

CLIMATE RISK: THE IMPACTS OF TEMPERATURE SHOCKS IN BRAZILIAN MARKET

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ABSTRACT. Climate change drives multiple effects on the stock market. The literature describes temperature shocks as a risk factor for companies and investors' portfolios. To date, however, few studies price temperature shock effects on economic sector. In addition, just recently scholars started adding asset-level information to financial modeling. Thus, in this study we propose to use a spatio-temporal model to create a temperature risk factor capturing the effects of global warming and check the existence of a risk premium for unanticipated temperature fluctuations. The temperature risk factor is defined as the difference between the expected and realized trend in temperature related to climate warming effects. The results provide evidence of mostly negative risk premium for temperature shocks for an array of economic sectors. The analysis also suggest that markets still do not price the risk of adverse temperature fluctuations in industry assets. Our findings imply that investors should account for weather-related shocks for optimizing their portfolios and regulators should provide weather-based responses to increase market efficiency.

Keywords: Climate Finance, Global Warming, Risk Premium, Temperature Risk.

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1. INTRODUCTION

Weather variability systematically affect economic activity. Floods, Heatwaves and droughts are some of the disasters provoked by extreme weather events. Such events are determined by anomalies in temperature variation as well as precipitation, and wind. In financial markets, the uncertainty related to the impact of temperature shocks represents a risk to companies' cash flow and stakeholders' returns (Gregory (2021); Burke et al. (2015)). Temperature shocks create a reallocation of factors of production, impacting the aggregate level of economic productivity¹. Similarly, temperature variation can cause disruption in economic production, increasing the systemic risk of businesses. Even though these effects are acquainted in several studies, the extent of the effects of temperature shocks in stock pricing remains poorly understood. Is the market pricing the risks of unanticipated fluctuations in temperature?

To answer this question, we propose the use of an augmented Fama-French (Fama and French (2015)) model to check the existence of a risk premium for temperature shocks. The standard Fama-French model links average returns with risk factors. The temperature risk factor is added to the five factors present in the Fama-French five-factor model². The risk factor is then tested using a portfolio selection of multiple economic sectors that follows the NAICS classifications³.

The novelty of this study is the construction of a temperature risk factor using a spatio-temporal model that uses geo-referenced meteorological information data to extract the permanent and transitory components factors driving the observed variations in temperature measurements, using the statistical decomposition proposed in Laurini (2019). To date, few studies address problems related to climate risk and asset pricing using asset-level data as the research field is relatively incipient (Hong et al. (2020)). Specifically, previous studies that account for temperature shocks on asset pricing disregard the spatial dependence of the climate events (Bansal et al. (2017); Balvers et al. (2017)).

This study is situated on the emergent spatial finance literature that unites geospatial information with finance studies (Patterson et al. (2020)). New methods of image capturing and processing now provide asset-level information, transforming the availability of information in the financial system. Similarly, recent advancements in statistics, computer science, and image capturing have also spurred new analytical tools in finance and enables more precise analyses (Bianchi et al. (2021)). These technological innovations have the advantage of increasing the precision and the accuracy of analytical assessments (Caldecott et al. (2018)).

The spatio-temporal model from Laurini (2019) used in the analysis allows decomposing the temporal and spatial heterogeneity observed in temperature measurements into permanent and transient factors, using a structure of common factors and spatial random effects.

¹See Zhang et al. (2018) for details.

²The Fama-French five-factors include the market portfolio factors (Rm minus Rf), the size (Small minus Big - SMB), the Book-to-Market ratio (High minus Low - HML), Winners Minus Losers Factor (WML) and liquid Minus Liquid Factor (IML).

³The NAICS code refers to North American Industry Classification System.

Common factors are given by trend, seasonality and cycle components, and spatial heterogeneity is captured using fixed effects of climate classification and latitude and random effects defined continuously in space using a non-stationary spatial covariance structure.

Thus, the decomposition allows identifying a risk factor associated with temperature, assuming that there is a systematic climate risk associated with unanticipated variations in temperature patterns. The framework described by Laurini (2019) allows the identification of permanent climate changes through the trend component, which is parameterized with a first-order random walk process. In this specification the trend component is the accumulation of all shocks with permanent effects, and, as the random walk representation is a Martingale process, variations in the trend component identify unanticipated shocks.

Finally, the proposed construction of the temperature factor as the difference from the trend is consistent with the definition of a systematic risk factor in a Multifactor risk model in the Arbitrage Pricing Theory framework. Assuming that the trend component is a common factor, we estimate the impact of the risk factor associated with unanticipated variations in temperature climate patterns on risk pricing for a set of portfolios.

The data sample used in this research is limited to the Brazilian market and its geographical location. Emerging markets, such as the Brazilian market, face a higher exposure and have significantly less resilience to physical climate risks (Chinowsky et al. (2011)). To illustrate, Brazil has a primarily economic activity and rely on renewable energetic sources that are highly susceptible to climate change (Pao and Fu (2013); Baer (2001)). Energy shortages and price changes normally follows severe droughts events in Brazil Prado Jr et al. (2016). Similarly, crops and cattle are constantly affected by wildfires due to temperature shocks Pivello et al. (2021). For these reasons, Brazil may serve as a good example of a place susceptible to climate shocks.

The results show that the temperature risk factor is significant for the economic sectors highly exposed to climate change, in line with previous studies (Bansal et al. (2017); Balvers et al. (2017)). The impact of temperature shocks varies across the selected portfolios, but the results point out a negative risk premium. This suggests that temperature shocks affect stock returns, but that the market is not pricing the risk associated with latent variations in the temperature. As temperature shocks have adverse effects on the economic activity, as exposed in the literature review, the results suggest that the risk associated with the temperature shock is not correctly priced. The robustness test using the observed temperature time series instead of the decomposed trend as a risk factor shows no significance in mostly portfolios, reinforcing the analysis, and revealing also the benefits of using asset-level analysis in asset pricing.

Our study has several implications. First, regulators and policymakers can better understand temperature trends followed by climate change's impacts on the stock market. Understanding the nature of the inefficiency can better inform regulatory responses, such as promoting mandatory climate risk disclosures for example. Second, investors can update their strategies by including climate risk factors in their asset valuation models. Finally, the study should bring implications for future research in the field of spatial finance.

The remainder of this paper is organized as follows: section 2 reviews scientific literature on the economic impact of temperature shocks. Section 3 describes the datasets used in this

study. Section 4 states the methodology of the spatio-temporal model and the Fama-french model specification. Section 5 exposes the main results and section 6 is the discussion of the findings. Finally, section 7 concludes the paper with a summary, suggestions for future research, and implications.

2. LITERATURE REVIEW

Literature reports ambiguous effects of temperature fluctuations on economic activity. From possible increase in crop productivity to reduced industrial output, the effects are sector-dependent (Dell et al. (2012); Nordhaus (2013); Burke et al. (2015)). Part of the events are predicted, leading to adaptation actions to temperature changes such as green roofs or crop biotechnology. However, climate changes create new unforeseen scenarios representing new forms of risk for economic agents.

In general, temperature shocks potentially reduce the economic growth in developing countries (Dell et al. (2012)). Far from having a uniform economic effect, studies show the effects are mainly perceived in firms that are labor- and capital-intensive (Zhang et al. (2018)). Using Chinese data, Zhang et al. (2018) detects an inverted U-shaped curve relationship between temperature and total factor productivity that can reduce the manufacturing output. The result is in line with Burke et al. (2015), who show a global non-linear effect of temperature on economic production.

Nonetheless, temperature fluctuations are far from being homogeneous throughout industries. Micro-level data suggests that temperature effects are sector-specific. One of the sectors hardest hit by fluctuations in temperature is farming. Although global production can potentially increase by a small increase in temperature, crop stresses caused by droughts or floods can affect food productivity, and are indirectly correlated also with temperature variability (Nordhaus (2013)). Energy production and consumption is also a sector affected by temperature shocks. Energy generation relies largely on natural sources in which production correlates with temperature fluctuations. Global warming affects the production of wind, hydroelectric, geothermal and other sources of energy (Pryor and Barthelmie (2010); Jacobson (2009); Hamududu and Killingtveit (2017)). Another example of a sector highly exposed to temperature fluctuation is civil construction. Pavement and concrete stress in higher temperature, increasing the speed of deterioration (Aniskin and Trong (2018); Yavuzturk et al. (2005)). Besides, unexpected temperature fluctuations can disrupt construction projects, increase costs, delay timelines, and impact the demand for construction services. These effects can potentially affect the financial performance of construction companies, which can in turn impact their stock prices.

Scholars agree that adaptation measures can mitigate the negative outcomes of temperature shock. However, adaptation requires investments that come at a cost to the market, and which are proportional to the intensity of (expected) climatic shifts (Bender et al. (2019); Lobell et al. (2013); Salinas and Mendieta (2013)). In addition, hazards and natural disasters occurring with an intensity and frequency different from historical events can squander existing transition efforts. Besides these difficulties, scholars also agree that

the current level of economic transition to greener climate-resilient options remains largely insufficient (Kaswan (2019)).

