Hedging Long-Run Climate Risk in Brazilian Equity Markets*

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Abstract

This paper investigates whether long-run climate risk, proxied by temperature variation, is priced in Brazilian equity markets. I construct hedge portfolios using the mimicking portfolio methodology of Engle et al. (2020), regressing various temperature measures—levels, long differences, and moving averages—on book-to-market sorted portfolios. The resulting hedge portfolios are compared to traditional benchmarks such as the minimum variance and maximum Sharpe ratio portfolios. I find that several climate hedge portfolios achieve higher Sharpe ratios than standard alternatives, particularly for intermediate horizons of temperature change. These results support the hypothesis that persistent climate risks affect asset returns. The approach relies only on observed temperature data and provides a simple, replicable way to measure and hedge climate risk in emerging markets. Future work will incorporate macroeconomic controls and a full pricing model to evaluate the factor structure of climate hedge returns.

1 Introduction

This paper constructs portfolios that hedge exposure to long-run temperature risk in Brazilian equity markets. I do this by regressing various transformations of temperature—levels, long differences, and moving averages—on portfolios sorted by book-to-market ratios, following the mimicking portfolio approach of Engle et al. (2020). The resulting portfolios are interpreted as climate hedge portfolios. I compare their risk-return profiles to those of minimum variance and maximum Sharpe ratio portfolios. I find that some of the climate hedge portfolios achieve higher Sharpe ratios than standard portfolios, suggesting that climate-related risks are priced and can be partially hedged. This working paper is a first step in building a market-based measure of exposure to climate risk in an emerging market context.

I focus on book-to-market (BM) sorted portfolios because prior literature suggests that high BM stocks are more sensitive to long-run risks (Hansen, Heaton, and Li, 2008). Long-run growth risk is one channel through which climate change may impact asset prices, especially if rising temperatures depress long-term economic activity. To capture this, I use long differences and moving averages of temperature at horizons ranging from one to five years, emphasizing persistent climate trends over short-run weather shocks.

This paper builds on Buscariolli (2024). This paper estimates the sensitivity of expected returns to temperature using the model of Bansal, Kiku, and Ochoa (2019) and shows that stocks with high book-to-market ratios, i.e., with higher long-run risks, tend to be more sensitive to temperature risk. The current paper shifts from pricing to hedging: I estimate portfolios that replicate temperature variation and evaluate their risk-adjusted returns. I contrast these results with traditional portfolio benchmarks. While the present version focuses on hedge construction, future work will extend the analysis to fully replicate the methodology in Engle et al. (2020), including factor exposures and dynamic strategies.

The remainder of the paper is structured as follows. Section 2 presents the theoretical framework, focusing on the hedge construction approach of Engle et al. (2020) and comparing it to the

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strategy used here. Section 3 describes the data and empirical methods. Section 4 presents the results. Section 5 concludes with directions for future research.

2 Theoretical Framework: Climate Hedge Portfolios

Engle et al. (2020) propose a methodology to empirically estimate hedge portfolios for climate news shocks. The key insight is that climate risk can be modeled as an unobservable factor, and the goal is to construct a portfolio whose return covaries strongly with this factor. Their approach begins with a climate news index CC_t, constructed from text-based analysis of news coverage, which serves as a proxy for climate risk shocks. They then estimate a mimicking portfolio that replicates the behavior of CC_t using a set of asset returns R_t:

$$CC_t = \alpha + w' R_t + \varepsilon_t, \tag{1}$$

where w is the vector of portfolio weights. The estimated portfolio $h_t = w' R_t$ is interpreted as a hedge portfolio for climate shocks. Engle et al. analyze the dynamics of this portfolio, its correlation with traditional risk factors, and its pricing implications in a multi-factor asset pricing model.

In the present paper, I follow the same mimicking portfolio idea but with a different target variable. Rather than constructing a text-based climate news index, I use actual temperature data—both levels and long-run changes—as proxies for climate risk. This choice is motivated by the theoretical literature (e.g., Bansal et al., 2019) which emphasizes long-run temperature variation as a driver of macroeconomic risk. In practice, I estimate:

$$T_t = \alpha + w' R_t + \varepsilon_t, \tag{2}$$

where T_t represents either raw temperature, demeaned temperature, or long-run temperature differences ($\Delta_K T_t = T_t - T_{t-K}$). The estimated weights w define the climate hedge portfolio.

Importantly, I focus on annual data and use book-to-market sorted portfolios as the asset set R_t, under the assumption that high BM portfolios are more exposed to long-run risks. The weights w are normalized to sum to one and inverted in sign, so the resulting hedge portfolio moves opposite to temperature risk.

