact of financial sector stress on more "capital-intensive" and riskier contracts.

Overall, the results in this paper 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.

[7] Also, see Zanjani (2002) and Born and Viscusi (2006)

The rest of the paper proceeds as follows. Section 2.3 describes the weather derivatives market, the main players and the main hedging strategy by energy companies. Section 2.4 discusses the data. Section 2.5 presents the research design and empirical results. Section 2.6 concludes.

1.3 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 ConEdison Company electric power at a discount if August temperatures were cooler than expected (Everitt and Melnick 2008). This simple financial innovation, contracting based on temperature realizations, was well received by the energy sector. The market for contracts based on temperature and other non-catastrophic weather outcomes, such as frost, snowfall and rainfall, grew dramatically from a notional value below \$2 billion in 1998 to \$32 billion in 2008 (WRMA surveys).

In 1999, the CME introduced standardized monthly temperature contracts on 10 locations in the United States. Exchange-traded contracts were not immediately popular. The market grew in the over-the counter 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 over-the-counter market and shifted trading to the CME. The CME has periodically added contracts on 14 new 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 2012, there were 47 locations around the world with temperature-based weather contracts traded on the

CME.

I focus on the U.S. monthly degree day futures in this paper. In 2005, temperature contracts accounted for over 95% of the entire 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 5 waves: 1999, 2000, 2003, 2005 and 2008. In Table A.1, I document the 18 U.S. locations with temperature-based weather derivatives traded on the CME pre-2008.[8] Purnanandam and Weagley (2013) show that 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. Open interest and notional value in the monthly temperature market closely mirrored the growth in the entire weather derivatives market during the 1999 to 2008 period.

[**Table** A.**1 Here**]

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 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.[9] Open interest decreases on less than 5% of trading days. The market's illiquidity is likely to amplify financial institutions' unwillingness to take risk and lead to larger price distortions during stress as predicted by Garleanu and Pedersen (2007).[10]

[8]The 6 locations added in 2008 were Colorado Springs, Jacksonville, Little Rock, Los Angeles, Raleigh Durham and Washington D.C.

[9]Calculated over the years 2006-2012 for the monthly temperature futures market

[10]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.

1.3.1 Contract Structure

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

$$HDD_{im} = \sum_{t=1}^{T_m} \max\{65 - Temp_{it}, 0\}, \tag{1.1}$$

$$CDD_{im} = \sum_{t=1}^{T_m} \max\{Temp_{it} - 65, 0\}, \tag{1.2}$$

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 heating degree day (cooling degree day) index is high, temperatures are cold (hot) and consumers need more energy to *heat* (*cool*) their homes and buildings.

1.3.2 Main Players and Their Hedging Tactics

In this section, I will argue 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, and allows me to calculate a risk premium charged by financial institutions.

In 2004-05, the Weather Risk Management Association documented that 69% of over-the-counter 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.[11] 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 to heat or cool their building. 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 (Perez-Gonzales and Yun 2013). Every state in the United States, has purchased gas adjustments (PGA) for natural gas utilities (American Gas Association, 2007). The 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."[12] Perez-Gonzales and Yun (2013) find that energy firms 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.

[11] The year-by-year OTC percentage of end user demand attributed to the energy sector was: 56% in 2003-04, 69% in 2004-05, 46% in 2005-06, 47% in 2006-07, 36% in 2007-08, 59% in 2008-09, 58% in 2009-10 and 46% in 2010-11

[12] "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/`

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

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 were introduced 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.[13] In 2009, natural gas utilities in 36 states had non-volumetric rate designs. Electric utilities in only 9 states had decoupling mechanisms.[14] Not all utilities have these

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

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

adjustments. 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 Perez-Gonzales and Yun (2013) for a more complete discussion). Even with the prevalence of regulatory mechanisms, Perez-Gonzales and Yun (2013) find that one-quarter of utilities use weather derivatives and the CME reports that 35% of energy companies used weather derivative instruments in 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 Washington DC area. In its 2012 10-K filing, Washington Gas describes its weather derivative usage as such:

> 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' position in the weather derivatives market 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, Perez-Gonzales and Yun (2013) 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.

To hedge low revenues due to mild temperatures, energy companies will *sell* monthly futures. This 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 (Perez-Gonzales and Yun 2013, 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 in both HDD and CDD contracts for three U.S. locations over January 2002 to February 2004. Similarly, I find a positive, but insignificant average risk premium in my sample. I maintain the assumption that financial institutions are net long in the market throughout my analysis.

1.4 Data Description

End-of-day price, open interest and margin data for the Chicago Mercantile Exchange monthly temperature futures was provided by the Chicago Mercantile Exchange. 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 6 U.S. locations that were introduced in 2008, leaving 18 U.S. locations. The sample covers monthly contracts from the first month traded, October 1999, to February 2012. The temperature data was obtained from MDA Information Systems, Inc. MDA is the provider of official temperatures used to settle CME temperature contracts.

In Figure A.4, I plot the average price and open interest of February HDD contracts by location. HDD contracts capture deviations in temperature below 65^oF. Prices and open interest in the weather derivatives market vary as would be expected.

Prices are higher in locations with more extreme temperature, e.g. Minneapolis, and open interest is higher in locations with more economic interest, e.g. New York.

[**Figure A.4 Here**]

In the first panel of Table A.2, I present summary statistics for contract open interest. Contracts are defined along location, index, month and year dimensions. The sample is limited to the 1,104 contracts that were open at least 32 days before maturity. Open interest is the maximum open interest achieved at least 32 days before maturity. The mean open interest over the entire period is 236 per contract. There is a lot of variation in open interest with a 10th percentile of 12 and a 90th percentile of 550.[15] There is slightly more open interest per contract in CDD contracts than HDD contracts, but fewer contracts traded.

[**Table** A.**2 Here**]

A sample of 1,104 contracts is relatively small considering there would be 432 contracts traded each year if every available contract were traded. In 2008, the number of contracts traded peaked at 154 contracts. There are a few reasons why the actual number of contracts traded is below the number of available contracts. First, weather risks are seasonal, so there is rarely an HDD and CDD contract traded on the same location in the same month. HDD contracts are mainly traded in the winter months, while CDD contracts are mainly traded in the summer months. Second, there is little activity in the months of April and October. These are considered transition months in the weather derivatives market because temperatures are relatively mild. Third, different locations face different risks. For example, locations with warmer climates are less likely to have significant hedging demand in HDD contract markets. Fourth,

[15] The open interest 32 days before maturity is typically about one-half of the maximum open interest achieved during the trading period. Summary statistics for the maximum open interest achieved during the trading period are: mean=455, standard deviation=734, 10th percentile=20, 50th percentile=200, 90th percentile=1,150 and 1,661 contracts traded.

the level of economic interest tied to temperature risks can vary across locations even if the climates are identical. Fifth, I examine contracts that were trading 32 days before maturity, while some markets might first experience trading closer to maturity. These reasons limit the number of contracts that trade each month.

In Table A.3, I summarize speculator maintenance margin requirements and the historical coefficient of variation of the contract index (for location specific margin requirements see Table A.1.). These are the main independent variables of interest in the difference-in-difference regressions. The maintenance margin requirements vary from 3.1% to 17%. Margin requirements are greater for CDD contracts on average. The mean maintenance margin requirement for HDD contracts is 5.4% and for CDD contracts is 7.7%. Margin requirements are likely lower for HDD contracts because margins are set based on price volatility and HDD contracts are less volatile than CDD contracts. The mean coefficient of variation for CDD contracts is 0.28 and for HDD contracts is 0.22. The distribution of total risk is right skewed. The mean coefficient of variation is 0.25 and the median is 0.21. Values range from .08 to 1.03, with a standard deviation of 0.13. Although margins are set based on price volatility, the correlation between margin and coefficient of variation is only 0.55. The relatively low correlation is due to margins being set at the location-index level, while coefficient of variation is calculated at the location-index-month level. Also, margins are set at round numbers and are unlikely to be a perfect linear function of contract risk.

[Table A.3 Here]

1.4.1 Estimating Risk Premiums

The risk premium for each contract is calculated as follows: $\frac{E[Payoff]}{Price} - (1 + r_f)$, where r_f is the monthly risk-free rate, $Price$ is the price 32 days from contract maturity and $E[Payoff]$ is the expected payoff based on information 32 days from maturity. The maturity date is the last day of the contract's specified month. 32 days was chosen as a trade-off between the number of contracts traded in the market and the amount of temperature information (realized or forecasted temperatures) embedded in prices. This also allows for a discussion of the risk premium as approximately a monthly risk premium.

To estimate the expected payoff I model the average daily temperature process for each location as a discrete-time AR(1) process following Bellini (2005) and Dornier and Querel (2000). 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 behavior of temperature in each location. In Figure A.3, I plot the average temperature versus the estimated mean temperature by day of the year for the 4 largest cities by population in my sample. In blue, I plot the average temperature for each day of the year calculated over the years 1999-2012. In green, I plot the estimated mean temperature. The model estimates appear to capture the mean temperature dynamics fairly well.

[Figure A.3 Here]

After the temperature process has been estimated, I calculate expected payoffs by using the temperature realization 32 days before contract maturity and simulating 500 temperature paths over the next 32 days until contract maturity. From the simulated temperatures, I apply the HDD and CDD temperature formulas to calculate the payoff of the contract for each path. The expected payoff is the average of the simulated contract payoffs. Once I have obtained the expected payoff, I can calculate a weather risk premium using the expected payoff, contract price, and the risk free rate.

In the second and third panels of Table A.2, I present summary statistics for the weather risk premium and realized contract returns. Realized contract returns are calculated as follows: $\frac{Payoff}{Price} - (1 + r_f)$, where $Payoff$ is the realized index value, $Price$ is the price 32 days before maturity and r_f is the risk-free rate. The risk premiums and realized returns are presented as percentages. Risk premiums are winsorized at the 1% level to reduce the impact of outliers. I cut the sample into CDD, HDD and all contracts. The mean weather risk premium for the entire sample is 0.16% and is not significantly different from 0. The mean risk premium for CDD contracts, 0.50, is higher than the mean risk premium for HDD contracts, -0.10. Neither mean is significantly different from zero. The median risk premium for the entire sample is -.79%. Examining the realized returns, the mean realized return is -1.08% and is statistically insignificant. The mean realized return for HDD contracts is -1.79% and for CDD contracts is -0.14%. The mean realized return for HDD contracts is statistically different from zero at the 5% level. The negative returns are concentrated in the low open interest (<300) contracts. High open interest HDD contracts have a positive mean return. The relatively low risk premiums and returns for heating degree day contracts could be due to the prevalence of regulatory mechanisms to hedge temperature risk during the winter months for many utilities. Most of the natural gas decoupling mechanisms are for the winter months and there are very few states with weather adjustment clauses for electric utilities.

Why would financial institutions participate in the market if risk premiums are near zero on average? Even if risk premiums are zero, financial institutions enjoy a diversification benefit from investing in weather derivatives. Second, as will be discussed in Section 1.5.4, returns on weather derivatives appear to be slightly negatively correlated with the market, so risk premiums should be zero or negative in a world with perfect capital markets.

1.5 Empirical Analysis

1.5.1 Research Design

My main hypothesis is that that a loss of financial sector capital and the inability of financial institutions to immediately and costlessly raise new capital causes financial institutions to decrease their supply of capital to the weather derivatives market. The decline in capital supply to the market will lead to higher risk premiums and lower open interest. To test this hypothesis, the ideal empirical design would compare risk premiums during periods of financial sector stress to the risk premiums that would exist if the financial sector were not stressed. This counterfactual does not exist; instead, I compare risk premiums during a period of financial sector stress, the 2008-09 financial crisis, to risk premiums pre- and post-crisis. The identifying assumption is that the fundamental values of the contracts are not systematically misestimated during the financial crisis period. This seems reasonable for three reasons: (1) the temperature processes are relatively stationary over time and are unaffected by financial sector stress, thus, it is unlikely there is an unmodeled change in the distribution of contract payoffs during the crisis, (2) contract risks are largely idiosyncratic, so risk premiums should not vary with the price of systematic risk, and (3) there is no counterparty risk since contracts clear on the exchange.

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

$$WRP_{imdy} = \alpha_{imd} + \beta \cdot FinancialCrisis_{ym} + \epsilon_{imdy}, \tag{1.3}$$

where $FinancialCrisis_{ym}$ is an indicator variable equal to 1 during the financial crisis period and is based on the contract year y and month m, α_{imd} is the contract fixed effect for the contract on location i, month m and index d. I control for contract fixed effects because risk premiums are likely to vary across contracts with different risk profiles, margin requirements, hedging demand and possibly other sources of heterogeneity. This test analyzes the annual variation in risk premiums for the same contract defined along the location, index and month dimensions. For example, the risk premium for the 2009 New York February HDD contract will be compared to the risk premiums for the New York February HDD contract in the years 2000-2008 and 2010-2012. β provides the coefficient estimate of interest. The main hypothesis predicts $\beta > 0$, i.e. risk premiums increase during the financial crisis. The financial crisis period is defined as the months including and between October 2008 and December 2009. The failure of Lehman Brothers in mid-September 2008 precipitated a systemic crisis in the global financial system (Brunnermeier 2009). October 2008 contracts should be the first impacted by Lehman's failure because risk premiums are based on prices measured 32 days before maturity. December 2009 is chosen as the ending date to capture the entire period of crisis. 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.

After controlling for contract fixed effects, any variation in estimated risk premiums should be due to movements in market expectations of forecasted 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 risk premiums due to changes in forecasted temperatures or market structure is uncorrelated with the financial crisis time period. The validity of this assumption is critical to the interpretation of my results, so I will briefly discuss each of the potential sources of bias.

I observe an increase in risk premiums during the financial crisis, therefore, prices relative to expected payoffs must have dropped. For this to be explained by a bias in temperature forecasts, forecasted temperatures must have been systematically more *mild* during the financial crisis leading to lower forecasted index levels and lower prices. This does not seem to be the case. In Figure A.4, I provide five maps of National Oceanic and Atmospheric Administration's three-month temperature forecasts during the financial crisis period. The maps are shaded based on the chances of temperatures being above or below normal. During this 15 month period, forecasted temperatures appear to be barely warmer than normal on average, not more mild. Even if there is a bias in forecasted temperatures, this will be partially adjusted for by the temperature process model, which uses realized temperatures to model future temperatures each month throughout the crisis. Additionally, in Appendix B, I analyze realized temperatures during the crisis and find that realized temperatures were significantly more extreme in the HDD months and insignificantly cooler in the CDD months. This is inconsistent with unusually mild temperature forecasts driving the results. Lastly, when realized temperatures are included as controls in the empirical tests there is no change in the statistical or economic significance of the estimates.

[**Figure** A.4 **Here**]

There are two main concerns about how the structure of the weather derivatives market may have changed during the financial crisis period. The first concern is that the fees the CME charged may have increased during the financial crisis time period. I only know the fees present in the market on September 13, 2013. The fee to trade weather products is under \$0.20, or about one fifty-thousandth of the average contract price. It is unlikely that any fee increase would have caused a significant increase in risk premiums. The second concern is that margin requirements may have changed over time and this is biasing my results. The CME held margins constant for all contracts in my sample from January 2008 to early 2010. The CME chooses margin levels to cover approximately 99% of price moves during a trading day. The volatility of the underlying temperature likely did not change during the crisis, so it is not surprising that margins did not change.

To further analyze the role of adverse capital shocks 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 will 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:

$$WRP_{imdy} = \alpha_{imd} + \beta \cdot FinancialCrisis_{ym} + \gamma \cdot FinancialCrisis_{ym} \cdot Margin_{imd} + \epsilon_{imdy}, \tag{1.4}$$

where $Margin_{imd}$ is the margin requirement for the contract on location i, month m and index d. I do not include the $Margin_{imd}$ variable as an additional regressor because each contract's margin is captured in the contract fixed effect. The financial crisis dummy controls for the average change in risk premiums due to financial sector stress *and* any fixed time effect in the mis-measurement of expected payoffs. γ will capture the differential change in risk premiums of high versus low margin contracts during the financial crisis. Only if the mis-measurement of expected payoffs was systematically different for high-margin contracts during the financial crisis would the regression be misidentified. If capital constraints are driving the increase in risk premiums, then γ should be greater than 0, as financial institutions should be less willing to take more "capital-intensive" positions during a period of stress.

1.5.2 Risk Premium Results

I estimate the impact of financial sector stress on risk premiums in the weather derivatives market by estimating Equation 1.3. Results of the main test are reported in Table A.4. The coefficient of interest is the indicator variable for the period of financial sector stress (Financial Crisis). In Column 1, I include all contracts. In Columns 2 and 3, the sample is limited to CDD and HDD contracts, respectively. I cluster standard errors at the year-month level in all regressions.[16] The coefficient estimates vary from 1.62 for HDD contracts to 7.97 for CDD contracts, with a coefficient of 3.34 for all contracts. An average increase in risk premiums of 3.34% per month, or 40.08% per year, during the financial crisis is economically quite large. The increased risk premium is about 7% of the average contract notional value (two times the historical standard deviation of the monthly degree day index) and more than half of the average margin requirement. The notional value of the CME temperature market in 2009 was $14.5 billion. If the effect in other temperature markets was similar to the effect in the monthly futures market, the direct increase in hedging costs would have been $900 million or more. This estimate does not consider the indirect costs due to the lower quantity of risk being shared in the market.

[**Table** A.**4 Here**]

It should be emphasized that both HDD and CDD contracts experienced an increase in risk premiums. This decreases the probability that warmer temperature forecasts are driving the results. If the market forecasted temperatures to be warmer than the model-predicted temperatures during the crisis period, then the financial crisis coefficient should only be significant for HDD contracts since warmer temperatures result in a mild winter, lower prices and a higher risk premium. Instead, the

[16] The main independent variable, $FinancialCrisis_{ym}$, is both serially and cross-sectionally correlated. If the regression error terms are serially or cross-sectionally correlated (or both), then OLS standard errors will be biased. The dependent variable, WRP_{imdy}, is likely correlated within months, as temperature fluctuations are, at a minimum, regionally correlated. To address this issue, I cluster the standard errors at the year-month level. Clustering at the year-month level will also address heteroskedasticity in risk premiums across months. It is also likely that risk premiums are correlated within contracts at the location, index & month level. The margin requirement, idiosyncratic volatility, systematic risk and hedging demand will vary across contracts and may affect the risk premium charged. To control for the time invariant difference in risk premiums across contracts, I include contract fixed effects in all regressions. Fixed effects seem more reasonable than imprecisely controlling for the effect of idiosyncratic volatility, systematic risk and margins on risk premiums. In unreported regressions, I also cluster standard errors at the contract level as hedging demand or other omitted variables may be serially correlated, but temporary. Clustering at the contract level does not meaningfully change the standard error estimates once contract fixed effects are included and standard errors are clustered at the year-month level.

results are even stronger for the CDD contracts. One possible reason the CDD contracts experienced a greater increase in risk premiums is that CDD contracts have larger margin requirements and more total risk in the underlying.

Next, I examine the impact of financial sector stress on contracts with different margin requirements. All else equal, if a financial institution faces costs to raising new capital and experiences an adverse capital shock, it will require greater returns on assets that are more capital intensive (Brunnermeier and Pedersen 2009). If an adverse shock to financial sector capital is driving the increase in risk premiums, we should see greater risk premiums in contracts with higher margin requirements. To test for the impact of financial sector stress on contracts with different margin requirements, I estimate Equation 1.4. I use the July 2008 maintenance margin requirements for speculators as the margin measure. The initial margin requirements are perfectly correlated with the maintenance margin requirements, so the results are identical if initial margins are used.

The results are reported in Table A.5. The regression including all, CDD and HDD contracts are presented in Columns 1, 2 and 3, respectively. Consistent with financial sector stress differentially impacting markets with greater margin requirements, the coefficient estimates range from 2.19 for CDD contracts to 3.38 for HDD contracts. The coefficient for all contracts is 2.66. The coefficient is significant at the 1% level for both the full sample and the HDD sub-sample and is significant at the 5% level for the CDD sub-sample. A coefficient of 2.66 corresponds to a 6.36% (76%) increase in the monthly (yearly) risk premium with a one standard deviation increase in margin requirements. For a Las Vegas HDD contract with a margin of 5.4%, the full (HDD) sample regression coefficient implies an increase in the risk premium of 2.25% (2.21%) per month during the crisis. For the higher margin Chicago CDD contract with a margin of 11%, the estimated increase in risk premium would be 17.15% per month using the full sample coefficient and 15.89% per month using the

CDD sample coefficient. These results imply a very large market-wide shadow cost of external capital. For this result to be explained by misestimation of risk premiums during the financial crisis, the misestimation would have to be systematically biased towards high-margin contracts. This bias would have to occur for both HDD and CDD indices, which capture opposing temperature extremes. This is highly unlikely.

[Table A.5 Here]

To further document the price impact of adverse capital shocks, I examine the differential impact of financial sector stress on contracts with different amounts of total risk. Froot and Stein (1998) show that if a financial institution faces costly external capital, its effective risk aversion will be decreasing in its internal capital. In other words, after an adverse shock to the financial institution's capital, it will become effectively more risk averse. Because contract risks cannot be perfectly hedged, an increase in the risk aversion of a financial institution will lead the financial institution to decrease its supply of capital to riskier contracts after a loss in capital. Additionally, if individual traders use value-at-risk metrics to determine their positions and their value-at-risk constraint tightens during periods of financial sector stress, contracts with greater total risk, all else equal, should experience a larger decline in capital supply.

