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# Climate Risk Premium: Evidence from Commodity Options

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## Climate Risk Premium: Evidence from Commodity Options

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#### Abstract

This paper examines how climate-related risks are priced in the commodity derivatives market. Leveraging a unique dataset of "brown" and "green" iron ore options traded on the Singapore Exchange, we document significant climate variance and skewness risk premiums. Further analysis reveals a nonlinear relationship between climate policy uncertainty and climate risk premiums: moderate uncertainty increases premiums by destabilizing market expectations, whereas extreme uncertainty suppresses market activity and reduces premiums. Additionally, climate policy uncertainty produces asymmetric effects: sustained levels and changes in uncertainty have a stronger impact than immediate fluctuations in uncertainty. These effects concentrate in short-maturity options, underscoring the transitional nature of policy risks. Utilizing a novel two-stage differencing method, this study provides a direct and robust measure of climate risk premiums, advancing our understanding of climate risk pricing in commodity derivatives markets and offering valuable insights for policymakers seeking to stabilize markets and promote sustainable investment.

Keywords: climate risk, risk premium, climate policy uncertainty, commodity options

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## 1 Introduction

Climate change has emerged as one of the most urgent global challenges of the 21st century, with significant ramifications for economies, societies, and financial markets worldwide. It poses both physical risks, such as extreme weather events, and transition risks linked to evolving policy, regulatory, and technological responses aimed at mitigating climate change. According to the World Economic Forum's Global Risks Report 2023,<sup>5</sup> environmental threats dominate the top ten global risks over the coming decade, with "failure to mitigate climate change" ranked as the most severe. As practitioners and researchers increasingly acknowledge the necessity of adapting to these complex and evolving risks, understanding how climate-related risks are priced in financial markets has become a central inquiry in financial economics.

The notion of a "climate risk premium" has gained notable attention in both theoretical and empirical finance research over the past decade. Theoretical consensus suggests that assets associated with high carbon emissions or environmental harm ("brown" assets) should command a positive climate risk premium, whereas those aligned with sustainable, climate-friendly activities ("green" assets) should earn negative premiums (Engle et al., 2020; Pástor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021; Hsu, Li, and Tsou, 2022).<sup>6</sup> This distinction arises because "brown" assets are more vulnerable to climate-related risks, while "green" assets are viewed as hedges against such risks. Consequently, "green" assets attract strong demand from climate-conscious investors, resulting in lower expected returns.

Empirical evidence, however, remains mixed. Some studies find that climate-related risks adversely affect "brown" assets through various channels, including depressed prices, heightened volatility, increased downside tail risk, and elevated costs of capital (e.g., Bolton and Kacperczyk, 2021, 2023; Seltzer, Starks, and Zhu, 2022; Ilhan, Sautner, and Vilkov, 2021; Chava, 2014). These findings align with standard risk compensation theory. In contrast, other works report insignificant or even contrary effects (e.g., Görgen et al., 2020; Bauer et al., 2022; Ardia et al., 2023; Byrd and Cooperman, 2018; Monasterolo and De Angelis, 2020; Bernardini et al., 2021; Duan, Li, and Wen, 2021; In, Park, and Monk, 2019; Zhang, 2024), suggesting that the pricing of climate-related risks may be more nuanced than initially posited.

Several factors likely account for these conflicting results. Differences in empirical methodologies, such as backward- or forward-looking designs or event studies, can yield divergent results. The choice of impact measures, whether focusing on asset prices, volatility, downside risk, or the cost of capital, can also influence conclusions. Moreover, the distinction between physical and transition climate risks, as well as the variety of asset classes examined (e.g., equities, corporate bonds, or real estate), adds further complexity. Finally, the evolving nature of investor awareness and practices introduces additional challenges in interpreting these findings, as market perceptions and strategies related to climate risks continue to develop. A key impediment to advancing this literature is the absence of clear and standardized definitions for "brown" and "green" assets. This lack of consistency constrains cross-study comparisons and underscores the need for further research to clarify how climate-related risks are incorporated into asset prices.

This study advances the climate finance literature by examining the existence and magnitude of the climate risk premium in the commodity derivatives market. Specifically, we analyze a proprietary dataset featuring two iron ore option contracts, one classified as "brown" and the other as "green," traded on the Singapore Exchange (SGX). Our primary objective is to determine whether climate-related considerations result in distinct forward-looking risk premiums for these option contracts. To this end, we conduct a novel comparative assessment of the term structure of risk-neutral distribution moments, particularly variance and skewness, derived from sustainable ("green") options relative to their more traditional, less

<sup>&</sup>lt;sup>5</sup>www.weforum.org/publications/global-risks-report-2023/

 $<sup>^{6}</sup>$ Throughout this paper, we focus exclusively on the environmental (E) component of ESG (see Starks (2023)). Accordingly, we define "green" assets as climate-friendly and "brown" assets as climate-unfriendly.

sustainable ("brown") counterparts. Our findings provide compelling evidence of a climate risk premium in commodity derivatives markets, offering new insights into how environmental considerations shape the pricing of financial assets.

Our study addresses three key challenges in the climate finance literature. First, we circumvent the endogeneity issue pervasive in empirical climate finance studies (Jahmane and Gaies, 2020), especially in equity markets, where the classification of "green" versus "brown" stocks is often ambiguous and entangled with firm-specific characteristics. To mitigate this, we exploit a proprietary dataset from the SGX featuring two distinct iron ore option contracts: the SGX TSI Iron Ore CFR China (62% Fe Fines) options and the SGX MB Iron Ore CFR China (65% Fe Fines) options. The former ("brown") requires more processing due to its lower iron content, thus rendering it less environmentally friendly, whereas the latter ("green") involves fewer climate-related risks. Since both contracts are identical aside from their environmental attributes, they offer a unique setting to directly measure exposure to climate risks without relying on additional controls.

Second, climate risk is a relatively recent and evolving phenomenon that might not have been fully recognized or priced in financial markets 10-15 years ago. As a result, historical data are limited, and traditional econometric techniques that rely on extensive data series often struggle to yield robust estimates of the climate risk premium (Dennis and Mayhew, 2002; Bakshi, Kapadia, and Madan, 2003; Jiang and Tian, 2005). Recognizing that backward-looking models cannot adequately capture emerging risks, Svartzman et al. (2021) advocate for forward-looking assessments of climate-related financial risks. We tackle this issue by leveraging the forward-looking nature of options, which embed market expectations and perceptions of future price volatility and downside tail risks (Christoffersen, Jacobs, and Chang, 2013). By using option-implied measures, our approach provides more efficient and reliable estimates of climate-related premiums than those derived solely from historical data.