Finally, temperature shocks hit differently around the globe, making it spatially dependent. Aspects such as ocean proximity and altitude can modify observed climate patterns, especially when combined with other spatial components like air mass flow, absorption of solar radiation and type of vegetation cover (Laurini (2019)). The market reaction to these events will also depend on how exposed the companies' activity are to these climate shocks. Hong et al. (2019) analyze the effects of droughts on the food sector, revealing market inefficiencies on stock pricing. A similar study shows that housing prices can be substantially affected in regions prone to wildfires, as discussed by Donovan et al. (2007).

3. DATA DESCRIPTION

The temperature model uses the Brazilian meteorological data provided by the National Institute of Meteorology (INMET - *Instituto Nacional de Meteorologia*), through the BD-MEP system. The BDMEP system provides daily and monthly meteorological data of historical series in digital format from the various conventional and automatic meteorological stations of the INMET station network. This system provides measurements in accordance with the international technical standards of the World Meteorological Organization. The data collection starts in 1961 and reports daily precipitation, dry bulb temperature, wet bulb temperature, mean and maximum temperature, the relative humidity, the atmospheric pressure at station level, the insolation, and the wind direction and speed. We use the daily data provided by INMET, and aggregate the data for a weekly frequency.

The choice for a weekly frequency is justified by the results obtained in Laurini (2019) who indicates that the weekly frequency is the most informative in the recovery of climate change patterns in temperature series. Lower frequencies do not allow recovering the temperature trend factor accurately, and daily frequencies introduce a measurement error generated by the non-persistent effects of daily weather variations in temperature.

We used the total sample from 1961 to 2022 of INMET dataset to estimate the spatio-temporal model, to increase the accuracy of the estimates of common and specific factors, and from this estimate we used the factors estimated in the period from January 2000 to June 2022 for the construction of the temperature risk factor. As discussed in Valente and Laurini (2022), accurate identification of climate change patterns requires a long time lag, especially to identify changes in the seasonal pattern of climate data.

In total, we used 1,589,456 observations in the estimation of the spatio-temporal model, corresponding to 3221 weeks and 555 meteorological stations. Note that the panel of observations is unbalanced, and so we may have missing data and also stations that are turned off or on after the beginning of the sample. The spatio-temporal model proposed by Laurini (2019) treat these missing observations as additional parameters to be estimated in the model, and so we automatically project the unobserved data in time and space.

Subfigure a) of Figure 1 shows the average weekly temperature for all INMET stations for the sample 1961-2022, and Subfigure b) of Figure 1 shows boxplots of temperature

distributions by year. We can observe that both the evolution of the weekly average temperatures and the annual temperature distributions show the evident effects of global warming on temperatures in Brazil, indicating a positive trend behaviour and also a change in the seasonal patterns.

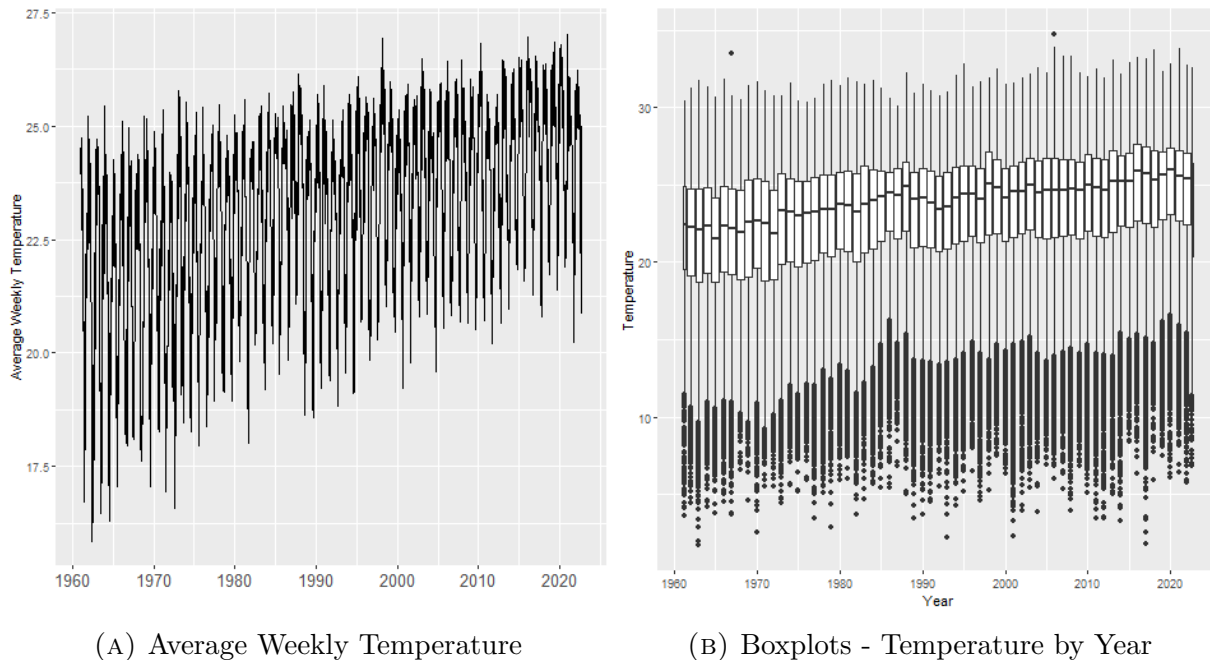


FIGURE 1. Average Weekly Temperature and Boxplots of Temperature Distribution by Year

Secondly, stock market returns data is collected from the Economatica database. We select all assets from 18 economic sectors, using NAICS classifications to construct industry portfolio returns, and covering all the main industries in Brazilian economy. The analyzed industries are: S1 - Electricity, gas and water company. S2 - Financial services and insurance. S3 - Mining, quarrying and oil and gas extraction. S4 - Agriculture, livestock forestry, fishing and hunting. S5 - Business and enterprise management. S6 - Construction. S7 - Manufacturing industry. S8 - Wholesale. S9 - Transport and storage. S10 - Information. S11 - Real estate and leasing of other assets. S12 - Medical and social assistance. S13 - Retail business. S14 - Hotel and restaurant. S15 - Education. S16 - Business support services and waste management. S17 - Arts, entertainment and recreation. S18 - Scientific and technical professional services. The data sample for the asset pricing estimations starts on January, 2, 2000 and ends on July, 27, 2022, and in total consists of 1,123 weekly observations.

The industry portfolios are constructed using weekly returns, assuming equal weights for the assets in each portfolio. We also build market cap weighted portfolios, but the results are similar to equal weighted portfolios.

The risk factors we use in the multifactor pricing model are constructed and made publicly available by NEFIN (Brazilian Center for Research in Financial Economics of the University of São Paulo) using data from the Brazilian stock market, and the five risk factors include the Market Portfolio factor (Rm minus Rf), the Size (Small minus Big - SMB), the Book-to-Market ratio (High minus Low - HML), Winners Minus Losers Factor (WML) and liquid Minus Liquid Factor (IML). Risk factors are built in on a daily basis, and we accumulate these returns on a weekly frequency.

	Assets	Obs	Min	Mean	Max	Stdev	Skewness	Kurtosis
S1	250	1123	-0.23272	0.00430	0.13515	0.02777	-0.99384	8.95125
S2	301	1123	-0.22694	0.00275	0.13979	0.02944	-0.78023	7.41618
S3	38	1123	-0.30972	0.00118	0.30965	0.04764	-0.09522	7.27650
S4	20	1081	-0.37156	0.00263	1.11514	0.06870	5.10218	78.13061
S5	163	1123	-0.18346	0.00472	0.40801	0.03454	1.72065	20.12422
S6	92	1123	-0.38946	0.00163	0.24020	0.05004	-0.34634	6.19044
S7	526	1123	-0.23514	0.00322	0.10382	0.02769	-1.48394	10.16757
S8	24	1123	-0.28679	0.00115	0.32982	0.04146	-0.18887	9.54806
S9	138	1123	-0.31845	0.00025	0.30848	0.05088	-0.19657	7.60339
S10	147	1123	-0.23290	0.00018	0.20094	0.03566	-0.40736	5.23160
S11	30	1111	-0.34759	0.00352	0.33076	0.05202	0.16855	7.71270
S12	22	920	-0.21041	0.00161	0.16813	0.03749	-0.14123	3.55289
S13	89	1123	-0.25814	0.00378	0.13518	0.03504	-0.89485	6.56697
S14	14	847	-0.42744	0.00360	1.23319	0.10610	4.43245	42.84446
S15	20	807	-0.54090	0.00214	1.86075	0.08873	11.16718	239.64246
S16	13	887	-0.43644	0.00069	1.59949	0.07511	10.93586	233.74389
S17	14	775	-0.57894	-0.00135	0.33304	0.06654	-0.46357	10.06251
S18	8	961	-0.31326	0.00692	0.97329	0.09077	2.84964	21.92964
Rm-Rf	*	1123	-0.21744	0.00075	0.15830	0.03280	-0.56126	4.45023
SMB	*	1123	-0.13067	-0.00017	0.10509	0.02162	-0.11421	3.56546
HML	*	1123	-0.12202	0.00131	0.08696	0.02016	-0.03148	2.73660
WML	*	1123	-0.16717	0.00288	0.09779	0.02561	-0.77105	4.07911
IML	*	1123	-0.14426	0.00034	0.11976	0.02164	-0.14119	4.37622
Temp	**	1113	-0.00043	0.00008	0.00091	0.00017	0.57885	1.45379

