Ioannis Tzoumas
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PhD Candidate, Department of Economics, +44 07547754241
Lund University
[05/08/2025]

To the Selection Committee,

I am a doctoral candidate in Economics at Lund University and am writing to apply for the NBER PhD Student Workshop on Climate Finance. Alongside this application, I am submitting a working paper entitled *"Pricing the Unknown: Forward-Looking Climate Risk and Belief Divergence"*, which proposes a structural framework for quantifying climate-related uncertainty in derivative markets. By combining expected utility theory with climate model simulations, the paper constructs a forward-looking measure of climate risk priced into US weather derivatives, offering a novel perspective on how markets internalise Knightian uncertainty.

My broader dissertation agenda explores the intersection of climate finance, corporate finance and market microstructure. My second co -authored paper investigates how access to climate risk insurance can mitigate the green transition by crowding out investments in decarbonisation. The third, project examines how the green liquidity premium is mainly attributable to market microstructural channels.

My academic work is shaped by prior professional experience in financial regulation and policy, and by an international academic path that has taken me across Greece, the United Kingdom, Japan, and Sweden. I have also completed the international *Financial Economics of Climate and Sustainability* course which deepened my understanding of the field's empirical and theoretical challenges and directly informed my current research agenda. This background has enabled me to approach climate finance from both a practical and interdisciplinary perspective.

I expect to complete my PhD in June 2027. My primary supervisor is Anders Vilhelmsson (anders.vilhelmsson@nek.lu.se) from Lund University, and my assistant supervisor is Björn Hagströmer (bjorn.hagstromer@sbs.su.se) from Stockholm Business School.

I look forward to the opportunity to exchange ideas with peers and established researchers in the field, and to receive constructive feedback that can strengthen my work.

Thank you for your time and consideration.

Sincerely,

Ioannis Tzoumas

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EDUCATION

Lund University — **Lund, Sweden**
Ph.D in Economics — 08/2023 – 06/2027

Research area: Financial Economics**:** Green Finance, Market Microstructure.
Coursework: Microeconomic Thoery, Macroeconomic Thoery, Econometric Theory, Dynamic Optimization, Survery Evidence in Finance (Aalto University & Boston College), Continuous-Time Models for Empirical Corporate Finance (Aarhus University & London Business School), Household Finance (Lund University & Monash Business School), Network Science (University of Copenhagen), Financial Economics of Climate Change and Sustainability, Research Ethics.
Relevant Activities: Participated in the Chicago Booth Behavioural Finance Reading Group.

Lund University — **Lund, Sweden**
Master of Science in Economics — 08/2022 – 06/2023

GPA: A
Relevant Coursework: Advanced Mathematical Methods; Advanced Econometrics; Advanced Microeconomics; Advanced Macroeconomics; Degree Project in Economics.
Dissertation: "Quantifying the Impact of EU-US "Distressed" Financial Market Integration on European Credit Supply" (Grade: "A").
Relevant Activities: Student Representative; Part of LINC (Lund University's Finance Society); EASA (Lund University's East Asia Student Association).

Lund University — **Lund, Sweden**
Master of Science in Finance — 08/2021 – 06/2022

GPA: A
Relevant Coursework: Financial Econometrics and Machine Learning; Theory of Corporate Finance; Empirical Finance; Managerial Finance; Financial Valuation and Risk Management; Degree Project in Finance.
Dissertation: "Quantifying the Impact of Energy Prices on Financial Stability" (Grade: "A").
Relevant Activities: Part of LINC (Lund University's Finance Society); EASA (Lund University's East Asia Student Association).

University of Glasgow — **Glasgow, United Kingdom**
Bachelor of Accountancy (Honours) in Accounting and Finance — 09/2017 – 06/2021

GPA: 1st Class Honours
Awards: Beta Gamma Sigma Membership by AACSB (for achieving a GPA within the top 10% of all undergraduate students within the business school); Glasgow Global Gold Certificate (Awarded for engaging with contemporary international issues and internationalizing during my university career).
Dissertation: "The Impact of SARS-Cov-2 ("Covid-19") Lockdown Announcements on Global Capital Markets" (Grade: "A5; Distinction").
Relevant Coursework: Financial & Management Accounting; Auditing; Finance; Statistics; Business Law
Relevant Activities: Treasurer for the Japan Society; Student Representative; International Student Mentor / Junior Financial Analyst for GUTIC (Glasgow University Trading and Investment Club).

Keio University — **Tokyo, Japan**
Study Abroad as part of degree at the University of Glasgow — 09/2019 – 06/2020

Awards: Japan Student Services Organization (JASSO) Scholarship awarded to support students who have demonstrated excellent academic and personal records at their home universities (880,000 JPY).
Relevant Activities: Undertook and submitted a thesis ("Independent Study") on the impact of Quantitative Easing on Exchange Rates; Participated in the advanced bracket of Keio University's Japanese Speech Competition.

Fukushima University — **Fukushima, Japan**
Summer Programme as part of degree at the University of Glasgow — 08/2018 – 08/2018

Programme: Completed an academic and philanthropic programme on the revitalization of Fukushima.

Secondary Education **Athens, Greece**
A-Levels (AAA) & Greek High School Diploma (18.3/20) 09/2014 – 08/2017
Awards: Award for achieving 18.3 during my final year of Greek highschool.

PROFESSIONAL EXPERIENCES

Stockholm Business School (Stockholm University) **Stockholm, Sweden**
Visiting Doctoral Researcher at the Finance Department *01*/2025 – 06/2025
Research: Green Finance, Market Microstructure.

Lund University **Lund, Sweden**
Doctoral Researcher 08/2023 – 01/2027
Research: Financial Economics: Green Finance, Market Microstructure.
Teaching: MSc Thesis Supervising (2024), Financial Econometrics (Masters, 2024), Financial Risk Management (Masters, 2024,2025); Data Science (2023,2024);

European Investment Fund **Luxembourg, Luxembourg**
Economic Research Trainee at the Research and Market Analysis Division 09/2022 – 01/2023
Conducted research on:
-The financial markets of the European Region.
-The European macro environment.
-Venture Capitalists and Private Equity Mid-Market.
-Co-authored two governmental papers on EU Venture Capitalist & Private Equity Mid Market's market sentiment.

Eu-Japan Centre For Industrial Cooperation **Brussels, Belgium**
Research Intern 2022 – 2022
Conducted research in both English and Japanese regarding:
-Financial Issues facing EU firms in the Japanese Market (access to Finance; Banking; Payment Methods).
-Understanding Japanese Firm Longevity & Managerial Organisation.
-Summarizing and Looking into Dual Taxation between EU countries and Japan.
-Authored two governmental papers, one on Japanese firm longevity and one on double taxation.

Glasgow University **Tokyo, Japan**
Study Abroad Ambassador 2019 – 2020
Engaged in the digital promotion and marketing of studying abroad in Japan across a variety of social media platforms (Facebook, Instagram, YouTube, Wordpress). This resulted in an increase of post engagement rates.