Third, the option-based framework we employ facilitates a two-stage differencing approach that effectively isolates the climate risk premiums, overcoming the key identification challenge in existing empirical work. In the first stage, we compare the option-implied risk-neutral measure ( $\mathbb{Q}$ ) with the physical measure ( $\mathbb{P}$ ) to capture the overall risk premium for each asset. In the second stage, we contrast "brown" options with their "green" counterparts to isolate the portion of the premium attributable specifically to climate and environmental characteristics. This methodology circumvents the need for subjective rating systems, such as ESG scores, which are often criticized for their inconsistency and lack of standardization (Berg, Koelbel, and Rigobon, 2022; Chatterji et al., 2016; Dimson, Marsh, and Staunton, 2020; Clementino and Perkins, 2021), and also avoids reliance on narrow event windows related to regulatory changes, disclosure mandates, or international climate agreements (Ramelli, Ossola, and Rancan, 2021; Seltzer, Starks, and Zhu, 2022; Monasterolo and De Angelis, 2020; Barnett, 2019; Cassidy, 2024). By exploiting the inherent environmental distinctions of the underlying commodity option contracts, our approach provides a more objective, forward-looking, and robust measure of the climate risk premiums, representing a meaningful advancement over traditional methodologies.

Our initial results indicate that the iron ore options market embodies positive and statistically significant climate risk premiums. Specifically, less sustainable ("brown") iron ore options exhibit higher climate variance and skewness risk premiums than their "green" counterparts, reflecting investors' forward-looking perceptions of both underlying price volatility and the likelihood of extreme downside events. These results align with theoretical predictions of how climate risks should influence asset pricing (Pástor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021; Hsu, Li, and Tsou, 2022) and corroborate empirical evidence of a carbon premium in equity markets (e.g., Bolton and Kacperczyk, 2021, 2023; Faccini, Matin, and Skiadopoulos, 2023).

Next, we examine the drivers of climate risk premiums, with a particular focus on climate policy uncertainty, especially originating from China, the target market for these options and the world's leading importer and producer of iron ore. Previous research highlights how elevated uncertainty, whether



economic or political, tends to increase stock market volatility and raise risk premiums (Bloom, 2009; Baker, Bloom, and Davis, 2016; Pástor and Veronesi, 2012, 2013; Kelly, Pástor, and Veronesi, 2016). Our analysis reveals a strong nonlinear relationship between China's climate policy uncertainty and the option-implied climate variance risk premium (Climate-VRP). At moderate levels of uncertainty, rising uncertainty destabilizes market expectations about future climate-related measures, increasing implied volatility and elevating the climate-VRP. Beyond a certain threshold, however, increases in uncertainty reduce the climate-VRP, suggesting a shift in investor perceptions and risk management strategies. This inverted U-shaped pattern can be interpreted as an interplay between standard risk compensation theory and a "real options" effect. Initially, heightened uncertainty demands greater compensation for perceived risks. However, as uncertainty reaches extreme levels, investors often become more cautious, delay decision-making, or adopt alternative hedging strategies, thereby mitigating its impact on risk premiums. A similar pattern emerges for the option-implied climate skewness risk premium (Climate-SRP): it initially increases with uncertainty, reflecting greater concern over downside risks, but declines once uncertainty surpasses a critical threshold, reinforcing the nonlinear dynamics observed for the climate-VRP.

Although daily changes in policy uncertainty also influence the climate-VRP, their impact is less pronounced than that of sustained uncertainty levels. This observation suggests that investors place greater emphasis on persistent uncertainty rather than transient shocks. In line with this interpretation, we do not observe significant effects of daily uncertainty fluctuations on the climate-SRP. Moreover, our results indicate that market participants respond more strongly to increases in uncertainty than to decreases, further underscoring the asymmetric role that climate policy uncertainty plays in shaping investor behavior and risk assessments.

Notably, these effects are concentrated in short-maturity contracts. This is consistent with the conventional view that policy- or regulation-driven climate risks are transitional in nature and are more pronounced over shorter horizons, whereas physical climate risks, which evolve gradually, affect longerterm time frames (Stroebel and Wurgler, 2021). Taken together, these findings shed new light on how investors interpret and manage climate-related risks across different financial markets and under varying uncertainty regimes.

We further explore the dynamics of climate risk premiums along the time-to-maturity dimension, taking advantage of the risk premium term structure. Our analysis reveals that the climate-VRP is significantly higher for long-maturity options compared to short-maturity options, aligning with the premise that longer-maturity options involve greater climate-related uncertainty and thus command higher premiums. These findings are consistent with prior literature on the term structure of variance risk premiums, such as Egloff, Leippold, and Wu (2010) and Aït-Sahalia, Karaman, and Mancini (2020), while uniquely isolating and documenting this behavior in climate-specific risk premiums. The results further indicate that while climate-VRP consistently increases with time-to-maturity, short-maturity options exhibit higher volatility. Similarly, the climate-SRP is positive across all maturities and generally increases with time-to-maturity, although it exhibits a decreasing trend for short maturities.

Our study makes several contributions to the climate finance literature. First, we address the persistent endogeneity challenge that has long impeded empirical research in the literature. By exploiting a unique empirical setting, which is based on two iron ore option contracts that are nearly identical except for their climate-related attributes, we obtain a direct and robust estimate of the climate risk premium in the commodity derivatives market. This empirical setting circumvents the need for complex controls and mitigates biases stemming from confounding factors, a problem commonly encountered in empirical studies that focus on equities.

Second, we capitalize on the inherently forward-looking nature of options markets to develop a novel methodological framework to identify and isolate the climate risk premium.<sup>7</sup> The proposed two-stage

<sup>&</sup>lt;sup>7</sup>Our approach is related to Ilhan, Sautner, and Vilkov (2021), who also leverage risk-neutral measures from options to examine carbon risk pricing. However, our focus on commodity markets rather than equities is a key differentiating feature.



differencing strategy compares risk-neutral and physical measures of both "green" and "brown" options, thereby delivering a clean and efficient indicator of market participants' perceptions of climate-related risks. Unlike methodologies reliant on subjective rating systems or narrow event windows, our approach provides a more reliable and temporally integrated measure of the climate risk premium.

Third, our work is the first to document the existence of a climate risk premium using iron options. In doing so, we extend the scope of climate finance research beyond traditional asset classes such as equities (e.g., Ramelli, Ossola, and Rancan, 2021; Bolton and Kacperczyk, 2021, 2023; Faccini, Matin, and Skiadopoulos, 2023), bonds (e.g., Huynh and Xia, 2021; Baker et al., 2022; Seltzer, Starks, and Zhu, 2022), and real estate (e.g., Giglio et al., 2021; Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020). By examining an under-explored segment of the financial markets, our study enriches the literature's understanding of how climate-related risks are priced across a broader spectrum of financial instruments.

Finally, our research offers important implications for policymakers and regulators. By demonstrating that climate policy uncertainty affects risk premiums in a nonlinear and asymmetric fashion, our findings imply that clearer and more predictable policy guidelines can help stabilize market expectations. Such transparency and consistency in environmental regulations can reduce uncertainty, facilitate more efficient climate risk pricing, and ultimately encourage greater investment in sustainable assets, thereby contributing to broader climate-change mitigation objectives.