Note: Sectors - S1 - Electricity, gas and water company. S2 - Financial services and insurance. S3 - Mining, quarrying and oil and gas extraction. S4 - Agriculture, livestock forestry, fishing and hunting. S5 - Business and enterprise management. S6 - Construction. S7 - Manufacturing industry. S8 - Wholesale. S9 - Transport and storage. S10 - Information. S11 - Real estate and leasing of other assets. S12 - Medical and social assistance. S13 - Retail business. S14 - Hotel and restaurant. S15 - Education. S16 - Business support services and waste management. S17 - Arts, entertainment and recreation. S18 - Scientific and technical professional services. * - Details about factor construction can be found in https://nefin.com.br/data/risk_factors.html. ** Section 4.1 details the construction of this factor.

TABLE 1. Descriptive Statistics

4. METHODOLOGY

4.1. Estimation of Temperature Trend. To estimate the trend factor we used the decomposition of the temperature series into components of trend, cycle, seasonality and a spatial random effect proposed in Laurini (2019). This decomposition makes it possible to separate permanent and transient variations in climate series, and thus recover the effects of climate change through the estimated trend component. The trend component, parameterized as a first-order random walk process, incorporates all changes in the series that are not associated with short-term effects, and thus estimates the impact of long-term climate change. The specification of the trend as an random walk process is it's very common in modeling climatic processes (see, e.g., Gordon (1991), Grassi et al. (2013) and Proietti and Hillebrand (2017)). The seasonal component is represented on a formulation of mean effects by period, under the restriction that these effects most sum to zero, and represent a stochastic dummie representation of seasonal effects. To capture the cyclic components, we adopt a representation analogous to the so-called unobserved component models (Clark (1987)), where the cyclical (period) effects is based on a latent factor with a second-order autoregressive (AR) structure.

This decomposition is given by the following structure:

$$\begin{aligned}
 (1) \quad y(s, t) &= \mu_t + s_t + c_t + z(s, t) \beta + \xi(s, t) + \epsilon(s, t) \\
 \mu_t &= \mu_{t-1} + \eta_\mu \\
 s_t &= s_{t-1} + s_{t-2} + \dots + s_{t-m-1} + \eta_s \\
 c_t &= \phi_1 c_{t-1} + \phi_2 c_{t-2} + \eta_c \\
 \xi(s, t) &= \omega(s, t) \\
 Cov(\omega(s, t)) &= \mathcal{C}(h)
 \end{aligned}$$

where $y(s, t)$ represents the observation y at location s and in period t , μ_t , s_t and c_t are the components of trend, seasonality and cycle, with independent Gaussian innovation components η_μ , η_s and η_c ; $z(s, t)$ is a set of covariates observed in the location s and period t , and $\xi(s, t)$ is a spatial random effect, incorporating the spatial variation in the process by means of spatially continuous covariance function $\mathcal{C}(h)$ of the Matérn family, given by

$$(2) \quad \mathcal{C}(h) = \frac{1}{\Gamma(\nu)2^{\nu-1}} (kh)^\nu K_\nu(kh)$$

with K_ν a modified Bessel function of the second type. We use the continuous representation of spatial effects proposed in Lindgren et al. (2011) to represent and perform a Bayesian estimation of the parameters of the spatial covariance, using the following parameterization in terms of $\log \tau$ and $\log \kappa$ for the covariance function:

$$\log \tau = \frac{1}{2} \log \left(\frac{\Gamma(\nu)}{\Gamma(\alpha)(4\pi)^{d/2}} \right) - \log \sigma - \nu \log \rho$$

$$\log \kappa = \frac{\log(8\nu)}{2} - \log \rho$$

The main advantage of this form is that, conditional on the value of ν , it results in two parameters to be estimated. Lindgren et al. (2011) discuss this property and the interpretation of parameters in this class of models. To incorporate the observed heterogeneity in the spatial distribution of temperature patterns, we use an extension that allows to make the spatial covariance structure non-stationary in space, by making the parameters of the spatial covariance matrix space varying, using a regression structure, and introducing an additional parameter into the model. See Section 5 in Krainski et al. (2021) for a detailed discussion on this formulation. The parameters of the covariance function are now defined using a basis expansion, defined as:

$$(3) \quad \begin{aligned} \log(\tau(s)) &= b_0^{(\tau)}(s) = \sum_{k=1}^p b_k^{(\tau)}(s)\theta_k \\ \log(\kappa(s)) &= b_0^{(\kappa)}(s) = \sum_{k=1}^p b_k^{(\kappa)}(s)\theta_k \end{aligned}$$

This formulation of spatio-temporal model is also interesting because permits the use of Bayesian estimation methods. Stacking the observations of vectors $\mathbf{y}(s, t)$, $\mathbf{z}(s, t)$ and $\xi(s, t)$ as \mathbf{y} , \mathbf{z} and $\boldsymbol{\xi}$, the posterior distribution of the spatio-temporal model, in terms of a constant of proportionality, can be written as:

$$\pi(\theta, \boldsymbol{\xi}|\mathbf{y}) \propto \pi(\mathbf{y}|\boldsymbol{\xi}, \theta)\pi(\theta)$$

Assuming independent prior distributions for $\pi(\theta)$, and exploring the spatial Markov property, the elements of \mathbf{y} are conditionally independent, and the posterior distribution is given by:

$$\pi(\theta, \boldsymbol{\xi}|\mathbf{y}) \propto \left(\prod_{t=1}^T \pi(\mathbf{y}|\boldsymbol{\xi}, \theta) \right) \pi(\theta).$$

Under the Gaussian Markov random field structure, this posterior can be represented by:

$$\begin{aligned} \pi(\theta, \boldsymbol{\xi}|\mathbf{y}) &= (\sigma_\varepsilon^2)^{d/2} \exp\left(-\frac{1}{\sigma_\varepsilon^2} (\mathbf{y} - \mathbf{z}\beta - \boldsymbol{\xi})' (\mathbf{y} - \mathbf{z}\beta - \boldsymbol{\xi})\right) \\ &\times (\sigma_\omega^2)^{-d/2} |\tilde{\Sigma}|^{-1/2} \exp\left(\frac{1}{2\sigma_\omega^2} \boldsymbol{\xi}' \tilde{\Sigma} \boldsymbol{\xi}\right) \\ &\times \prod_{i=1}^{\dim(\theta)} \pi(\theta_i) \end{aligned}$$

with the component $\tilde{\Sigma}$ a d -dimensional covariance matrix with elements $\sigma_\omega^2 \mathcal{C}(|h|)$.

To estimate this model, we use the class of Integrated Nested Laplace Approximations proposed by Rue et al. (2009), which permits accurate and computationally efficient estimation of Bayesian models using deterministic approximations.

4.2. Multifactor Risk Pricing. To determine the impact of climate risks associated with unexpected changes in temperature patterns, we use a Multifactor pricing model framework based on the Arbitrage Pricing theory framework proposed by Ross (1976). A detailed discussion of asset pricing based on the no-arbitrage assumption can be found at Musiela and Rutkowski (2008), and on the use of factor models in risk pricing in Connor et al. (2010). In this structure we assume that the return of an asset i is determined by a set of risk factors in a linear structure, in the form:

$$r_i = \beta_0 + \beta_{i,1}f_1 + \beta_{i,2}f_2 + \dots + \beta_{i,k}f_k + \epsilon_i$$

The risk factors f_i are systematic risk components, that is, they are responsible for co-movements in returns between assets and must be uncorrelated or weakly correlated (Chen et al. (1986), Connor et al. (2010)). The specific impact (sensitivity) of each factor on the return r_i is given by the factor loadings $\beta_{i,k}$. The central idea of Ross (1976) arbitrage pricing is that, in the absence of arbitrage, we can price assets through the composition of the sensitivities of each asset to risk factors. In this structure, systematic risk is priced by systematic factors, and idiosyncratic effects are placed in the ϵ_i component, and by definition we expect $cov(\epsilon_i, \epsilon_j) = 0$.