While my method omits some steps from Engle et al. (2020)—such as the use of dynamic conditional correlation models or macroeconomic controls—it retains the core mimicking approach. Future versions of this paper will extend the methodology to incorporate factor exposures and compare the pricing of the hedge portfolio in a full asset pricing model.

The next section describes the data sources and empirical implementation in detail.

3 Data and Empirical Strategy

The dataset comprises annual returns of Brazilian stocks, aggregated into ten portfolios sorted by book-to-market ratios. Data on prices, returns, market capitalization, and book values are sourced from Economatica, covering the period from 1995 onward. I exclude the top and bottom 10

As a proxy for the risk-free rate, I use the average CDI rate (interbank certificates of deposit), following standard practice in the Brazilian literature. Temperature data are provided by Xavier et al. (2022), who construct a nationwide gridded temperature series with 0.1° resolution using topographic corrections and interpolation methods. The resulting dataset spans 1961–2020 and captures long-run climate trends across Brazil.

To proxy for long-run temperature shocks, I construct two types of climate variables: (i) $\Delta_K T_t = T_t - T_{t-K}$, the long difference in average temperature over K years; and (ii) moving averages of temperature over K years. These transformations aim to isolate persistent changes in climate from short-run weather fluctuations.

For each specification, I run a regression of the climate variable (e.g., T_t, $\Delta_1 T_t$, ..., $\Delta_5 T_t$) on the ten book-to-market portfolios. The regression coefficients are interpreted as weights of a mimicking portfolio. I normalize the weights to sum to one and invert the sign to obtain a hedge portfolio—that is, one that moves in the opposite direction of temperature shocks.

I compare the performance of the climate hedge portfolios to two benchmarks. First, I construct a minimum variance portfolio using historical covariances of the ten portfolios. Second, I compute the tangency portfolio that maximizes the Sharpe ratio. I report mean returns, standard deviations, and Sharpe ratios for each portfolio, and compare them to the Markowitz-implied Sharpe ratio for the same expected return.

4 Empirical Results

This section presents the main empirical results. I begin by estimating the sensitivity of excess returns to temperature-based variables using Fama-MacBeth regressions. These estimates capture the price of long-run climate risk under the assumption that exposure to temperature variation is a priced factor. I then construct hedge portfolios based on temperature exposures and evaluate their risk-return profiles. Finally, I contrast their performance with classical portfolio optimization benchmarks and discuss implications relative to existing literature.

Table 1 shows the results of Fama-MacBeth regressions of excess returns on the market return and temperature-based variables. The analysis is conducted both in nominal and real terms. The coefficient on the market return is close to unity in all regressions, indicating that the portfolios effectively span market risk.

The climate coefficients reflect the sensitivity of asset returns to temperature changes, which can be interpreted as climate betas. When using raw temperature levels (T), the coefficient is statistically significant and large (8.32 in nominal terms and 8.34 in real terms), suggesting that rising average temperatures are associated with increased expected returns. This could reflect compensation for holding assets exposed to detrimental long-term climate trends.

However, when using short-run changes in temperature ($\Delta_1 T$), the coefficients are close to zero and insignificant, indicating that transient weather fluctuations are not priced. In contrast, the two- and three-year differences ($\Delta_2 T$, $\Delta_3 T$) yield large negative and statistically significant coefficients. This implies that long-run temperature increases depress expected returns, which is consistent with models such as Bansal, Kiku, and Ochoa (2019) that link global warming to lower long-term growth.

These estimates provide evidence that long-run temperature shocks are priced in cross-sectional returns, and that their sign can vary depending on the horizon. The estimates can be interpreted as market-implied prices of climate risk: they measure how much excess return an investor demands per unit of exposure to a given temperature transformation.

Next, I evaluate the out-of-sample performance of the climate hedge portfolios constructed from the regression weights. Each hedge portfolio is designed to move in the opposite direction of a given temperature measure, and weights are normalized to sum to one.

Table 2 reports the mean return, standard deviation, and Sharpe ratio for each hedge portfolio, alongside the minimum variance portfolio. The hedge portfolio based on $\Delta_4 T$ achieves the highest Sharpe ratio (0.19), followed by those based on $\Delta_5 T$ and $\Delta_2 T$. These values are higher than that of the minimum variance portfolio, which has a negative Sharpe ratio (-0.41), driven by a large negative mean return.