The remainder of the paper is organized as follows. Section 2 introduces our data sample and details the methodologies used to construct option-implied measures. In Section 3, we discuss our two-stage differencing strategy for isolating climate risk premiums. Section 4 reports the empirical findings, and Section 5 concludes the paper.

## 2 Data and Option-implied Measures

In this section, we begin by describing the iron ore option contracts that form the basis of our analysis. We then present our data sources, detail the data cleaning and filtering procedures, and explain the construction of the option-based measures employed in this study.

## 2.1 SGX Iron Ore Option Contracts

The estimation of climate risk premiums from commodity option prices centers on two specific iron ore option contracts traded on the Singapore Exchange (SGX). Strategically located within the Asia-Pacific region, SGX has established itself as a prominent trading hub for a wide array of commodities, efficiently catering to the growing demand driven by expanding infrastructure and industrial capabilities in emerging markets. Iron ore, in particular, is a critical input in steel production and thus serves as a foundational element of the global economy. Reflecting its pivotal role, SGX has handled over one billion megatons  $(10^{15} \text{ tons})$  of iron ore annually since 2015, underscoring the exchange's significant role as a nexus for global commodity transactions.

SGX lists two types of iron ore option contracts: the SGX TSI Iron Ore CFR China (62% Fe Fines) options and the SGX MB Iron Ore CFR China (65% Fe Fines) options. These derivative contracts are structured as options on futures, with their respective underlying assets being actively traded iron ore index futures on SGX. A key differentiating factor between the two contracts is the grade of iron ore they represent. Higher-grade (65% Fe) iron ore requires a smaller quantity of material to produce the same volume of steel as the lower-grade (62% Fe) variant. This distinction not only contributes to energy savings but also reduces reliance on coke, a coal-based, high-carbon input integral to iron ore smelting. Since the iron and steel industry is the world's largest industrial source of carbon emissions (IEA, 2007), the use of higher-grade iron ore can have meaningful environmental implications by curbing



carbon-intensive processes. Beyond its environmental implications, combustion of coke also produces byproducts detrimental to human health. According to the U.S. Environmental Protection Agency (EPA), chronic exposure to coke oven emissions can lead to conjunctivitis, severe dermatitis, respiratory and digestive system lesions, and an increased risk of cancer.<sup>8</sup> Recognizing these environmental and health considerations, the 65% Fe Fines iron ore is regarded as a more environmentally and socially sustainable alternative to the 62% Fe Fines variety. Therefore, options on the 65% Fe Fines iron ore are considered "green" relative to their 62% Fe Fines ("brown") counterparts.

Despite the distinctions in their environmental implications, both options share identical contract specifications. Each contract corresponds to one lot of the underlying futures contract, representing 100 tons of iron ore, and both are denominated in U.S. Dollars. The minimum price fluctuation (tick size) is set at \$0.01. Additionally, both contracts have expiration dates that coincide with the last trading day of their respective expiry months.<sup>9</sup>

#### 2.2 Data

Our primary data source consists of iron ore option contract data from the Singapore Exchange. The dataset includes daily observations for each contract, with expiration year and month, strike price, and settlement price, all denominated in U.S. Dollars. The sample period extends from January 1, 2022, to December 31, 2022.

Following standard practices in the options literature, we apply standard filters to refine our options data. We exclude deep out-of-the-money options, defined as contracts with strike prices more than 20% above or below the underlying index value. We also restrict the sample to options with maturities ranging from 30 to 500 days. Furthermore, we remove any observations that violate the following no-arbitrage conditions:

$$max[0, S - Ke^{-r\tau}] \le C \le S \tag{1}$$

$$max[0, Ke^{-r\tau} - S] \le P \le Ke^{-r\tau} \tag{2}$$

where S is the value of the underlying, K is the option strike price, r is the corresponding U.S. Treasury yield,  $\tau$  is the time to maturity. C and P are the price for call options and put options, respectively.

To ensure a balanced and meaningful comparison, we conduct a matching procedure that pairs each 65% Fe Fines option observation with a corresponding 62% Fe Fines option. The matching criteria include trading date, option type, maturity, and the nearest strike price. This process yields 3,662 matched pairs of option-day observations, providing a well-aligned sample for our comparative analysis. By pairing observations with closely matched characteristics, we obtain a more accurate assessment of the climate risk premium embedded in sustainable iron ore options.

Table 1 reports the summary statistics of the filtered and matched option sample. For both iron ore grade contracts, the statistics (i.e., mean, standard deviation, and median) for calls and puts are closely aligned for the strike price, time-to-maturity, and implied volatility.

We also obtain the daily closing prices for the underlying iron ore indexes—specifically, the MB Iron Ore CFR China (65% Fe Fines) index and the STI Iron Ore CFR China (62% Fe Fines) index—from Refinitiv. Additionally, we collect the U.S. Treasury yields from the Federal Reserve Bank of St. Louis (FRED). To explore the drivers of the climate risk premiums, we collect the daily China Climate Policy Uncertainty index value from Ma et al. (2023). Also from Refinitiv, obtain the daily closing prices for the ten largest publicly listed steel producers in the Asia-Pacific region, ranked by their steel production in 2021. Production data of these companies is sourced from the World Steel Association.<sup>10</sup>

 $<sup>^8{</sup>m See}$  www.epa.gov/sites/default/files/2016-09/documents/coke-oven-emissions.pdf.

 $<sup>^9\</sup>mathrm{For}$  more details, see www.sgx.com/derivatives/products/iron-ore.

<sup>&</sup>lt;sup>10</sup>https://worldsteel.org

|              |             | St     | Strike price         |        | Time-to-maturity |        |        | Implied volatility |                      |        |
|--------------|-------------|--------|----------------------|--------|------------------|--------|--------|--------------------|----------------------|--------|
|              | Option type | mean   | $\operatorname{std}$ | median | mean             | std    | median | mean               | $\operatorname{std}$ | median |
| 62% Fe Fines | Call        | 118.53 | 8.30                 | 118.00 | 237.37           | 133.68 | 231.00 | 0.36               | 0.10                 | 0.34   |
|              | Put         | 116.86 | 5.48                 | 117.00 | 257.61           | 127.71 | 260.00 | 0.56               | 0.10                 | 0.55   |
| 65% Fe Fines | Call        | 121.00 | 7.58                 | 120.54 | 237.37           | 133.68 | 231.00 | 0.37               | 0.13                 | 0.35   |
|              | Put         | 119.65 | 5.02                 | 120.54 | 257.61           | 127.71 | 260.00 | 0.52               | 0.09                 | 0.51   |

Table 1. Option sample statistics

## 2.3 Option-based Measures

Using our matched data sample, we compute two key option-based variables: implied variance and implied skewness. Implied variance captures the market's perception of future price fluctuation, reflecting overall price risk. Implied skewness offers insights into the market's expectations regarding the likelihood of large price drops relative to price increases, serving as a measure of downside tail risk. Together, these variables provide a comprehensive understanding of the risk dynamics embedded in iron ore options, enabling us to assess the value of protection against various risks and estimate the climate risk premium.