In this decomposition we expect that each risk factor captures orthogonal sources of variation in the structure of returns, and thus each factor in theory should capture a different source of risk. To impose this restriction we usually work in a factor surprises representation:

$$r_i = \beta_0 + \beta_{i,1}\hat{f}_1 + \beta_{i,2}\hat{f}_2 + \dots + \beta_{i,k}\hat{f}_k + \epsilon_i$$

where we assume that $E(\hat{f}_i) = 0$. A simple way to impose this restriction is to assume that the factors \hat{f}_i are given by the difference between the observed value and the predicted value using all available information, in the form $\hat{f}_i = f_i - E(f_i|\mathcal{F}_\square)$, where \mathcal{F}_\square represents the set of information available at the time of the forecast, representing a filtration⁴. Assuming a no-arbitrage structure, the best prediction for a risk factor using the information contained in the filtration \mathcal{F}_\square in period t would be given by its value in the previous period, given by a Martingale⁵ process:

$$E(f_{i,t}|\mathcal{F}_\square) = f_{i,t-1}$$

This structure is equivalent to assuming that the risk factor evolution in discrete time is given by a random walk process. A simple and consistent way to construct risk factors with the no-arbitrage hypothesis is to define the risk factors as factor surprises in the form $\hat{f}_{i,t} = f_{i,t} - f_{i,t-1}$, since $E(f_{i,t}|\mathcal{F}_\square) = f_{i,t-1}$. We use this representation to construct the risk factor associated with climate changes in temperature, as described below.

⁴See Musiela and Rutkowski (2008) for the definition of a filtration.

⁵See Musiela and Rutkowski (2008) for a detailed exposition between the relationship between Martingale processes and asset pricing.

4.3. Temperature Risk Factor Definition. The temperature risk factor is constructed from the trend component estimated by the spatio-temporal model described in Section 4.1. We depart from the usual interpretation of a risk factor as the unexpected variation in a systematic (non-diversifiable) variable relevant to the determination of asset returns in an economy. In this interpretation, the risk factor should capture unexpected shocks to this relevant variable, which would not be captured by the other risk factors included in the model. The use of the unexpected variation is given by the fact that the expected variations would already be contained in the past price of the assets, assuming that the assets are free of arbitrage in the risk-neutral measure, and thus, in this measure, the price process is a Martingale, as discussed in the previous section.

Our identification strategy for the risk factor associated with climate change impacts on temperature is given by the fact that we are defining the temperature component as a random walk process, which by construction is a Martingale. Thus, the first difference of the estimated temperature trend component directly captures unanticipated variations with a permanent effect on the long-term values for temperature, thus being consistent with the usual interpretation of a risk factor as the unexpected variation of a systematic risk process.

Thus, our temperature risk factor is defined as the variation in the estimated trend for temperatures in Brazil. It is important to remember that this identification strategy also controls for all other transient and expected effects that may affect temperatures, which in our model are captured by seasonality and cycle factors, which are dependent stochastic processes and thus can be predicted in the model. As these effects are predictable and not permanent, they should not affect asset returns, and thus should not be priced. Another important point is that the spatial random effect, combined with the fixed effects of Köppen climate region and latitude are important to identify the temperature trend as the common temperature factor for the entire analyzed region, and this common factor interpretation is also key to identifying the trend as a systematic risk factor.

5. RESULTS

5.1. Temperature Factor Estimation. In this section we describe the estimation of the temperature factor, using the methodology described in Section 4.1. Sub-figure a) of Figure 2 shows the network of INMET stations used in our estimations.

To estimate the space-temporal model, we need to build a mesh to perform an approximation (discretization) of the Brazilian territory, which is used to estimate the continuous spatial covariance matrix associated with spatial random effects. We use a mesh constructed using a Delaney triangulation, resulting in an approximation containing 2014 triangles. The mesh used in the work is shown in sub-figure b) of Figure 2. The mesh contains internal and external regions of the analyzed region, and the external region is necessary for the construction of approximation solutions of the spatial covariance matrix in the external limits of the analyzed region.

To estimate the spatio-temporal model we used as fixed effects the latitude of each weather station, and also the Köppen climate classification for Brazil, constructed using

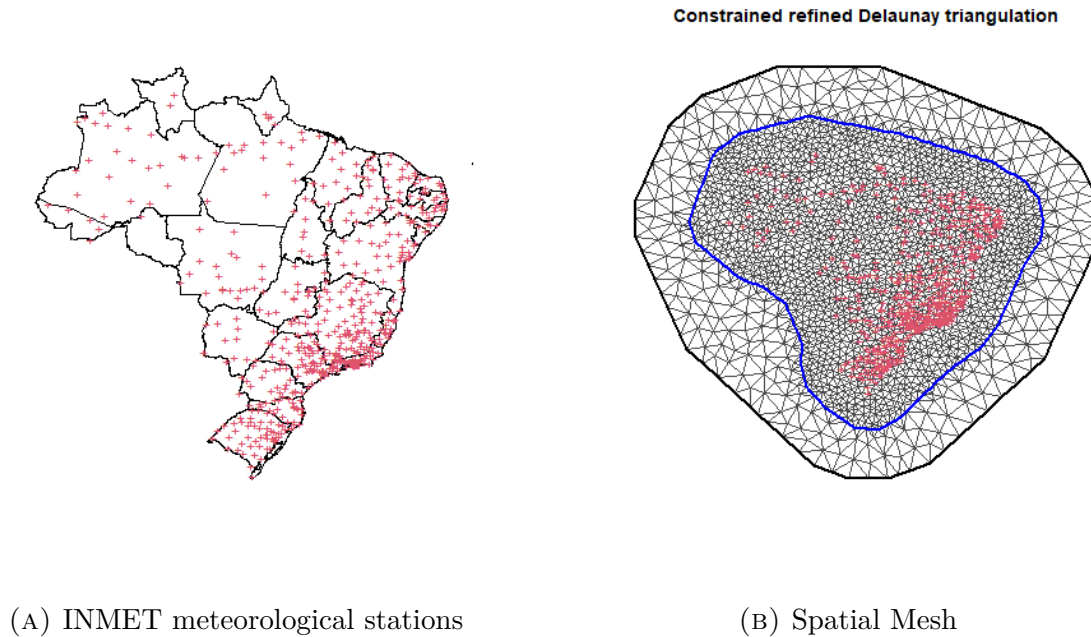


FIGURE 2. Spatial Distribution of INMET Meteorological Stations and Spatial Mesh

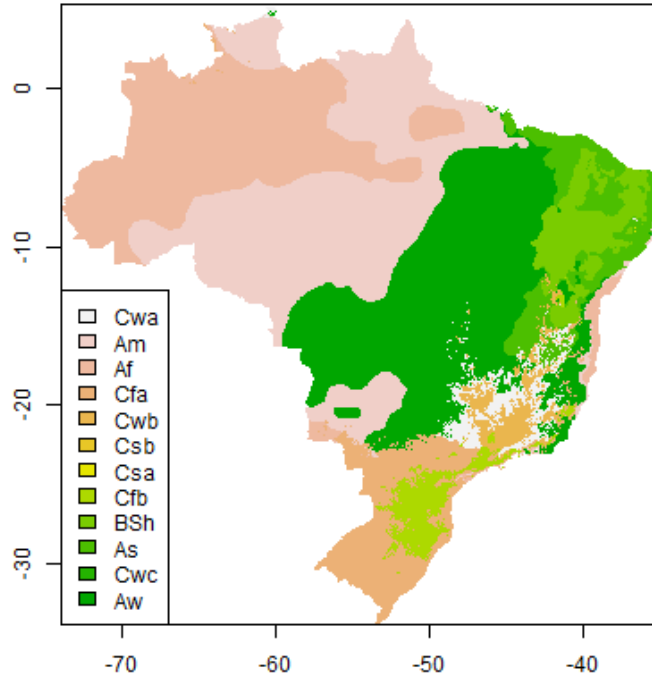
the Alvares et al. (2013) methodology, which enter as dummies for each climate region. Figure 3 shows the climate classifications for Brazil. The Köppen dummies capture the mean temperature for each climate classification.

The model, as discussed in Section 4.1 contains trend, cycle and seasonality random effects, and a spatial random effect. The trend factor is defined using weekly periodicity, while we define cycle and seasonal components in monthly frequencies⁶.

The estimated parameters for the model are reported in Table 2. The table reports summaries for the posterior Bayesian estimation of the parameters associated with the fixed effects, and the hyperparameters for the precision of the random effects of trend, cycle and seasonality components, and the hyperparameters of the Matérn spatial covariance function.