To test for the differential effect of stress on contracts with greater total risk, I run difference-in-difference regressions with total risk as the cross-sectional variable of interest. 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.[17]

Results are presented in Table A.6. The coefficient of interest is the interaction term for the contract's coefficient of variation and the financial crisis indicator variable, CV*Financial Crisis. Results for regressions including all, CDD and HDD contracts are presented in Columns 1, 2 and 3, respectively. The coefficient estimates range from 28.83 for CDD contracts to 63.37 for the HDD contracts and the coefficient for the full sample is 51.61. The coefficient is significant at the 1% level for both the full sample and the HDD sub-sample. These results indicate that more volatile contracts experienced relatively higher risk premiums in the financial crisis. Economically, a one-standard deviation increase in a contract's coefficient of variation is associated with an increase in monthly (yearly) risk premiums of approximately 6.7% (80%) during the financial crisis. For a Cincinnati April HDD contract, which has the median coefficient of variation of 0.21, the coefficient estimates imply an increase in monthly risk premiums of 4.45% (1.14%) during the crisis based off the full (HDD) regression. For the higher risk New York May CDD contract with a coefficient of variation of .62, the coefficient estimates imply an increase in monthly risk premiums of 23.23% (18.12%) based off the full (CDD) regression. These results support the notion that financial institutions become effectively more risk averse after capital losses.

[Table A.6 Here]

Margin requirements are based off market conditions, mainly price volatility. If margin requirements are just proxies for idiosyncratic risk, then the results presented above may be redundant and it would be difficult to disentangle the increase in risk premiums due to margin from the increase due to total risk. Beneficial for this study, margins are not a linear function of total risk. The correlation between margin

[17]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.

requirements and coefficients of variation is 0.55. 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 crisis dummy. If both margin requirements and contract risk are drivers of risk premiums during financial sector stress, there should be a positive and significant coefficient on the three-way interaction.

Results are reported in Table A.7. Consistent with margin *and* total risk affecting risk premiums, the coefficient on the triple interaction is positive in all regressions. The coefficient is 8.10 and statistically significant at the 10% level for the regression with all contracts. For the HDD contracts, the coefficient is 26.30 and is significant at the 1% level. The coefficient is 4.51 and insignificant for the CDD sample. Examining the regressions without the triple interaction term, both margin and contract risk have positive coefficients. For the regression with all contracts, the effect of margin is significant at the 5% level and the coefficient on contract risk is positive, but insignificant. In sum, it appears that both margin levels and contract risk appear to matter to stressed financial institutions.

[**Table** A.**7 Here**]

I have shown that margin requirements and total risk matter for asset prices during a period of financial sector stress, but do they also matter during periods when the financial sector is healthy? To answer this question, I run separate regressions of contract risk premiums on contract characteristics over the entire period, in the crisis period and in normal times. Regressions are of the form:

$$WRP_{imdy} = \gamma * X_{imd} + \delta_m + \epsilon_{imdy},$$

where the dependent variable is the weather risk premium for location i, month m, degree day index d and year y, X_{imd} is either $Margin_{imd}$ or CV_{imd}, and δ_m is a month fixed effect. I do not include a contract specific fixed effect because the margin requirement and coefficient of variation are fixed at the contract level.

Regression results are reported in Table A.8. Regressions with margin requirements (coefficient of variation) as the independent variable are reported in Columns 1-3 (4-6). The entire period regressions are labeled "Entire" and are reported in Columns 1 and 4, the periods outside of the financial crisis are labeled "Normal" and are reported in Columns 2 and 5, and the crisis period regressions are labeled "Crisis" and are reported in Columns 3 and 6. Focusing on the impact of margin requirements on risk premiums, we see that risk premiums are positively related to margins over the entire sample period, but the coefficient is statistically insignificant and small. The positive relationship between margins and premiums is due to the crisis period. The normal period regression shows that margins are insignificantly negatively related with risk premiums during periods of financial sector health with a coefficient of -0.32. The coefficient during stress is positive and large at 2.23, and is significant at the 1% level. We see a similar pattern in the total risk analysis. The results suggest that total risk and margin only affect contract pricing during periods of financial sector stress.

[Table A.8 Here]

1.5.3 Notional Value and Open Interest

The previous results show that risk premiums increase during a period of financial sector stress and the effect is strongest for higher margin and riskier contracts. 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 increase in risk premiums, then the open interest and the notional value of contracts should have increased during the crisis. If a decrease in the supply of capital is driving the rise in risk premiums, then these quantities should have decreased.

In Figure A.5, I plot total open interest in the monthly temperature futures market by quarter. Open interest grew rapidly from introduction until the fourth quarter of 2008, then fell by nearly 40% with the start of the crisis. The decrease in open interest is consistent with a decrease in the supply of financial institution capital, not solely an increase in end user hedging demand during the crisis period. 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 failure. 36 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 that traded during the crisis period.[18]

[Figure A.5 Here]

The monthly temperature futures market did not fully recover after the crisis during the sample period. The lack of renewed activity is likely due to participant concerns about market liquidity after the crisis. Participants discussed the rapid growth of the market pre-crisis as "liquidity breeding liquidity" in the market.[19] After the crisis, participants were likely hesitant to take positions, concerned others would not participate in the market and create liquidity.

Another reason for the lack of renewed activity in the monthly temperature futures market is that some activity migrated to the OTC and seasonal futures market after the crisis (WRMA Survey 2010). A concern is that activity just shifted across

[18] 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.

[19]

markets and the quantity of risk shared did not change. This is not the case. The notional value of the entire weather derivatives market decreased dramatically during the financial crisis. The Weather Risk Management Association surveys market participants and the Chicago Mercantile Exchange 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. The April 2007 to March 2008 notional value was \$32B, the 2008/9 value was \$15B and the 2009/10 value was \$10B. The 50% decline in notional value between 2007/8 and 2008/9 is remarkable and contradicts an increase in hedging demand driving the increase in the risk premiums. The entire weather derivatives market did not completely rebound after the crisis, but the notional value increased by 20% to \$12B in 2010/11.

To further examine the effect of financial sector stress on the supply of capital to a market, I examine whether a contract's margin requirement and total risk affected its likelihood of collapsing in the crisis. I run probit regressions with the dependent variable equal to 1 if the contract collapsed. I define a market as collapsing if the contract traded in the 12 months pre-crisis, but did not trade in the first 12 months after the start of the crisis. Whether or not the contract traded is based on open interest 32 days before maturity. If the supply of capital is driving the collapse, we would expect margin and total risk to be positively correlated with a contract collapsing. In Table A.9, I report the results. When each explanatory variable is included separately, the coefficients are positive and significant. When margin and risk are both included in the probit, the coefficients are positive, but insignificant. When an interaction term is included, the coefficient is just slightly negative and insignificant, and the coefficients on margin and contract risk are positive. Overall, the results are consistent with financial sector stress causing a decrease in capital supply to the market. In fact, because the higher margin and more volatile contracts were more likely to collapse, I may be underestimating the effect of financial sector stress on risk premiums.

[Table A.9 Here]

1.5.4 Robustness

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 writes "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 2 different measures: "physical" returns and realized returns. The "physical" returns are $\frac{Payoff}{E[Payoff]} - 1$, where $Payoff$ is the realized payoff of the contract and $E[Payoff]$ is the model implied expected payoff of the contract 32 days before maturity. The "physical" return proxies for contract returns if contracts were priced at their actuarially fair value. The realized returns are calculated as follows: $\frac{Payoff}{Price} - 1$, $Payoff$ is the realized payoff of the contract and $Price$ is the outstanding price 32 days before maturity. The realized return is the more natural return for a CAPM style regression. For the "physical" return regressions, I include a location-month in the portfolio return calculation if a contract was ever open 32 days before maturity for that location and month. If both an HDD and CDD contract trade for the same month and location, then I use the index with the highest expected payoff. For the realized return regression, only those contracts with a market price 32 days before maturity are included in the regression. The regressions include month fixed effects to soak up any seasonality in the returns. I calculate White standard errors as there is likely heteroskedasticity in returns.

The results are reported in Table A.10. The results from the "physical" return regressions are reported in Columns 1-3 and the realized returns in Columns 4-6. I run regressions for all contracts, as well as CDD contracts and HDD contracts separately. The beta is significant at the 10% level in the realized return and the physical return regressions with all contracts. The coefficients range from -.32 to -.55. The coefficients imply that the market does poorly when temperatures are extreme. It appears that a portion of the risk in the temperature market is systematic risk, but the amount of systematic risk is negative.

[Table A.10 Here]

One may be concerned that an increase in the price of systematic risk is driving the relationship between financial sector stress and risk premiums. This is not the case. If the price of systematic risk increased during the crisis, we would expect risk premiums to drop on average because the market has negative systematic risk. If anything, not adjusting for systematic risk will bias the regressions against finding an increase in risk premiums. As further evidence that risk premiums are not being driven by systematic risk, in Appendix A.3, I calculate location specific betas and find that there is no relationship between a location's beta and its average estimated risk premium. Also in Appendix A.3, I control for a location's beta in the difference-in-difference regressions and the coefficients on margin and total risk are basically unchanged and still highly significant. High beta contracts experienced higher risk premiums during the crisis, but the effect is insignificant. In sum, it does not appear that risk premiums increased in the weather derivatives market due to an increase in the price of systematic risk.

For my tests to be properly identified, the model estimated expected payoff must not be systematically biased during the financial crisis. This bias may manifest if market forecasted temperatures were systematically biased during the crisis and not captured by my model. To explain the observed results, forecasted temperatures would have to be significantly warmer in the winter and cooler in the summer during the financial crisis and the bias stronger for high-margin and riskier contracts. This assumption is impossible to test without precise knowledge of the market's forecasted temperatures. As a robustness, I can control for market expectations using the realized payoffs of contracts. I run regressions where the negative logarithm of the contract price is the dependent variable and I include the logarithm of realized index payoffs as a control. The realized index payoffs should proxy for market expectations of contract payoffs. I use the negative logarithm of contract price because the financial institutions are net long in the weather derivative's market; an increased risk premium is associated with a decline in price. I also control for the risk-free rate and the logarithm of the realized degree index on the contract's location during the previous month. By controlling for the realized payoff, this regression gives the market a lookahead bias.

I present the results in Table A.11. In Column 1, I include the financial crisis dummy variable and the control variables. The coefficient is .054 and significant at the 1% level. Not surprisingly, this coefficient is of similar magnitude as in the risk premium regression (3.34). It does not appear that a bias in the my pricing model is driving the main result. In Columns 2-4 (5-7), I include the interaction between contract margin (coefficient of variation) and the financial crisis dummy. The results are very similar to the risk premium regressions. The interaction between margin and the financial crisis is positive and significant in all regressions. The coefficient on the interaction between the crisis and the coefficient of variation is positive in all specifications and is significant at the 1% level for the entire sample and the HDD subsample. If realized temperatures are a reasonable proxy for forecasted temperatures, then systematic bias in market temperature forecasts is not driving the results.

[Table A.11 Here]

Another concern is that there was an unobserved shift in the structure and use of the weather derivatives market around the start of the crisis (e.g. new regulation of the financial sector or the decline in natural gas prices following the shale gas boom) and this led to high risk premiums and low open interest. The fact that open interest did not rebound by the end of 2009 is consistent with a long-term structural shift. Natural gas prices remained low relative to their 2007-2008 peak and any regulatory regime shift likely did not ease through the sample period. If a structural shift is driving the results, we would expect contract prices to continue to remain low after the crisis. In Table A.11, Column 8, I include a dummy variable for the post-crisis period. This coefficient will capture the difference in contract price post-crisis relative to pre-crisis. The coefficient is -.0170 and is insignificant. Prices post-crisis were relatively higher than pre-crisis, i.e. risk premiums were actually lower. It does not appear that a shift in regulation or the decline in natural gas prices is driving the increase in risk premiums.

As a further test, I run the difference-in-difference regressions with realized returns instead of implied risk premiums as the dependent variable. There is little justification for using realized returns considering ex post returns are not a good proxy for ex ante premiums over such a short time period. In unreported results, in the regression with all contracts, I find the coefficient on the financial crisis, margin interaction and coefficient of variation interaction are positive, but insignificant. For the HDD sub-sample, results are similar. For the CDD sub-sample, realized temperatures were slightly cooler than normal in the summer of 2009, which led to a negative realized return on CDD contracts during the crisis period. Overall, there is very little evidence that a systematic bias in the difference between the model estimated expected payoffs and market expectations during the crisis is driving the results.

1.6 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. Supporting this notion, I document that during a period of financial sector stress, risk premiums in the weather derivatives market increased by over 30% and notional value declined by 50%. Higher margin contracts experienced a greater shift in capital supply as financial institutions were less willing to supply capital to these capital intensive markets. Consistent with the theories of Froot and Stein (1998) and Garleanu, Pedersen and Poteshman (2009), which argue that financial institutions willingness to bear risk is decreasing in the unhedgeable portion of the asset's variance, contracts with more total risk also experienced a greater decline in capital supply during the crisis.

Overall, these results show that financial institutions' funding constraints lead to lower risk-sharing between hedgers and financial institutions during periods of financial sector stress. Hedgers may experience lower investment, increased costs of debt and debt-like contracts (lines of credit, labor contracts, etc.) and lower firm values when the financial sector is under stress. 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.

CHAPTER II

Can Markets Discipline Government Agencies? Evidence from the Weather Derivatives Market

2.1 Abstract

The Chicago Mercantile Exchange has introduced several temperature related derivative contracts on different U.S. cities in a staggered fashion since 1999. The payoffs of these contracts depend on the temperature levels at a specific weather station in the underlying city. We show that the introduction of these contracts improves the accuracy of temperature measurement by the dedicated weather station of the National Weather Services (NWS) in that city. We argue that temperature-based financial markets generate additional scrutiny of the temperature data measured by the NWS, which in turn motivates the agency to minimize measurement errors. Consistent with this idea, stations with higher economic interests in weather derivatives see greater improvement in measurement accuracy. Our results indicate that the visibility and scrutiny generated by financial markets can improve the efficiency of government agencies even in the absence of explicit incentive contracts.

2.2 Introduction

How do financial markets affect real outcomes? This is a question of fundamental importance to economists and policymakers. It has long been argued that market prices can influence real decisions of economic actors by aggregating information in a meaningful way (Hayek, 1945). Similarly, markets can enable individuals and households to achieve optimal risk-sharing in the economy (Allen and Gale, 1994). An additional channel through which markets can influence real outcomes is via their role in affecting the economic agent's effort level. While this line of research has been studied well for corporations, little is known about the role of markets in influencing the performance of government agencies. Our paper fills this gap in the literature by exploiting an interesting empirical setting: the launch of a new financial market that has payoffs linked to the measurement of temperature by National Weather Service (NWS).[1]

There is a rich theoretical and empirical literature highlighting the importance of financial markets in disciplining corporate managers.[2] This line of research argues that market participants such as block-holders and pension funds can discipline corporate managers through explicit or implicit performance-based incentive contracts (e.g., see Shleifer and Vishny (1986), Holmstrom and Tirole (1993), Burkart, Gromb, and Paunzi (1997), Bolton and Von Thadden (1998), Gopalan (2009), Admati and Pfleiderer (2009), and Edmans (2009).). But why should a government bureaucracy respond to financial markets when there is no market-based incentive mechanism in place?

[1]Our study also contributes to the literature on the role of financial innovations and derivative contracts on real outcomes (e.g., Froot, Scharfstein, and Stein (1993), Tufano (2003), and Stulz (2004)). Unlike the prior empirical literature that studies the effect of derivative contracts on firms using them, we study their effect on the actions of a government bureaucracy.

[2]There are numerous important contributions in this area. They have been nicely summarized in survey articles such as Shleifer and Vishny (1997), Gillan and Starks (1998), Black (1998), Karpoff (1998), Romano (2001), Hermalin and Weisbach (2003), and Becht, Bolton, and Roell (2003) among others.

We argue that the launch of financial markets linked to NWS reported temperature numbers generates additional visibility and scrutiny of its actions, which in turn produces better outcomes by the agency even in the absence of any explicit incentive contract. The underlying motivations behind better outcomes can range from the avoidance of potential reputational losses to career concerns of the NWS officers. In analyzing the motivations and biases of bureaucrats, Prendergast (2007) notes that the clients of a bureaucracy typically point out errors when it harms them. As the client's capability in pointing out these mistakes increases, it is even more likely that the mistakes are caught and immediately pointed out. The introduction of derivative contracts creates a new set of clients for the NWS, who are likely to be both skillful and motivated in pointing out measurement errors. This additional scrutiny increases the likelihood that the NWS will suffer reputational loss due to poor measurement. If a public agency experiences a loss in reputation they may be subject to political hearings and downsizing. Noted social scientist James Q. Wilson observes, "The head of a business firm is judged and rewarded on the basis of the firm's earnings–the bottom line. The head of a public agency is judged and rewarded on the basis of the *appearance* of success, when success can mean reputation, influence, charm, the absence of criticism, personal ideology, or victory in public debate" (Wilson (1989), page 197).

In a similar spirit, Dewatripont, Jewitt, and Tirole (1999) stress the importance of career concerns as a motivating tool for bureaucrats. Finally, once a weather-related financial market opens up, there is a higher probability of disputes arising out of improper recording of the temperature since an error can now cause immediate and direct financial loss to third parties. Even though the government agency may not be a party in resulting litigations, they may experience negative publicity or a loss of reputation due to the lawsuit.[3]

[3] We provide a number of pieces of descriptive evidence, collected from a variety of sources such as NWS's directives and the industry interest groups' documents, in support of these channels.

Our empirical tests exploit the staggered introduction of weather derivative contracts based on daily temperature levels of several U.S. cities over the past 14 years. Weather has a large impact on a variety of economic and social decisions. While there has always been a need for hedging weather related risk by sectors such as utilities and crop production, it was only in 1999 that the Chicago Mercantile Exchange (CME) introduced its first exchange traded weather derivative instruments. Since then, the CME has introduced weather contracts on a number of U.S. cities in waves. A vast majority of these instruments are temperature related, allowing the end-users to hedge their exposure to undesirable warm or cold weather conditions.[4] These contracts are city specific and are settled based on the temperature readings of a specific NWS weather station within or near the contract city. These stations are almost always located at the underlying city's main airport, and are prone to measurement errors due to factors such as improper calibration of the sensors, poor maintenance, and lax monitoring of the equipment. The introduction of derivative contracts directly ties the NWS reported temperature measures at these stations to the large economic interests of traders and hedgers in the market.

As of June 30, 2012 there are 24 U.S. cities with temperature related derivative contracts trading on them. These contracts were issued in four different waves in 1999-2000, 2003, 2005, and 2008. Our empirical setting allows us to compare the improvement in temperature accuracy of the weather stations with derivatives (the treatment group) around the derivative launch dates with a set of non-shocked stations (the control group) during the same period. The staggered nature of the derivative launch allows us to separate the effect of any time trend in error rate or any general improvement in NWS's technology over time from improvements due to derivative introduction. Our empirical setting has another important advantage in terms of establishing causality. Unlike stocks, bonds, or foreign currencies, the vari-

[4] As per the survey results of Weather Risk Management Association (WRMA), an industry body for weather risk, in notional terms, more than 95% of these contracts are temperature related.

able underlying the weather derivatives contract is not a traded commodity and is completely exogenous. Thus the introduction of the derivative contract is not going to affect the value of the underlying asset – a concern that is always present in studies that analyze the effect of derivative contracts on the underlying assets.

We obtain the initial or raw temperatures from a report, called METAR report, produced hourly by the NWS. These reports contain the initial record of temperature for each weather station and are disseminated immediately to users. The initial temperature records can sometimes be erroneous due to reasons such as equipment malfunction, improper installation of the equipment, or improper calibration and maintenance of the station.[5] At the time of its initial report, NWS makes it clear that the initial temperature numbers are preliminary and subject to change based on their data cleaning and verification exercise. To compute the accuracy of these numbers, we obtain corrected temperature data from two sources. National Climatic Data Center (NCDC), an affiliated agency of NWS, is mandated with the task of correcting mistakes in NWS measurement and issuing a restatement after a time lag. In addition, a private company called MDA Information Systems Inc. (MDA) specializes in correcting the raw temperature data from the NWS. They use a number of techniques to correct the error in initial measurement including recovering data from alternative sources, using their proprietary model to correct mistakes, cross-checking the NWS data against other nearby stations and by calling up the climate centers, including NWS field offices, to discuss possible errors. We define measurement error as any discrepancy between the raw values obtained from METAR reports and the corrected values. Our results are not dependent on the source of corrected temperature values since NCDC and MDA reported temperatures are almost identical.

We obtain measurement error data for all the weather stations with derivative contracts along with a set of control stations. Using a sample period of 1999-2012

[5]For example, see NWS instruction number 10-1302 or NWS 10-1004 for steps undertaken by the weather stations to minimize errors in the data gathering exercise.

for 49 treatment and control stations, we find that the median weather station in our sample has an error rate of 12 days per year. To examine the effect of derivative introduction on error rate, we estimate a difference-in-differences model using station and year fixed effects. Our estimation shows that after the introduction of weather derivative contracts, the treated station's error rate comes down significantly by 1.6 to 2.4 days depending on the model specification. The decline in error rate represents about 13-20% of the median error rate in our sample. Thus, weather stations with derivative contracts have lower incidence of inaccurate data after their recorded temperature numbers become reference points for billions of dollars of financial contracts in an open market.