LANGUAGES & OTHER SKILLS

Languages: Fluent in English & Greek; Low-Advanced Proficiency in Japanese; Beginner in Mandarin & Latin.
Technical Skills: R-Studio; MatLab; Stata; Python; Excel; Bloomberg; Refinitiv Eikon Datastream, Latex.
Certifications & Training: Bloomberg Market Concepts; Deep & Machine Learning OnRamp MathWorks.

POLICY & GOVERNMENTAL RESEARCH PUBLICATIONS

Kraemer-Eis H., Block J., Botsari A., Diegel W., Lang F., Legnani D., Lorenzen S., Mandys F., Tzoumas I., (2022), "EIF Private Equity Mid-Market Survey 2022: Market sentiment and impact of the current geopolitical & macroeconomic environment", ***EIF Working Paper 2022/85****,* pp: 1-76, December 21st. Online Available at: https://www.eif.org/news_centre/publications/EIF_Working_Paper_2022_85.htm

Tzoumas I., (2022), "A Comparative Study on Understanding Japanese Firm Longevity through a Management and Strategy Lens: A Social Capital Approach", ***EU-Japan Center for Industrial Cooperation****,* pp: 1-23, November 8th. Online Available at: https://www.eubusinessinjapan.eu/library/publication/report-understanding-japanese-firm-longevity

Tzoumas I., (2022), "Guide to Double Taxation Conventions between the EU and Japan", ***EU-Japan Center for Industrial Cooperation****,* pp: 1-24, November 2nd. Online Available at: https://www.eubusinessinjapan.eu/library/publication/report-guide-to-double-taxation-conventions-between-eu-and-japan

Kraemer-Eis H., Block J., Botsari A., Diegel W., Lang F., Legnani D., Lorenzen S., Mandys F., Tzoumas I., (2022), "EIF VC Survey 2022: Market sentiment and impact of the current geopolitical & macroeconomic environment", ***EIF Working Paper 2022/82***, pp: 1-80, October 12th. Online Available at: https://www.eif.org/news_centre/publications/EIF_Working_Paper_2022_82.htm

ACADEMIC THESIS

Tzoumas I., (2022), "Quantifying the Impact of EU-US "Distressed" Financial Market Integration on European Credit Supply", *Lund University,* pp: 1-75, Online Available at: https://lup.lub.lu.se/student-papers/search/publication/9117712

Tzoumas I., (2022), "Quantifying the Impact of Energy Prices on Financial Stability", *Lund University,* pp: 1-100, Online Available at: https://lup.lub.lu.se/student-papers/search/publication/9084226

WORKING PAPERS

Tzoumas I., (2024), "Pricing the Unknown: Forward-Looking Climate Risk and Belief Divergence", Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5047843

Tzoumas I., (2024), "The Green Liquidity Premium"

Tzoumas I., (2024), "Belief Segmentation, Informational Misallocation and Threshold Arbitrage: Evidence from Pegged Currency Markets"

Tzoumas I., Mandys F., (2025), "Crowding Out the Energy Transition: Moral Hazard and Climate Risk Finance"

CONFERENCES, PRESENTATIONS & WEBINARS

"Pricing the Unknown: Forward-Looking Climate Risk and Belief Divergence", by Ioannis Tzoumas, At ***Cambridge University***, *Department of Land Economy, Early career researcher's conference 2025, 09/05/2025*

"Pricing the Unknown: Forward-Looking Climate Risk and Belief Divergence", by Ioannis Tzoumas, At ***Stockholm Business School (Stockholm University)*** *Finance Seminar,* 17/03/2025

"Pricing the Unknown: Forward-Looking Climate Risk and Belief Divergence", by Ioannis Tzoumas, ***Lund University Finance***, *Econometrics and Macroeconomics (FEM) Seminar,* 25/02/2025

Discussing of: ["Discontinued Positive Feedback Trading and the Decline of Return Predictability" by Ben-David I., Li J., Rossi A. and Song Y., *Working Paper Series*, Online available at: http://www.nber.org/papers/w28624.] At the ***Chicago Booth Behavioural Finance Reading Group***, 15/11/2023: Online available at: https://sites.google.com/view/behavioral-finance-group/quarterly-programs/discussion-slides?authuser=0

"Understanding Japanese Firm Longevity", Presented Paper: "A Comparative Study on Understanding Japanese Firm Longevity through a Management and Strategy Lens: A Social Capital Approach", by Ioannis Tzoumas, *EU-**Japan Centre For Industrial Cooperation***, February, 2023, Online available at: https://www.eubusinessinjapan.eu/library/event/about-japan-webinar-series-206-understanding-japanese-firm-longevity

"Update on the European Venture Capital Market 2022 by EIF", Presented Paper: "EIF VC Survey 2022: Market sentiment and impact of the current geopolitical & macroeconomic environment", ***Swedish Private Equity & Venture Capital Association (SVCA) in conjunction with the Nordic and Baltic associations***, Online available at: https://www.svca.se/kalenderevent/update-on-the-european-venture-capital-market-2022-by-eif/

References

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Working Paper

"Pricing the Unknown: Forward-Looking Climate Risk and Belief Divergence"

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Lund University

Autumn 2024

Abstract

This paper introduces a market based framework that uses market prices of weather derivatives to infer forward-looking beliefs about physical climate risk. Leveraging derivative-implied payouts and benchmark projections from NASA's CMIP6 climate model ensemble, this paper constructs two local uncertainty indices: the Market Bias Uncertainty Index (MBUI), capturing directional divergence between market and scientific expectations; the Market Mispricing Uncertainty Index (MMUI), quantifying absolute disagreement. These indices are validated across key commodity markets, including agricultural and energy, showing significant predictive power. These indices provide regulators, insurers, and investors with a real-time gauge of market-implied climate risk.

JEL classification codes: Q54, C58, G13, Q51

1 Introduction

Uncertainty about the pace, scope, and local effects of climate change poses a fundamental challenge for policy and financial decision-making. Physical climate models provide probabilistic forecasts, but there is no established mechanism for translating them into the real-time expectations used by financial markets when pricing climate risk. This difficulty reflects not only risk but also ambiguity in the Knightian sense, since market and scientific models may diverge. Yet it is precisely these market-implied beliefs that shape investment flows, insurance premia, and adaptation strategies, mak-

ing their measurement essential.

This paper develops a market-based framework that infers forward-looking climate expectations from the prices of temperature-linked weather derivatives. Using a structural indifference-pricing model with constant absolute risk aversion in an incomplete-market setting to ground the empirics, this paper extracts the implicit forecast embedded in each station-month futures contract and benchmarks it against ensemble projections from NASA's CMIP6 climate models. The comparison yields two locally disaggregated indices of climate uncertainty. The Market Bias Uncertainty Index (MBUI) captures directional divergence between market and scientific expectations, indicating whether markets systematically anticipate warmer or cooler outcomes. The Market Mispricing Uncertainty Index (MMUI) measures the absolute magnitude of that disagreement.[1]

To assess whether these indices reflect systematic information rather than statistical noise, this paper examines their relationship with real economic variables through Granger-causality tests and impulse response functions. Across a panel of agricultural and energy fuel commodities, this paper finds that both MBUI and MMUI exhibit statistically significant predictive content. These relationships remain robust under multiple-testing corrections suggesting that the indices embed meaningful forward-looking signals about physical climate risk.