The estimated trend, seasonality, and cycle components are presented in Figure 4, which presents the posterior mean and a credibility interval constructed using the .025 and .975 quantiles of the estimated posterior distribution of these components. Note that the trend component is estimated as the deviations from the mean effects estimated by the Köppen climate factor dummies and the latitude covariate. We can observe in the trend component an increase of about .33C in the average temperature in Brazil in the period 1961-2022, measured by the evolution of the trend in relation to the average effects measured by the fixed effects of the model. The credibility interval indicates that the growth in the

⁶See Section 6 in Laurini (2019) for the definition of mixed-frequency components in the spatio-temporal model



Af = Equatorial climate, Am = Monsoon weather, Aw or As = Savanna climate, BWh = Hot arid climate, BWk = Cold arid climate, BSh = Warm semi-arid climate, BSk = Cold semi-arid climate, Cfa = Humid subtropical climate, Cfb = Temperate oceanic climate, Cfc = subpolar oceanic climate, Cwa = Humid subtropical climate influenced by monsoons, Cwb = Altitude subtropical climate, Cwc = Altitude cold subtropical climate, Csa = Mediterranean hot summer climate, Csb = Mediterranean cool summer climate, Csc = Mediterranean cool summer climate.

FIGURE 3. Köppen Climate Classification - Brazil

temperature trend is statistically relevant. We can also observe a change in the seasonal temperature pattern by the estimated seasonal component, and a relevant cyclical effect for several periods in the sample.

Figure 5 shows the posterior mean for the estimated spatial random effect. We can observe that the spatial effects correct for specific regions in the Brazilian spatial continuum where it is necessary to control for temperature patterns that are not captured by the fixed effects associated with the Köppen climate classification and latitude.

5.2. Temperature Factor Estimation. Figure 6 shows the first difference of the trend component, which conforms the discussion in sections 4.2 and 4.3, identifies the temperature risk factor in our analyses. In this figure we show the estimated values of this risk factor for the period 2000-2022, which will be the period analyzed in the risk pricing models, which will be discussed below.

	Mean	SD	0.025quant	0.5quant	0.975quant	Mode
<i>Fixed effects</i>						
Köppen Cfb	23.448	2.197	19.142	23.448	27.753	23.448
Köppen Cfa	24.277	2.197	19.971	24.277	28.582	24.277
Köppen Cwb	23.754	2.197	19.448	23.754	28.060	23.754
Köppen BSh	22.540	2.197	18.234	22.540	26.846	22.540
Köppen Cwa	21.555	2.197	17.250	21.555	25.861	21.555
Köppen BWh	20.729	2.197	16.423	20.729	25.034	20.729
Köppen Aw	27.483	2.197	23.176	27.483	31.789	27.483
Köppen AM	23.791	2.197	19.485	23.791	28.097	23.791
Köppen Af	24.805	2.197	20.499	24.805	29.111	24.805
latitude	0.154	0.193	-0.224	0.154	0.532	0.154
<i>Random effects</i>						
Prec. Gaussian ($\epsilon(s, t)$)	2.95e-01	0.000	2.95e-01	2.95e-01	2.96e-01	2.95e-01
Prec. trend (η_μ)	6.28e+05	9194.450	6.10e+05	6.28e+05	6.46e+05	6.28e+05
Prec. seasonal (η_s)	5.25e+00	0.076	5.11e+00	5.25e+00	5.41e+00	5.25e+00
Prec. cycle (η_c)	1.85e+00	0.027	1.80e+00	1.85e+00	1.90e+00	1.85e+00
PACF1 for cycle	3.81e-01	0.006	3.69e-01	3.81e-01	3.94e-01	3.81e-01
PACF2 for cycle	-1.30e-01	0.007	-1.44e-01	-1.30e-01	-1.16e-01	-1.30e-01
Theta1 for spatial	-2.50e+00	0.014	-2.53e+00	-2.50e+00	-2.48e+00	-2.50e+00
Theta2 for spatial	-5.51e-01	0.015	-5.80e-01	-5.51e-01	-5.22e-01	-5.51e-01
Theta3 for spatial	6.00e-02	0.003	5.40e-02	6.00e-02	6.70e-02	6.00e-02

Note - Prec. indicates the precision (inverse of the variance of each latent component). The parameters for the cycle component as represented by the first and second partial autocorrelations (PACF1 and PACF1). See Eq. 3 for the definition of the parameters of the spatial covariance function. Parameters estimated using Bayesian estimation by Integrated Nested Laplace Approximations (INLA).

TABLE 2. Posterior Distribution of Estimated Parameters - Spatio-temporal model

5.3. Risk Premium Estimation. To assess the impact of the temperature risk factor on asset pricing we use this factor in a Multifactor risk premium estimation framework, using the factor structure derived from the Fama-French framework (Fama and French (1992)). In the structure proposed by Fama and French (1992) the risk factors are constructed through observed characteristics of the companies, using the observed returns. The factors are constructed through the difference between portfolios ordered by the characteristic of interest, where the factor is estimated by the difference between the portfolio formed by the returns of companies in a high percentile in the ordering in relation to this characteristic and another portfolio formed by the returns of companies belonging to the low percentile in the characteristic sorting.

We add the temperature factor in addition to the market portfolio factors (Rm minus Rf), Size (Small minus Big - SMB), the Book-to-Market ratio (High minus Low - HML), Winners Minus Losers Factor (WML) and liquid Minus Liquid Factor (IML). To verify the impact of the temperature factor on the Brazilian economy, we estimate the risk premium

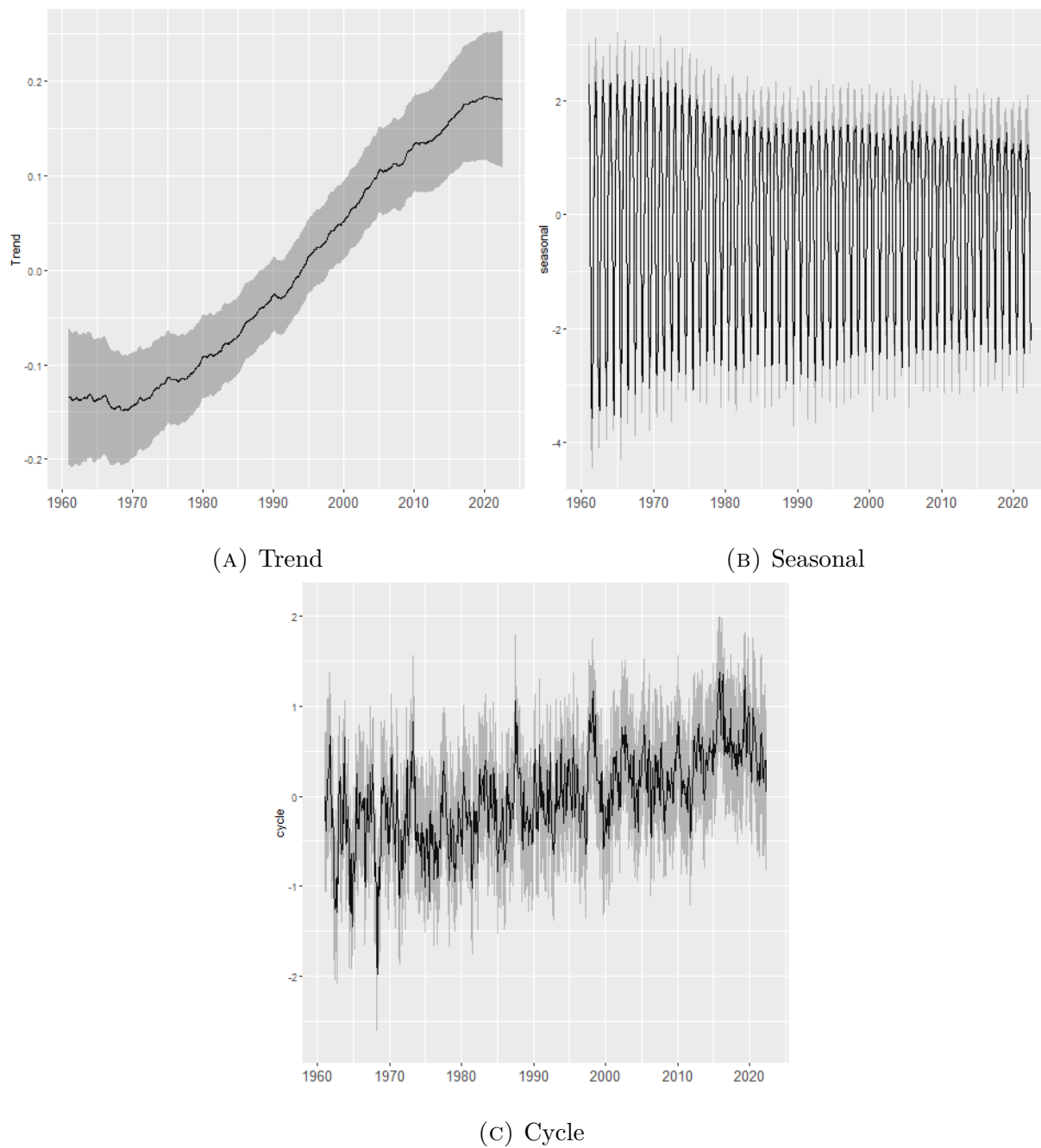


FIGURE 4. Posterior Distribution of Trend, Seasonal and Cycle decomposition

for portfolios formed in sectors of the economy (industry portfolios), and thus we can interpret the results according to the impact of temperature on economic activities.