Are these improvements driven by economic interests generated by the financial contracts? To answer this question, we conduct three tests. First, we show that the improvement is larger for stations that received derivative contracts in earlier waves. These stations are likely to have relatively higher economic interests based on CME's revealed preference. Second, we show that the effects are stronger for cities with relatively higher populations, i.e., for cities that are likely to have higher energy demands and hence higher economic interests in weather derivative products. In our third test, we exploit an interesting seasonality of this market. An overwhelming majority of these contracts are traded in very hot and cold months. The Heating Degree Day contracts (HDD) are used by hedgers in the winter months to hedge against variability in cold weather. Conversely, the Cooling Degree Days (CDD) contracts are used in summer months to hedge against variability in hot weather. There are two months of the year, called the "cross-over months" by many market participants, when there is very little activity in either contract's market. These are the months of April and October. Consistent with our assertion that economic interests influence measurement accuracy, we find that all the accuracy improvements come from months excluding April and October, and there is no change in the measurement accuracy in these two months.[6] Overall these results establish our main claim that the launch of weather derivatives results in better measurement outcomes by the NWS and the result is most likely linked with economic interests generated through derivative contracts.

There are two main channels of improvement that could lead to the decrease in error rates: better technology or better effort by NWS employees. If the NWS improves its technology at the derivative launch stations precisely at the time of derivative introduction, then the effect that we document would come mainly from this improvement. We provide both anecdotal and empirical evidence to the contrary. While NWS weather stations undergo regular upgrades in their measurement technology, we show the major shift in technology happened before September 1999, i.e., before the launch of CME weather derivatives. Additionally, our test based on the seasonality of this market allows us to separate the two channels as well. If the NWS selectively introduces better equipment at these stations at the time of derivative launch then the improvement in measurement accuracy should be felt throughout the year. If, on the other hand, better effort is put forth by officials when economic interests are high, then we expect to see higher improvement in peak months and not much of a difference in April and October. As mentioned above, our results support the latter interpretation. Finally, we investigate the extent of maintenance activity performed by NWS at these weather stations to directly link the launch of derivatives launch to the agency's actions. Consistent with our effort based interpretation, we document a significant increase in the frequency of maintenance operations by the NWS for derivative stations with higher economic interests.

Our results have important implications for the role of markets in improving efficiency. While there has been a large body of research on the role of markets in improving the allocative efficiency of the economy, little is known empirically about

[6] As a robustness exercise, we widen the cross-over period to six months including months immediately preceding and following April and October. We show that our results mainly come from the peak activity months of June-August and December-February, i.e., from a period of high economic interest in this market.

the role of markets in improving government agencies' actions. Our evidence shows that while governments often regulate markets for better behavior by market participants, markets can regulate governments through the channels of increased scrutiny and visibility. These improvements in government performance can affect real outcomes as the benefits accrue to society as a whole. The positive externality of better weather measurement could be enjoyed by the many businesses that rely on timely and accurate temperature measurements to make decisions. As an example, energy companies use both high and low frequency temperature data to plan energy production. An improvement in temperature accuracy will lead to better production planning by such companies. Indeed, NCDC has established a number of sector-specific user engagement programs that highlight the needs for timely and accurate data by a diverse set of industries such as energy, transportation, tourism, and construction.[7] In this respect, our study directly relates to the role of financial innovations and derivatives in affecting real outcomes.[8] Our study also relates to the literature on the effect of financial derivatives on firm valuation. Perez-Gonzalez and Yun (2012) analyze the effect of weather risk-management on energy utilities. They show that derivative usage leads to higher valuation, investments and leverage for such firms.[9]

Finally, our study contributes to the corporate governance literature that focuses on the role of markets in disciplining corporate managers. Our paper complements this literature by providing evidence on the monitoring role of markets in a public sector setting. Researchers have for long recognized the difficulty in achieving efficient outcomes in government bureaucracies through performance based incentive contracts (e.g., see Heckman, Heinrich, and Smith (1997)). The difficulty arises mainly because

[7] see http://www.ncdc.noaa.gov/oa/userengagement/userengagement.html .

[8] See Tufano (2003) for a survey on financial innovation including the role of innovation on society. See Stulz (2004) for a survey of the literature and discussions on costs and benefits of derivatives.

[9] There is a large literature on the effect of financial derivatives on firm valuation and investment decisions in non-weather risk related context as well. For example, see Allayannis and Weston (2001), Carter, Rogers, and Simkins (2006), Purnanandam (2007), and Berrospide, Purnanandam, and Rajan (2010) among others.

the goals of a public agency are not easily defined and the performance relative to these goals is also hard to quantify. Heckman et al. (1997) study the performance standard systems of Job Training Partnership Act (JTPA) to assess the effectiveness of incentive contracts in such a setting.[10] Our study shows that visibility generated through financial contracts that are tied to the bureaucracies' actions can work as a device to obtain better outcomes from these agencies. This mechanisms can be especially useful for agencies that face difficulty in establishing performance based contracts. Overall our study has important implications for the literature on the efficiency of public enterprise (see Karpoff (2001)) and financial markets' role in making public bureaucracies more efficient.

The rest of the paper is organized as follows. In Section 2.3 we describe the weather derivatives market in detail and highlight some key aspects of temperature measurement by the NWS. Section 2.4 describes the data and provides sample statistics. Section 2.5 provides the empirical design and results of the paper. Section 2.6 concludes.

2.3 Weather Derivatives Market

Weather has a significant impact on the operating and financial performance of several industries, municipalities, and households. Some survey evidence suggests that over $3 trillion of the U.S. GDP is associated with weather-sensitive industries.[11] Industries such as energy, construction, food processing, retail, and transportation are especially exposed to weather risk. Weather derivative products can provide insurance against weather related losses to these businesses. In addition, these products provide an alternative investment and diversification opportunity to the financial in-

[10] Heinrich (2002) provides a detailed discussion of outcome-based performance management for public sector agencies. Dixit (2002) provides an overview of the theory of incentives with a special focus on the public sector.

[11] See Dutton (2002) for details.

vestment community. While the need for insurance against weather conditions has been felt for a long time, it was only in 1999 that the first set of exchange traded weather contracts was listed on the Chicago Mercantile Exchange (CME). The exchange launched temperature based futures and options contracts on 10 U.S. cities within 13 months of September 1999. It launched contracts on several other cities in three more waves in 2003, 2005, and 2008. As of June 30, 2012, CME weather contracts are available for 24 U.S. cities spanning all broad meteorological areas of the country.[12] We provide a timeline of the introduction of these contracts in Figure B.1. As described in detail later, the staggered introduction of these contracts provides us with several econometric advantages in identifying the effect of the derivatives market on the NWS station's error rate.

[Figure B.1 Here]

As of September 2005, approximately the middle point of our sample period, the total notional value of all CME traded weather contracts amounted to about $22 billion and an overwhelming majority of weather contracts are based on temperature. Based on survey evidence, the Weather Risk Management Association (WRMA) reported that over 95% of the CME contracts, in notional value terms, were related to temperature in 2005-06 (WRMA Survey Report (2006)). Other major categories included contracts on rain, wind, and snow. Temperature related contracts insure the buyers from either excessive heat or cold during a specified period of time. There are two types of contracts under this category: Heating Degree Days (HDD) and Cooling Degree Days (CDD) contracts. The buyer of an HDD contract receives payments for cold days defined as days with average temperature below 65^0F; conversely the buyer of a CDD contract receives payments for hot days defined as days with average

[12] In addition to these 24 cities, CME also has snowfall contracts on Newark and the hurricane index on the Eastern US from Brownsville, Texas to Eastport, Maine. We do not include these two locations in our analysis since our focus is on city specific temperature related contracts.

temperature exceeding 65^0F. These contracts are written on observed temperature of a specific city for a specific period.

An Example Contract: As an illustration, consider a CDD option contract on Chicago for the month of August. The contract specifies a weather station in Chicago as the reference station for this trade. The weather station is typically located near the underlying city's airport and is identified by a WBAN number.[13] The Chicago contracts in our example are settled based on the weather station at O'Hare International Airport with WBAN station number 94846. Every day in August the CDD contract compares the average of daily maximum and minimum temperatures (T_{avg}) reported at this station with 65^0F and computes the cooling degree for the day as $max[0, T_{avg} - 65]$. These degree days are cumulated over the entire month of August and payments are made based on the cumulative month-end number called the CDD index for August. Typically, one point in the index entitles the buyer to a payment of $20 from the seller. With hundreds of thousands of such contracts in the market, the reported temperature at these stations has tremendous economic implications for the market participants.

The final settlement of these contracts are based on the CDD or HDD index reported by MDA Information Systems, Inc. The settlement occurs on the second business day after the contract month.[14] MDA (formerly Earth Satellite Corporation, founded in 1969) is a private company and a leading provider of weather data to the weather trading industry. CME uses MDA's services to obtain temperatures based on NWS data for its trade settlements. MDA obtains weather data reported from the NWS and performs several quality control checks before transmitting it to the CME for trade settlements. MDA's quality checks are based on cross-verification, consistency of the data with other nearby stations, and their own meteorological

[13]WBAN, an acronym for Weather-Bureau-Army-Navy, is a five-digit weather station number that uniquely identifies a measurement location.

[14]See the guidelines on CME's website at: http://www.cmegroup.com/trading/weather/files/Monthly-CDD-Index-Futures-Final-Settlement-Procedure.pdf

models. For example, NWS occasionally reports missing temperature data for a weather station. The missing data can arise due to improper recording or other instrument malfunctions. In such cases, "MDA Federal first attempts to recover this data from alternative data sources, such as Climate Summary Reports, contacting the local NWS office or local media reports, as appropriate." (quoted from MDA's procedure manual). This is one direct example of increased outside scrutiny and visibility of the temperature numbers reported by the NWS.

2.3.1 Temperature Measurement and Sources of Error

There are many government agencies that coordinate to meet the public's weather needs. The ultimate weather authority is the Department of Commerce (DOC), which is a Cabinet department of the federal government. Within the DOC, the National Oceanic and Atmospheric Administration (NOAA) is a bureau "focused on the condition of the oceans and the atmosphere." NOAA oversees 6 main offices out of which 2 offices focus on surface temperatures: the National Weather Service (NWS) and the National Environmental Satellite, Data and Information Service (NESDIS). The NWS handles most weather related government activities, including producing and disseminating temperature readings. The NESDIS manages and archives data collected by many government agencies. The National Climactic Data Center (NCDC) is an office within the NESDIS that archives and processes past weather records. In summary, the NWS and NOAA are the main agencies ensuring accurate on site measurement of temperatures throughout the United States, while the NCDC handles cleaning and storing past temperatures.

As mentioned earlier, weather derivative contracts are settled on the basis of temperature readings produced by the underlying WBAN stations. Although there could be multiple weather stations within a city, 23 out of 24 CME derivative stations are located at the city's main airport. A great degree of care is needed to obtain temperature with high accuracy even in a laboratory setting (e.g., see McGee (1988) for a detailed analysis of temperature measurement issues). These WBAN stations measure temperature in an outside environment, which can be even more difficult to measure with precision. A wide variety of factors affect accurate temperature measurement at a WBAN station. These factors can be broadly classified into three (non-exclusive) groups: (a) technological, (b) environmental, and (c) human. The technological factors relate to basic quality of the thermometer such as the sensor's effectiveness, calibration errors, and self-heating of the instrument. Environmental factors relate to issues such as the location of the sensors and the effect of nearby electric disturbances, radiation, sunlight, and wind. The human factor captures the effect of manual intervention needed to measure temperature accurately. These interventions come in several forms such as active maintenance of the instrument, proper calibration, and minimizing the impact of environmental factors that can lead to inaccurate reports.

An Example of Measurement Error: A well publicized case from the Oahu weather station in Hawaii provides an illustrative example of measurement error in temperature. In June, 2009, the NWS weather station at the Honolulu airport reported a daily maximum temperature of 92^0F for 6 consecutive days. On the same days, a nearby tsunami warning station located about 3 miles away reported temperature that was about 6^0F to 9^0F below the Honolulu station's recordings. Once this discrepancy was pointed out, NOAA officials investigated the situation and detected an error at the Honolulu station. After reparation of the Honolulu station, the temperature recordings of the two stations converged. In this example, the initial temperature recorded at the Honolulu station would be subsequently corrected/restated to reflect this error.

NOAA and NWS have detailed procedure manuals for collecting these readings in a timely and accurate manner. They also issue regular directives to their field offices on best practices in measuring temperature. These directives can be obtained from NOAA's website.[15] As an example, consider the NWS instruction 10-1302, dated June 21, 2010. It details out requirements and standards for NWS temperature and precipitation recordings.[16] It lays out procedures for proper installation, monitoring, and maintenance of these instruments. A few examples of these guidelines are: (a) the instrument must be placed at least 100 feet from any concrete or paved surface; (b) all attempts should be made to avoid areas with rough terrain, air drainage, areas where water tends to collect, and areas where drifting snow collects; (c) the instrument should not have any major obstruction (for example nearby buildings, trees, or fence) close-by that can affect its readings. Similarly, the NWS directive 10-1004 issued on February 17, 2011 provides a detailed set of instructions on the monitoring of surface weather stations. These instructions point out the possible sources of error in temperature measurement and the NWS's attempts at training their staff to minimize these error rates. These guidelines also show the role of humans in measuring weather variables in an accurate manner.

In addition to CME and MDA, traders and financial parties regularly monitor these numbers and establish financial positions in this market based on their needs. Weather scientists have taken note of the increased attention paid to climate observations by the private sector in recent years (e.g., see Changnon and Changnon (2010)). As expected, NOAA, NWS and weather industry professionals have all recognized the need for better data quality from the WBAN stations. A number of initiatives such as joint conferences and exchange of ideas have taken place between these groups in light of the weather derivatives introduction. A workshop report in 2002 by the American Meteorological Society (Muranane et al. (2002)) discusses the data needs of the private sector of the weather derivatives market.

We argue that the introduction of a weather derivative market attaches immediate

[15] http://www.nws.noaa.gov/directives/010/010.htm.
[16] See http://www.nws.noaa.gov/directives/sym/pd01013002curr.pdf

and large economic importance to the NWS temperature numbers, which in turn results in tremendous scrutiny of these numbers by investors, media, and other related parties. Indeed, the NWS also recognizes the need for better data collection exercises in light of the increased scrutiny by outside parties. In the Appendix, we provide an excerpt from an NWS directive to the field offices that highlights this aspect of monitoring. We also provide an excerpt from a meeting of NWS officials with weather industry representatives regarding the need for better data in the Appendix. In the rest of the paper we empirically test our main hypothesis that markets improve the measurement accuracy of NWS temperature recordings.

2.4 Data

We collect data from several sources and combine them together for our analysis. We first collect information on the launch dates of monthly derivative contracts on a city's temperature from the CME and press releases. For some cities, the CME introduced weekly and seasonal contracts at a later date as well. These contracts were introduced after the monthly contracts, hence we focus on the monthly contract introduction dates. There are 24 weather stations with temperature derivative contracts as of June, 2012. In addition, we identify 25 stations without weather derivative contracts as the control group. The 25 control weather stations are chosen by sorting all U.S. metropolitan areas by population and using the 25 highest population cities without weather derivatives. We use the 2011 population estimates for metropolitan areas from the United States Census Bureau for this purpose.[17] We identify the WBAN number (i.e., the exact station number) of all derivative cities based on the contract specification. For the control cities, we use the weather station at the largest nearby airport. In total we have 49 weather stations in our sample. These weather stations, their WBAN identification number, and the derivative introduction dates

[17] http://www.census.gov/popest/data/metro/totals/2011/

for the treatment group are provided in Table B.1. There have been four main waves of derivative introductions: 1999-2000, 2003, 2005, and 2008. The list of derivative stations cover mostly large cities as well as a few smaller cities that are likely to have large economic interests tied to weather.

[Table B.1 Here]

We obtain all weather data from MDA Information Systems, Inc. As mentioned earlier, MDA is a leading provider of weather data to weather traders as well as to the CME. We obtain two pieces of information for each weather station: (i) the raw temperature readings, and (ii) the cleaned or corrected temperature values. The raw temperature readings are the actual reported temperature numbers by the NWS or an affiliated organization for each station on a given day. We obtain data on the daily maximum and minimum temperature because the weather derivative contracts are settled based on the average of these two values. The raw temperature comes from METAR readings, which are standardized weather reports produced by Automated Surface Observing Systems stations. These stations are collectively operated by the Federal Aviation Administration, National Weather Service and the Department of Defense. For expositional simplicity we call these stations NWS operated stations throughout the paper since they are the main nodal agency for temperature related activities. MDA obtains the raw temperature data for each WBAN station from the NWS METAR reports.[18]

The second key measure is the 'cleaned' or 'corrected' temperature value for every station-date pair. MDA uses a detailed five step process to clean the raw temperature values obtained from the government agencies. Through this process they ensure that

[18]The NWS stations produce hourly weather reports, 6-hour min/max temperature reports and 24-hour min/max temperature reports at midnight local time. We obtain the 24-hour min/max temperature values as the measures of raw temperature. If this value is not available for a specific station-date, then MDA provides us with the minimum and maximum temperature based on 6-hour or hourly reports.

the data is consistent with nearby reporting stations, and it conforms to meteorological consistency. They also take care of missing temperature values, which occur in the NWS reports due to reasons such as improper or incomplete METAR recordings. If the raw data has missing values, MDA uses other sources, such as NWS Climate Summary Reports, contacts at the local NWS office or local media reports to obtain temperature values. Equally important, MDA checks all the raw temperatures for erroneous values by checking "the data against itself and against alternative data sources, such as hourly data, Climate Summary Reports, surrounding stations, and additional observations, as appropriate." MDA's meteorologists then examine the temperatures to ensure they are meteorologically consistent, i.e., they conform to basic consistency checks against other weather related variables. If temperatures are missing or erroneous, then new values are created using proprietary estimation techniques of the MDA. Using this detailed process, MDA arrives at a clean temperature measure that is used widely by the financial services industry as well as several other sectors. In essence, the MDA cleaned values are third-party corrected temperature numbers for these weather stations. We use the difference between the corrected and raw value as our key measure of measurement error in NWS temperature recordings.

We also obtain data on cleaned temperatures with corrections to the raw NWS temperature numbers from the NCDC. NCDC issues these official temperatures with a couple months' time lag. These corrections, or restatements, by the NCDC provide us with yet another measure of measurement accuracy at the time of initial report. Further information on preliminary and cleaned data can be obtained from NWS instruction manuals such as NWSI 10-1004 dated February 17, 2011 (NWS, 2011) and NWSPS 10-10 dated September 29, 2010 (NWS, 2010). NCDC restated numbers are extremely close to the MDA corrected values. Therefore, we use the difference between NWS raw numbers and MDA corrected values as the main variable in all our tests. We prefer the MDA based clean values because it alleviates the concern that the government agencies may be less inclined to restate their recordings after these contracts begin to trade. Figure B.2 provides a timeline of initial temperature measurement by the NWS, the corrections reported by MDA for contract settlement by CME, and the final cleaned value generated by NCDC.

[**Figure** B.**2 Here**]

2.4.1 Descriptive Statistics

Our sample covers all 49 stations, 24 with derivative contracts and 25 control stations, from 1999 to 2011. We begin in 1999 because we are unable to obtain high quality historical data on raw NWS temperature values for years prior to 1999. This data restriction should have only a minor impact on our study because 20 out of 24 treatment stations received derivative contracts after 1999. Thus we have 20 stations for which we have data on both before and after the derivatives' introduction – we exploit the variation generated by these stations around the launch date in our empirical tests.

We take the number of days a given station reports erroneous or missing values as the main measure of temperature inaccuracy. These are the dates when the raw and corrected values differ from each other. We aggregate this number at the yearly level and use the yearly count as the key measure of measurement error rate of a station in a year. We have 49 annual observations spread over 13 years in our sample. Some station-years show considerable error rate leading to skewness in the data. The Los Angeles weather station, for example, has very high levels of error rate across many years. In our empirical tests we remove such station specific effects using station fixed effects. Further, we winsorize the data at 5% from both tails to ensure that our results are not driven by outlier observations. We also use log transformed error rate as an alternative measure of the dependent variable to alleviate concerns about outliers. As reported later, our results remain robust to either specification. Summary statistics are presented in Table B.2. A representative median station reports about 12 error days per year. There is considerable cross-sectional variation in the data as evident by the 90th (20 days) and 10th (5 days) percentiles of error days in the sample (see also Figure B.3). In unreported results, we find that raw and final numbers remain the same for 96.69% of days. Of the remaining 3.31% days, 2.12% have a difference of 1^0F between the raw and cleaned data. The remaining 1.19% observations have considerably large discrepancies mostly ranging from 2-10^0F.

[**Table** B**.2 Here**]

[**Figure** B**.3 Here**]

In addition to the main data on temperature recordings, we also obtain open interest data from the Chicago Mercantile Exchange. We use this information to analyze the relationship between derivative introduction and temperature accuracy across months with high and low economic interest.