This paper engages with multiple strands of literature in climate finance, asset pricing under uncertainty, and the economics of weather derivatives. It

[1]While "climate risk" is a broad term, this paper refers specifically to temperature-related uncertainty. This is a deliberate choice: temperature is the most measurable, economically salient, and "tradable" component of physical climate risk in market settings.

contributes most directly to the literature on belief dispersion and climate risk pricing (e.g., Moore et al. 2019, Hoogendoorn et al. 2020).

The closest related work is Bae et al. (2024), who derive a Weather Variance Risk Premium (WRVP) from option prices and relate it to credit spreads. While their measure captures second-moment risk using market-implied volatility, the approach in this paper embeds uncertainty directly into physical temperature forecasts using CMIP6 model outputs, capturing the more nuanced Knightean risk.

This paper is also related to Kruttli et al. (2025), who construct a variance risk premium based on hurricane path uncertainty and examine its pricing implications, though only in the context of discrete disaster events. In effect, this paper develops a physical climate analogue to canonical uncertainty indices such as Baker et al. (2016).

Although weather derivatives are thinly traded, prior research shows that they embed meaningful expectations about local temperature variation. Chincarini (2011) finds that prices in these markets reflect efficient forecasts, while Schlenker & Taylor (2021) show that derivative-implied expectations outperform CMIP5 projections in capturing long-term temperature trends. Purnanandam & Weagley (2016) further documents that the introduction of weather derivatives improves the quality of weather station reporting, highlighting a feedback loop between market prices and environmental data quality. This paper exploits this raw informativeness of weather derivatives.

The theoretical analysis draws on the literature on equilibrium-based pricing of climate and weather risk (e.g., Cao & Wei 2004, Zhou et al. 2019, Hess 2024), where temperature-linked cash flows are priced under preferences and

market incompleteness. These models provide rich theoretical insight but often lack empirical tractability.

At the other end of the spectrum, financial engineering studies apply flexible statistical methods to extract climate risk premia from historical data (Härdle & Cabrera 2012, Benth & Benth 2007, Campbell & Diebold 2005). While empirically rich, these approaches tend to be backward-looking and sacrifice interpretability. By grounding our theoretical framework in a structural pricing model, this paper bridges the two traditions.

This paper also contributes to an empirical literature on the pricing of physical climate risk in financial markets (Addoum et al. 2020, Dell et al. 2014, Severen et al. 2018, Bansal et al. 2019, Auffhammer 2018) and its measurement (De Nard et al. 2023, Gavriilidis 2021, Bouri et al. 2022). Many of these studies rely on low-frequency or spatially coarse data, conflate physical and transition risk, or focus on infrequent "one-off" events. By contrast, the approach here is continuous, geographically disaggregated, and designed to avoid endogeneity and measurement error common in text-based or disaster-event methods.

The rest of the paper is structured as follows: Section 2 provides institutional background on weather derivatives. Section 3 develops the indifference pricing framework and derives the indices. Section 4 describes the data. Section 5 constructs and validates the indices. Section 6 presents the conclusion.

2 Institutional Background

Weather derivatives emerged in the late 1990s as tools for hedging temperature-related risk and have been actively traded on the Chicago Mercantile Exchange (CME) since the early 2000s. These temperature-linked contracts dominate the environmental hedging market in terms of liquidity, standardization, and historical coverage. They are the only instruments with sufficient depth to support robust empirical analysis. Furthermore, temperature is the canonical physical climate variable within scientific assessments (see: IPCC 2021).

Temperature also underpins most economic impact models, and is frequently used in policy and infrastructure planning. Prior research shows that temperature futures embed meaningful expectations about future realizations (Chincarini 2011) and often outperform meteorological forecasts in tracking long-term climate dynamics (Schlenker & Taylor 2021). Their economic relevance is also well established: temperature derivatives have been integrated into government climate systems (Purnanandam & Weagley 2016), and temperature shocks are known to affect firm performance and asset prices (Addoum et al. 2020).

Contracts come in two standard forms: Heating Degree Day (HDD) contracts, which pay out in colder-than-average conditions, and Cooling Degree Day (CDD) contracts, which pay out in warmer-than-average conditions. Both use 65°F (18°C) as a baseline. Daily temperatures below this threshold contribute to HDDs; those above contribute to CDDs. Monthly settlement values are determined by multiplying cumulative degree days by a fixed tick

size, typically 20 USD per unit for U.S. contracts.

Formally, cumulative degree days are defined as:

$$\text{HDD}_{\text{Total}} = \sum_{t=1}^{H} \max(65 - T_{a,t}, 0), \tag{1}$$

$$\text{CDD}_{\text{Total}} = \sum_{t=1}^{H} \max(T_{a,t} - 65, 0), \tag{2}$$

where $T_{a,t}$ is the average daily temperature at location a on day t, and H is the number of days in the contract period.

In practice, derivative prices evolve with weather expectations. Early in the contract's life, prices reflect high forecast uncertainty; as expiration nears, they converge toward realized values (Schlenker & Taylor 2021).

3 Theoretical Framework

The weather derivatives market is inherently incomplete: temperature is non-tradable, and contracts are rarely dynamically hedged. Pricing therefore resembles insurance, with sellers demanding a premium for bearing unhedgeable risk (Brockett et al. 2009). Beyond standard risk, this setting embodies Knightian uncertainty: the probability distribution of temperature outcomes itself is ambiguous, with scientific and market agents relying on distinct models. Our framework interprets derivative prices as embedding one set of beliefs and uses divergence from CMIP6 benchmarks to capture this ambiguity

This section, thus, derives the pricing framework used to construct market-

implied uncertainty indices. The analysis follows a standard single-agent CARA indifference-pricing model (e.g., Cochrane 2001, Brockett et al. 2009, Xu et al. 2008).

Throughout, contracts are indexed by the ordered pair (a, m), where a denotes the reference weather station and m the contract's settlement month. All variables refer to a single contract; aggregate cash flows scale linearly in quantity. Subscripts (a, m) are suppressed when context allows.

3.1 Economic Environment

1. **Contract Payoff.** One weather futures contract pays:

$$X_m = q \sum_{t \in m} \left[\max(\theta - T_t, 0) + \max(T_t - \theta, 0) \right], \quad \text{with } q = 20\,\text{USD},\ \theta = 65^\circ\text{F},$$

   where T_t is the average daily temperature at station a on day t during month m.

2. **Scientific Benchmark.** Climate model forecasts yield:

$$\mu^\star_{CMIP6} = \mathbb{E}_{\text{CMIP6}}[X_m], \qquad \sigma^2_{CMIP6} = \text{Var}_{\text{CMIP6}}[X_m],$$

   where expectations are taken under the CMIP6 ensemble distribution.