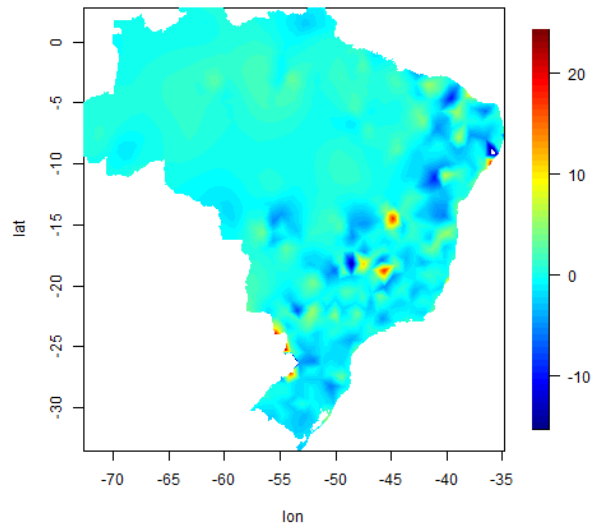


FIGURE 5. Posterior Mean of Spatial Random Effect

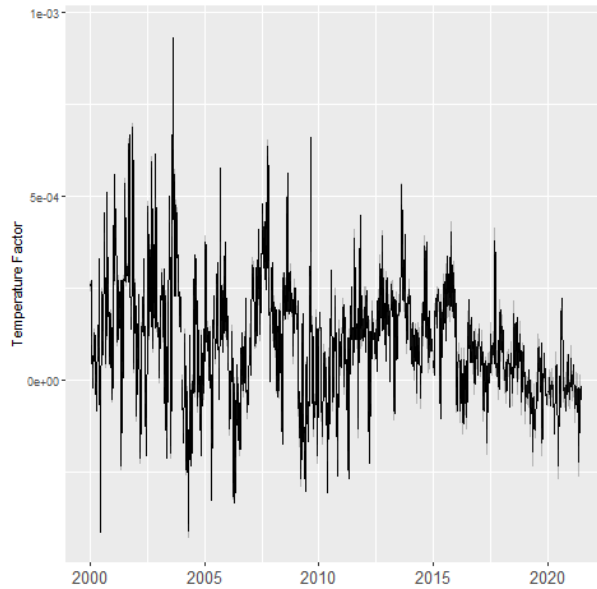


FIGURE 6. Posterior Distribution of Temperature Risk Factor - $\mu_t - \mu_{t-1}$

As described in Section 3, we used 18 economic sectors using NAICS classifications in the construction of the portfolios. We report the results of the Fama-French model estimation by Ordinary Least Squares in Table 3 (Sectors S1-S9) and Table 3 (Sectors S10-S18). The Tables report the estimated sensitivity for each factor, the respective estimated

standard deviation and the R-Squared and Adjusted R-Squared for each sector. The different number of observations is given by the presence of missing data, caused by the absence of transactions in the portfolio on that date, and is linked to lower liquidity and the number of companies in some sectors.

	S1	S2	S3	S4	S5	S6	S7	S8	S9
(Intercept)	0.002*** (0.001)	0.000 (0.001)	-0.001 (0.001)	0.001 (0.002)	0.003*** (0.001)	-0.001 (0.001)	0.001 (0.001)	-0.002 (0.001)	-0.001 (0.001)
Rm_minus_Rf	0.612*** (0.018)	0.716*** (0.017)	1.010*** (0.033)	0.473*** (0.069)	0.569*** (0.028)	0.819*** (0.038)	0.658*** (0.015)	0.806*** (0.031)	0.813*** (0.041)
SMB	0.154*** (0.040)	0.285*** (0.037)	0.302*** (0.073)	0.108 (0.160)	0.184*** (0.064)	0.839*** (0.085)	0.351*** (0.034)	0.410*** (0.070)	0.644*** (0.091)
HML	0.160*** (0.028)	-0.038 (0.026)	0.134** (0.052)	-0.482*** (0.110)	0.081* (0.045)	0.027 (0.060)	0.036 (0.024)	-0.107** (0.050)	-0.054 (0.065)
WML	-0.008 (0.023)	-0.027 (0.021)	-0.012 (0.041)	-0.078 (0.088)	-0.007 (0.036)	-0.052 (0.048)	0.043** (0.019)	0.059 (0.039)	0.028 (0.051)
IML	0.095** (0.041)	-0.008 (0.037)	-0.063 (0.074)	0.275* (0.165)	0.039 (0.064)	-0.082 (0.086)	0.081** (0.035)	0.008 (0.071)	0.067 (0.092)
Temp.	-4.281 (3.174)	-1.032 (2.919)	-9.939* (5.791)	1.055 (12.028)	-9.571* (5.037)	-0.389 (6.735)	-3.214 (2.704)	1.202 (5.553)	-15.398** (7.197)
R ²	0.581	0.684	0.527	0.061	0.319	0.423	0.692	0.430	0.352
Adj. R ²	0.579	0.683	0.524	0.055	0.316	0.420	0.691	0.427	0.348
Num. obs.	1113	1113	1113	1071	1113	1113	1113	1113	1113

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

Note: Sectors - S1 - Electricity, gas and water company. S2 - Financial services and insurance. S3 - Mining, quarrying and oil and gas extraction. S4 - Agriculture, livestock forestry, fishing and hunting. S5 - Business and enterprise management. S6 - Construction. S7 - Manufacturing industry. S8 - Wholesale. S9 - Transport and storage.

TABLE 3. Multifactor Estimation - Sectors S1-S9

We can observe that in general the sign of the temperature factor is negative, indicating that an unanticipated increase in the temperature trend implies a reduction in the portfolio's expected returns, indicating a general pattern of negative effect of temperature on the cross-section of returns of assets in Brazil. This negative impact is statistically significant for sectors S3 (Mining, quarrying and oil and gas extraction), S5 (Business and enterprise management), S9 (Transport and storage), S10 (Information), and S16 (Business support services and waste management). We also observed a positive but not statistically significant impact for the sectors S4 (Agriculture, livestock forestry, fishing and hunting), S8 (Wholesale), S15 (Education) e S16 (Business support services and waste management), and a positive and statistically significant impact for sector S13 (Retail business).

5.4. Alternative Definition of the Temperature Risk Factor. The identification strategy defined in Section 4.3 and used in the estimates reported in the Tables Tables 3-3 (Sectors S10-S18) for the temperature risk factor is based on estimating the risk factor as the first difference of a temperature trend process, estimated using a decomposition of unobserved components in a space-time model.

	S10	S11	S12	S13	S14	S15	S16	S17	S18
(Intercept)	-0.001*	0.002	-0.000	0.000	0.003	-0.002	-0.002	-0.002	0.006*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Rm_minus_Rf	0.747***	0.751***	0.719***	0.764***	0.737***	0.987***	0.888***	0.719***	0.860***
	(0.025)	(0.045)	(0.035)	(0.024)	(0.130)	(0.063)	(0.086)	(0.078)	(0.102)
SMB	0.308***	0.626***	0.428***	0.351***	0.460	0.867***	0.517**	0.887***	0.093
	(0.056)	(0.103)	(0.085)	(0.053)	(0.311)	(0.158)	(0.210)	(0.196)	(0.241)
HML	-0.063	-0.261***	-0.454***	-0.173***	0.191	-0.472***	-0.185	-0.106	-0.131
	(0.040)	(0.073)	(0.058)	(0.038)	(0.209)	(0.105)	(0.143)	(0.130)	(0.164)
WML	-0.045	0.070	-0.026	0.058*	0.241	0.209***	-0.133	0.032	-0.152
	(0.031)	(0.057)	(0.044)	(0.030)	(0.160)	(0.079)	(0.108)	(0.097)	(0.124)
IML	0.115**	-0.103	0.132	0.219***	-0.037	0.226	0.135	0.159	0.692***
	(0.056)	(0.106)	(0.091)	(0.054)	(0.336)	(0.171)	(0.227)	(0.213)	(0.260)
Temp.	-10.715**	-9.285	-0.141	10.662**	-24.423	15.062	26.092*	-1.322	-11.508
	(4.405)	(7.942)	(6.342)	(4.193)	(23.859)	(11.565)	(15.601)	(14.612)	(17.520)
R ²	0.513	0.267	0.419	0.541	0.062	0.364	0.173	0.229	0.100
Adj. R ²	0.510	0.263	0.415	0.539	0.055	0.359	0.168	0.223	0.094
Num. obs.	1113	1101	911	1113	838	798	880	768	952

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

Note: Sectors - S10 - Information. S11 - Real estate and leasing of other assets. S12 - Medical and social assistance. S13 - Retail business. S14 - Hotel and restaurant. S15 - Education. S16 - Business support services and waste management. S17 - Arts, entertainment and recreation. S18 - Scientific and technical professional services.