2.5 Empirical Design and Analysis

2.5.1 Research Design

We estimate the effect of weather derivative introduction on the accuracy of temperature measurement in a difference-in-differences framework. We compare the measurement accuracy of a weather derivative station after the shock (i.e., after the introduction date) with the same station's accuracy before the shock to get the first margin of difference. The second margin of difference comes from the change in the accuracy level of non-shocked stations around the same time period. The underlying assumption is that the changes in the non-shocked stations' accuracy level separates out the effect of other (i.e., non-derivative related) factors on the accuracy level of the shocked stations. These non-derivative related changes in accuracy can come from sources such as technological advancement over time, climatic changes, or NWS' overall effort in improving its accuracy levels across all its stations. A key advantage of the staggered launch of weather derivative contracts across cities is that it allows us to remove the effect of any such macro-economic or broad climatic factors on measurement accuracy. We implement this research design using the following regression model using both station and year fixed effects:

$$y_{st} = \alpha_s + \beta \times derivative_{st} + year_t + \epsilon_{st} \tag{2.1}$$

y_{st} denotes measurement error at the WBAN station s in year t; α_s stands for station fixed effects; $year_t$ denotes the year fixed effects. $derivative_{st}$ takes a value of one for station-year observations after the introduction of derivatives, zero otherwise. The year of introduction is included in the post-introduction period. In this specification, station fixed effects remove the station specific component of measurement error whereas year fixed effects control for broad time-specific effects including the possibility of any secular improvement in measurement accuracy across all stations. Thus, the coefficient on $derivative_{st}$ provides the difference-in-differences estimate of interest.

The key identifying assumption behind our empirical exercise is that the weather derivative's launch is not correlated with any unobserved improvements in the station's ability to measure the temperature. It is unlikely that the unobserved ability of the station officers change precisely at the same time when the derivative contracts are launched. The staggered nature of our shock makes it even less likely that our results are confounded by any such omitted factors. Further, our maintained assumption is that the CME's selection of these derivative contracts is primarily driven by the demand for these hedging products at these cities, and not by *anticipated* improvement in the accuracy level of temperature measurement. Note that it poses no identification challenge for us if the CME chooses these stations based on their historical measurement accuracy. Station fixed effects separate out any such effect from our analysis. Our estimation comes from within-station changes in the accuracy level and not from the average differences between the stations.

Before presenting our main results, we estimate a simple selection model to understand the key drivers behind the selection of these stations. We estimate a Probit model with a cross-section of 281 metropolitan cities obtained from the U.S. census data.[19] The dependent variable equals one for the 24 cities that have weather derivatives and zero for the remaining cities. We include only three explanatory variables in the model as proxies for the demand of weather derivative products. These variables are: (a) the city's population rank,[20] (b) whether the city has any financial or commodity exchange or not,[21] and (c) whether the city is the largest city in a top 15 crop producing state.[22] The key idea behind the selection of these variables is to capture the effect of hedging demands from energy and farming sectors, two main end-users of the weather derivative products, and the presence of financial intermediaries in these cities. A city's population is used as a proxy for energy demand. The largest city in a top crop producing state is likely to have large trading interests related to the farming sector. Finally, if a city has exchanges, such as the Kansas City Board of Trade, then it is less costly for the financial intermediaries to trade with the end users. Exchanges may also proxy for central locations in local economies that are

[19]For the selection model we use all metropolitan cities available in the U.S. census data. In subsequent tests involving measurement errors, we limit our attention to control cities that are highly populated. This ensures comparability across our treatment and control stations on important dimensions such as the NWS-designated service level of the weather station.

[20]2011 population estimates from the U.S. Census Bureau

[21]Financial exchange cities are: Chicago (CBOE, CME, etc.), Jersey City (EDGA, NSE), New York (NYSE, NASDAQ, etc.), Philadelphia (Philadelphia Stock Exchange), Boston (Boston Stock Exchange) and Lenexa (BATS Exchange). Commodities exchange cities: Chicago (CBOT, CME, etc.), Atlanta (Intercontinental Exchange), Kansas City (KCBT), Memphis (Memphis Cotton Exchange), Minneapolis (Minneapolis Grain Exchange) and New York (NY Mercantile Exchange)

[22]Crop rankings are based on the state's value-added to the U.S. economy by the agriculture sector in 2011. Data is from the United States Department of Agriculture Economic Research Service: http://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics

likely to have common weather risks.

With these three variables we estimate the Probit model and present the results in Column 1 of Table B.3. Larger cities, top cities in farming states, and cities with trading exchanges are all more likely to have a derivative contract, although the coefficient on farming states is not significant. The McFadden's Psuedo R^2 of the model is reasonably high, indicating that these simple measures of hedging demand capture a large variation in the selection of these contracts.[23] In Column 2, we estimate a model that predicts the likelihood of receiving a derivative contract in the first wave, i.e., in 1999-2000. The dependent variable equals one for stations that received derivative contracts in the first wave, and zero otherwise. The coefficient estimate on the high crop variable increases in economic magnitude and is now significant at the 10% level. The coefficients on population and exchange cities continue to be significant and have similar economic magnitude. Overall these findings are consistent with our claim that demand side considerations played a major role in the selection of these cities. Further, cities chosen in earlier cohorts are more likely to have higher demands for weather hedging products from energy and farming sectors.

[Table B.3 Here]

2.5.2 Empirical Analysis

We estimate the difference-in-differences model using data on 49 weather stations for the 1999-2011 period. As mentioned earlier, 24 stations have the weather derivative contract, whereas 25 do not. The 25 control stations are the 25 most populated cities that do not have a weather derivative contract. In addition to their population, the treatment and control cities are comparable on several other relevant dimensions as well. In particular, they are similar in terms of the NWS's designated service level

[23]For interpretational simplicity of R^2, we also estimate these models using a linear regression model and obtain traditional R^2 in the range of 30%.

for the maintenance of the weather station. NWS classifies weather stations into 4 service levels (A,B,C, and D) based on air traffic and bad weather outcomes. Service Level D stations are completely automated. Service Level C stations have an additional human observer when the tower is open. Service Levels A and B have a human observer practically all the time, and the observers have more responsibilities at these stations. Almost all of our treatment and control stations belong to category A, i.e., to a category that requires the utmost care from human observers.[24] More important, the service level of our treatment and control stations are comparable as documented in Table B.1. Thus the control group is likely to serve as a reasonable counterfactual for our study. We also document some other key characteristics of the treatment and control group in the Table. These groups are comparable in terms of population and air traffic level as well.[25] In sum, the control cities are not very different from the treatment cities in terms of their designated service levels and non-derivative related interests in temperature.

As a prelude to the main regression analysis, we provide the average number of error days for the shocked stations (treatment group) for the 3 years before and after the shock and compare that to the corresponding averages of the control firms. We take the average number of error days for all control stations during the given calendar year for this exercise. We compute the average error days across the two groups for the periods before and after the shock and plot them in Figure B.4.[26] The error rate drops slightly for the control group before and after the shock, whereas there is a remarkable drop in the corresponding number for the treatment group. The average error rate drops from 12.86 to 11.29 days per year for the treatment group compared

[24]Service level data comes from the Aviation Weather Assets Database: http://apps.avmet.com/awad/AWADReport.cfm

[25]Air traffic ranks come from the Airports Council International: http://www.aci-na.org/content/airport-traffic-reports

[26]For this figure, we are unable to use the data for stations that received derivatives in the first wave of 1999-2000. We do not have data for the past three years for these stations. All our formal tests, presented in the rest of the paper, include these stations as well.

to a corresponding drop from 13.16 to 12.44 days per year for the control stations. In our regression model, we formally assess the statistical significance of the difference after removing the station and year fixed effects.

[Figure B**.4 Here]**

Results of the estimation exercise are provided in Table B.4. Models 1 and 2 use the number of error days as the dependent variable, whereas Models 3 and 4 use its log transformed values. Model 1 presents the results without year fixed effects. We obtain a coefficient of -2.36 on the *derivative* variable, indicating a decline of about 2.36 days in the annual error rate. The effect is statistically significant at the 1% level. In Model 2 we include the year fixed effects to remove the effect of any secular improvement in weather measurement technology over time or other macroeconomic and climatic changes that might affect the measurement error of all stations. We obtain a coefficient estimate of -1.63 that is also significant at the 1% level. Models 3 and 4 obtain similar results and ensure that our estimates are not driven by outliers. These baseline results establish the effect of derivatives introduction on measurement accuracy: NWS reported raw temperature readings become significantly more accurate once there is a direct financial market interest tied to these readings. In real terms, depending on the model specification these estimates translate into a decline of about 13-20% in the error rate of the median station after the introduction of the derivative contracts.

[Table B**.4 Here]**

As a robustness exercise, we check for and rule out the presence of any pre-existing declining trend in the error days of the shocked stations. We compute the change in error days from three years before to the year before derivative introduction. Before the shock both treatment and control stations show an increase, not a decrease, in the error rate. The shocked stations experienced an average change of +7% in the error rate during the pre-introduction period as compared to the control stations. The difference in the rate of change for the two groups during the pre-shock period is statistically indistinguishable from zero. After the introduction of the derivative, however, the treatment stations experience a steady decline over the next three years. By the end of the third year after the shock, there is a decline of about 20% in the error rate of the shocked stations as compared to the corresponding decline for the control stations. This shows that there is no declining trend in measurement error of shocked stations before the launch, but a remarkable decline afterwards. The improvement, therefore, is likely caused by the introduction of financial markets.

Overall these results show that the introduction of temperature related financial contracts results in better measurement outcomes by the NWS. We argue that these effects arise due to increased economic interests and the resulting scrutiny of these measures by market participants. As economic interests increase, the reputational costs of measurement error are likely to increase as well. Market participants are more likely to monitor these numbers and point out mistakes when economic interests are high.

If an increase in economic interests is driving the improvement in temperature readings, then we would expect locations with higher economic interests to see greater improvement. Our next set of tests is designed to exploit the cross-sectional variation in the level of economic interests across cities to provide evidence in support of this channel.

2.5.3 Economic Interests and Channels of Improvement

2.5.3.1 Cohort Analysis

We first exploit the variation generated by the year of introduction of these contracts to relate economic interests to measurement errors. Contracts introduced in earlier cohorts are likely to have higher economic interests as compared to later cohorts. This is based on the underlying assumption that CME's incentive to introduce a weather contract in a city is primarily driven by the demand for weather hedging products in that city. Thus cities with higher demand are likely to get these contracts in earlier cohorts. This assumption is consistent with our results in the selection model discussed earlier in Section 2.5.1 of the paper. We expect a higher impact of derivative launch on measurement accuracy for the earlier cohort as compared to later ones.

We separately estimate the effect of derivative introduction on measurement accuracy for each cohort as a first test of this hypothesis. We take all the shocked stations for a given cohort and include data from 1999 (i.e., the beginning year of the sample) to three years after the introduction year in the sample. We limit the sample to three years post-derivative introduction to estimate our main effects in the immediate aftermath of the launch. As an example, for the 2003 cohort, we include data from 2000 to 2006 for all the stations that launched derivative contracts in 2003 (Kansas City, Houston, Boston, Minneapolis, and Sacramento) in the treatment group. All the non-derivative stations during these years are included in the control group. Results are provided in Table B.5. We obtain a negative coefficient on the *derivative* variable for all four cohorts, with significant coefficients for all but one. Consistent with our hypothesis, the strongest effect comes from the earliest cohort (2000) in the sample, whereas the weakest result comes from the last cohort (2008). For the 2000 cohort, we find a decline of almost 5 days per year in the error rate. The corresponding improvements are -2.0, -2.7, and -1.0 for the 2003, 2005, and 2008 cohorts, respectively.

[**Table** B.**5 Here**]

As an additional empirical test of the cohort effect, we estimate the following model:

$$y_{st} = \alpha_s + \beta_{early} \cdot derivative_{st}^{early} + \beta_{late} \cdot derivative_{st}^{late} + year_t + \epsilon_{st} \tag{2.2}$$

In this model $derivative_{st}^{early}$ equals one for years after the derivative launch for all cities in the 1999/2000 cohorts, and zero otherwise; $derivative_{st}^{late}$ equals one for years after the derivative launch for all cities in the later cohorts, and zero otherwise. This model modifies our base case specification by allowing us to separately estimate the effect for the earliest cohort versus the rest. We estimate this model with data from the entire sample period. Results are provided in the last column of Table B.5. The coefficient estimate of -5.1 on $derivative_{st}^{early}$ is considerably larger than the estimate of -1.2 on $derivative_{st}^{late}$ variable. The difference is statistically significant at the 11% level.

The improvement in measurement accuracy comes from all cohorts, with the strongest effect from the 2000 cohort. The evidence is consistent with the idea that higher economic interests leads to higher visibility and better monitoring effects.

2.5.3.2 End-user Interest

The energy sector is the most important set of end-users of weather derivative products. Cities with high demand for energy are, therefore, likely to have relatively higher interest in weather derivative products. We exploit this heterogeneity across weather derivative cities to provide further support for our main claim that when economic interests are high, there is a higher improvement in measurement accuracy.

We take a city's population as a proxy for its energy demand. If a city falls among the top 25 population cities in the U.S., then we classify it as a high energy demand location for our empirical test. Further, consistent with the analysis of the previous section, if a city gets a derivative contract in the first two waves (1999 and 2000), we consider it as a high demand station as well. We create an indicator variable *High Demand* that equals one if the weather derivative station falls among the top 25 population cities or belongs to the early cohort. We similarly create another indicator variable *Low Demand* that equals *One minus High Demand*. There are six cities in the *Low Demand* category: cities that received their derivative contract in later cohorts and are among the low energy demand places. We expect these cities to have relatively lower economic interests and market scrutiny as compared to the remaining treatment cities in the sample. Our test is designed to pick up these differences in market scrutiny on the measurement outcomes.

We estimate our main regression model after including *High Demand* and *Low Demand* variables separately in the model. Results are provided in Table B.6. We find that the improvements are concentrated in the subset of high demand cities. The coefficient estimate on *High Demand* variable is almost four times larger: -2.22 as compared to -0.66 for *Low Demand*. The difference is significant at the 6% level. In the log specification, the estimated coefficient on the *High Demand* variable is almost twice as large as the coefficient on *Low Demand*. The difference in these coefficients is statistically significant at a p-value of 0.11. Overall these results are consistent with the notion that measurement outcomes improve with economic interests and market scrutiny.

[**Table** B**.6 Here**]

2.5.3.3 Effort versus Technology

We have shown that the introduction of financial markets improves the actions of the NWS by bringing more visibility and scrutiny of the reported temperature numbers. We now focus on the sources of improvement. In particular, there are two possible, not mutually exclusive, channels of improvement. First, the NWS might install better thermometers or sensors at these stations precisely at the time when derivatives start trading. We call this the *technology* channel. Second, the NWS officers might put forth more effort to better capture the temperature data in an accurate manner after contract introduction. We call this the *effort* channel. While the net effect of both these channels remains the same, i.e., an improvement in the measurement of weather, our focus is more on the second channel. Said differently, we want to investigate the disciplining effect of market purely on account of higher effort put in by the government officials. These improvements can come through better maintenance and monitoring of the weather stations to minimize erroneous reports.

One of the most important recent changes in the NWS's temperature measurement technology was the installation of Automated Surface Observing Systems (ASOS). Although the NWS consistently upgrades these stations, the installation of ASOS was the most important event on the technology side of temperature measurement. We collected data on the ASOS installation dates for 48 out of 49 weather stations in our sample.[27] For each one of these stations, the ASOS was commissioned before September 1999. This rules out the possibility of any major change in measurement technology for weather derivative stations just after the introduction of the derivative contract. In addition, we correlate the year of introduction of ASOS with an indicator variable that equals one for the treatment group, and zero for the control group. The correlation coefficient is almost zero. Thus, we do not find any evidence that derivative stations in our sample get better and/or earlier technology from the NWS as compared to the control stations.

We empirically separate the *effort* and *technology* channels by exploiting an important cross-sectional variation in trading activities across calendar months in the weather derivatives market. This test also allows us to strengthen our claim that economic interests drive more accurate measurement. As mentioned earlier, the end-users of the weather derivatives market are typically sectors such as utilities, farming,

[27]The data for the Los Angeles Station is not available.

transportation, retail, and food products. A majority of their hedging demands arise in the months with higher levels of heat or cold. Not surprising, an overwhelming majority of these contracts are based in peak summer and peak winter months (see Figure B.5). This leaves the months of April and October as the least traded months on the exchange. We estimate the basic regression model separately for these two months and the rest of the year. The key idea is to assess the improvement in measurement efforts keeping the underlying measurement technology the same.

[**Figure** B.**5 Here**]

We aggregate all the error days in April and October for the first analysis and similarly the error days in the remaining months for the second analysis. Results are provided in Columns (1) and (2) of Table B.7, respectively. Examining Column 1, we find no improvement in October and April, whereas there is significant improvement in the active trading months. In an additional test, we separate the sample into two groups by clubbing ±1 month around April and October in one group, and the rest in another. Thus we have exactly six months in each group. As shown in Columns (3) and (4) of the Table, we find negative coefficients for both groups, but the coefficient is significant only for the peak months. Further, the coefficient for the peak months' sub-sample is more than double the off-peak months' regression coefficient. Thus even at the same station, the improvement comes from months with active trading interest. These are the months where the pressure and monitoring from the outside market is likely to be the highest. In these months, the frequency of follow ups with the NWS stations and analysis of the weather data by the trading professionals is expected to be higher than the remaining months. Our result supports the view that financial markets induce higher effort by the stations in measuring the temperature accurately.

[**Table** B.**7 Here**]

2.5.3.4 Station Maintenance

In this section we provide some direct evidence on actions undertaken by the NWS in improving weather measurement. We investigate the frequency of maintenance performed by NWS officers at the weather stations before and after the launch of derivative instruments. MDA Inc, our data vendor, maintains a list of major maintenance operations for all the derivative trading stations since the year 2003. Similar data for the control stations is not available.[28] Since the data is available for only the trading stations, we are only able to exploit the cross-sectional variation within these stations. Following the variable definition in Section 2.5.3.2, we create an indicator variable called *High Demand*. *High Demand* equals one for stations with potentially higher economic interest in weather derivative products after the introduction of the derivative contract. We analyze the difference in maintenance frequency across the low and high demand categories of derivative stations using the same empirical design as in in our base case estimates.

These maintenance operations are performed only occasionally. Most maintenance operations include fixing and recalibrating sensors that have been corroded, damaged or failed. We create a variable called *Maintenance* that equals the number of days a maintenance was performed at the station. We use its log transformed value in the regression model to avoid the impact of outliers. As an alternative measure, we create an indicator variable, *Any Maintenance*, that equals one for that station-year observation if there is any maintenance during the year, and zero otherwise. Results are provided in Table B.8. In Models 2 and 4, we include year fixed effects and in all Models we include station fixed effects. Since we use station fixed effects, this estimation exploits changes in maintenance frequency for stations with derivative introduction in either 2005 and 2008 only. Despite this data limitation, we find

[28]The non-availability of maintenance data for the control stations is consistent with our basic assertion that market players pay relatively higher attention to the performance of stations with weather contracts.

that stations with higher demand of derivative products perform more maintenance after the derivative launch as compared to their low demand stations. Based on the coefficient estimate of Model 2 in the Table, high demand stations perform 1.40 times higher maintenance than their low demand counterparts. Overall these results provide evidence in support of one potential channel of higher effort to measure the temperature numbers correctly. In addition to the maintenance channel, the weather measurement outcomes can be improved through channels such as better monitoring of the stations and proper calibration of sensors. While we are unable to directly document the role of all these channels in our empirical analysis, our overall evidence supports the view that the introduction of financial contracts leads to efficient outcomes.

[**Table** B.**8 Here**]

2.5.4 Robustness Tests

2.5.4.1 NCDC Cleaned Values

All our results so far have been based on the difference between a third-party (MDA) certified measure of clean data and the NWS raw data for a station's temperature. We also obtain the corrected or restated data produced by an affiliated government agency of the NWS, namely the NCDC. The NCDC is responsible for producing the government's final data after removing measurement errors by the station. These cleaned data become NOAA's official data and are widely used in meteorological studies.

We begin with all 49 stations in our sample. However, we do not have high quality NCDC data for the year 1999. In addition, the agency did not produce corrected values for two control stations (San Jose and Riverside) during our sample period. Hence, we lose the year 1999 and two control stations from the sample. Also, the NCDC did not produce corrected values for 8 stations in December 2001, so we lose one observation month for this part of the study. We re-estimate our main regression models based on the NCDC data and report the results in Table B.9. As can be seen from the Table, the results are almost identical to the ones reported using MDA values. These results provide confidence in our measure of temperature accuracy since data from both these parties – MDA, a third-party private company, and NCDC, an affiliated government agency – produce similar results. Their broad agreement on the cleaned or correct temperature value alleviates the concern that we might have a bad measure of temperature accuracy. Indeed, on the set of overlapping observations, common to both MDA and NCDC, we find that they agree on the correct temperature values in almost all cases. There are only 4 instances out of over 200,000 daily observations where there is a disagreement between the two agencies about the correct temperature value. Therefore, it is not surprising that we get almost identical results using either one of these measures.