3. **Investor Preferences and Market Structure.** A representative underwriter has constant absolute risk aversion (CARA) utility $U(W) = -\exp(-\gamma_s W)$ and trades a one-period bond with gross return R_f. The underwriter sells $Q_m > 0$ contracts and cannot dynamically hedge tem-

perature risk.

All derivative prices M_m are quoted and paid at time $t = 0$; multiplying by R_f gives their settlement-date value.

3.2 Indifference Pricing under CARA Preferences

The market price equates the seller's certainty equivalents with and without the derivative position. The result is summarized below; the full derivation appears in Appendix B.

Proposition 1 (Seller Indifference Price) *An underwriter who shorts Q_m contracts at price M_m and holds beliefs (μ_m, σ_m^2) is indifferent to trading if:*

$$R_f M_m = \mu_m + \frac{\gamma_s}{2}\sigma_m^2 Q_m.$$

Interpretation. The seller receives the expected payout μ_m, plus a premium for bearing unhedgeable risk. This premium increases with forecast variance, contract size, and risk aversion. In principle, μ_m reflects a subjective distribution. However, when multiple probability models coexist, markets versus scientific benchmarks, this expectation is not uniquely defined. The difference between the two can be interpreted as a market-based manifestation of Knightian uncertainty. Our indices, introduced below, quantify this divergence

3.3 Deriving Market-Implied Expectations

The model allows recovery of market-implied expectations net of risk adjustments. From Proposition 1, the seller's implicit expectation is:

$$\hat{\mu}_m^{\text{sell}} = R_f M_m - \frac{\gamma_s}{2}\sigma_m^2 Q_m, \tag{3}$$

where $R_f M_m$ is the grossed-up market price, σ_m^2 is the forecast variance, and Q_m is open interest. This yields a lower bound on the expected payout.

Similarly, a buyer with risk aversion γ_b has an implied expectation:

$$\hat{\mu}_m^{\text{buy}} = R_f M_m + \frac{\gamma_b}{2}\sigma_m^2 Q_m, \tag{4}$$

which reflects a willingness to pay above actuarial value for hedging. Averaging gives a midpoint estimator:

$$\hat{\mu}_m^{\text{mid}} = \frac{1}{2}(\hat{\mu}_m^{\text{sell}} + \hat{\mu}_m^{\text{buy}}) = R_f M_m + \frac{\gamma_b - \gamma_s}{4}\sigma_m^2 Q_m. \tag{5}$$

When $\gamma_b \approx \gamma_s$, this simplifies to:

$$\hat{\mu}_m^{\text{mid}} \approx R_f M_m.$$

This approximation is consistent with prior empirical findings. Xu et al. (2008) estimate small and symmetric risk aversion for buyers and sellers. Turvey (2008) finds that weather risk has negligible systematic covariance, while Chincarini (2011) and Schlenker & Taylor (2021) show that market prices closely track actuarial values in efficient settings. Weagley (2019) note

that while financial frictions may influence pricing, deviations remain small. These findings justify using $R_f M_m$ as an unbiased estimator in baseline analysis.[2]

3.4 Index Definitions

This paper introduces two forward-looking indices that quantify climate risk by comparing market-implied forecasts from weather derivatives to scientific benchmarks.

Market Bias Uncertainty Index (MBUI). MBUI measures the directional deviation between market prices and model expectations:

$$\text{MBUI}_m = \frac{\hat{\mu}_t - \mu^{\star}_{CMIP6}}{\mu^{\star}_{CMIP6}}.$$

A positive MBUI indicates that the market anticipates more extreme outcomes than those projected by the CMIP6 benchmark. The numerator captures the absolute difference between market and model expectations, while the denominator scales this difference relative to the scientific benchmark.

Market Mispricing Uncertainty Index (MMUI). MMUI captures the magnitude of disagreement:

$$\text{MMUI}_m = |\text{MBUI}_m|.$$

[2]Given the known veracity issues of open interest (see: Schlenker & Taylor 2021) within weather derivatives data this paper, uses this a further reason to avoid the use of open interest. However, in practice one should only focus on instruments that open interest can be identified and construct said indices only from prices with verifiable open interest.

Where MMUI is simply the absolute MBUI. Taking the absolute value ensures that MMUI reflects the magnitude of disagreement, independent of whether the market expects warmer or cooler outcomes than the model projection.

3.5 Empirical Estimation of MMUI

The empirically estimated Market Mispricing Uncertainty Index (MMUI) is defined as the relative absolute difference between total market-implied and CMIP6-projected degree days:

$$\widehat{\mathrm{MMUI}}_m = \frac{\widehat{\mathrm{TDD}}_m^{\mathrm{mkt}} - \widehat{\mathrm{TDD}}_m^{\mathrm{CMIP}}}{\widehat{\mathrm{TDD}}_m^{\mathrm{CMIP}}} \tag{6}$$

Here, $\widehat{\mathrm{TDD}}_m^{\mathrm{mkt}}$ denotes the total number of degree days, defined as the sum of expected Heating Degree Days and Cooling Degree Days, over contract month m as implied by market prices. $\widehat{\mathrm{TDD}}_m^{\mathrm{CMIP}}$ represents the equivalent degree-day total projected by the CMIP6 climate model ensemble.

4 Data

4.1 Weather Derivative Data

The primary data source is Bloomberg, which provides monthly and seasonal settlement prices for Heating Degree Day (HDD) and Cooling Degree Day (CDD) futures. The dataset covers contracts from 24 U.S. airport-based weather stations (see Appendix A). European contracts are also ignored as

they only trade on CDD days and not HDD.

The remaining sample offers sufficient variation across locations, seasons, and pricing conditions to support construction of forward-looking measures of climate-related uncertainty. The geographic resolution and temporal consistency of these contracts make them uniquely suited to extract market-based expectations about physical climate variation.

4.2 Climate Data

This paper's forward-looking forecasts rely on Phase 6 of the Coupled Model Intercomparison Project (CMIP6). This paper uses NASA's NEX-GDDP-CMIP6 output based on the GISS-E2-1-G model (Thrasher et al. 2021, 2022), which provides daily projections at $0.25^\circ \times 0.25^\circ$ under a suite of SSP scenarios (Riahi et al. 2017). For each airport station this paper extracts the mean of the projected temperature series from the nearest grid cell[3] to obtain $\widehat{\text{HDD}}_{a,t}$, $\widehat{\text{CDD}}_{a,t}$, and their variances.

4.2.1 Financial Data

To compute risk-neutral valuations, projected derivative payouts are discounted using the shortest horizon treasury bill's constant maturity yield, sourced from the Federal Reserve Bank of St. Louis (FRED). That is the 3-month T-Bill up until the 2000s and then the 1-month T-Bill from there onwards. It is assumed that at the start of the month the interest rate is fixed. This is to avoid any interest rate projection noise.

[3]Grid-cell matching is performed by minimizing great-circle distance via the Haversine formula, $d = 2r \arcsin\sqrt{\sin^2(\frac{\Delta\varphi}{2}) + \cos(\varphi_1)\cos(\varphi_2)\sin^2(\frac{\Delta\lambda}{2})}$, where $r = 6371\,\text{km}$.