To compute the option implied volatility (IV), we invert the Black and Scholes (1973) option pricing formula. Implied skewness (IS) captures the asymmetry of the risk-neutral distribution of returns, calculated using the model-free methodology proposed by Bakshi, Kapadia, and Madan (2003). This measure reflects the relative cost of protection against downside risk (left tail events) compared to upside risk (right tail events) in the distribution of underlying iron ore prices. Higher values of implied skewness indicate that protection against downside risks is less expensive than protection against upside risks, suggesting that investors prioritize hedging adverse price movements on the downside.

For each day t and maturity  $\tau$ , we compute IS for both traditional 62% Fe options and sustainable 65% Fe options as:

$$IS_{t,\tau} = \frac{e^{r\tau}W_{t,\tau} - 3\mu_{t,\tau}e^{r\tau}V_{t,\tau} + 2\mu_{t,\tau}^3}{(e^{r\tau}V_{t,\tau} - \mu_{t,\tau}^2)^{3/2}}$$
(3)

where  $V_{t,\tau}$  is the price of variance contracts;  $W_{t,\tau}$  is the price of cubic contracts; r is the prevailing risk free rate with the corresponding maturity (linearly interpolated if option maturity does not match available federal rates' terms);  $\mu_{t,\tau}$  is the risk neutral mean of the underlying return.<sup>11</sup> For the two iron ore options, separately, we further drop the observations where the estimated *IS* is more than four standard deviations away from the sample mean.

## 3 Two-stage Differencing Identification Approach

To identify and isolate the climate risk premium, we employ a two-stage differencing approach. The first difference compares the risk-neutral measure ( $\mathbb{Q}$ ) to the physical measure ( $\mathbb{P}$ ), capturing the overall risk premium. The second difference contrasts the "brown" (62% Fe) options with the "greener" (65% Fe) options to obtain the climate risk premium. Formally,

$$RP_{Climate} = RP_{Brown} - RP_{Green}$$
  
=  $(M_{Brown}^{\mathbb{Q}} - M_{Brown}^{\mathbb{P}}) - (M_{Green}^{\mathbb{Q}} - M_{Green}^{\mathbb{P}})$   
=  $(M_{Brown}^{\mathbb{Q}} - M_{Green}^{\mathbb{Q}}) - (M_{Brown}^{\mathbb{P}} - M_{Green}^{\mathbb{P}})$  (4)

<sup>&</sup>lt;sup>11</sup>For a more detailed explanation, please refer to Bakshi, Kapadia, and Madan (2003).



In the literature, risk premiums are commonly measured as the difference between risk-neutral and physical measures  $(M^{\mathbb{Q}} - M^{\mathbb{P}})^{12}$  While risk-neutral measures can be derived directly from option-implied densities, computing physical measures is often challenging due to their sensitivity to factors such as data frequency, sample periods, and the alignment of historical versus forward-looking information (e.g., Jacobs and Li, 2023). By assuming that the physical distributions for the two iron ore indexes are identical, we can avoid the complexities inherent in estimating separate physical measures for each contract. This assumption allows us to obtain the climate risk premium simply by differencing risk-neutral measures between the two options, as shown below:

$$RP_{Climate} = M_{Brown}^{\mathbb{Q}} - M_{Green}^{\mathbb{Q}}, \quad if \quad M_{Brown}^{\mathbb{P}} = M_{Green}^{\mathbb{P}}$$

$$\tag{5}$$

As a result, our measure of the climate risk premium is "clean," free from the complications associated with separately identifying their physical distributions.

#### Figure 1. Iron ore underlying index

This figure plots the daily prices of the two underlying indexes, standardized by the price at the beginning of our sample period. The underlying index for the tradition 62% Fe option is the TSI Iron Ore CFR China index, and the underlying index for the sustainable 65% Fe option is the MB Iron Ore CFR China index.

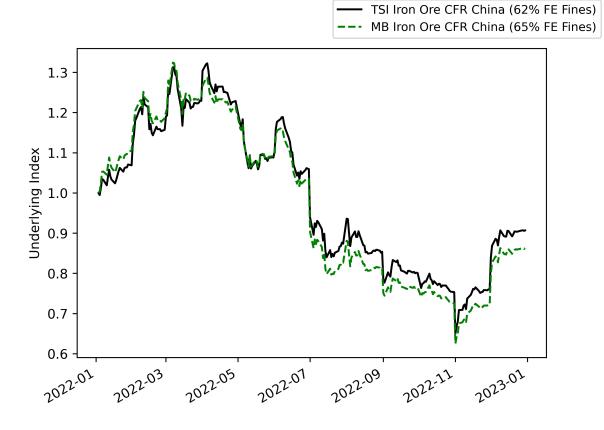


Figure 1 illustrates the standardized daily prices of the two underlying indexes. Both series exhibit similar patterns, suggesting comparable physical return distributions. Furthermore, Table 2 reports the

<sup>&</sup>lt;sup>12</sup>See, for example, Bollerslev, Tauchen, and Zhou (2009), Bekaert and Hoerova (2014), Bollerslev, Todorov, and Xu (2015), Bollerslev, Li, and Zhao (2020), Chow et al. (2020), Finta and Ornela (2022).



mean, standard deviation, skewness, and kurtosis for the two return series. Column (3) in Table 2 shows the differences in these moments, and column (4) presents the *p*-values from tests examining whether the differences are statistically significant. For means and standard deviations, we use standard *t*-tests and *F*-tests, respectively. For skewness and kurtosis, we resample these moments using a Jackknife Bootstrap approach and then apply *t*-tests. None of the differences in distributional moments is statistically significant, confirming that the two series share similar physical distributions and supporting the validity of our dual-differencing strategy.

## Table 2. Underlying index return distribution

This table reports the mean, standard deviation, skewness, and kurtosis of the 62% Fe index returns (column 1) and the 65% Fe index returns (column 2). Column (3) shows the difference between the two return series, and column (4) reports the *p*-value testing the hypothesis that the return distribution moments equal to zero. We use *t*-test and *F*-test for the mean and standard deviation respectively. For the difference in skewness and kurtosis, we resample these moments using the Jackknife Bootstrap method and then run the *t*-test for mean difference.

|                            | 62% Fe Index<br>(1) | 65% Fe Index<br>(2) | Difference<br>(3) | <i>p</i> -value<br>(4) |
|----------------------------|---------------------|---------------------|-------------------|------------------------|
| Mean (annualized)          | 0.059               | 0.008               | 0.051             | 0.424                  |
| Standard Dev. (annualized) | 0.371               | 0.352               | 0.019             | 0.799                  |
| Skewness (daily)           | -0.640              | -0.953              | 0.313             | 0.423                  |
| Excess Kurtosis (daily)    | 8.750               | 12.674              | -3.925            | 0.179                  |

Given the similarity of the two underlying indexes under the physical measure, we can capture the climate risk premium by examining only the risk-neutral measures. For our option-based measures, the climate variance risk premium (Climate-VRP) is defined as the difference in squared implied volatility:

$$ClimateVRP = IV_{Brown}^2 - IV_{Green}^2$$

Similarly, the climate skewness risk premium (Climate-SRP) is the difference in option-implied skewness:

$$ClimateSRP = IS_{Brown} - IS_{Green}$$

## 4 Empirical Results

In this section, we present and discuss the results of our empirical analyses, examining climate risk premiums from both a temporal perspective and with respect to time-to-maturity.