[Table B.9 Here]

2.5.4.2 Controlling for Changes in Weather Condition

It is unlikely that weather conditions become more conducive to better measurement outcomes after the launch of derivative contracts in a city. If that were not the case, then an improvement in measurement accuracy could simply be an artifact of changes in weather condition itself. To rule out this possibility, we re-estimate our main empirical model after including the volatility of annual temperature and the level of temperature as additional explanatory variables in the model. The key idea is to separate out the effect of volatile weather conditions or changes in average temperature from the main effect that we are interested in. Results are produced in Table B.10. The coefficient on *derivative* remains negative and significant. In fact the inclusion of these two variables does not change the magnitude of estimated coefficient in any meaningful manner as compared to our base case estimate.

[**Table** B.**10 Here**]

2.6 Conclusion

We show that the launch of a weather derivatives market on a city's temperature results in more accurate temperature measurement by the dedicated weather station for that city. After the launch of these contracts, the NWS reported numbers become reference points for billions of dollars of contracts in the private market. Thus there is an increased interest and monitoring of these numbers by third parties, which in turn creates more pressure on the NWS to produce better measures. The increased pressure can come in the form of potential reputational loss or the possibility of future disputes among the contracting parties.

Our results highlight an important role of financial markets. They can work as a disciplining device even in the absence of explicit incentives and monitoring mechanisms that are present in the corporate settings. Here, the numbers reported by a government agency become more accurate after the markets open up. To the extent that we care about accurate measurement of these numbers, there is a positive externality that comes from the financial markets. Indeed there are several industries, most notably the energy sector, that directly benefit from high frequency accurate data. Overall, our study provides one of the first empirical estimates of the impact of financial innovations on the real outcomes produced by parties that are not directly affected by the payoffs from the contract.

APPENDICES

APPENDIX A

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

A.1 Estimating Risk Premiums

The risk premium for each contract is calculated as follows:

$$r_{imdy} = \frac{E[Payoff_{imdy}]}{Price_{imdy}} - (1 + r_f) \tag{A.1}$$

where r_{imdy} is the risk premium on the location i, month m, degree day index d and year y contract, $E[Payoff_{imdy}]$ is the model-based expected payoff, $Price_{imdy}$ is the price of the contract and r_f is the monthly risk-free rate for month m and year y. I use the contract price 32 days from contract maturity and calculate expected payoffs based on information 32 days from maturity. The maturity date is defined as the last day of the contract's specified month. The closer to contract maturity, the more realized temperatures are embedded in the price and the less risk that needs to be hedged. The further away from contract maturity, the fewer open contracts. 32 days was chosen as a trade-off between the amount of contracts with prices and the amount of information in prices. This also allows for a discussion of the risk premium as approximately a monthly risk premium.

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

$$dT(t) = \frac{d\theta(t)}{dt} + e^{-\kappa}[\theta(t) - T(t)]dt + \sigma(t)dW(t) \tag{A.2}$$

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.[1] The mean, $\theta(t)$, and standard deviation, $\sigma(t)$, of temperature vary with the day of the year:

$$\text{Mean Temperature} = \theta(t) = \beta_0 + \delta t + \sum_{p=1}^{P} \beta_p \sin(\frac{2\pi}{365}pt + \phi_p) \tag{A.3}$$

$$\text{Std. Dev. of Temperature} = \sigma(t) = \gamma_0 + \sum_{q=1}^{Q} \gamma_p \sin(\frac{2\pi}{365}qt + \psi_p) \tag{A.4}$$

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

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

than annual frequencies.

Bellini (2005) shows that the continuous process in equation A.2 can be represented in discrete-time as an AR(1) process:

$$T(t) = \rho T(t-1) - \rho\theta(t-1) + \theta(t) + s(t)\epsilon(t) \tag{A.5}$$

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

$$s^2(t) = \int_{t-1}^{t} e^{-2\kappa(t-u)}\sigma^2(u)du \tag{A.6}$$

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. I estimate a maximum likelihood function, where the conditional likelihood of each temperature observation is:

$$f(T(t)|T(t-1),\Theta) = (2\pi\sigma^2(t))^{-\frac{1}{2}} e^{-\frac{1}{2\sigma^2(t)}(T(t)-\theta(t)-\rho(T(t-1)-\theta(t-1)))^2} \tag{A.7}$$

The maximum log-likelihood function is:

$$\begin{aligned} \ln\, L(\Theta|\{T\}_{t=2}^{N}) = -\frac{N-1}{2}\ln\, 2\pi - \frac{1}{2}\sum_{t=2}^{N}\ln\, \sigma^2(t) \\ -\frac{1}{2}\sum_{t=2}^{N}\frac{1}{\sigma^2(t)}(T(t)-\theta(t)-\rho(T(t-1)-\theta(t-1)))^2 \end{aligned} \tag{A.8}$$

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 paper.

The resulting parameter estimates are presented in Table A.12. The mean reversion parameter (κ) has a mean value of .33, which corresponds to a $\rho = e^{-\kappa}$ of .72. The speed of mean reversion is inversely related to κ, so Colorado Springs and Boston have the slowest speed of reversion, while the warmer climates (Los Angeles, Las Vegas, Tucson) have the fastest mean reversion. In Column 3, I present the amount of long-term drift in temperature ($\mu 0$). 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 .000 and .004. There appears to be a modest amount of warming over time at 21 of the 24 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 and Colorado Springs have the lowest estimates with mean temperatures slightly less than 50. The magnitude of seasonality in temperature is captured by parameter β_1. The least "seasonal" location is Los Angeles with a β_1 equal to 8.04, much lower than the estimates for other cities. 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 19 of the 24 cities. For 9 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 (Los

Angeles, 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 ($Q \geq 2$), 7 have at least 3 and Tucson has 4 seasonal frequencies in the standard deviation.[2]

[Table A.12 Here]

After the temperature process has been estimated, I calculate expected payoffs by using the temperature realization 32 days before contract maturity and simulating 500 temperature paths over the next 32 days until contract maturity. From the simulated temperatures, I apply the HDD and CDD temperature formulas to calculate the payoff of the contract for each path. The expected payoff is the average of the simulated contract payoffs.

[2]My estimates for the optimal P and Q vary slightly from Bellini's (2005) estimates. She estimates parameters for 4 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.

A.2 Temperature Outcomes

[Table A.13 Here]

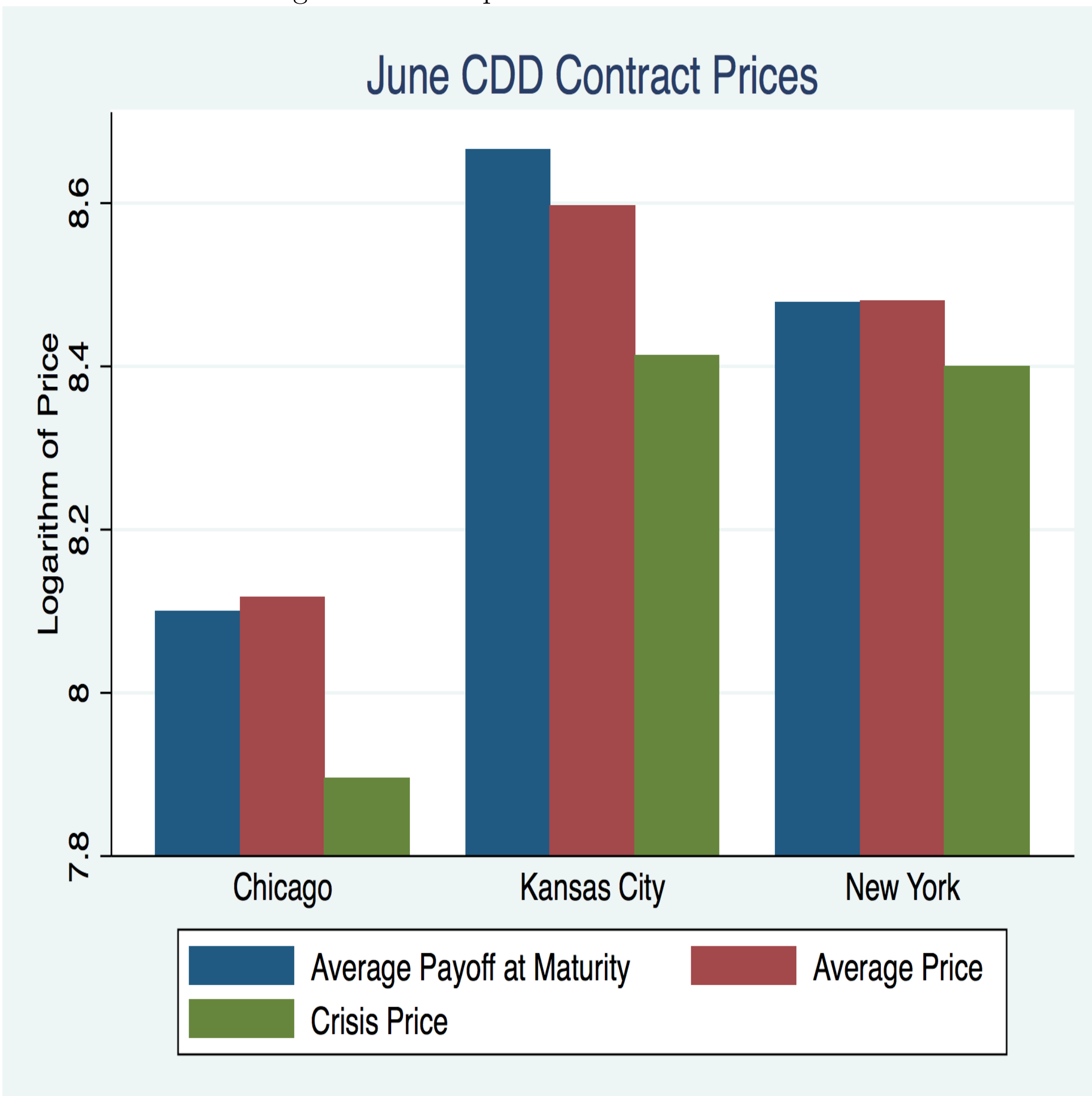
A.3 Systematic Risk Results

[Table A.14 Here]

[Table A.15 Here]

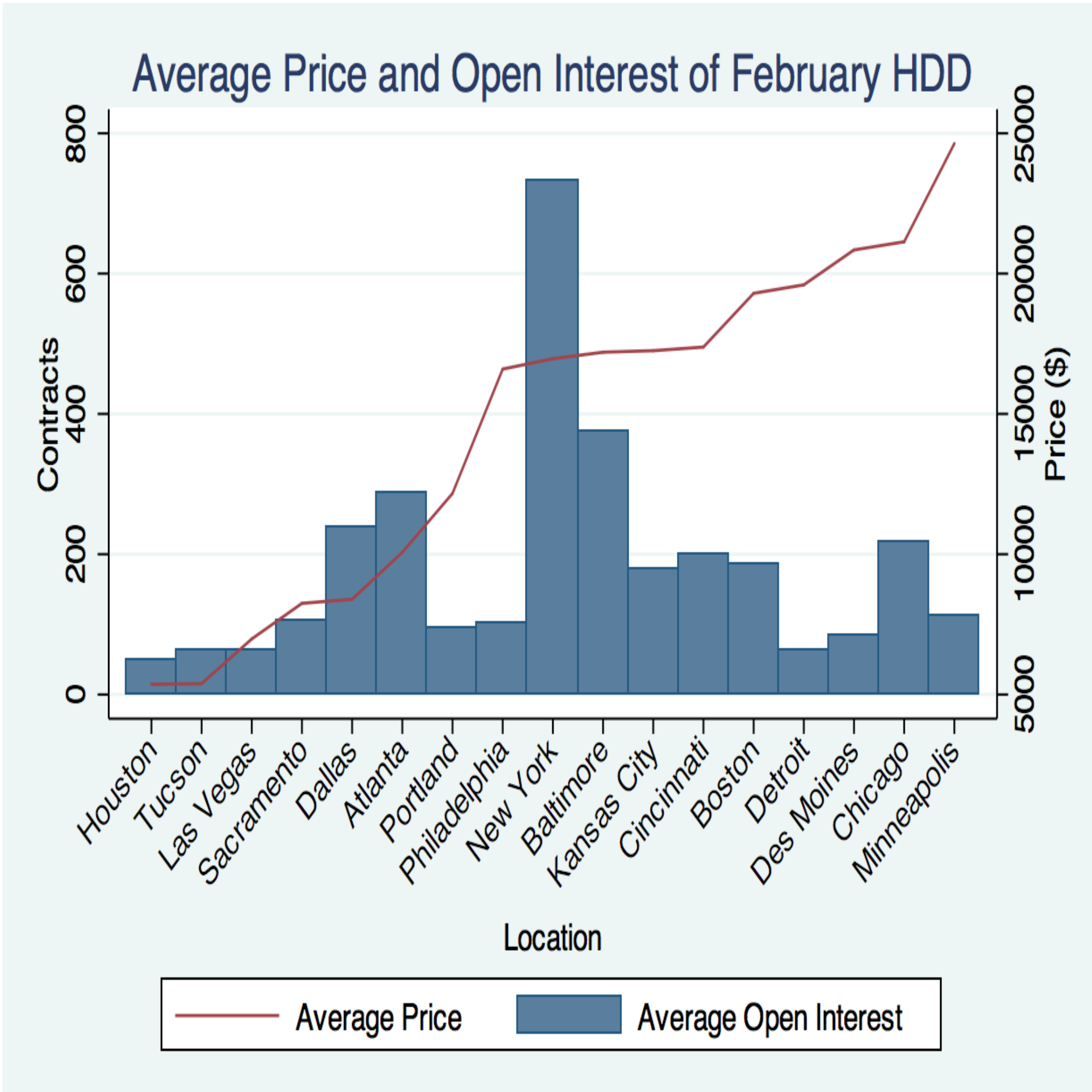
A.4 Figures

Figure A.1: Sample of June CDD Contracts



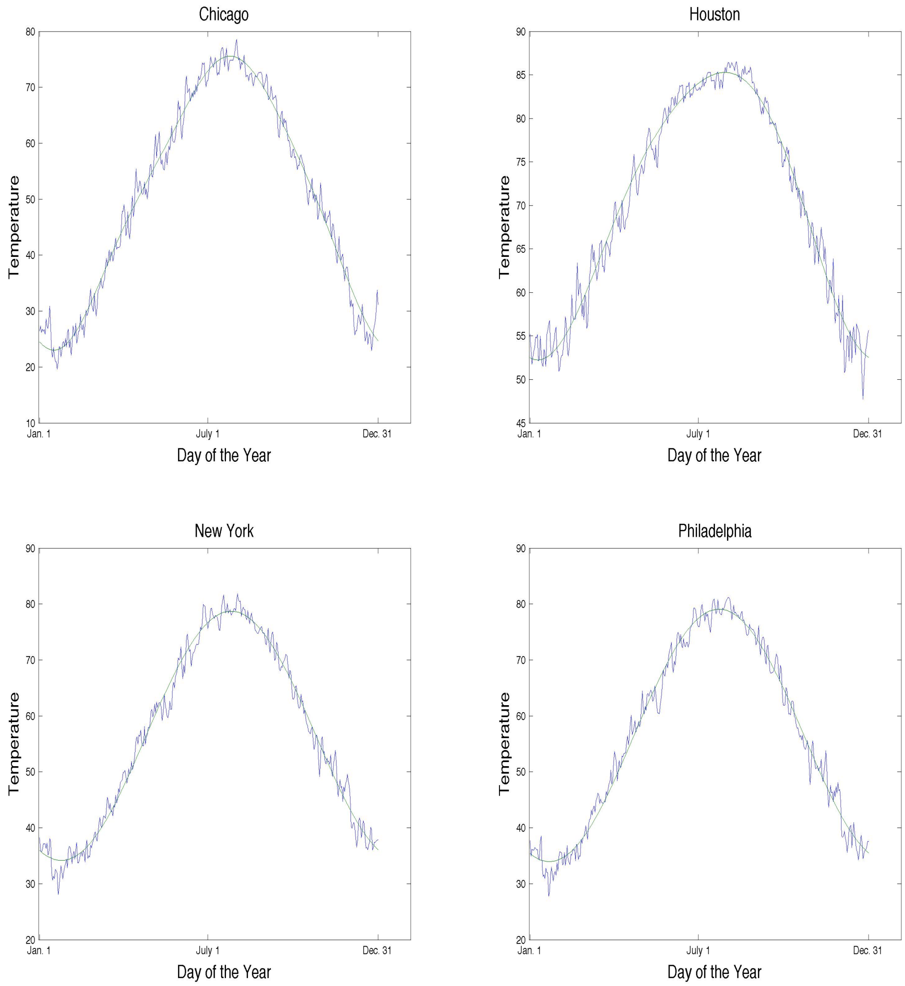
This figure shows the average logarithm of the contract price 32 days before maturity (Average Price), the average logarithm of the contract settlement value at maturity (Average Payoff at Maturity) and the average logarithm of the contract price 32 days before maturity during the crisis (Crisis Price) for three June cooling degree day contracts (Chicago, Kansas City and New York). Averages are taken over the years 2000-2012.

Figure A.2: Average Price and Open Interest for February HDD Contracts



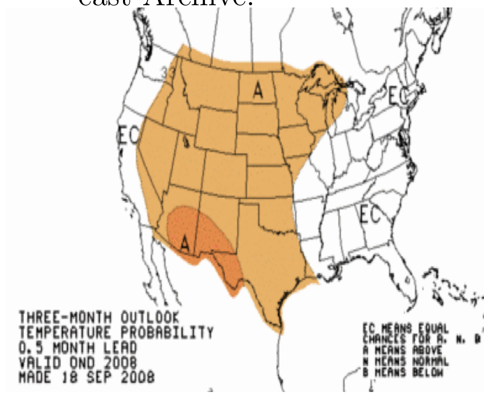
This figure shows the average price and open interest (32 days before maturity) for February HDD contracts from 2000 to 2011.

Figure A.3: Estimated Mean Temperature vs. Average Temperature

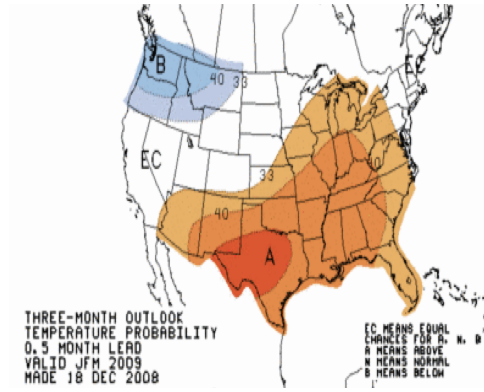


I plot the estimated mean temperature (θ_t) and the average temperature for each day of the year for Chicago, Houston, New York and Philadelphia. The parameters of the mean temperature process are estimated separately for each city. The average temperature is calculated over the period from January 1,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

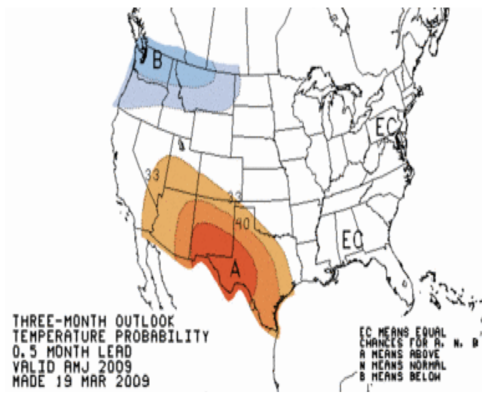
Figure A.4: NOAA's Temperature Forecasts from the CPC Monthly & Seasonal Forecast Archive.