Once, the indices are constructed we then turn to validating them. Specifically, to test the informational content of the climate uncertainty indices, this paper analyzes their predictive relationships with pan-U.S. agricultural and fuel producer prices. The agricultural commodities are segmented into categories based on their crop type, as it is already known that (see: Tran et al. 2025) temperature affects crops differently. Uncategorised crops are sorted into the "Special" category. This paper also makes use of pre-aggregated crop types as well. All the data is taken from FRED. Table 1 below gives an overview of the commodities.

Table 1: List of Commodities Used in Granger Causality Tests

Category	**Commodity**	**FRED Code**
Grains / Cereals	Barley	WPU01220101
	Corn	WPS012202
	Oats	WPU012203
	Rough Rice	WPU01230103
	Wheat	WPU0121
Oilseeds	Canola	WPU01830171
	Peanuts	WPU01830111
	Soy	WPU01830131
	Sunflower	WPU01830161
Animal Feed	Alfalfa Hay	WPU01810101
	Hay and Hay Seeds	WPU0181
Root Vegetables	Carrots	WPU01130212
	Potatoes	WPU01130603
Speciality	Almonds	WPU01190102
	Cotton	WPU015
Energy Commodities	Natural Gas (Spot)	WPU0531
	Coal	WPS051
	Gasoline	WPS0571
	No. 2 Diesel Fuel	WPS057303
	Natural Gas (Henry Hub)	DHHNGSP
Aggregates	Farm Products	WPU01
	Fruits and Nuts	WPU011
	Grains	WPU012

Notes: This table lists all commodity price series included in the Granger causality and impulse response analyses. Series were selected based on availability from the FRED database, grouped by category, and include both disaggregated goods (e.g., barley, diesel) and aggregate indices (e.g., grains, farm products).

5 Empirical Strategy and Validation

5.1 Index Construction and Patterns

This paper first constructs monthly values of MBUI and MMUI for each location and contract pair using futures prices and CMIP6-based expectations. The tables below give summary statistics of the indices.

Table 2: MBUI Summary Statistics

Location	Count	Mean	Std	Min	25%	50%	75%	Max
Atlanta	269	0.0451	0.3667	-0.8678	-0.1634	-0.0009	0.1920	2.3987
Baltimore	126	0.0651	0.5153	-0.9402	-0.1984	0.0287	0.2265	3.7417
Boston	162	-0.1166	0.3033	-0.9391	-0.2091	-0.0547	0.0499	0.5066
Burbank	7	0.3645	0.3035	-0.1873	0.2103	0.5067	0.5954	0.6204
Chicago	283	-0.0433	0.4046	-0.9623	-0.2151	-0.0336	0.1314	1.8059
Cincinnati	165	0.1375	0.7123	-0.9967	-0.0917	0.0418	0.2280	6.1577
Dallas	273	0.0361	0.3424	-0.9938	-0.1512	0.0197	0.1747	1.6794
Des Moines	192	-0.0098	0.3842	-0.9053	-0.1728	-0.0023	0.1526	2.0663
Detroit	117	-0.1497	0.3915	-0.9779	-0.3812	-0.0822	0.1227	0.8119
Houston	160	0.0108	0.3241	-0.6551	-0.1801	-0.0079	0.1506	1.8572
Jacksonville	53	-0.1340	0.1794	-0.5293	-0.2091	-0.1428	0.0072	0.2717
Kansas City	150	0.0255	0.3383	-0.8546	-0.1779	0.0167	0.1791	1.3957
Little Rock	93	0.0105	0.4005	-0.8893	-0.1667	-0.0392	0.1790	1.7150
Los Angeles	92	0.0098	0.4451	-0.8634	-0.3349	-0.0232	0.3460	1.3079
Minneapolis	210	-0.0902	0.3753	-0.9619	-0.2276	-0.0109	0.1041	1.1913
New York	285	0.0245	0.3361	-0.7932	-0.1351	-0.0102	0.1648	1.5860
Portland	119	-0.5303	0.5629	-0.9982	-0.9777	-0.7132	-0.2143	1.3044
Raleigh	91	-0.0155	0.3289	-0.8122	-0.2138	-0.0302	0.1526	1.4401
Sacramento	206	-0.0554	0.2983	-0.7864	-0.2383	-0.0700	0.1181	1.2813
Tucson	193	0.1184	0.4790	-0.8811	-0.0784	0.0448	0.2262	3.1084
Washington	91	0.0055	0.3065	-0.9036	-0.1752	-0.0289	0.1905	0.9750

Note: Descriptive statistics for each location's MBUI. Count is number of monthly observations; Mean, Std (standard deviation), Min, Max summarize the distribution; 25th, 50th (median), and 75th are the respective percentiles.

The MBUI and MMUI indices exhibit substantial cross-market variation, reflecting local divergence between derivative-implied expectations and CMIP6 projections. The directional MBUI within several locations shows persistent positive values, including Burbank (mean = 0.36) and Cincinnati

Table 3: MMUI Summary Statistics

Location	**Count**	**Mean**	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
Atlanta	269	0.2509	0.2708	0.0009	0.0824	0.1754	0.3215	2.3987
Baltimore	126	0.3192	0.4087	0.0053	0.1190	0.2264	0.4001	3.7417
Boston	162	0.2174	0.2411	0.0008	0.0525	0.1389	0.2754	0.9391
Burbank	7	0.4180	0.2080	0.1471	0.2304	0.5067	0.5954	0.6204
Chicago	283	0.2794	0.2954	0.0020	0.0703	0.1678	0.3679	1.8059
Cincinnati	165	0.3026	0.6590	0.0012	0.0645	0.1575	0.3188	6.1577
Dallas	273	0.2332	0.2528	0.0015	0.0732	0.1639	0.2981	1.6794
Des Moines	192	0.2615	0.2811	0.0007	0.0728	0.1585	0.3650	2.0663
Detroit	117	0.3195	0.2700	0.0009	0.0934	0.2573	0.4305	0.9779
Houston	160	0.2231	0.2347	0.0020	0.0779	0.1664	0.2796	1.8572
Jacksonville	53	0.1732	0.1411	0.0014	0.0573	0.1553	0.2428	0.5293
Kansas City	150	0.2452	0.2336	0.0005	0.0758	0.1831	0.3383	1.3957
Little Rock	93	0.2797	0.2853	0.0101	0.0963	0.1790	0.3598	1.7150
Los Angeles	92	0.3570	0.2635	0.0065	0.1228	0.3401	0.5295	1.3079
Minneapolis	210	0.2670	0.2782	0.0019	0.0621	0.1628	0.3682	1.1913
New York	285	0.2304	0.2455	0.0005	0.0614	0.1493	0.3041	1.5860
Portland	119	0.6938	0.3392	0.0038	0.4580	0.8180	0.9866	1.3044
Raleigh	91	0.2356	0.2286	0.0010	0.0852	0.1790	0.2855	1.4401
Sacramento	206	0.2312	0.1958	0.0018	0.0983	0.1716	0.3152	1.2813
Tucson	193	0.2815	0.4048	0.0007	0.0583	0.1599	0.3392	3.1084
Washington	91	0.2282	0.2033	0.0040	0.0745	0.1789	0.3008	0.9750

Note: Descriptive statistics for each location's MMUI. Count is the number of monthly observations; Mean, Std (standard deviation), Min, Max summarize the distribution; 25th, 50th (median), and 75th are the respective percentiles.