## 4.1 Climate Risk Premiums

We begin our empirical analysis by investigating the extent to which climate risks are reflected in the pricing of iron ore options. Specifically, we compare the unconditional averages of option-implied variance  $(IV^2)$  and skewness (IS) between the two types of iron ore option contracts, "brown" (traditional 62% Fe) and "green" (sustainable 65% Fe), and analyze their differences, which represent the climate risk premiums embedded in the option pricing structure.

The first row of Table 3 shows that, on average, the option-implied variance  $(IV^2)$  for traditional 62% Fe options is higher than that for "green" 65% Fe options (0.217 vs. 0.206), resulting in a statistically significant climate variance risk premium of 0.011 (p < 0.01). This indicates that market participants anticipate greater price volatility for "brown" iron ore futures compared to their "green" counterparts and are prepared to pay more for protection against such potential volatility.

#### Table 3. Positive climate risk premiums

This table presents the average values for implied variance  $(IV^2)$  and model-free implied skewness (IS) for traditional 62% Fe and "greener" 65% Fe iron ore options. The risk premium (column 3) represents the differences in these measures between the two categories, while the *p*-values (column 4) indicate the statistical significance of the observed differences.

|                                    | 62% Fe<br>(1) | 65% Fe<br>(2) | Climate Risk Premium (3) | <i>p</i> -value (4) |
|------------------------------------|---------------|---------------|--------------------------|---------------------|
| Implied Variance $(IV^2)$          | 0.217         | 0.206         | 0.011                    | 0.000               |
| Model-free Implied Skewness $(IS)$ | 6.556         | 0.099         | 6.457                    | 0.000               |

Similarly, a significant climate skewness risk premium of 6.457 (p < 0.01) is observed in the second row of Table 3, driven by the difference in *IS* between 62% Fe and 65% Fe iron ore options. This suggests that the market expects a higher likelihood of extreme price movements for the "brown" iron ore than for its "green" counterpart, prompting investors to demand a higher premium to compensate for this downside tail risk.

In summary, the results in Table 3 demonstrate that climate-related risks are a significant factor in the iron ore options market. "Greener" iron ore options command lower climate risk premiums as they are perceived to carry less risk by investors, reflected in their lower option-implied volatility and skewness. On the other hand, "browner" iron ore options exhibit higher climate risk premiums, driven by their greater price volatility and the greater perceived downside tail risk. These results align with the recent findings on the pricing of climate risks in the equity options market (Cao et al., 2023; Ilhan, Sautner, and Vilkov, 2021). This consistency underscores the pervasive influence of climate-related risks on asset pricing across different financial instruments and markets.

## 4.2 Drivers of Climate Variance Risk Premium

In this section, we analyze the key drivers behind the variations in climate risk premiums observed in the previous section, with a specific focus on climate policy uncertainty in China. Our investigation is motivated by prior research demonstrating that uncertainty surrounding government actions adversely affects financial markets, leading investors to demand higher risk premiums (Pástor, Stambaugh, and Taylor, 2021; Pástor and Veronesi, 2013; Kelly, Pástor, and Veronesi, 2016). Furthermore, China is a key target market for the Singapore Exchange's commodity products, and it dominates the global iron ore market, accounting for 66.1% of worldwide import volume.<sup>13</sup> This market concentration underscores the pivotal role of China's climate policies in influencing the pricing of iron ore options traded on the Singapore Exchange.

To measure climate policy uncertainty, we employ the daily China Climate Policy Uncertainty (CCPU) index developed by Ma et al. (2023). This index shares methodological similarities with Engle et al. (2020), who construct a U.S.-based uncertainty measure through textual analysis of news articles. However, the CCPU index improves upon traditional policy uncertainty metrics, which often rely solely on keyword counting, by employing a deep learning model that automatically identifies complex linguistic patterns indicative of climate policy uncertainty. This approach reduces potential biases associated with manual keyword selection, offering a more accurate and nuanced measure of climate policy uncertainty.

In addition to analyzing climate policy uncertainty, we also incorporate the performance of the steel production industry into our analysis. As a sector with a substantial carbon footprint, steel production is particularly vulnerable to climate regulatory changes, making it highly relevant for evaluating climate

<sup>&</sup>lt;sup>13</sup>As of 2021, the year of our analysis. See the Observatory of Economic Complexity, https://oec.world/en/profile/hs/iron-ore?yearSelector1=2021.

risk premiums. Specifically, we construct a portfolio of the ten largest publicly listed steel producers in the Asia-Pacific region, ranked by production output in 2021.<sup>14</sup> We then calculate their aggregate market performance by computing production-weighted daily returns, which serve as an industry benchmark.<sup>15</sup> This measure complements our examination of climate policy uncertainty by providing additional insights into how industry dynamics interact with climate-related risks and impact the pricing of climate risk premiums.

For our regression analysis, we begin by estimating the following baseline model:

$$ClimateRP = c + \beta_1 CCPU + \beta_2 Ret_{pw} + \beta_3 Ret_{pw}^2 + \varepsilon$$
(6)

In this model, the dependent variable, ClimateRP, represents the option-based climate risk premium, as previously defined in Section 3. The independent variables include the China Climate Policy Uncertainty index (CCPU), the production-weighted return of the steel production industry ( $Ret_{pw}$ ), and its squared return ( $Ret_{pw}^2$ ). This specification captures the direct effect of CCPU on the climate risk premium, while also accounting for the potential impact of the steel production industry.

The regression results for the climate variance risk premium (ClimateVRP) are presented in Table 4. In column (1) of Table 4, the coefficient of CCPU is positive and significant (0.029, p < 0.01), indicating that rising climate policy uncertainty in China increases the climate variance risk premium in the iron ore commodity market. This finding aligns with Kelly, Pástor, and Veronesi (2016), who document that investors demand compensation for risks associated with unpredictable policy environments.