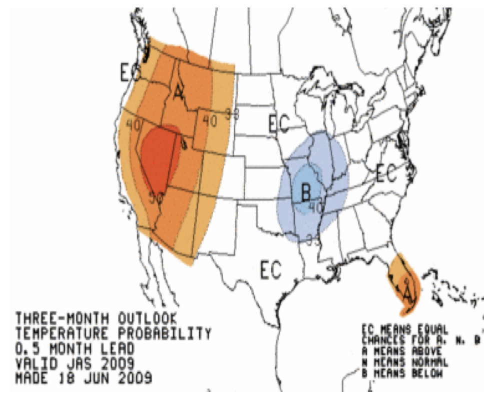
Oct.-Dec. 2008



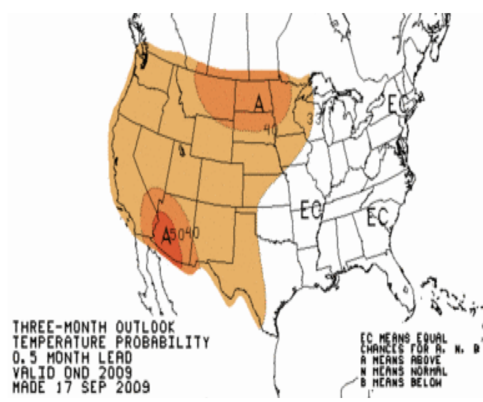
Jan.-Mar. 2009



Apr.-Jun. 2009



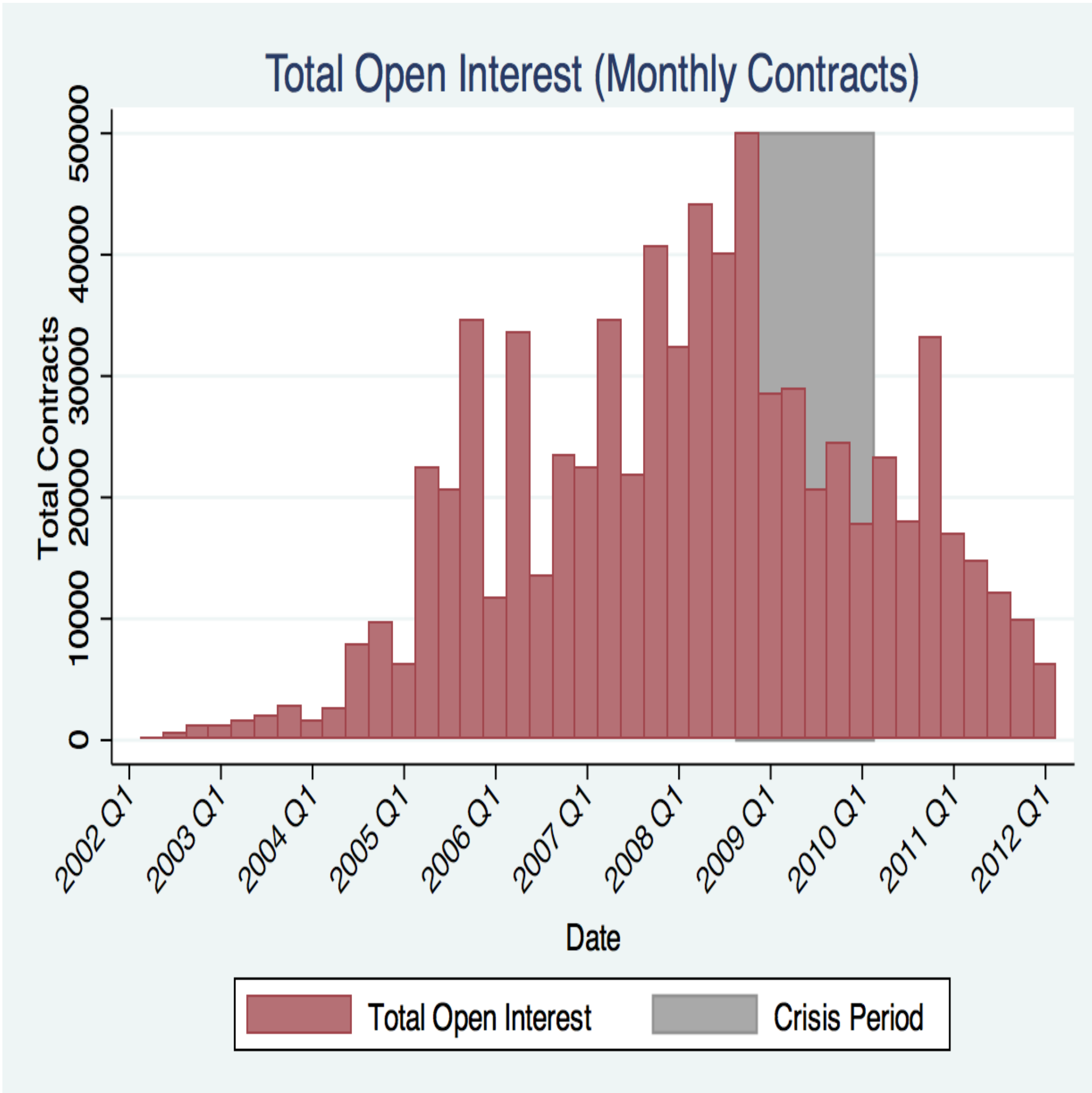
Jul.-Sep. 2009



Oct.-Dec. 2009

These maps give NOAA's three month temperature outlook for the United States. The maps are from the 18th of the month before the start of the three month period. A stands for a higher probability of above normal temperatures, EC stands for an equal chance of above, normal or below normal temperatures, and B stands for a higher probability of below normal temperatures.

Figure A.5: Monthly Open Interest



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

A.5 Tables

Table A.1: Contract Information by Location

This table presents information on contract locations and margin requirements. City is the closest city to the underlying weather station. Intro. Year is the year the location was introduced. Open Interest Rank is the location's rank based on total open interest between 2006 and 2012. Initial and Maint. are the initial and maintenance margin requirements for speculators, respectively. Margins are presented as percentages.

		Open Interest	**HDD Margin (%)**		**CDD Margin (%)**	
City	**Intro. Year**	**Rank**	**Initial**	**Maint.**	**Initial**	**Maint.**
Atlanta	1999	3	8.1	6	7.56	5.6
Baltimore	2005	16	6.21	4.6	9.45	7
Boston	2003	10	4.19	3.1	6.48	4.8
Chicago	1999	2	6.48	4.8	14.85	11
Cincinnati	1999	5	7.02	5.2	12.15	9
Dallas	2000	4	10.8	8	5.4	4
Des Moines	2000	7	6.08	4.5	12.15	9
Detroit	2005	17	7.02	5.2	12.15	9
Houston	2003	12	11.75	8.7	5.4	4
Kansas City	2003	8	6.75	5	9.45	7
Las Vegas	2000	11	7.29	5.4	5.4	4
Minneapolis	2003	6	5.54	4.1	12.15	9
New York City	1999	1	5.4	4	9.45	7
Philadelphia	2000	9	6.21	4.6	9.45	7
Portland	2000	15	6.35	4.7	22.95	17
Sacramento	2003	14	6.48	4.8	12.15	9
Salt Lake City	2005	18	10.8	8	14.85	11
Tucson	2000	13	9.59	7.1	5.4	4
Mean	-	-	7.3	5.4	10.4	7.7
Std. Dev.	-	-	2.1	1.5	4.5	3.3

Table A.2: Summary Statistics for Open Interest, Contract Risk Premiums and Realized Returns

This table presents summary statistics for contract open interest measured 32 days before contract maturity, the model implied risk premiums and realized returns. Contracts are grouped by heating degree day index contracts (HDD), cooling degree day index contracts (CDD) and all contracts (All). I present the mean (Mean), standard deviation (Std. Dev.), 10th percentile (10th), median (Median), 90th percentile (90th) and the number of observations (N). Each observation is a location-month-index-year.

Open Interest						
Index	Mean	Std. Dev.	10th	Median	90th	N
CDD	282	512	20	120	700	475
HDD	202	348	10	97	500	629
All	236	428	12	100	550	1,104
Risk Premiums (Monthly %)						
Index	Mean	Std. Dev.	10th	Median	90th	N
CDD	0.50	12.15	-13.33	-0.32	15.74	475
HDD	-0.10	10.86	-12.35	-0.93	13.32	629
All	0.16	11.43	-12.55	-0.79	14.10	1,104
Realized Returns (Monthly %)						
Index	Mean	Std. Dev.	10th	Median	90th	N
CDD	-0.14	28.56	-33.02	-0.64	32.21	475
HDD	-1.79	18.64	-23.44	-1.24	17.62	629
All	-1.08	23.43	-25.93	-1.17	21.84	1,104

Table A.3: Summary Statistics for Margin Requirements and Coefficients of Variation
This table presents summary statistics for contract margin requirements and coefficients of variation. Contracts are grouped by heating degree day index contracts (HDD), cooling degree day index contracts (CDD) and all contracts (All). I present the mean (Mean), standard deviation (Std. Dev.), 10th percentile (10th), median (Median), 90th percentile (90th) and the number of observations (N). Each observation is a location-month-index-year.

Maintenance Margin (%)						
Index	Mean	Std. Dev.	10th	Median	90th	N
CDD	7.15	2.96	4.00	7.00	11.00	475
HDD	5.16	1.31	4.00	4.80	8.00	629
All	6.01	2.39	4.00	5.20	9.00	1,104

Coefficient of Variation						
Index	Mean	Std. Dev.	10th	Median	90th	N
CDD	0.28	0.16	0.12	0.26	0.45	475
HDD	0.22	0.10	0.14	0.20	0.31	629
All	0.25	0.13	0.14	0.21	0.41	1,104

Table A.4: The Effect of Financial Sector Stress on Risk Premiums

This table reports the main regression results. The regression model is:

$$WRP_{imdy} = \beta * FinancialCrisis_{my} + \delta_{imd} + \epsilon_{imdy},$$

The dependent variable is the weather risk premium for location i, month m, degree day index d and year y. $FinancialCrisis_{my}$ is an indicator variable equal to 1 during the time period when financial institutions were under stress (October 2008 to December 2009). δ_{imd} is the contract fixed effect for the contract on location i, month m and index d. R-squared is the within contract r-squared. The regression results presented in Column 1 includes all contracts. The regression in Column 2 (3) includes only CDD (HDD) contracts. Standard errors are clustered at the year-month level.

	(1)	(2)	(3)
VARIABLES	WRP-All	WRP-CDD	WRP-HDD
Financial Crisis	3.340**	7.968**	1.620
	(1.632)	(2.994)	(1.761)
Observations	1,104	475	629
R-squared	0.016	0.051	0.005
Number of Contracts	207	90	117
Contract Dummies	Yes	Yes	Yes
HDD contracts	Yes	No	Yes
CDD contracts	Yes	Yes	No

Standard Errors Clustered by Year-Month in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

Table A.5: Margins

This table reports the regression results examining the effect of margin requirements on risk premiums during a period of financial sector sector stress. The regression model is:

$$WRP_{imdy} = \beta * FinancialCrisis_{my} + \beta_{mar} * Margin_{imd} * FinancialCrisis_{my} + \delta_{imd} + \epsilon_{imdy},$$

The dependent variable is the weather risk premium for location i, month m, degree day index d and year y. $FinancialCrisis_{my}$ is an indicator variable equal to 1 during the time period when financial institutions were under stress (October 2008 to December 2009). $Margin_{imd}$ is the maintenance margin requirement for the contract on location i, month m and index d. δ_{imd} is the contract fixed effect for the contract on location i, month m and index d. R-squared is the within contract r-squared. Column 1 includes all contracts. The regression in Column 2 (3) includes only CDD (HDD) contracts. Standard errors are clustered at the year-month level.

VARIABLES	(1) WRP-All	(2) WRP-CDD	(3) WRP-HDD
Financial Crisis	-12.12***	-8.222	-16.03***
	(3.746)	(5.525)	(4.673)
Margin*Financial Crisis	2.661***	2.192**	3.378***
	(0.650)	(0.848)	(0.961)
Observations	1,104	475	629
R-squared	0.068	0.089	0.051
Number of Contracts	207	90	117
Contract Dummies	Yes	Yes	Yes
HDD contracts	Yes	No	Yes
CDD contracts	Yes	Yes	No

Standard Errors Clustered by Year-Month in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

Table A.6: Contract Risk

This table reports the regression results examining the effect of contract risk on risk premiums during a period of financial stress. The regression model is:

$$WRP_{imdy} = \beta * FinancialCrisis_{my}$$
$$+\beta_{cv} * CV_{imd} * FinancialCrisis_{my} + \delta_{imd} + \epsilon_{imdy},$$

The dependent variable is the weather risk premium for location i, month m, degree day index d and year y. $FinancialCrisis_{my}$ is an indicator variable equal to 1 during the time period when financial institutions were under stress (October 2008 to December 2009). CV_{imd} is the coefficient of variation of historical contract payoffs (calculated over the years 1974-2011) for the contract on location i, month m and index d. δ_{imd} is the contract fixed effect for location i, month m and index d. R-squared is the within contract r-squared. Column 1 includes all contracts. The regression in Column 2 (3) includes only CDD (HDD) contracts. Standard errors are clustered at the year-month level.

	(1)	(2)	(3)
VARIABLES	WRP-All	WRP-CDD	WRP-HDD
Financial Crisis	-8.725**	0.269	-12.41***
	(3.761)	(4.864)	(3.331)
CV*Financial Crisis	51.61***	28.83	63.37***
	(16.47)	(27.37)	(12.10)
Observations	1,104	475	629
R-squared	0.056	0.062	0.069
Number of Contracts	207	90	117
Contract Dummies	Yes	Yes	Yes
HDD contracts	Yes	No	Yes
CDD contracts	Yes	Yes	No

Standard Errors Clustered by Year-Month in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

Table A.7: Margins & Contract Risk

This table reports results for regressions examining the effect of contract risk and margin requirements on risk premiums during a period of financial sector stress. The regression model is:

$$WRP_{imdy} = \beta * FinancialCrisis_{my} + \beta_{cv} * CV_{imd} * FinancialCrisis_{my} + \beta_{mar} * Margin_{imd} * FinancialCrisis_{my} \\ + \beta_{int} * CV_{imd} * Margin_{imd} * FinancialCrisis_{my} + \delta_{imd} + \epsilon_{imdy},$$

The dependent variable is the weather risk premium for location i, month m, degree day index d and year y. $Crisis_{my}$ is an indicator variable equal to 1 during the time period when financial institutions were under stress. $Margin_{imd}$ is the maintenance margin for the contract on location i, month m and index d. CV_{imd} is the coefficient of variation of historical contract payoffs (calculated over the years 1974-2011) for the contract on location i, month m and index d. δ_{imd} is the contract fixed effect for location i, month m and index d. The regressions in Columns 1 & 2 include all contracts. The regressions in Columns 3 & 4 (5 & 6) are run for CDD (HDD) contracts. Standard errors are clustered at the year-month level.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	WRP-All	WRP-All	WRP-CDD	WRP-CDD	WRP-HDD	WRP-HDD
Financial Crisis	-14.18***	-0.109	-8.404*	0.398	-16.13***	22.48**
	(3.650)	(7.618)	(4.502)	(7.104)	(4.742)	(10.88)
Margin*Financial Crisis	1.955**	-0.512	2.158*	0.675	1.293	-4.955***
	(0.809)	(1.328)	(1.168)	(1.458)	(1.229)	(1.780)
CV*Financial Crisis	26.34	-24.25	1.603	-27.12	49.64***	-124.3**
	(18.70)	(35.17)	(27.54)	(40.54)	(17.09)	(48.66)
CV*Margin*Financial Crisis		8.099*		4.508		26.30***
		(4.126)		(4.087)		(5.898)
Observations	1,104	1,104	475	475	629	629
R-squared	0.074	0.080	0.089	0.091	0.072	0.097
Number of Contracts	207	207	90	90	117	117
Contract Dummies	Yes	Yes	Yes	Yes	Yes	Yes
HDD contracts	Yes	Yes	No	No	Yes	Yes
CDD contracts	Yes	Yes	Yes	Yes	No	No

Standard Errors Clustered by Year-Month in Parentheses

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

Table A.8: Normal and Financial Stress Periods

This table reports regression results examining the effect of contract risk and margin requirements on weather risk premiums over the full sample, in the crisis and outside of the crisis period. The regression model is:

$$WRP_{imdy} = \beta * X_{imd} + \delta_m + \epsilon_{imdy},$$

where the dependent variable is the weather risk premium for location i, month m, degree day index d and year y, X_{imd} is either $Margin_{imd}$ or CV_{imd}, and δ_m is a contract month fixed effect. $Margin_{imd}$ is the maintenance margin for the contract on location i, month m and index d. CV_{imd} is the coefficient of variation of historical contract payoffs (calculated over the years 1974-2011) for the contract on location i, month m and index d. Margin (contract risk) results are reported in Columns 1-3 (4-6). In Columns 1 and 4, regressions are run on the entire sample period (labeled "Entire"). In Columns 2 and 5, regressions are run on time periods outside of the stress period (all months except those from October 2008 to December 2009; labeled "Normal"). In Columns 3 and 6, regressions are run on observations during the financial stress time period (October 2008 to December 2009; labeled "Crisis") All regressions include both HDD and CDD contracts. R-squared is the within contract r-squared. Standard errors are clustered at the year-month level.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Entire	Normal	Crisis	Entire	Normal	Crisis
Margin	0.0520	-0.317	2.233***			
	(0.228)	(0.215)	(0.512)			
CV				7.079	0.383	28.68***
				(6.253)	(7.419)	(8.475)
Observations	1,104	940	164	1,104	940	164
R-squared	0.074	0.068	0.458	0.078	0.064	0.418
HDD contracts	Yes	Yes	Yes	Yes	Yes	Yes
CDD contracts	Yes	Yes	Yes	Yes	Yes	Yes

Standard Errors Clustered by Location-Index in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

Table A.9: Collapsed Markets

This table reports results for probit regressions examining the probability the market for a contract collapsed during the crisis period. The regression model is:

$$P(Collapsed = 1) = \\ \Phi(\beta_m * Margin_{imd} + \beta_{CV} * CV_{imd} + \beta_{Int} * CV_{imd} * Margin_{imd}),$$

The dependent variable is an indicator variable equal to 1 if the contract for location i, month m, degree day index d and year y traded in the 12 months preceding the distress, but not in the 12 months post-distress. $Margin_{imd}$ is the maintenance margin for the contract on location i, month m and index d. CV_{imd} is the coefficient of variation of historical contract payoffs (calculated over the years 1974-2011) for the contract on location i, month m and index d. All regressions include both HDD and CDD contracts. Standard errors are clustered by month.

VARIABLES	(1) Collapsed	(2) Collapsed	(3) Collapsed	(4) Collapsed
Margin	0.119*		0.0597	0.103
	(0.0669)		(0.0670)	(0.103)
CV		2.539**	2.023	3.016**
		(1.098)	(1.262)	(1.501)
CV*Margin				-0.137
				(0.221)
Observations	136	136	136	136
Pseudo R-squared	0.0432	0.0667	0.0747	0.0759

Standard Errors Clustered by Month in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

Table A.10: Systematic Risk

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

$$R_p - R_f = \beta * (R_m - R_f) + \alpha_m,$$

where R_p is the equal-weighted return on a portfolio of weather derivatives, R_f is the monthly risk-free rate and α_m is the month fixed effect. In Columns 1-3, R_p is the "physical" return calculated as follows: $\frac{Payoff}{E[Payoff]} - 1$, where $Payoff$ is the realized degree index value and $E[Payoff]$ is the expected payoff calculated 32 days before maturity based on the temperature model. In Columns 4-6, R_p is the realized return on the opened contracts calculated as follows: $\frac{Payoff}{Price} - 1$, where price is the outstanding price 32 days before maturity. The sample contains all months from February 1999 to January 2012. Only those location-month-indices that have a contract based on the specific index trade at least once from September 1999 to January 2012 are included in the sample. For months in which HDD and CDD contracts trade, I include only the index with the highest $E[Payoff]$ for each location-month in the regression with both indices. For the weather risk premium and realized return regressions, only year-months in which contracts are traded are included in the regression. All regressions are standard OLS regressions. Regressions in Columns 1 and 4 include all contracts. Regressions in Columns 2 and 5 (3 and 6) include only the CDD (HDD) index contracts. Standard errors are White standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Phy.-All	Phy.-CDD	Phy.-HDD	Real.-All	Real.-CDD	Real.-HDD
Mkt-Rf	-0.436*	-0.426	-0.553	-0.510*	-0.424	-0.323
	(0.242)	(0.322)	(0.343)	(0.286)	(0.587)	(0.305)
Constant	0.296	-0.726	1.893	-1.598	0.642	-2.823*
	(1.117)	(1.929)	(1.741)	(1.432)	(2.959)	(1.481)
Observations	156	91	91	129	60	76
R-squared	0.095	0.074	0.228	0.086	0.091	0.119
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
HDD contracts	Yes	No	Yes	Yes	No	Yes
CDD contracts	Yes	Yes	No	Yes	Yes	No

Standard Errors in Parentheses

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

Table A.11: Price Regressions

VARIABLES	(1) All	(2) All	(3) CDD	(4) HDD	(5) All	(6) CDD	(7) HDD	(8) All
Financial Crisis	0.0540***	-0.0943**	-0.0698	-0.145**	-0.0894**	-0.0387	-0.112***	0.0460**
	(0.0174)	(0.0461)	(0.0668)	(0.0579)	(0.0386)	(0.0503)	(0.0406)	(0.0192)
Margin*Financial Crisis		0.0256***	0.0203*	0.0376***				
		(0.00855)	(0.0108)	(0.0122)				
Log(Realized Index)	-0.0888***	-0.0823***	-0.0557*	-0.130***	-0.0865***	-0.0551	-0.141***	-0.0873***
	(0.0262)	(0.0260)	(0.0330)	(0.0302)	(0.0260)	(0.0331)	(0.0309)	(0.0265)
Last Month Index	-0.0492***	-0.0486***	-0.0538***	-0.0408**	-0.0505***	-0.0560***	-0.0412**	-0.0485***
	(0.0110)	(0.0108)	(0.0136)	(0.0162)	(0.0111)	(0.0139)	(0.0159)	(0.0108)
Risk-Free Rate	0.0873**	0.0904**	0.0262	0.134**	0.0865**	0.0251	0.129**	0.0595
	(0.0408)	(0.0404)	(0.0512)	(0.0603)	(0.0408)	(0.0523)	(0.0598)	(0.0506)
CV*Financial Crisis					0.613***	0.445	0.736***	
					(0.178)	(0.281)	(0.170)	
Post-Crisis (2010-12)								-0.0170
								(0.0181)
Observations	1,104	1,104	475	629	1,104	475	629	1,104
R-squared	0.163	0.203	0.229	0.213	0.211	0.223	0.237	0.165
Number of Contracts	207	207	90	117	207	90	117	207
Contract Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HDD contracts	Yes	Yes	No	Yes	Yes	No	Yes	Yes
CDD contracts	No	Yes	Yes	No	Yes	Yes	No	No

Standard Errors Clustered by Year-Month in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

The dependent variable is the negative of the logarithm of the contract price 32 days before contract maturity ($-log(Price)$). Financial Crisis is an indicator variable equal to 1 during the time period when financial institutions were under stress (October 2008 to December 2009). CV*Financial Crisis is an interaction between the coefficient of variation of the relevant monthly degree day index and Financial Crisis. Margin*Financial Crisis is an interaction between the contract's margin requirement and Financial Crisis. Log(Settle) is the logarithm of the price of the contract on the settlement date. Last Month is the logarithm of the relevant index in the previous month for a specific location. Risk-Free Rate is the risk-free rate of return. All regressions are standard OLS regressions. All regressions include contract fixed effects. Standard errors are clustered at the year-month level. R-squared is the within contract r-squared. Columns 1 and 4 include all contracts. Regressions in columns 2 & 5 (3 & 6) are run on the CDD (HDD) contracts only.