TABLE 4. Multifactor Estimation - Sectors S10-S18

A relevant question is whether an alternative definition of the temperature factor, based on a directly observable process, would not be sufficient to capture the impact of temperatures on portfolio pricing. To verify this hypothesis, we tested an alternative specification where the temperature risk factor is defined as the first difference of the average weekly temperature observed across the country. Figure 7 shows the temperature factor constructed using this definition.

Note that this specification is also valid in defining a risk factor as the unanticipated component (surprise factor) of a variable, but with the limitation that this risk factor does not directly control for transient (and previsible) components of the process, such as seasonal and cyclical components, nor does it control for spatial heterogeneity controlled by the fixed effects of Köppen climate classification and latitude and the spatial random effects.

We report the results of this alternative definition of the temperature risk factor in Tables 5-5. We can observe that in this specification this risk factor is generally not statistically significant, and we only reject that the factor load is statistically equal to zero for S4 and S13 portfolios, and the magnitude of this coefficient is close to zero.

These results indicate that our identification strategy is relevant to obtain the risk premium for the temperature factor, which is consistent with risk pricing based on a risk premium for the unanticipated and permanent component of the process, in our construction based on the variation of the trend component of the temperature series.

Another important result is that our results seem to indicate that we do in fact have a risk premium for the unanticipated effects of climate change on the temperature series,

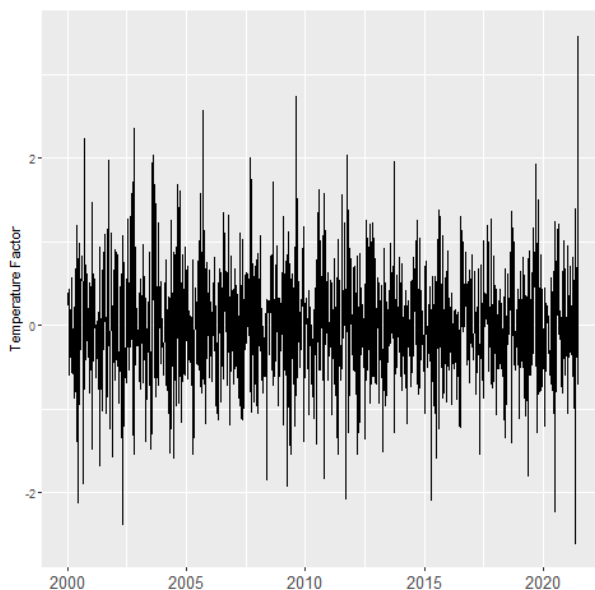


FIGURE 7. Alternative Temperature Factor - First Difference of average weekly temperature

that is, the unanticipated effects of global warming on the risk pricing structure. Thus, the agents anticipate the expected variations in the temperature series, given by the transitory components, and place a risk premium for the differences observed in the trend of the temperature series, which captures the non-reversible effects of global warming effects on temperatures.

5.5. Robustness to Sample Period Choice. To verify the robustness of the results obtained in estimating the risk premium for the temperature factor, we performed an alternative estimation focusing on the period 2010-2022, using the same specification of sectors and factors described in the previous section. This alternative sample makes it possible to analyze whether the risk premium pattern is maintained over time, or whether it indicates changes in the pricing of this risk factor in relation to the perception of impacts and adaptation to climate change in a more recent period.

The Tables 7 (Sectors S1-S9) and 7 (Sectors S10-S18) report the Fama-French estimations for the period 2010-2022. We can observe in these tables relevant changes in the response to the temperature risk factor. Factor loadings are no longer significant for sectors S5, S9 and S10, and become positive and statistically significant for sectors S12 and S14, indicating a change in response to the temperature risk factor.

We can observe in Figure 6 that the variations in the temperature factor are more extreme in the pre-2010 period, indicating that the changes in the temperature factor are more predictable after 2010. To verify this hypothesis we performed a variance change test between the estimation allowing a change on the variance after 2010, and an estimate assuming constant variance between 2000 and 2022. The test is based on analysis of

	S1	S2	S3	S4	S5	S6	S7	S8	S9
(Intercept)	0.002*** (0.001)	0.000 (0.001)	-0.002* (0.001)	0.001 (0.002)	0.002** (0.001)	-0.001 (0.001)	0.000 (0.000)	-0.002 (0.001)	-0.002* (0.001)
Rm_minus_Rf	0.613*** (0.018)	0.715*** (0.017)	1.011*** (0.033)	0.462*** (0.069)	0.568*** (0.029)	0.817*** (0.038)	0.659*** (0.015)	0.806*** (0.032)	0.811*** (0.041)
SMB	0.151*** (0.040)	0.285*** (0.037)	0.298*** (0.074)	0.119 (0.159)	0.183*** (0.064)	0.842*** (0.086)	0.349*** (0.034)	0.411*** (0.071)	0.641*** (0.092)
HML	0.160*** (0.028)	-0.038 (0.026)	0.134** (0.052)	-0.480*** (0.110)	0.081* (0.045)	0.028 (0.060)	0.036 (0.024)	-0.107** (0.050)	-0.054 (0.065)
WML	-0.009 (0.023)	-0.026 (0.021)	-0.013 (0.041)	-0.065 (0.089)	-0.006 (0.036)	-0.049 (0.048)	0.042** (0.019)	0.059 (0.040)	0.029 (0.051)
IML	0.098** (0.041)	-0.009 (0.037)	-0.060 (0.074)	0.260 (0.164)	0.040 (0.065)	-0.085 (0.086)	0.082** (0.035)	0.008 (0.071)	0.068 (0.092)
Temp.	0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)	-0.006* (0.003)	-0.001 (0.001)	-0.001 (0.002)	0.000 (0.001)	-0.000 (0.001)	-0.001 (0.002)
R ²	0.581	0.684	0.526	0.064	0.317	0.423	0.692	0.430	0.349
Adj. R ²	0.578	0.683	0.523	0.059	0.314	0.420	0.690	0.427	0.346
Num. obs.	1113	1113	1113	1071	1113	1113	1113	1113	1113

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

Note: Sectors - S1 - Electricity, gas and water company. S2 - Financial services and insurance. S3 - Mining, quarrying and oil and gas extraction. S4 - Agriculture, livestock forestry, fishing and hunting. S5 - Business and enterprise management. S6 - Construction. S7 - Manufacturing industry. S8 - Wholesale. S9 - Transport and storage.

TABLE 5. Multifactor Estimation - Sectors S1-S9 - Temperature factor defined as the difference of temperature weekly averages

variance, reported in Table 9. The results of this test indicate an F statistic of 88.452, indicating a p-value of zero for the equality of residual variances in the temperature factor between these two periods.

6. DISCUSSION

The results of Fama-French five-factor model (Table 2 and 3) using all sample shows that temperature risk factor is significant for the respective sectors: mining, quarrying and oil and gas extraction; business and enterprise management; transport and storage; information; retail business; business support services and waste management. These results suggest that part of the temperature fluctuation risk is not entirely priced by the market.

Excepting for *business support services and waste management*, the loadings on the temperature factor are negative in the industry portfolios. The literature reveals that most effects of the temperature on economic sectors are adverse. Industries like mining, manufacturing, construction, and transportation presents higher vulnerability to temperature variations (Graff Zivin and Neidell (2014)). Besides, adjustment costs arise when capital stock is dependent on climate factors for their optimal location and depreciate slower than usual to allow climate adjustments (Quiggin and Horowitz (2003)). In that case, the negative risk premium shows the market is not considering a positive risk premium for