As pointed out by Svartzman et al. (2021), the impact of climate change on financial markets may exhibit nonlinearity and path dependency, necessitating models that can capture these complex dynamics when analyzing asset pricing in the context of the low-carbon transition. To account for the possibility that different levels of climate policy uncertainty might have distinct impact on climate risk premium, we extended our baseline regression model by incorporating a squared term for CCPU. The estimation results are presented in column (2) of Table 4. We find that the coefficient on  $CCPU^2$  is negative and statistically significant (-0.086, p < 0.05), while the coefficient on CCPU remains positive and significant. This result indicates an inverted U-shaped relationship between CCPU and climate-VRP, suggesting that as climate policy uncertainty rises, its initial effect is to increase climate-VRP, and that beyond a certain threshold, further increases in uncertainty reduce climate-VRP. This nonlinear pattern can be interpreted through two lenses. First, at low to moderate levels, rising climate policy uncertainty amplifies market volatility and increases investor demand for protection against potential price fluctuation, leading to higher climate-VRP. However, when uncertainty reaches extreme levels, investors tend to adopt a "waitand-see" approach, hesitating to pay high costs for protection against future volatility. This reduction in market activity lowers the demand for risk hedging, consequently decreasing the climate-VRP. This behavior aligns with the real options theory (Dixit and Pindyck, 1994), which provides a theoretical framework for understanding how heightened uncertainty influences investment and risk-taking behaviors.

The impact of climate policy and regulations is generally regarded as short-term or transitional, in contrast to the effects of physical climate risks, such as rising sea levels, temperature shifts, and extreme weather events (Stroebel and Wurgler, 2021; Campiglio et al., 2023). To examine the temporal dimension of this relationship, we extend the baseline regression by introducing a dummy variable and its interaction with CCPU to account for differences in option maturity. Specifically, we define a dummy variable,  $1_{Short}$ , which equals 1 for option contracts with maturities of 250 days or fewer (48.8% of the sample) and 0 for contracts with maturities longer than 250 days (51.2% of the sample). This setup allows us to assess whether climate policy uncertainty has a differential impact on climate risk premiums across different time horizons. The estimation results in column (3) of Table 4 confirm our hypothesis. The interaction term

<sup>&</sup>lt;sup>14</sup>The list of firms includes prominent names, such as China Baowu Group, Ansteel Group, and Nippon Steel Corporation, among others. These companies' production data is obtained from the World Steel Association (www.worldsteel.org).

 $<sup>^{15}\</sup>mathrm{Our}$  results remain robust when using equally weighted returns.



#### Table 4. Climate variance risk premium

This table presents the regression results for the option-implied climate variance risk premium (ClimateVRP). The independent variables in the different models include the China Climate Policy Uncertainty Index (CCPU) from Ma et al. (2023), its squared value ( $CCPU^2$ ), and its first difference ( $\Delta CCPU$ ).  $Ret_{pw}$  represents the production-weighted stock return of the 10 largest publicly listed steel producers in the Asia-Pacific region, while  $Ret_{pw}^2$  represents its squared value. The analysis also includes two dummy variables:  $1_{Short}$ , which equals 1 for options with a time-to-maturity shorter than 250 days and 0 otherwise, and  $1_{\Delta CCPU \geq 0}$ , which equals 1 if  $\Delta CCPU \geq 0$  and 0 otherwise. The sample period covers the year 2022. The table reports coefficient estimates with standard errors provided in parentheses. Note: p<0.1; p<0.05; p<0.01.

|  | Dependent variable: ClimateVRP |                |           |               |               |          |  |  |  |
|--|--------------------------------|----------------|-----------|---------------|---------------|----------|--|--|--|
|  | (1)                            | (2)            | (3)       | (4)           | (5)           | (6)      |  |  |  |
| CCPU                                       | 0.029***                       | 0.228***       | 0.002     |               |               |          |  |  |  |
|  | (0.005)                        | (0.029)        | (0.007)   |               |               |          |  |  |  |
| $CCPU^2$                                   | ( )                            | -0.086***      | · · · ·   |               |               |          |  |  |  |
|  |                                | (0.012)        |           |               |               |          |  |  |  |
| $CCPU \times 1_{Short}$                    |                                | · · · ·        | 0.052***  |               |               |          |  |  |  |
|  |                                |                | (0.009)   |               |               |          |  |  |  |
| $\Delta CCPU$                              |                                |                |           | $0.008^{*}$   | -0.001        | -0.026** |  |  |  |
|  |                                |                |           | (0.004)       | (0.006)       | (0.011)  |  |  |  |
| $\Delta CCPU \times 1_{Short}$             |                                |                |           | · · · ·       | 0.018**       | · · ·    |  |  |  |
|  |                                |                |           |               | (0.009)       |          |  |  |  |
| $\Delta CCPU \times 1_{\Delta CCPU \ge 0}$ |                                |                |           |               |               | 0.049*** |  |  |  |
| _  |                                |                |           |               |               | (0.015)  |  |  |  |
| $Ret_{pw}$                                 | -0.140                         | -0.075         | -0.144    | -0.163        | $-0.165^{*}$  | -0.228** |  |  |  |
| *  | (0.098)                        | (0.098)        | (0.098)   | (0.100)       | (0.099)       | (0.101)  |  |  |  |
| $Ret_{pw}^2$                               | 0.358                          | -0.467         | 1.366     | -2.321        | -2.014        | -1.945   |  |  |  |
| 1  | (4.642)                        | (4.583)        | (4.600)   | (4.677)       | (4.668)       | (4.666)  |  |  |  |
| $1_{Short}$                                |                                |                | -0.062*** |               | -0.007***     |          |  |  |  |
|  |                                |                | (0.010)   |               | (0.003)       |          |  |  |  |
| $1_{\Delta CCPU \ge 0}$                    |                                |                |           |               |               | 0.004    |  |  |  |
| _  |                                |                |           |               |               | (0.004)  |  |  |  |
| Intercept                                  | -0.020***                      | $-0.129^{***}$ | 0.011     | $0.011^{***}$ | $0.014^{***}$ | 0.003    |  |  |  |
|  | (0.005)                        | (0.017)        | (0.007)   | (0.001)       | (0.002)       | (0.003)  |  |  |  |
| Observations                               | 1786                           | 1786           | 1786      | 1786          | 1786          | 1786     |  |  |  |
| $R^2$                                      | 0.021                          | 0.047          | 0.041     | 0.003         | 0.009         | 0.010    |  |  |  |
| Adjusted $R^2$                             | 0.019                          | 0.045          | 0.038     | 0.002         | 0.006         | 0.007    |  |  |  |

 $CCPU \times 1_{\text{Short}}$  is positive and statistically significant (0.052, p < 0.01), while the coefficient on CCPU itself becomes statistically insignificant. These findings suggest that investor awareness of and sensitivity to climate policy uncertainty are predominantly concentrated in short-maturity option contracts.

So far, our analysis has focused on the impact of sustained climate policy uncertainty, as captured by the levels of the CCPU index. In the next three columns of Table 4, we shift our attention to immediate changes in policy uncertainty, measured by the first difference of the CCPU index ( $\Delta CCPU$ ). There are two primary reasons for this exercise. From an economic perspective,  $\Delta CCPU$  more effectively captures market perceptions of immediate shifts in climate policy uncertainty, providing insights into how investors react to day-to-day changes in uncertainty. Statistically, first differencing removes trend components from the data and mitigates potential autocorrelation issues, leading to more reliable statistical inference.