(mean = 0.14), indicating expectations of more extreme temperatures than CMIP6 model projections. Others, such as Portland (mean = -0.53) and Detroit (mean = -0.15), exhibit consistent underpricing. The absence of a clear geographic pattern suggests market expectations are locally formed and model-inconsistent.

MMUI measures the absolute scale of disagreement. Most locations fall between 0.20 and 0.30, though Portland (mean = 0.69) and Baltimore (mean = 0.32) show elevated values. Even large, liquid markets like Chicago and New York display persistent mispricing relative to climate model benchmarks.

5.2 Validation: Granger Causality

To test for Granger causality between variables X_t and Y_t, this paper estimates the following vector autoregression (VAR) system with p lags:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} Y_{t-i} + \sum_{i=1}^{p} \beta_{1i} X_{t-i} + \varepsilon_{1t}, \tag{7}$$

$$X_t = \gamma_0 + \sum_{i=1}^{p} \gamma_{1i} X_{t-i} + \sum_{i=1}^{p} \delta_{1i} Y_{t-i} + \varepsilon_{2t}. \tag{8}$$

This paper then tests the following null hypotheses:

- $H_0^{X \to Y} : \beta_{1i} = 0 \quad \forall i = 1, \ldots, p$ (i.e., X does not Granger-cause Y),
- $H_0^{Y \to X} : \delta_{1i} = 0 \quad \forall i = 1, \ldots, p$ (i.e., Y does not Granger-cause X).

F-tests are conducted on each null hypothesis using the standard Wald test, while lags are automatically found through the AIC. Series are made stationary before being fit. The tables below showcase the overall results (including corrections) of the relationship results.

To ensure that the indices can be employed in a continuous manner this paper limits the sample only to the periods with the longest continuous uninterrupted series. Furthermore, this sample is limited only to locations that have greater than 80 observations. Using this as the basis this paper then conducts the Granger causality tests. Table 4 below gives an overview of all locations for completeness:

Given the extensive number of hypothesis testing run, this paper employs corrective measures to ensure robustness in its results. The corrective

Table 4: Time span and length by location

Location	Observations	Start	End
Atlanta	178	2005-07-01	2020-04-01
Baltimore	102	2008-01-01	2016-06-01
Boston	153	2003-10-01	2016-06-01
Burbank	7	2024-07-01	2025-01-01
Chicago	176	2005-07-01	2020-02-01
Cincinnati	7	2003-10-01	2004-04-01
Colorado	0	0	0
Dallas	177	2005-07-01	2020-03-01
Des Moines	102	2008-01-01	2016-06-01
Detroit	84	2008-02-01	2015-01-01
Houston	125	2006-01-01	2016-05-01
Jacksonville	7	2010-04-01	2010-10-01
Kansas City	83	2006-01-01	2012-11-01
Little Rock	77	2010-01-01	2016-05-01
Los Angeles	77	2010-01-01	2016-05-01
Minneapolis	167	2006-01-01	2019-11-01
New York	177	2005-07-01	2020-03-01
Phil	0	0	0
Port	0	0	0
Portland	7	2009-04-01	2009-10-01
Raleigh	35	2010-01-01	2012-11-01
Sacramento	143	2006-01-01	2017-11-01
Salt	0	0	0
Tucson	126	2006-01-01	2016-06-01
Washington	35	2010-01-01	2012-11-01

Note: Table reports the longest continuous sample characteristics and time span, locations with zero observations have tradable derivatives, however, there is no continuous trading of said derivatives greater than 1 observation.

measures employed are the False-Discovery-Rate (FDR) and the more conservative Bonferroni correction. The corrections are applied to each segmented commodity group, as well as prediction and type of index. Table 5 gives an overview of the results.

Table 5: Significant Granger Causality Relationships across Commodities (Bonferroni-corrected, with FDR and $p < \alpha$)

Commodity	**Item → MBUI**	**MBUI → Item**	**Item → MMUI**	**MMUI → Item**
Animal Feed				
Alfalfa Hay	5 (5,9)	9 (9,9)	2 (4,7)	1 (3,4)
Hay and Hayseeds	5 (5,10)	8 (5,6)	5 (7,10)	3 (3,3)
Total (out of 40)	**10 (10,19)**	**17 (14,15)**	**7 (11,17)**	**4 (6,7)**
Grains				
Barley	1 (1,3)	0 (1,2)	1 (1,6)	0 (0,1)
Corn	1 (1,2)	1 (2,2)	0 (0,0)	1 (2,2)
Oats	3 (4,9)	0 (0,3)	0 (0,1)	0 (0,3)
Rough Rice	2 (2,3)	0 (0,1)	0 (0,5)	1 (1,4)
Wheat	1 (1,1)	1 (1,3)	0 (0,2)	1 (1,2)
Total (out of 100)	**8 (9,18)**	**2 (5,12)**	**1 (2,14)**	**3 (5,12)**
Root Vegetables				
Carrots	3 (5,6)	0 (1,2)	3 (4,6)	0 (0,3)
Potatoes	4 (4,8)	1 (3,6)	7 (7,8)	6 (6,8)
Total (out of 40)	**7 (9,14)**	**1 (4,8)**	**10 (11,14)**	**6 (6,11)**
Oilseeds				
Canola	4 (5,10)	1 (1,3)	3 (3,9)	0 (0,1)
Peanuts	1 (1,2)	1 (2,7)	0 (1,3)	1 (2,2)
Soy	2 (2,3)	0 (1,6)	1 (2,6)	2 (4,4)
Sunflower	2 (2,3)	0 (1,6)	1 (2,6)	2 (4,4)
Total (out of 77)	**9 (10,18)**	**2 (5,22)**	**5 (8,24)**	**5 (10,11)**
Specialty Crops				
Almonds	2 (2,1)	2 (2,5)	2 (2,4)	8 (8,8)
Cotton	0 (0,0)	0 (0,0)	0 (0,0)	1 (2,2)
Total (out of 40)	**2 (2,1)**	**2 (2,5)**	**2 (2,4)**	**9 (10,10)**
Fuels				
GasSpot	1 (1,4)	1 (1,3)	1 (3,5)	2 (2,6)
Coal	0 (0,4)	0 (0,0)	1 (1,2)	0 (0,6)
Gasoline	0 (0,1)	0 (0,1)	1 (1,1)	4 (4,6)
Diesel Fuel	0 (0,4)	0 (0,2)	0 (0,1)	1 (1,4)
Natural Gas	2 (2,7)	2 (2,5)	1 (1,6)	1 (2,4)
Total (out of 100)	**3 (3,17)**	**3 (3,13)**	**4 (6,15)**	**8 (9,20)**

Note: Each entry shows number of significant Granger-causal links at the Bonferroni level, followed in parentheses by (FDR count, raw $p < \alpha$ count). Data is aggregated from all tables across sectors and directions.