Table A.12: 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
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	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
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
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

Table A.13: Temperature Indices Outcomes in the Financial Crisis

The dependent variable is the logarithm of the relevant degree day index. The HDD regressions use the heating degree day indices for months October through March. The CDD regressions use the cooling degree day indices for months April through September. Financial Crisis is a dummy for the financial crisis period. Margin*Financial Crisis is an interaction between the contract's maintenance margin in July 2008 and the Financial Crisis dummy. CV*Financial Crisis is an interaction between the coefficient of variation of the relevant monthly degree day index and Financial Crisis. Year is the contract year minus 1974. Each observation is a location-month. The sample includes the 18 weather stations that received a weather derivative before 2008. The sample months are January 1974 through March 2012.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HDD	CDD	HDD	CDD	HDD	CDD
Financial Crisis	0.0816***	-0.0490	0.0816***	-0.0483	0.0867***	-0.0432
	(0.0234)	(0.0564)	(0.0234)	(0.0564)	(0.0235)	(0.0564)
Margin*Financial Crisis			-0.0149	0.00790		
			(0.0150)	(0.0176)		
Year	-0.00388***	0.00475***	-0.00388***	0.00475***	-0.00388***	0.00476***
	(0.000412)	(0.000834)	(0.000412)	(0.000834)	(0.000412)	(0.000834)
CV*Financial Crisis					0.349**	0.387***
					(0.147)	(0.149)
Observations	4,114	3,939	4,114	3,939	4,114	3,939
R-squared	0.896	0.836	0.896	0.836	0.896	0.837
Location-Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Months	Oct-Mar	Apr-Sep	Oct-Mar	Apr-Sep	Oct-Mar	Apr-Sep

Standard Errors in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

Table A.14: Systematic Risk By Location

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

$$R_p - R_f = \beta * (R_m - R_f) + \delta_m,$$

where R_p is the "physical" return, R_f is the monthly risk-free rate and δ_m is a month fixed effect. R_p is calculated as follows: $\frac{Payoff}{E[Payoff]} - 1$, where $Payoff$ is the realized degree index value and $E[Payoff]$ is the expected payoff calculated 32 days before maturity based on the temperature model. Regressions are run separately for each location. The sample contains all months from February 1999 to January 2012. Only those location-month-indices that had a contract based on the specific index trade at least once from September 1999 to January 2012 are included in the sample. For months in which HDD and CDD contracts trade, I include only the index with the highest $E[Payoff]$ for each location-month. The CAPM β is reported in the column labeled β. The regression constant is reported in the column labeled "Constant" (note: this is not the CAPM α, as the regressions include month fixed effects. Standard errors calculated using Huber-White sandwich estimators are reported in parentheses in the column to the right of the coefficient. N is the number of observations and R-squared is the regression r-squared. All regressions are standard OLS regressions.

WBAN	β	s.e.	α	s.e.	N	R-squared
Dallas	-0.43	(0.48)	-2.52	(2.00)	156	0.06
Kansas City	-0.72	(0.43)	-0.08	(2.07)	156	0.05
Houston	-0.09	(0.61)	-1.64	(2.16)	156	0.03
Philadelphia	-0.88 **	(0.38)	-0.40	(1.86)	156	0.14
Atlanta	-1.04 **	(0.50)	1.01	(2.01)	156	0.12
New York	-0.76 **	(0.38)	-0.75	(1.77)	156	0.18
Boston	-0.95 *	(0.50)	-0.54	(2.27)	156	0.08
Minneapolis	-1.40 **	(0.61)	-1.48	(2.48)	156	0.09
Des Moines	-0.95 **	(0.39)	-1.23	1.91	156	0.09
Tucscon	-0.37	(0.53)	-1.52	(1.95)	156	0.08
Las Vegas	1.00 *	(0.55)	-0.09	(2.52)	156	0.07
Sacramento	0.77	(0.48)	2.93	(2.42)	156	0.07
Salt Lake City	-0.50	(0.43)	-1.15	(2.54)	52	0.14
Portland	1.75 *	(1.01)	10.85 **	(5.26)	156	0.27
Baltimore	-0.60	(0.40)	-1.46	(1.74)	91	0.11
Cincinnati	-0.86 **	(0.42)	-0.35	(2.08)	156	0.08
Chicago	-1.30 ***	(0.49)	1.46	(2.28)	156	0.07
Detroit	-0.90 ***	(0.33)	-0.06	(1.81)	117	0.09
Mean	-0.46 *	(0.23)	0.17	(0.70)	144	-

Correlation($\overline{WRP_i}$,$\hat{\beta}_i$) = -.09, p-value=.73

Table A.15: Systematic Risk and Stress

This table reports results for regressions examining the effect of contract risk, margin requirement and the location CAPM beta on weather risk premiums during a period of financial stress. The regression model is:

$$WRP_{imdy} = \beta * Crisis_{my} + \beta_X * X_{imd} * Crisis_{my} + \beta_{beta} * Beta_i * Crisis_{my} + \beta_{int} * X_{imd} * Beta_i * Crisis_{my} + \delta_{imd} + \epsilon_{imdy},$$

The dependent variable is the weather risk premium for location i, month m, degree day index d and year y. $Crisis_{my}$ is an indicator variable equal to 1 during the time period when financial institutions were under stress. X_{imd} is either the margin requirement or coefficient of variation for the contract on location i, month m and index d. $Beta_i$ is the CAPM beta for location i. δ_{imd} is the contract fixed effect for location i, month m and index d. All regressions include both HDD and CDD contracts. R-squared is the within contract r-squared. Standard errors are clustered at the year-month level.

VARIABLES	(1) WRP	(2) WRP	(3) WRP	(4) WRP	(5) WRP
Financial Crisis	3.678**	-12.71***	-12.53***	-8.523**	-9.859***
	(1.640)	(3.293)	(3.451)	(3.592)	(3.210)
Beta*Financial Crisis	0.608	-0.659	2.674	0.317	-3.117
	(1.147)	(1.024)	(2.251)	(1.076)	(3.001)
Margin*Financial Crisis		2.700***	2.718***		
		(0.626)	(0.633)		
Beta*Margin*Financial Crisis			-0.533		
			(0.397)		
CV*Financial Crisis				51.50***	57.26***
				(16.36)	(14.42)
Beta*CV*Financial Crisis					15.18
					(13.96)
Observations	1,104	1,104	1,104	1,104	1,104
R-squared	0.016	0.068	0.071	0.056	0.059
Number of Contracts	207	207	207	207	207
Contract Dummies	Yes	Yes	Yes	Yes	Yes
HDD contracts	Yes	Yes	Yes	Yes	Yes
CDD contracts	Yes	Yes	Yes	Yes	Yes

Standard Errors Clustered by Year-Month in Parentheses

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

APPENDIX B

Can Markets Discipline Government Agencies? Evidence from the Weather Derivatives Market

B.1 Some Descriptive Evidence & Supporting Claims

In this appendix we produce pieces of evidence collected from several sources such as the NWS directives, NOAA, weather trading industries, and atmospheric science journals that are relevant to our study. We present some key facts and opinions from these sources as well as our summary of the material below:

1. NWS directives on data collection exercise: NWS issues directives to its regional offices and weather stations on a regular basis on a range of issues including data quality control and assurance standards. Some of these directives highlight the need for more accurate and consistent data in light of increased outside scrutiny. We provide an example from the NWS's directive (number NWSI 10-1305) issued on April 28, 2008:

   "The NWS has the responsibility of collecting and providing weather and climate observation data. However, the methods for the collection, quality control, and delivery of these data vary from office to office. Many of the data quality initiatives between the NWS and NCDC have been uncoordinated. Even with the NWS itself such activities vary greatly between field offices. This situation must change in the interest of efficiency, data record integrity and public use.

   Today, with the ever increasing use of observational data by the research community, the media, private industry, and the general public it is of the utmost importance to accurately and consistently apply QC/QA at all field offices. In order to ensure the highest quality data and data products within Central Region, the QC/QA methods discussed in this supplement are highly recommended at each WFO."

   Note: Emphasis added by the authors. QC/QA stand for quality control and quality assurance in the above quote.

2. NOAA's information on preliminary (i.e., raw) versus official (i.e., clean) data: Below we provide some examples of Frequently Asked Questions and their Answers from the NOAA's web-site about the raw versus cleaned data.

"Are the data in NOWData considered 'official' for legal and other such purposes?

No. NOWData provides up-to-date information based on archived AND preliminary data holdings by NOAA. For official data, you should contact NOAAs National Climatic Data Center or the Regional Climate Centers. NCDC provide official certification for data being used in U.S. courts."

"I noticed that the most recent data does not match data that I found of the NCDC web site. Why is that?

Preliminary data can be different from NCDC official data for a number of reasons related to quality assurance and processing schedules, as well as synchronization of the NCDC and ACIS databases. Ultimately, when processing is completed, the two data files will match."

Note: NOWData stands for NOAA Online Weather Data, which comes from METAR readings, which is also our source of initial data recording.

3. A summary of the meetings between NWS and weather industry representatives: There have been quite a few meetings between the NWS officials and the weather derivative professionals regarding the weather derivatives market. The weather industry has often expressed its need for better quality data from the weather station. Here is an excerpt from a meeting between NOAA staff and the representatives of the weather derivative industry during the very early stages of this market (meeting dated March 12, 1998).[1] This meeting occurred before the launch of official CME contracts.

   "Data issues, both short and long-term, pertaining to these contracts were the immediate reason for this meeting. On their own initiative, industry participants have chosen to use daily temperature data from the National Weather Service to calculate their cumulative degree day indices upon which the contracts are based and which will be used to settle the contracts.

   One concern they had was regarding the difference between preliminary and official data. NOAA indicated that the preliminary data are usually quite close to the official historical data, which are published with a lag of two to three months. With this understanding, the firms said they felt more comfortable using the preliminary data for initial settlement of the contracts, subject to a "true-up" to the official data several months later.

   A second interest was that there be one set of tailored data for common reference. This could reduce disputes that might arise from different sources for the weather data."

4. Meridian Environmental Technology is a company specializing in atmospheric information and technology (amongst other things). Their website provides evidence of private enterprise's need for accurate weather information:

   "Power production planning requires accurate and reliable weather information. Meridian has been providing historical and forecasted site-specific weather information to the agriculture, transportation, and utilities industries for years. Whether you are needing hourly, daily, weekly or longer information, Meridian can help you!

[1] See the full document at http://www.srh.noaa.gov/topics/attach/html/ssd98-14.htm

We understand your needs for forecasted power production and the high penalties a wrong estimate can cost...”[2]

5. NOAA’s NCDC Sectoral Engagement Fact Sheets[3] document industries that depend on quality weather information from NOAA. NOAA lists Agriculture, Civil Infrastructure, Coastal Hazards, Energy, Health, Insurance, Litigation, Marine and Coastal Ecosystems, National Security, Tourism, Transportation and Water Resources as industries sensitive to the climate. Not all of these industries will be directly affected by inaccurate temperature measurements, but some are. For example, in the Energy Fact Sheet NOAA writes about how companies are:

   “Using temperature information to aid in the assessment of equipment requirements for heavy power line loads during extremely hot weather.”

   These loads will be determined by weather measurements produced by the government. If the numbers are incorrect, energy companies may use the incorrect amount or type of equipment.

B.2 Figures

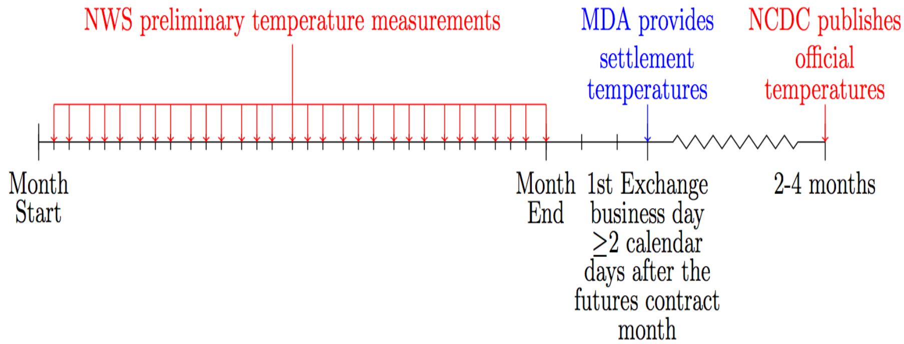
Figure B.1: Derivative Introduction Dates

This figure shows the introduction years of U.S. weather derivatives listed on the CME. For each year, we list the locations that received a derivative.

[2] http://www.meridian-enviro.com/pages.pl?pg=usf

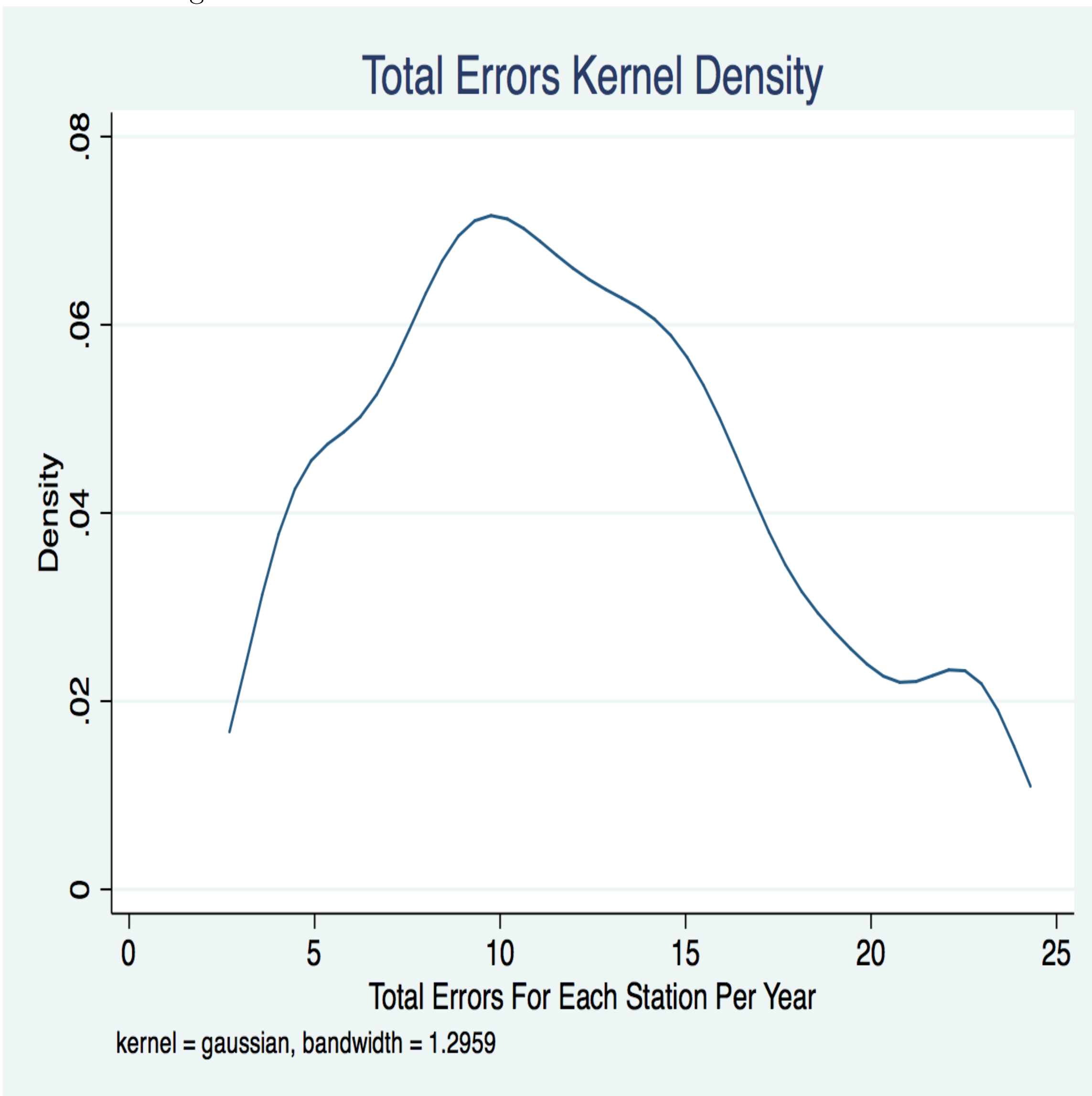
[3] http://www.ncdc.noaa.gov/oa/userengagement/userengagement.html

Figure B.2: Weather Measurement Timeline



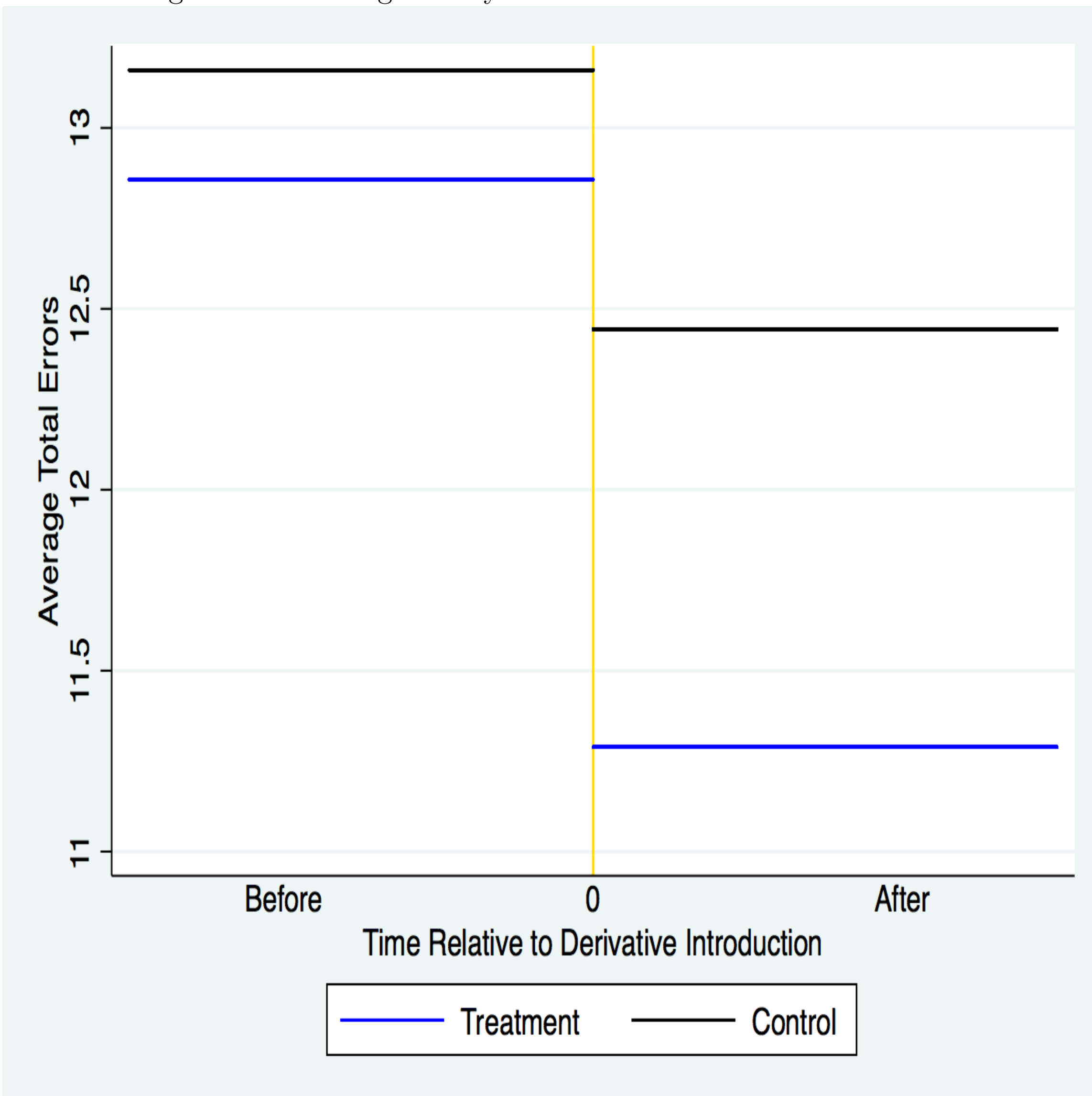
This figure shows the timeline of initial temperature measurement by the NWS, the corrections reported by MDA for contract settlement, and the final cleaned value generated by NCDC.