In columns (4) and (5) of Table 4,  $\Delta CCPU$  shows a positive but statistically weaker influence on the climate-VRP (0.008, p < 0.10) compared to the impact of sustained uncertainty levels (*CCPU*). Furthermore, this effect is stronger for short-maturity options, consistent with the notion that immediate changes in uncertainty predominantly affect nearer-term risk perceptions. These results indicate that market participants respond to immediate changes in climate policy uncertainty in a manner broadly similar to their response to sustained uncertainty levels. However, they do not appear to overreact to these daily shocks in the short run. This response contrasts with prior studies showing that immediate changes in political or economic uncertainty often trigger sharp increases in risk premiums in the equity market, driven by flight-to-safety behavior or investor overreaction (Barberis, Shleifer, and Vishny, 1998; Bollerslev, Li, and Xue, 2018; Pástor and Veronesi, 2013).

To further explore the potential asymmetric effects of  $\Delta CCPU$ , we incorporate a dummy variable, where  $1_{\Delta CCPU \ge 0} = 1$  if  $\Delta CCPU \ge 0$  (indicating rising uncertainty) and 0 otherwise, along with an interaction term between  $1_{\Delta CCPU \ge 0}$  and  $\Delta CCPU$  in column (6) of Table 4. The results show that the interaction term is positive and statistically significant (0.049, p < 0.01), indicating that the market demands compensation for increases in policy uncertainty. This suggests greater risk aversion during periods when climate policy uncertainty is rising. Conversely, decreases in policy uncertainty appear to have a muted effect on climate-VRP.

#### 4.3 Drivers of Climate Skewness Risk Premium

In this section, we repeat the previous set of analyses for the option-implied climate skewness risk premium and present the results in Table 5.

In column (1) of Table 5, we find a significant negative relationship between CCPU and the climate-SRP, suggesting that greater climate policy uncertainty corresponds to lower skewness risk premiums. At first glance, this result may appear counterintuitive, as higher uncertainty is generally expected to increase the probability of extreme negative outcomes, thereby raising the cost of downside protection and ultimately leading to a higher climate-SRP (Bollerslev, Li, and Xue, 2018; Kelly, Pástor, and Veronesi, 2016; Bali, Brown, and Tang, 2017). To further examine this relationship, column (2) of Table 5 introduces a squared term for CCPU to capture potential nonlinear effects. The estimated coefficients for CCPU and  $CCPU^2$  have opposite signs: 5.834 (p < 0.01) and -2.992 (p < 0.01), respectively. The positive coefficient on CCPU suggests that at lower levels of uncertainty, rising climate policy uncertainty is associated with a higher climate-SRP, consistent with the standard risk-return framework in the uncertainty literature. In contrast, the negative coefficient on the squared term indicates that beyond a certain threshold of uncertainty, investors' perceptions and demand for downside protection shift. Under these more extreme conditions, the complexity of forecasting future regulatory outcomes appears to decrease the climate-SRP. Notably, this nonlinear pattern parallels our earlier results for the climate-VRP.

Column (3) shows that these effects are concentrated in short-maturity option contracts, suggesting that the influence of climate policy uncertainty on climate-SRP is primarily short-term. Turning to columns (4)-(6), which use the first difference of the CCPU index ( $\Delta CCPU$ ) as the main explana-

#### Table 5. Climate skewness risk premium

This table presents the regression results for the option-implied climate skewness risk premium (ClimateSRP). The independent variables in the different models include the China Climate Policy Uncertainty Index (CCPU) from Ma et al. (2023), its squared value ( $CCPU^2$ ), and its first difference ( $\Delta CCPU$ ).  $Ret_{pw}$  represents the production-weighted stock return of the 10 largest publicly listed steel producers in the Asia-Pacific region, while  $Ret_{pw}^2$  represents its squared value. The analysis also includes two dummy variables:  $1_{Short}$ , which equals 1 for options with a time-to-maturity shorter than 250 days and 0 otherwise, and  $1_{\Delta CCPU \geq 0}$ , which equals 1 if  $\Delta CCPU \geq 0$  and 0 otherwise. The sample period covers the year 2022. The table reports coefficient estimates with standard errors provided in parentheses. Note: p<0.1; p<0.05; p<0.01.

|  | Dependent variable: ClimateSRP |                 |                 |                 |                 |              |  |  |  |
|--|--------------------------------|-----------------|-----------------|-----------------|-----------------|--------------|--|--|--|
|  | (1)                            | (2)             | (3)             | (4)             | (5)             | (6)          |  |  |  |
| CCPU                                       | -1.099***                      | 5.834***        | -0.256          |                 |                 |              |  |  |  |
|  | (0.296)                        | (1.818)         | (0.403)         |                 |                 |              |  |  |  |
| $CCPU^2$                                   | · · ·                          | -2.992***       | · · · ·         |                 |                 |              |  |  |  |
|  |                                | (0.774)         |                 |                 |                 |              |  |  |  |
| $CCPU \times 1_{Short}$                    |                                | · · ·           | $-1.726^{***}$  |                 |                 |              |  |  |  |
|  |                                |                 | (0.569)         |                 |                 |              |  |  |  |
| $\Delta CCPU$                              |                                |                 |                 | 0.059           | 0.248           | 1.007        |  |  |  |
|  |                                |                 |                 | (0.274)         | (0.372)         | (0.688)      |  |  |  |
| $\Delta CCPU \times 1_{Short}$             |                                |                 |                 |                 | -0.425          |              |  |  |  |
|  |                                |                 |                 |                 | (0.528)         |              |  |  |  |
| $\Delta CCPU \times 1_{\Delta CCPU \ge 0}$ |                                |                 |                 |                 |                 | $-1.612^{*}$ |  |  |  |
|  |                                |                 |                 |                 |                 | (0.901)      |  |  |  |
| $Ret_{pw}$                                 | $-16.624^{***}$                | $-14.349^{**}$  | $-16.737^{***}$ | $-16.232^{***}$ | $-16.377^{***}$ | -14.025**    |  |  |  |
| -  | (6.086)                        | (6.091)         | (5.856)         | (6.118)         | (5.903)         | (6.239)      |  |  |  |
| $Ret_{pw}^2$                               | $-539.945^{*}$                 | $-568.677^{**}$ | $-487.581^{*}$  | -460.774        | -381.692        | -473.888*    |  |  |  |
| 1  | (286.806)                      | (285.788)       | (276.154)       | (287.515)       | (277.523)       | (287.514)    |  |  |  |
| $1_{Short}$                                |                                |                 | 0.105           |                 | -1.716***       |              |  |  |  |
|  |                                |                 | (0.625)         |                 | (0.152)         |              |  |  |  |
| $1_{\Delta CCPU>0}$                        |                                |                 |                 |                 |                 | -0.016       |  |  |  |
| _  |                                |                 |                 |                 |                 | (0.247)      |  |  |  |
| Intercept                                  | 7.710***                       | $3.932^{***}$   | $7.648^{***}$   | $6.521^{***}$   | 7.347***        | 6.709***     |  |  |  |
|  | (0.333)                        | (1.032)         | (0.448)         | (0.092)         | (0.115)         | (0.183)      |  |  |  |
| Observations                               | 1786                           | 1786            | 1786            | 1786            | 1786            | 1786         |  |  |  |
| $R^2$                                      | 0.012                          | 0.021           | 0.087           | 0.005           | 0.074           | 0.007        |  |  |  |
| Adjusted $R^2$                             | 0.011                          | 0.018           | 0.084           | 0.003           | 0.072           | 0.004        |  |  |  |

