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, we propose in this study 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. The study should bring implications for regulators concerned in mitigating climate change and investors interested in optimizing portfolios.

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1. Introduction

Temperature fluctuations systematically affect economic activity. Floods, Heatwaves and droughts are some of the disasters provoked by unexpected variations in temperature. In financial markets, the uncertainty related to impact of temperature shocks represents a risk to companies' cash flow and stakeholders' returns (Gregory (2021); Burke et al. (2015)). The temperature shocks creates a reallocation of factors of production, impacting the aggregate level of economic productivity[1]. Similarly, the temperature variation effects causes unexpected disruption in economic production, increasing the specific risk of the business. Even though these effects are highly known in the literature, the extent of temperature shocks in stock pricing, however, remains poorly understood. Is the market pricing the risks of unanticipated fluctuations in temperature?

To answer this question, we propose an augmented Fama-French (Fama and French (2015)) model to check the existence of a risk premium for temperature shocks. The temperature risk factor is added to the finance model alongside the five other factors commonly present in the Fama-French five-factor model[2]. The risk factor is then tested using a portfolio selection of multiple economic sectors that follows the NAICS classifications[3].

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)).

Therefore, the study relies on the recent advancements in statistics, econometrics, and computer science that have spurred new analytical tools in finance, enabling more precise analyses Bianchi et al. (2021). Similarly, new geospatial datasets can now provide asset-level information, transforming the availability of information in the financial system (Patterson et al. (2020)). These technological innovations have the advantage of increasing the accuracy and the accuracy of analytical assessments (Caldecott et al. (2018)).

The spatio-temporal model 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. 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.

[1]See Zhang et al. (2018) for details.

[2]The 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).

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

Thus, the decomposition allows identifying a risk factor associated with temperature, assuming that there is a systematic climate risk associated with unanticipated variations in climate change patterns. In particular, the effects of global warming in the trend of temperatures. The framework in 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)). In addition, 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)). For these reasons, Brazil becomes a good example of a place susceptible for 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 the temperature shock varies across the selected portfolios, but the results points out to a negative risk premium. This result suggests that temperature shocks affects stock returns, but the market is not pricing the risk associated with latent variations in the temperature. As temperature shocks has 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 geospatial analysis in asset pricing.

A couple of implications can be derived from this study. First, regulators and policymakers can better understand 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: The section 2 exposes the literature review 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

The literature reports ambiguous effects of temperature fluctuation on economic activity. From crop increased 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 policies to temperature changes such as green roofs or crop resilience. 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), that shows a global non-linear effect of temperature on economic production. Temperature fluctuation affects the dynamics of the factors production influencing the overall economic productivity.

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, indirect effects of temperature fluctuation such as floods and droughts can negatively strike food production (Nordhaus (2013)). Energy production and consumption is another natural 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)).

Scholars agree that adaptation procedures can mitigate the negative outcomes of temperature shock. However, adaptation requires a investment rate at the same pace of climate transformations and represents an expenditure (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 the transition efforts. Besides these difficulties, scholars also agree that the current level of economic transition to greener 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)). Markets also react differently in regions that are more or less prone to 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). These few examples illustrate part of the growing trend of publication in the spatial finance literature, as discussed by Patterson et al. (2020).

3. Data Description

This study relies on two different data sets. The first data set reunites geospatial data from Brazilian public sources to construct the temperature risk factor. The second data set refers to finance weekly data of risk factors and asset returns.

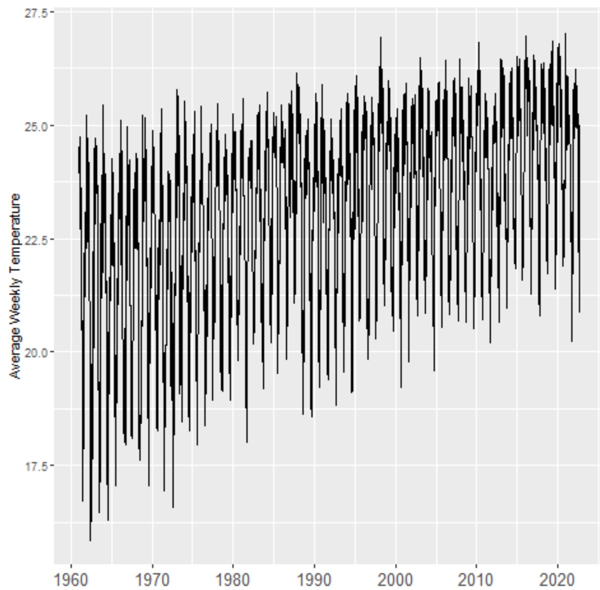
The temperature model uses the Brazilian meteorological data provided by the National Institute of Meteorology (INMET - *Instituto Nacional de Meteorologia*), through the BDMEP system. The BDMEP system provides daily and monthly digital meteorological data of historical series from the various conventional and automatic meteorological stations of the INMET station network. In addition, this system provides measurements in accordance with the international technical standards of the World Meteorological Organization. The data collection starts in 1961 and reports the precipitation occurred in the last 24 hours, the dry bulb temperature, the 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 given by the results obtained in Laurini (2019) which indicate 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.