The principal finding is that both the Market Bias Uncertainty Index (MBUI) and the Market Mispricing Uncertainty Index (MMUI) exhibit statistically significant predictive relationships with commodity prices even when accounting for multiple hypothesis testing, though the strength and direction of these relationships vary by commodity segment and geographical location. These results support the interpretation of derivative-implied uncertainty measures as forward-looking, economically meaningful signals of climate-related risk.

Within the agricultural sector, grains and oilseeds display the most consistent evidence of climate sensitivity. Notably, oats and barley show robust Granger-causal relationships with MBUI, indicating that market participants could incorporate expectations of climate deviation into the pricing of temperature-exposed staple crops. These effects remain significant under multiple testing corrections, suggesting that MBUI captures shifts in anticipated climate risk with relevance for market behaviour. Oilseeds such as canola and soy exhibit both forward and reverse causality, consistent with a more dynamic interaction in which prices respond to climate uncertainty while also influencing market perceptions through observable disruptions to supply or regional weather patterns.

Results for speciality crops and root vegetables are more heterogeneous, though they continue to provide useful insights. Almonds, for example, display significant relationships primarily with MMUI, implying that absolute forecast disagreement, rather than directional bias, may be more pertinent in markets where production is highly vulnerable to climatic extremes. Potatoes exhibit predictive relationships with both indices, reflecting the relevance of

climate uncertainty for crops where yield and storage are closely linked to seasonal conditions. These findings suggest that different commodities absorb different dimensions of climate uncertainty. Some are more responsive to the direction of expected deviation from climate models, while others react to the level of disagreement among forecasts.

The energy and industrial input categories provide further evidence of the informational value of the proposed indices. Natural gas spot prices show bidirectional Granger-causality with both MBUI and MMUI, indicating that these markets both reflect and shape prevailing climate uncertainty. Similar patterns are evident in upstream producer price indices, including those for fertilisers and refined fuels, where anticipatory adjustments may be driven by hedging activity or demand-side responses to projected climate conditions. This is consistent with a mechanism whereby derivative-implied indices serve not only as indicators of physical climate risk, but also as inputs into the broader formation of expectations across the production chain.

Taken together, the findings indicate that MBUI and MMUI convey economically relevant climate signals that are reflected in the pricing of key commodities. MBUI, in particular, demonstrates stronger and more consistent forward-looking performance, especially under more stringent significance thresholds. This suggests that directional divergence between market expectations and scientific projections carries greater informational value for pricing than the overall level of disagreement. The responsiveness of commodity markets to climate uncertainty appears to vary systematically across segments.

5.3 Impulse Response Functions

To complement the Granger causality analysis and better understand the dynamic relationship between climate uncertainty indices and commodity prices, impulse response functions are estimated for each bivariate system involving a commodity series and either the MBUI or MMUI index.

Impulse responses are calculated using orthogonalised one-standard-deviation shocks, with identification based on the Cholesky decomposition of the residual covariance matrix. Each response is traced over a 12-month horizon to capture both short-run and medium-term dynamics. Statistical inference is conducted via Monte Carlo simulation with 1,000 replications to construct 95 percent confidence intervals for the response paths. A response is considered statistically significant if zero is excluded from the confidence interval at any forecast horizon. Table 6 contains the results as shown below.

Several clear patterns emerge. Bidirectional responses are strongest in energy and producer prices: Gas spot prices, coal, gasoline, diesel, and natural gas show balanced, significant effects in both directions for MBUI and MMUI, indicating tight feedback between climate uncertainty and energy markets.

Agricultural commodities exhibit more heterogeneous dynamics. Among grains, oats show stronger causality from prices to MBUI, suggesting thin markets contribute to index construction rather than respond to it. Rough rice and wheat display more symmetric interactions. Root crops, especially potatoes, respond in all directions, while carrots react sharply to MMUI, consistent with seasonal exposure and storage volatility.

Table 6: Significant Impulse Response Functions across Commodities

Commodity	**Item → MBUI**	**MBUI → Item**	**Item → MMUI**	**MMUI → Item**
Animal Feed				
Alfalfa Hay	9	11	7	6
Hay and Hayseeds	10	12	6	11
Total (out of 40)	**19**	**22**	**11**	**17**
Grains				
Barley	6	4	3	8
Corn	5	1	2	2
Oats	5	11	5	1
Rough_Rice	3	3	2	5
Wheat	4	1	5	3
Total (out of 100)	**23**	**20**	**17**	**19**
Vegetables				
Carrots	6	6	5	5
Potatoes	7	4	8	8
Total (out of 40)	**13**	**10**	**13**	**13**
Oilseeds				
Canola	4	10	2	11
Peanuts	6	3	4	6
Soy	7	4	5	7
Sunflower	6	6	4	7
Total (out of 77)	**23**	**23**	**15**	**31**
Specialty crops				
Almonds	5	5	11	7
Cotton	0	3	1	4
Total (out of 40)	**5**	**8**	**12**	**11**
Fuels				
GasSpot	6	6	8	5
Coal	1	4	7	8
Gasoline	5	5	7	8
No. 2 Diesel Fuel	6	6	5	3
Natural Gas	7	8	5	9
Total (out of 100)	**25**	**29**	**32**	**33**

Note: Number of U.S. locations out of 100 where the impulse response function between each commodity and the climate uncertainty indices MBUI and MMUI was statistically significant at any forecast horizon, using orthogonalized one standard deviation shocks with Monte Carlo confidence intervals. Each column shows the direction of causality from a VAR model.

Oilseeds are mixed. Canola displays stronger effects from prices to uncertainty, while soy and sunflower show two-way links. In specialty crops,

almonds respond primarily to MMUI, suggesting absolute disagreement matters more than directional bias for climate-sensitive perennials. Cotton shows little connection, likely reflecting either weak exposure or poor market coverage. The hay products exhibit broad, bidirectional effects, underscoring its tight link to temperature variability.

Overall the impulse response functions exhibit consistent patterns with the Granger causality results, reinforcing the validity of the identified relationships. Commodities that show statistically significant Granger-causal links with the climate uncertainty indices, such as animal feed, oilseeds, and fuels, also display robust and persistent dynamic responses in the IRFs, particularly in bidirectional settings.

6 Conclusion

This paper develops and validates a structural, market-based framework for extracting forward-looking climate risk signals from weather derivative prices. By comparing derivative-implied payouts with benchmark projections from NASA's CMIP6 climate models, this paper constructs two novel indices: the Market Bias Uncertainty Index (MBUI), capturing directional divergence in expectations, and the Market Mispricing Uncertainty Index (MMUI), measuring the magnitude of disagreement. Both indices are theoretically grounded in an indifference-pricing model under market incompleteness and empirically validated through predictive relationships with commodity prices.