tory variable, we find no statistically significant relationship with climate-SRP. This lack of significance implies that daily fluctuations in uncertainty may be perceived as too transitory or noisy to affect investors' longer-term expectations regarding climate policy. Instead, it appears that market participants rely more on sustained levels of uncertainty, as captured by the CCPU index, rather than short-lived shocks, to inform their views on future skewness risk. Finally, in column (6), we observe a marginally significant coefficient on the interaction term  $\Delta CCPU \times 1_{\Delta CCPU \geq 0}$ , suggesting that increases in climate policy uncertainty attract greater investor attention and exhibit a stronger influence on climate-SRP than decreases.

## 4.4 Climate Risk Premiums and Option Time-to-maturity

Another advantage of utilizing options is the ability to analyze the term structure of risk premiums. In this section, we examine how climate risk premiums evolve with time-to-maturity. Tables 4 and 5 show that the

estimated coefficients of the dummy variable  $1_{Short}$  are negative and statistically significant,<sup>16</sup> indicating that, on average, both the estimated climate variance and skewness risk premiums are significantly higher for long-maturity options than for short-maturity peers.

To explore these results further, we plot the average climate variance risk premium (Climate-VRP) and climate skewness risk premium (Climate-SRP) against time-to-maturity in Figure 2. Specifically, Panel A illustrates that the climate-VRP tends to rise with longer option maturities, in line with our earlier findings. Notably, the climate-VRPs extracted from short-maturity options (particularly under 120 days) exhibit higher volatility than those from long-maturity options.

A similar trend is observed in Panel B of Figure 2 for the climate-SRP. First, the average climate-SRP remains positive across all maturities, consistent with the positive skewness risk premium found in the previous section. Moreover, the overall pattern suggests that climate-SRPs increase with option time-to-maturity, albeit with a short-term decline for maturities under 150 days.

The term structure of variance risk premiums has been documented in the literature. For instance, Egloff, Leippold, and Wu (2010) observe that equity index swap variance rates are positive and increase with time-to-maturity. Aït-Sahalia, Karaman, and Mancini (2020) find that integrated variance risk premiums are negative and strongly decrease with the holding horizon. Jacobs and Li (2023) report similar results in the energy commodity markets, documenting negative risk premiums that decline as time-to-maturity increases.<sup>17</sup> Our analysis isolates the climate-VRP and identifies the an increasing pattern—both climate variance risk premiums and skewness risk premiums increase with time-to-maturity.

## 5 Conclusion

Climate risk premium remains a topic of debate in the climate finance literature. This study provides robust evidence of such premiums in the commodity derivatives market, focusing on iron ore options on the Singapore Exchange. By leveraging a unique dataset of two otherwise identical option contracts, "brown" (62% Fe) and "green" (65% Fe) with distinct environmental profiles, we demonstrate how climate-related risks shape financial asset pricing.

Our findings indicate that, on average, carbon-intensive "brown" options command higher climate variance risk premium (Climate-VRP) and climate skewness risk premium (Climate-SRP) than "greener" options, in line with theories predicting greater risk compensation for assets more vulnerable to climate risks. We also highlight the critical role of climate policy uncertainty, particularly in China, as a key driver of these premiums. Specifically, our analysis uncovers a nonlinear, inverted U-shaped relationship: moderate uncertainty elevates premiums by destabilizing market expectations (consistent with standard risk compensation theory), whereas extreme uncertainty lowers them through reduced market activity, a result aligning with the real options theory.

Furthermore, we find that sustained uncertainty levels play a central role in shaping market perceptions and risk pricing, whereas immediate changes in policy uncertainty (i.e., daily changes) exert a weaker influence. Asymmetric responses to uncertainty increases versus decreases further highlight the complexity of investor behavior in evolving policy environments. These effects concentrate predominantly in short-maturity options, reflecting the transitional nature of policy risks when compared to longer-horizon physical climate risks.

By employing a novel two-stage differencing method, we address the identification challenge often encountered in empirical climate finance research and circumvent the need for subjective ratings or narrowly defined event windows. Our forward-looking, options-based methodology yields a more direct and robust measure of climate risk premiums in commodity derivatives markets, extending climate finance research

<sup>&</sup>lt;sup>16</sup>The estimated coefficient in column (3) of Table 5 is positive but statistically insignificant.

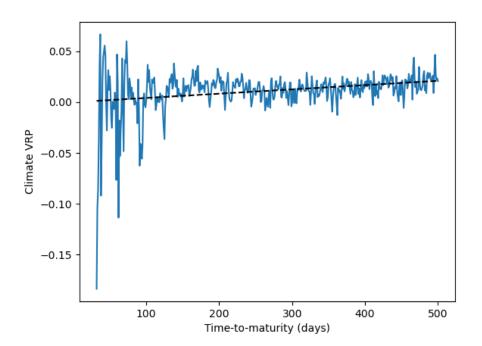
<sup>&</sup>lt;sup>17</sup>The variance risk premium in Aït-Sahalia, Karaman, and Mancini (2020) and Jacobs and Li (2023) is defined as the physical variance minus the risk-neutral variance. Consequently, its sign is opposite to that of swap variance rate and the climate-VRP documented in our paper.



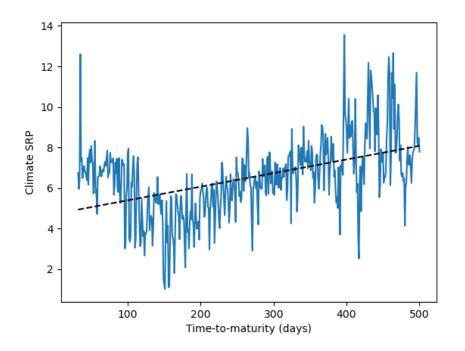
## Figure 2. Climate Risk Premiums and Option Time-to-maturity

The figure plots the average climate variance risk premium and climate skewness risk premium for each option time-to-maturity in Panel A and Panel B, respectively. The dotted line represents the fitted value of the corresponding climate risk premium regressed on option time to maturity.

Panel A: Climate variance risk premium



Panel B: Climate skewness risk premium



beyond equities, bonds, and real estate. Finally, our results emphasize the importance of transparent, predictable policy guidance: reducing uncertainty can stabilize markets, foster more efficient risk pricing, and encourage sustainable investment.



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