While these Sharpe ratios are not particularly high in absolute terms, they are meaningful given that the portfolios are constructed solely to hedge climate variation. The hedge portfolios

Table 1: Fama-MacBeth Regressions: Nominal and Real Returns

	Nominal						Real					
VARIABLES	T	$\Delta_1 T$	$\Delta_2 T$	$\Delta_3 T$	$\Delta_4 T$	$\Delta_5 T$	T	$\Delta_1 T$	$\Delta_2 T$	$\Delta_3 T$	$\Delta_4 T$	$\Delta_5 T$
Market return	0.99***	0.98***	0.97***	0.99***	0.95***	0.98***	0.99***	0.99***	0.97***	0.99***	0.95***	0.99***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Temperature	8.32***	0.12	-5.64***	-8.17***	-5.83	-3.12	8.34***	0.20	-5.62***	-8.21***	-5.95	-3.12
	(2.32)	(2.06)	(1.64)	(2.57)	(3.99)	(3.85)	(2.53)	(2.17)	(1.72)	(2.54)	(3.64)	(3.69)
Constant	-229.60***	-14.89***	-13.77***	-13.27***	-11.81***	-12.19***	-230.37***	-14.99***	-13.93***	-13.34***	-12.08***	-12.33***
	(60.38)	(0.78)	(0.68)	(0.73)	(0.93)	(0.82)	(65.89)	(0.69)	(0.58)	(0.64)	(0.81)	(0.80)
Observations	240	240	230	220	210	200	240	240	230	220	210	200
Groups	10	10	10	10	10	10	10	10	10	10	10	10
R^2	0.85	0.85	0.86	0.87	0.86	0.85	0.84	0.83	0.85	0.85	0.84	0.85

are not optimized for Sharpe performance, yet some of them outperform standard benchmarks. This finding is consistent with Engle et al. (2020), who report that their climate hedge portfolio generates positive returns, low correlation with market factors, and statistically significant alpha.

The last row in Table 2 reports the Sharpe ratio that would be implied by a Markowitz frontier calibrated to the same average return. The implied ratios are consistently higher, reflecting that the hedge portfolios are not mean-variance efficient. Still, the comparison reveals the trade-off between targeting risk exposures (temperature) and achieving efficient allocation. Similar to the findings in Barnett et al. (2020) and Pástor et al. (2021), this suggests that incorporating climate considerations may shift the efficient frontier, especially for long-term investors.

Table 2: Portfolio Performance: Climate Hedge vs. Minimum Variance

	Temperature	Demeaned T	$\Delta_1 T$	$\Delta_2 T$	$\Delta_3 T$	$\Delta_4 T$	$\Delta_5 T$	Min Var
Mean return	5.82	5.82	6.70	6.78	6.60	8.22	7.74	-7.87
Std. dev.	42.92	42.92	42.43	43.38	43.33	43.50	42.25	19.05
Sharpe ratio	0.14	0.14	0.16	0.16	0.15	0.19	0.18	-0.41
Implied Sharpe	0.29	0.29	0.34	0.34	0.33	0.42	0.39	-0.40

These results provide initial but promising evidence that temperature-based hedge portfolios contain priced information and offer diversification benefits. In future work, I will assess whether these portfolios earn positive alpha in a multi-factor setting and how their exposures evolve in a dynamic context.

5 Conclusion and Future Work

This paper develops and evaluates hedge portfolios for long-run temperature risk in Brazilian equity markets. Using a mimicking portfolio approach inspired by Engle et al. (2020), I construct portfolios that replicate changes in various temperature measures—levels, long differences, and moving averages. The weights are estimated via regressions on book-to-market sorted portfolios, and the resulting hedge portfolios are compared to standard minimum variance and maximum Sharpe ratio portfolios.

The findings suggest that some temperature-based hedge portfolios outperform traditional portfolios in risk-adjusted terms, particularly for intermediate horizons of temperature variation. The results support the hypothesis that climate risk, particularly long-run temperature trends, is priced in financial markets. These results are notable because they emerge from a relatively simple empirical setup without imposing a full asset pricing model or requiring a constructed climate news index.

Several extensions are left for future research. First, a natural next step is to implement a more complete version of the Engle et al. (2020) methodology. This would include incorporating macroeconomic control variables, modeling dynamic conditional correlations, and estimating the pricing of the hedge portfolios via cross-sectional regressions. Second, future work could construct climate hedge portfolios using firm-level data or explore heterogeneity across sectors and regions.

Third, and more broadly, it would be valuable to investigate whether the climate hedge portfolios developed here can explain cross-sectional variation in expected returns. This would require embedding the portfolios into a multifactor asset pricing framework and testing their explanatory power alongside standard risk factors. Finally, while this paper focuses on temperature data as a climate proxy, future work might explore alternative climate indicators, including news-based indices, sea level trends, or emissions data.

This paper contributes to the growing literature on climate finance by providing an intuitive and replicable method for constructing hedge portfolios tied to observable climate variables. The results indicate that temperature-based risks are relevant for asset pricing and may be used to inform portfolio construction in the presence of long-run climate uncertainty.

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