The results showcase that these indices capture economically meaningful dynamics across commodity segments. MBUI exhibits stronger forward-

looking content, particularly in energy and climate-exposed agricultural markets, while MMUI provides complementary insights into the level of disagreement between market and model beliefs. Importantly, several commodities not only respond to climate uncertainty but also appear to inform it, indicating a feedback loop between market behaviour and climate-risk perception.

This paper thus concludes by offering a framework that opens new avenues for measuring and pricing climate uncertainty in real time. The indices developed here may serve as tools for investors, insurers, and policymakers seeking to monitor the evolving landscape of physical climate risk. Future research could extend this approach to broader asset classes, construction approaches and explore its implications for long-term climate hedging, infrastructure planning, or regulatory disclosure.

7 Appendix A: Data

7.1 Weather Derivative City Data

Table 7: Climate Data Availability for US Airports.

City	**Airport Name and Code**	**HDD Years**	**CDD Years**
Atlanta	ATLANTA HARTSFIELD JACKSON INTERNATIONAL AIRPORT, GA US (USW00013874)	1999/10-2025/01	2002/05-2024/07
Baltimore	BALTIMORE WASHINGTON INTERNATIONAL AIRPORT, MD US (USW00093721)	2005/12-2014/12	2006-06-2015/09
Boston	BOSTON LOGAN INTERNATIONAL AIRPORT, MA US (USW00014739)	2004/02-2024/12	2004/05-2024/08
Chicago	CHICAGO OHARE INTERNATIONAL AIRPORT, IL US (USW00094846)	1999/10-2025/01	2002/06-2024/09
Cincinnati	CINCINNATI NORTHERN KENTUCKY INTERNATIONAL AIRPORT, KY US (USW00093814)	1999/10-2025/01	2005/03-2006/03
Dallas	DAL FTW WSCMO AIRPORT, TX US (USW00003927)	2002/11-2025/01	2000/06-2024/08
Houston	HOUSTON INTERCONTINENTAL AIRPORT, TX US (USW00012960)	2004/04-2016/03	1993/03-2024/08

Table 7 (continued)

City	Airport Name and Code	HDD Years	CDD Years
Des Moines	DES MOINES INTERNATIONAL AIRPORT, IA US (USW00014933)	2002/11-2014/12	2000/07-2014/07
Detroit	DETROIT METRO AIRPORT, MI US (USW00094847)	2008/11-2014/12	2010/08-2013/06
Kansas City	KANSAS CITY INTERNATIONAL AIRPORT, MO US (USW00003947)	2003/10-2014/10	2004/05-2014/07
Las Vegas	MCCARRAN INTERNATIONAL AIRPORT, NV US (USW00023169)	2000/03-2025/01	2000/05-2020/10
Los Angeles	LOS ANGELES DOWNTOWN USC, CA US (USW00093134)	2013/12-2013/12	2008/08-2016/05
Burbank	BURBANK GLENDALE PASADENA AIRPORT, CA US (USW00023152)	2024/10-2025/01	2024/07-2024/10
Minneapolis	MINNEAPOLIS ST. PAUL INTERNATIONAL AIRPORT, MN US (USW00014922)	2003/10-2025/01	2004/05-2021/07
New York	LAGUARDIA AIRPORT, NY US (USW00014732)	1999/11-2025/01	2002/05-2024/10
Philadelphia	PHILADELPHIA INTERNATIONAL AIRPORT, PA US (USW00013739)	2002/01-2025/01	2003/05-2024-09

Table 7 (continued)

City	Airport Name and Code	HDD Years	CDD Years
Portland	PORTLAND INTERNATIONAL AIRPORT, OR US (USW00024229)	1999-2020	2002/07-2015/07
Raleigh	RALEIGH DURHAM INTERNATIONAL AIRPORT, NC US (USW00013722)	1999-2020	2005-2020
Salt Lake City	SALT LAKE CITY INTERNATIONAL AIRPORT, UT US (USW00024127)	2007/11-2014/02	2006/07-2013/06
Tucson	TUCSON INTERNATIONAL AIRPORT, AZ US (USW00023160)	2002/11-2016/03	2000/05-2014/08
Washington	WASHINGTON REAGAN NATIONAL AIRPORT, VA US (USW00013743)	2008/11-2014/11	2011/09-2011/09
Colorado Springs	COLORADO SPRINGS MUNICIPAL AIRPORT, CO US (USW00093037)	2011/01-2023/02	2011/08-2013/06
Jacksonville	JACKSONVILLE INTERNATIONAL AIRPORT, FL US (USW00013889)	NA	NA
Little Rock	LITTLE ROCK AIRPORT ADAMS FIELD, AR US (USW00013963)	1999-2020	2010/09-2015/08

Table 7 (continued)

City	Airport Name and Code	HDD Years	CDD Years
Sacramento	SACRAMENTO AIRPORT ASOS, CA US (USW00023232)	2003/11-2022/12	2004/06-2024/07

This table lists the available Heating Degree Days (HDD) and Cooling Degree Days (CDD) data for various US airports. The columns represent the years for which data is available for HDD and CDD. The airport names are followed by their respective station codes.

8 Appendix B: Proofs of Main Theoretical Results

8.1 Proof of Proposition 1

Let initial wealth be W_0. The underwriter shorts $Q_m > 0$ contracts at time 0, receives $M_m Q_m$ and invests the proceeds at the gross risk–free rate R_f. At settlement date m her terminal wealth is

$$W_1 \;=\; W_0 R_f \;+\; R_f\, M_m\, Q_m \;-\; X_m\, Q_m. \tag{9}$$

Under CARA utility $U(W) = -\exp(-\gamma_s W)$ the certainty equivalent of W_1 is

$$\begin{aligned} \mathrm{CE}(W_1) &= \mathbb{E}[W_1] \;-\; \tfrac{\gamma_s}{2}\,\mathrm{Var}(W_1) \\ &= W_0 R_f + \big(R_f M_m - \mu_m\big) Q_m - \tfrac{\gamma_s}{2}\,\sigma_m^2\, Q_m^2, \end{aligned} \tag{10}$$

where $\mu_m = \mathbb{E}[X_m]$ and $\sigma_m^2 = \mathrm{Var}(X_m)$. Indifference to not trading (certainty equivalent $W_0 R_f$) requires

$$\big(R_f M_m - \mu_m\big) Q_m - \tfrac{\gamma_s}{2}\,\sigma_m^2\, Q_m^2 = 0.$$

Dividing by Q_m and rearranging gives exactly

$$R_f M_m = \mu_m + \tfrac{\gamma_s}{2}\,\sigma_m^2\, Q_m, \tag{11}$$

which is Proposition 1.

8.2 Uniqueness of the Indifference Price

For fixed $(\mu_m, \sigma_m^2, \gamma_s, Q_m)$ the map

$$M_m \;\mapsto\; R_f M_m - \mu_m - \tfrac{\gamma_s}{2}\,\sigma_m^2\,Q_m$$

is strictly increasing in M_m. Hence there is a unique solution

$$M_m = R_f^{-1}\Big(\mu_m + \tfrac{\gamma_s}{2}\,\sigma_m^2\,Q_m\Big).$$

That completes the proof of our index definitions.

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