Figure B.3: Weather Station-Year Total Errors Distribution



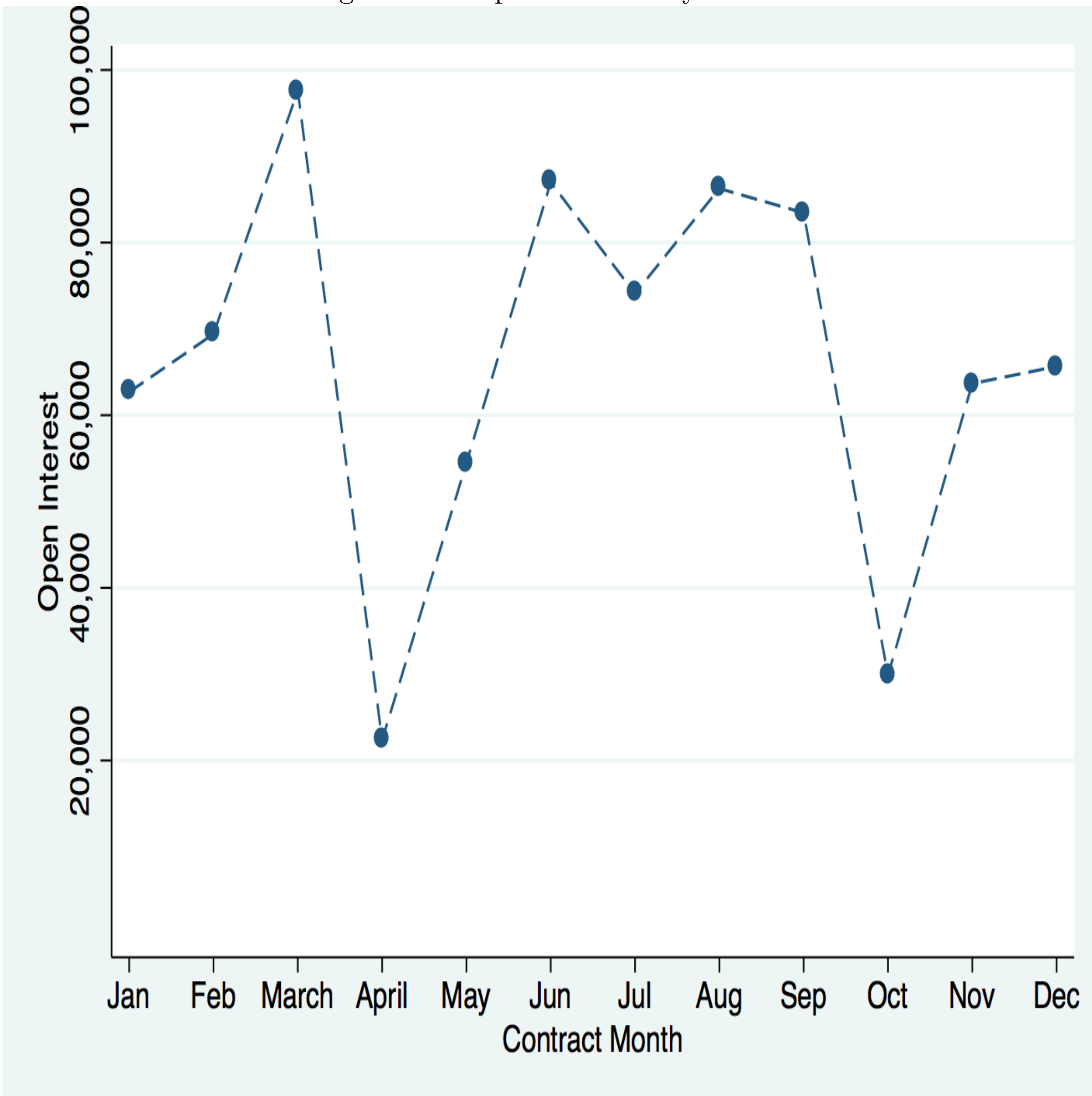
This figure shows the kernel density of the total errors each year for each weather station in our sample. We use the Gaussian kernel and a bandwidth that minimizes the mean integrated squared error assuming the data were Gaussian.

Figure B.4: Average Yearly Errors Pre- and Post- Introduction



This figure graphs the average errors for the treatment and control groups before and after weather derivative introduction. The Before period is the 3 years before introduction and the After period is the year of introduction plus the 3 years afterwards. The treatment group consists of the 14 weather stations that experienced a weather derivative introduction after 2002 and the control group consists of the 25 stations that never experienced a weather derivative introduction during our sample period.

Figure B.5: Open Interest By Month



This figure plots open interest in each month during our sample. For each contract, we calculate the maximum open interest during the contract's trading period. We then sum this value across all contracts that settle based on temperatures in month i during our sample. We include all futures and option contracts of monthly durations. The open interest data starts with the initial opening of the CME temperature derivative market (September 22, 1999) and ends December 4, 2012.

B.3 Tables

Table B.1: Weather Stations

This table presents information on the weather stations in our sample. Our sample includes the 24 derivative stations and 25 control stations. Station Location is the specific location of the weather station. WBAN is the Weather Bureau Army Navy station identifier. Introduction Date is the first trading day of a temperature-based weather derivative contract settling based on the station's readings. City is the nearest major city. Pop. is the 2011 U.S. population rank of the nearest metropolitan area. Service is the weather station's service level classification by the National Weather Service. Service levels range from A to D with A being the highest service level. Traffic is the 2011 airport passenger traffic rank among U.S. airports.

Station Location	**WBAN**	**Intro. Date**	**City**	**Pop.**	**Service**	**Traffic**
Atlanta Hartsfield International Airport	13874	Sep. 22, 1999	Atlanta, GA	9	A	1
Chicago O'Hare International Airport	94846	Sep. 22, 1999	Chicago, IL	3	A	2
Cincinnati Northern Kentucky Airport	93814	Sep. 22, 1999	Cincinnati, OH	27	A	> 46
New York LaGuardia Airport	14732	Sep. 22, 1999	New York, NY	1	A	20
Dallas-Fort Worth International Airport	3927	Sep. 30, 2000	Dallas, TX	4	A	4
Des Moines International Airport	14933	Sep. 30, 2000	Des Moines, IA	88	A	> 46
Las Vegas McCarran International Airport	23169	Sep. 30, 2000	Las Vegas, NV	30	A	9
Philadelphia International Airport	13739	Sep. 30, 2000	Philadelphia, PA	6	A	18
Portland International Airport	24229	Sep. 30, 2000	Portland, OR	23	A	30
Tucson International Airport	23160	Sep. 30, 2000	Tucscon, AZ	52	C	> 46
Boston Logan International Airport	14739	Sep. 26, 2003	Boston, MA	10	A	19
Houston Bush Intercontinental Airport	12960	Sep. 26, 2003	Houston, TX	5	A	10
Kansas City International Airport	3947	Sep. 26, 2003	Kansas City, MO	29	A	32
Minneapolis-St. Paul International Airport	14922	Sep. 26, 2003	Minneapolis, MN	16	A	15
Sacramento Executive Airport	23232	Sep. 26, 2003	Sacramento, CA	25	C	> 46
Baltimore-Washington International Airport	93721	June 20, 2005	Baltimore, MD	20	A	23
Detroit Metropolitan Airport	94847	June 20, 2005	Detroit, MI	13	A	17
Salt Lake City International Airport	24127	June 20, 2005	Salt Lake City, UT	48	A	24
Colorado Springs Municipal Airport	93037	May 19, 2008	Colorado Springs, CO	81	C	> 46
Jacksonville International Airport	13889	May 19, 2008	Jacksonville, FL	40	A	> 46
Little Rock Adams Field	13963	May 19, 2008	Little Rock, AR	72	A	> 46
Los Angeles Downtown USC Campus	93134	May 19, 2008	Los Angeles, CA	2	-	3
Raleigh Durham International Airport	13722	May 19, 2008	Raleigh, NC	47	A	38
Washington Reagan National Airport	13743	May 19, 2008	Washington D.C.	7	A	25

Table 1 continued

Station Location	WBAN	Intro. Date	City	Pop.	Service	Traffic
Control Stations						
Austin-Bergstrom International	13904	-	Austin, TX	34	A	39
Charlotte Douglas International Airport	13881	-	Charlotte, NC	33	A	11
Cleveland Hopkins International Airport	14820	-	Cleveland, OH	28	A	37
Port Columbus International Airport	14821	-	Columbus, OH	32	A	> 46
Denver International Airport	03017	-	Denver, CO	21	A	5
Indianapolis International Airport	93819	-	Indianapolis, IN	35	A	> 46
Louisville Standiford Field	93821	-	Louisville, KY	42	A	> 46
Memphis International Airport	13893	-	Memphis, TN	41	A	40
Miami International Airport	12839	-	Miami, FL	8	A	12
Milwaukee Mitchell International Airport	14839	-	Milwaukee, WI	39	A	35
Nashville International Airport	13897	-	Nashville, TN	37	A	34
Norfolk International Airport	13737	-	Norfolk, VA	36	C	> 46
Oklahoma City Will Rogers World Airport	13967	-	Oklahoma City, OK	43	A	> 46
Orlando International Airport	12815	-	Orlando, FL	26	A	13
Phoenix Sky Harbor International Airport	23183	-	Phoenix, AZ	14	A	8
Pittsburgh International Airport	94823	-	Pittsburgh, PA	22	A	45
Providence T F Green State Airport	14765	-	Providence, RI	38	A	> 46
Riverside Municipal Airport	03171	-	Riverside, CA	12	C	> 46
San Antonio International Airport	12921	-	San Antonio, TX	24	A	46
San Diego Lindbergh Field	23188	-	San Diego, CA	17	B	28
San Francisco International Airport	23234	-	San Francisco, CA	11	A	7
San Jose International Airport	23293	-	San Jose, CA	31	B	44
Seattle-Tacoma International Airport	24233	-	Seattle, WA	15	A	16
St Louis Lambert International Airport	13994	-	St. Louis, MO	19	A	31
Tampa International Airport	12842	-	Tampa, FL	18	A	29

Table B.2: Summary Statistics for Total Weather Station Errors

This table presents summary statistics on weather station errors. Each observation is a weather station-year. The 49 stations consist of the 24 weather stations underlying a CME temperature contract and 25 control weather stations. Year is the year for which the summary statistics are calculated. N is the number of weather stations in the sample during the year. Mean and Median are the mean and median number of errors in that year, respectively. SD is the standard deviation of the number of errors across stations during the year. 10^{th} and 90^{th} are the 10^{th} and 90^{th} percentile cut-offs, respectively.

Year	**N**	**Mean**	**Median**	**SD**	**10^{th}**	**90^{th}**
1999	46	11.91	11.5	5.31	6	19
2000	49	11.49	11	5.40	4	19
2001	49	11.14	10	5.30	5	19
2002	49	15.51	16	5.21	8	23
2003	49	14.45	15	6.37	5	22
2004	49	13.57	13	5.83	6	23
2005	49	11.49	11	4.74	5	17
2006	49	10.57	9	4.82	4	17
2007	49	12.73	13	5.02	7	20
2008	49	12.47	12	4.59	5	19
2009	49	10.63	10	3.89	4	15
2010	49	10.49	10	4.36	4	16
2011	49	10.71	10	4.19	5	17
All	634	12.09	12	5.23	5	20

Table B.3: Location Selection Probit Regression

This table presents results for a probit model of the selection of derivative locations. The dependent variable in column 1 is a dummy variable equal to 1 if a location ever receives a derivative. The dependent variable in column 2 is a dummy variable equal to 1 if a location receives a derivative in the years 1999 or 2000. Population is zero minus the population rank (-population rank) based on 2011 metropolitan statistical area populations. Exchange is a dummy variable equal to 1 if the city has a major commodities or financial exchange. High Crop is a dummy variable equal to 1 if the location is the most populated location in a state with a top 15 rank in value-added from agriculture in 2011.

	(1)	(2)
VARIABLES	Derivative	1999-2000
Population	0.0205***	0.0141**
	(0.00537)	(0.00661)
Exchange City	1.514**	1.087**
	(0.664)	(0.546)
High Crop	0.620	0.799*
	(0.432)	(0.451)
Observations	366	366
McFadden's Pseudo R-squared	.5448	.4651

Standard Errors in Parentheses

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

Table B.4: The Effect of CME Derivative Introduction on Weather Station Errors

This table presents the results for our main regressions of weather station errors on CME derivative introduction. Observations are at the station-year level. The dependent variable in Columns 1 and 2 is the total number of weather station errors each year. The dependent variable in Columns 3 and 4 is the log of the total number of weather station errors each year. Derivative is a dummy variable equal to 1 in the year of CME derivative introduction on the station and all years afterwards. All regressions include station fixed effects. Columns 2 and 4 include year fixed effects. Standard errors are clustered by weather station.

	(1)	(2)	(3)	(4)
VARIABLES	Total Errors	Total Errors	Log(Total Errors)	Log(Total Errors)
Derivative	-2.358***	-1.631***	-0.183***	-0.148***
	(0.460)	(0.582)	(0.0377)	(0.0481)
Observations	634	634	634	634
R-squared	0.392	0.469	0.415	0.476
Year Fixed Effects	No	Yes	No	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Clustered Standard Errors in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

Table B.5: The Effect of CME Derivative Introduction on Weather Station Errors by Introduction Cohort

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Total Errors	Total Errors	Total Errors	Total Errors	Total Errors
2000 shock	-5.763**				
	(2.730)				
2003 shock		-1.977**			
		(0.925)			
2005 shock			-2.711**		
			(1.034)		
2008 shock				-0.976	
				(0.811)	
Early Cohorts					-5.092**
					(2.335)
Late Cohorts					-1.189**
					(0.496)
Observations	201	263	287	400	634
R-squared	0.604	0.524	0.511	0.476	0.473
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes	Yes

Clustered Standard Errors in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

This table presents results for regressions of weather station errors on CME derivative introduction by cohort. For each regression, we include only the derivative stations in the cohort of interest and all control stations. We run each regression for the years from 1999 to 3 years after the cohort's introduction. The dependent variable is the total number of weather station errors for each station-year observation. The regression in Column 1 includes weather stations with CME derivative introduction in year 2000 and all control stations for the years 1999-2003. The regression in Column 2 includes weather stations with CME derivative introduction in year 2003 and all control stations for the years 1999-2006. The regression in Column 3 includes weather stations with CME derivative introduction in year 2005 and all control stations for the years 1999-2008. The regression in Column 4 includes weather stations with CME derivative introduction in year 2008 and all control stations for the years 1999-2011. The regression in Column 5 includes all observations. Early Cohorts is an indicator variable equal to 1 if a station is in the 1999-2000 wave of introduction and has a derivative in that year. Late Cohorts is an indicator variable equal to 1 if a station is in the 2003, 2005 or 2008 waves of introduction and has a derivative in that year. All regressions include station and year fixed effects. Standard errors are clustered by weather station.

Table B.6: High Demand Locations and The Effect of CME Derivative Introductions on Weather Station Errors

This table presents results from regressions of weather station errors on CME derivative introduction where the sample is separated into high demand and low demand locations. The dependent variable in Column 1 is the total number of weather station errors for each station-year observation. The dependent variable in Column 2 is the log of the total number of weather station errors for each station-year observation. High Demand (Low Demand) is an indicator equal to 1 if a derivative is traded on the station in that year and the station is a high demand (low demand) location. High demand locations are locations with a population rank in the top 25 or in the first 2 cohorts (1999 and 2000). All regressions include year and station fixed effects. Standard errors are clustered by weather station.

	(1)	(2)
VARIABLES	Total Errors	Log(Total Errors)
High Demand	-2.222***	-0.189***
	(0.717)	(0.0626)
Low Demand	-0.661	-0.0799*
	(0.560)	(0.0456)
Observations	634	634
R-squared	0.471	0.477
Year Fixed Effects	Yes	Yes
Station Fixed Effects	Yes	Yes
t-test $\beta_H = \beta_L$	.0576	.1140

Clustered Standard Errors in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

Table B.7: Active Months and The Effect of CME Derivative Introductions on Weather Station Errors

This table presents results from regressions of weather station errors on CME derivative introduction where the sample is separated into active and inactive months. The dependent variable is the total number of weather station errors for each station-year observation. The regression in Column 1 **excludes** all months except April and October, the least active months based on open interest. The regression in Column 2 **includes** all months except April and October. Similarly, the regression in Column 3 **excludes** the top 6 active months based on open interest. The regression in Column 4 **includes** includes the top 6 active months based on open interest. Open interest for month i is calculated by summing across all contracts the average open interest for each contract that settles based on temperatures in month i. Derivative is an indicator equal to 1 if a derivative is traded on the station in that year. All regressions include year and station fixed effects. Standard errors are clustered by weather station.

	(1)	(2)	(3)	(4)
VARIABLES	Total Errors	Total Errors	Total Errors	Total Errors
Derivative	0.0546	-1.714***	-0.483	-1.164***
	(0.247)	(0.576)	(0.419)	(0.415)
Observations	634	634	634	634
R-squared	0.211	0.445	0.374	0.355
Year Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Active/Inactive Months	Inactive	Active	Inactive	Active

Clustered Standard Errors in Parentheses

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

Table B.8: The Effect of CME Derivative Introduction on Weather Station Maintenance

This table presents results from regressions of weather station maintenance on CME derivative introduction at high demand stations. The dependent variable in Columns 1 and 2 is the logarithm of the total number of days that documented maintenance was performed on each station within each year. The dependent variable in Columns 3 and 4 is an indicator variable equal to 1 if any maintenance was performed on a station during the year. High Demand is an indicator equal to 1 if a derivative is traded on the station in that year and the station is a high demand location. High demand locations are locations with a population rank in the top 25 or in the first 2 cohorts (1999 and 2000). The regressions are run for the outcomes during the years 2003 to 2011 at the 21 locations with maintenance data. All regressions include station fixed effects and regressions in Columns 2 and 4 include year fixed effects. Standard errors are clustered by weather station.

	(1)	(2)	(3)	(4)
VARIABLES	Log(Maintenance)	Log(Maintenance)	Any Maintenance	Any Maintenance
High Demand	0.410***	0.333**	0.338***	0.265*
	(0.0602)	(0.127)	(0.0761)	(0.128)
Observations	189	189	189	189
R-squared	0.067	0.200	0.086	0.229
Year Fixed Effects	No	Yes	No	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Clustered Standard Errors in Parentheses
*** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table B.9: The Effect of CME Derivative Introduction on Weather Station Errors Using NCDC Cleaned Values

This table presents regressions using NCDC cleaned values instead of MDA cleaned values to identify weather station errors. The dependent variable in columns 1-2 & 5-7 is the total number of weather station errors for each station-year observation. The dependent variable in columns 3 and 4 is the logarithm of the total number of weather station errors for each station-year observation. Derivative, 2003 shock, 2005 shock and 2008 shock are all a dummy equal to 1 if a weather derivative is traded on that location in that year. The regression in Column 5 includes only the control stations and those stations that received a derivative in 2003 for the years 2000-2006. The regression in Column 6 includes only the control stations and those stations that received a derivative in 2005 for the years 2000-2008. The regression in Column 7 includes only the control stations and those stations that received a derivative in 2008 for the years 2000-2011. The San Jose and Riverside stations are not included in these regressions. All regressions include station fixed effects. Columns 2 & 4-7 include year fixed effects. Standard errors are clustered by weather station.

VARIABLES	(1) Total Errors	(2) Total Errors	(3) Log(Total Errors)	(4) Log(Total Errors)	(5) Total Errors	(6) Total Errors	(7) Total Errors
Derivative	-2.169***	-0.918*	-0.175***	-0.0963*			
	(0.417)	(0.545)	(0.0319)	(0.0498)			
2003 shock					-2.370**		
					(1.132)		
2005 shock						-2.130**	
						(0.889)	
2008 shock							-0.382
							(0.850)
Observations	564	564	564	564	221	243	348
R-squared	0.466	0.554	0.480	0.542	0.628	0.617	0.567
Year Fixed Effects	No	Yes	No	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered Standard Errors in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

Table B.10: The Effect of CME Derivative Introduction on Weather Station Errors With Temperature Controls

This table presents the results for regressions of weather station errors on CME derivative introduction and temperature controls. Observations are at the station-year level. The dependent variable in Column 1 is the total number of weather station errors. The dependent variable in Column 2 is the logarithm of the total number of weather station errors. Derivative is a dummy variable equal to 1 in the year of CME derivative introduction on the station and all years afterwards. Average Temperature is the average daily temperature of a location each year. Temperature Volatility is the standard deviation of the daily temperature of a location each year. All regressions include station fixed effects. Columns 2 and 4 include year fixed effects. Standard errors are clustered by weather station.

	(1)	(2)
VARIABLES	Total Errors	Log(Total Errors)
Derivative	-1.592***	-0.145***
	(0.565)	(0.0477)
Average Temperature	-0.675***	-0.0582***
	(0.218)	(0.0182)
Temperature Volatility	-0.0183	0.00263
	(0.210)	(0.0180)
Observations	634	634
R-squared	0.479	0.487
Year Fixed Effects	Yes	Yes
Station Fixed Effects	Yes	Yes

Clustered Standard Errors in Parentheses
*** p<0.01 ** p<0.05 * p<0.1

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