	S10	S11	S12	S13	S14	S15	S16	S17	S18
(Intercept)	-0.002*** (0.001)	0.001 (0.001)	-0.000 (0.001)	0.001* (0.001)	0.001 (0.004)	-0.002 (0.002)	-0.001 (0.002)	-0.002 (0.002)	0.005* (0.003)
Rm_minus_Rf	0.747*** (0.025)	0.752*** (0.045)	0.722*** (0.035)	0.768*** (0.024)	0.729*** (0.130)	0.983*** (0.063)	0.886*** (0.086)	0.722*** (0.078)	0.856*** (0.102)
SMB	0.305*** (0.056)	0.623*** (0.104)	0.427*** (0.085)	0.349*** (0.053)	0.468 (0.311)	0.867*** (0.158)	0.510** (0.211)	0.884*** (0.196)	0.095 (0.241)
HML	-0.062 (0.040)	-0.263*** (0.073)	-0.455*** (0.058)	-0.174*** (0.038)	0.189 (0.209)	-0.471*** (0.105)	-0.186 (0.143)	-0.108 (0.129)	-0.132 (0.164)
WML	-0.045 (0.031)	0.068 (0.057)	-0.030 (0.044)	0.053* (0.030)	0.274* (0.160)	0.202** (0.079)	-0.150 (0.109)	0.029 (0.098)	-0.144 (0.124)
IML	0.117** (0.056)	-0.100 (0.106)	0.135 (0.091)	0.224*** (0.054)	-0.041 (0.336)	0.217 (0.171)	0.131 (0.227)	0.164 (0.213)	0.691*** (0.260)
Temp.	-0.000 (0.001)	0.001 (0.002)	0.002 (0.001)	0.002** (0.001)	-0.008 (0.005)	0.000 (0.003)	0.002 (0.003)	0.001 (0.003)	-0.003 (0.004)
R ²	0.510	0.266	0.420	0.540	0.064	0.362	0.171	0.229	0.100
Adj. R ²	0.508	0.262	0.416	0.538	0.057	0.358	0.165	0.223	0.094
Num. obs.	1113	1101	911	1113	838	798	880	768	952

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

Note: Sectors - S10 - Information. S11 - Real estate and leasing of other assets. S12 - Medical and social assistance. S13 - Retail business. S14 - Hotel and restaurant. S15 - Education. S16 - Business support services and waste management. S17 - Arts, entertainment and recreation. S18 - Scientific and technical professional services.

TABLE 6. Multifactor Estimation - Sectors S10-S18 - Temperature factor defined as the difference of temperature weekly averages

the adverse effects of latent temperature shocks. This result reveals the importance of the spatio-temporal decomposition analysis in stock pricing.

The analysis also reflects how asset-level information can provide substantial details for risk analysis (Patterson et al. (2020)). Previous models that test the effects of temperature shocks are mostly limited by not using geospatial data. The lack of this information can lead decision-makers to Thus, investors can enhance the risk-return profile of their investment portfolio using geospatial information-based decisions.

Finally, the analysis suggests that the current level of technology, adaptation and mitigation processes are not enough to dissipate the risk encountered in temperature fluctuation, with substantial effects on asset pricing. Improving mitigation and resilience can dissipate this shock, decreasing the degree of risk premium in the economic portfolios. Given that the results provide substantial information of change in the temperature patterns (Figure 3), it is possible that more effects on asset prices will be seen in the near future if the investment to countermeasure the climate change.

7. CONCLUSION

In this paper, we assessed whether the markets price temperature shocks effects on industries stock. To do so, we added a sixth temperature risk factor to the Fama-French five-factor model. Although various effects of temperature anomalies on economic activity are reported in literature, few studies quantified how such anomalies affected stock prices.

	S1	S2	S3	S4	S5	S6	S7	S8	S9
(Intercept)	0.001 (0.001)	-0.001** (0.001)	-0.003** (0.002)	-0.002 (0.001)	0.001 (0.001)	-0.004*** (0.001)	-0.001 (0.001)	-0.003** (0.001)	-0.001 (0.001)
Rm_minus_Rf	0.596*** (0.025)	0.800*** (0.021)	1.009*** (0.059)	0.398*** (0.058)	0.633*** (0.040)	0.965*** (0.042)	0.707*** (0.024)	0.983*** (0.051)	1.074*** (0.033)
SMB	-0.007 (0.061)	0.152*** (0.051)	0.366** (0.144)	0.572*** (0.143)	0.166* (0.099)	0.891*** (0.103)	0.235*** (0.058)	0.389*** (0.123)	0.809*** (0.081)
HML	0.068* (0.040)	-0.084** (0.034)	0.538*** (0.095)	-0.026 (0.094)	0.070 (0.065)	0.060 (0.068)	0.032 (0.038)	-0.373*** (0.081)	-0.360*** (0.053)
WML	0.062** (0.028)	0.040* (0.024)	-0.168** (0.067)	0.171** (0.066)	-0.044 (0.046)	0.076 (0.048)	0.076*** (0.027)	0.128** (0.057)	0.080** (0.038)
IML	0.257*** (0.067)	0.179*** (0.057)	-0.194 (0.159)	-0.024 (0.157)	0.010 (0.109)	0.211* (0.114)	0.266*** (0.064)	0.145 (0.136)	0.103 (0.089)
Temp.	-1.372 (4.617)	6.283 (3.888)	-29.418*** (10.923)	2.902 (10.786)	-7.214 (7.456)	-0.740 (7.812)	-3.458 (4.385)	0.236 (9.324)	-1.397 (6.115)
R ²	0.570	0.767	0.507	0.183	0.392	0.684	0.712	0.466	0.760
Adj. R ²	0.566	0.765	0.502	0.175	0.386	0.681	0.710	0.461	0.757
Num. obs.	647	647	647	647	647	647	647	647	647

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

Note: Sectors - S1 - Electricity, gas and water company. S2 - Financial services and insurance. S3 - Mining, quarrying and oil and gas extraction. S4 - Agriculture, livestock forestry, fishing and hunting. S5 - Business and enterprise management. S6 - Construction. S7 - Manufacturing industry. S8 - Wholesale. S9 - Transport and storage.

TABLE 7. Multifactor Estimation - Sectors S1-S9 - Sample 2010-2022

The results show that markets do not correctly price temperature shocks. The significant betas for temperature shocks (Table 3 and 4) reflects the negative risk premium for unexpected temperature shocks on the market.

We relied on a spatio-temporal model to create a space- and time-specific temperature risk factor. We also attempted to provide more insights to the emerging spatial finance literature by showing how geoinformation data can provide additional information to asset pricing.

This proposed investigation in this paper aims to fuel the emergent literature on spatial finance as well as provide new outputs for climate finance literature. Investors can also add elements of temperature shock for portfolio creation. Policymakers and regulators, on the other hand, can have a better understanding of how climate change shocks affect financial activity.

Future research can replicate the study in different markets and test new climate risk factors on financial markets. For example, rain patterns can also provide substantial information for asset pricing modelling. In addition, future research can investigate mechanisms that can efficiently mitigate the effects of temperature shocks on the stock market.

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	S10	S11	S12	S13	S14	S15	S16	S17	S18
(Intercept)	-0.003** (0.001)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.005* (0.002)	-0.001 (0.001)	-0.005*** (0.002)	-0.002 (0.002)	-0.000 (0.003)
Rm_minus_Rf	0.722*** (0.043)	0.982*** (0.038)	0.755*** (0.035)	0.889*** (0.029)	0.737*** (0.097)	1.110*** (0.056)	0.907*** (0.067)	0.913*** (0.096)	0.792*** (0.110)
SMB	0.344*** (0.104)	0.672*** (0.093)	0.181** (0.085)	0.545*** (0.072)	0.428* (0.236)	0.787*** (0.138)	0.751*** (0.163)	0.936*** (0.235)	0.363 (0.269)
HML	-0.145** (0.069)	-0.282*** (0.061)	-0.514*** (0.056)	-0.382*** (0.047)	-0.075 (0.155)	-0.620*** (0.090)	-0.282*** (0.107)	-0.279* (0.154)	0.217 (0.177)
WML	0.057 (0.048)	0.184*** (0.043)	0.041 (0.039)	0.025 (0.033)	0.130 (0.110)	0.145** (0.064)	0.105 (0.076)	0.014 (0.109)	0.036 (0.125)
IML	0.325*** (0.115)	0.120 (0.103)	0.401*** (0.094)	0.128 (0.079)	0.358 (0.260)	0.214 (0.152)	0.059 (0.180)	0.124 (0.259)	0.394 (0.297)
Temp.	-9.190 (7.893)	6.663 (7.044)	14.583** (6.413)	9.387* (5.432)	5.728 (17.830)	23.364** (10.414)	1.427 (12.316)	4.926 (17.759)	-17.434 (20.363)
R ²	0.458	0.653	0.520	0.713	0.162	0.524	0.367	0.260	0.162
Adj. R ²	0.453	0.650	0.515	0.710	0.154	0.519	0.361	0.253	0.154
Num. obs.	647	647	647	647	643	647	647	647	647

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

Note: Sectors - S10 - Information. S11 - Real estate and leasing of other assets. S12 - Medical and social assistance. S13 - Retail business. S14 - Hotel and restaurant. S15 - Education. S16 - Business support services and waste management. S17 - Arts, entertainment and recreation. S18 - Scientific and technical professional services.

TABLE 8. Multifactor Estimation - Sectors S10-S18 - Sample 2010-2022

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
M1	1112.000000	0.000032				
M2	1111.000000	0.000030	1.000000	0.000002	88.452851	0.000000

Note: The test is based on an analysis of variance between the regression of temperature factor on an intercept and a dummy for the period 2010-2022 (M1), and a restricted model with a regression of temperature factor on a Intercept (M2).

TABLE 9. Variance change analysis - Temperature Risk Factor

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