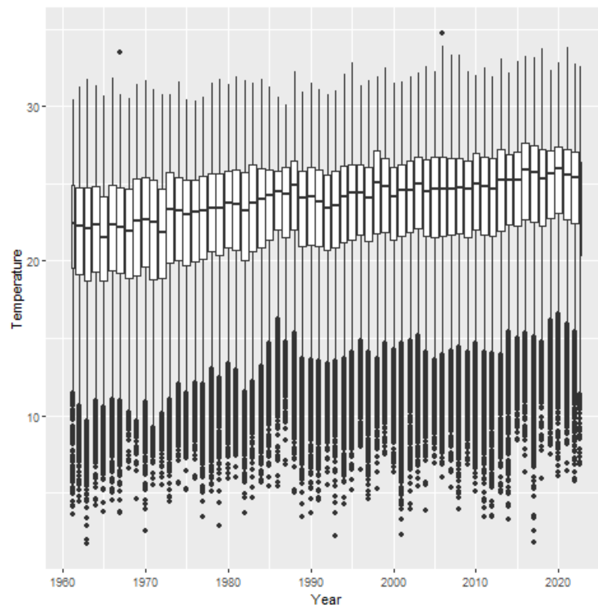
We used the total sample from 1961 to 2022 of INMET dataset to estimate the spatio-temporal model, to increase the accuracy of the estimates of common and specific factors, and from this estimate we used the factors estimated in the period from January 2000 to June 2022 for the construction of the temperature 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.



(A) Average Weekly Temperature



(B) Boxplots - Temperature by Year

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:

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

where $y\left(s,t\right)$ 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; $z\left(s,t\right)$ is a set of covariates observed in the location s and period t, and $\xi\left(s,t\right)$ is a spatial random effect, incorporating the spatial variation in the process by means of spatially continuous covariance function $\mathcal{C}\left(h\right)$ of the Matérn family, given by

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

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:

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

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

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

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

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

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

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

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

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:

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

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:

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

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 $\hat{f}_i = f_i - E(f_i|\mathcal{F}_\sqcup)$, where $\mathcal{F}_\sqcup$ represents the set of information available at the time of the forecast, representing a filtration[4]. Assuming a no-arbitrage structure, the best prediction for a risk factor using the information contained in the filtration $\mathcal{F}_\sqcup$ in period t would be given by its value in the previous period, given by a Martingale[5] process:

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

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 $E(f_{i,t}|\mathcal{F}_\sqcup) = f_{i,t-1}$. We use this representation to construct the risk factor associated with climate changes in temperature, as described below.

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

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

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

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 sistematic 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

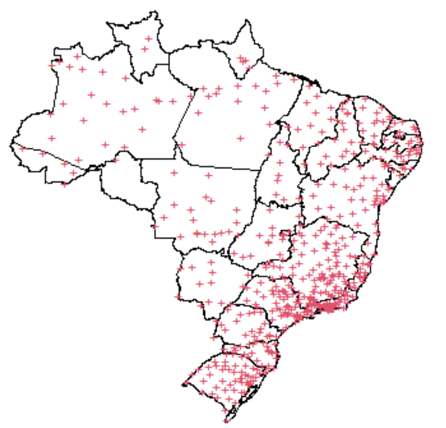
5.1. **Temperature Factor Estimation.** In this section we describe the estimation of the temperature factor, using the methodology described in Section 4.1. Sub-figure a) of Figure 2 shows the network of INMET stations used in our estimations.

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.

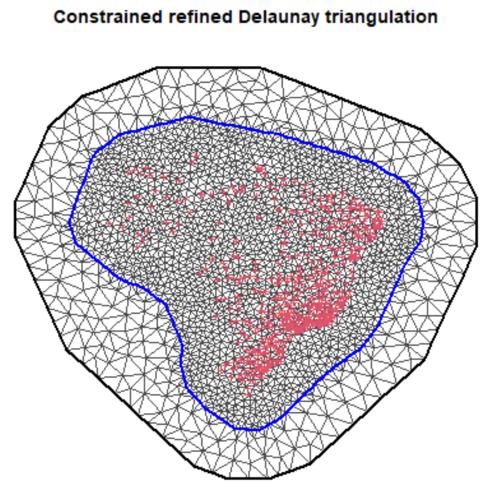
To estimate the spatio-temporal model we used as fixed effects the latitude of each weather station, and also the Köppen climate classification for Brazil, constructed using the Alvares et al. (2013) methodology, which enter as dummies for each climate region. Figure 3 shows the climate classifications 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 frequencies[6].

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



(A) INMET meteorological stations



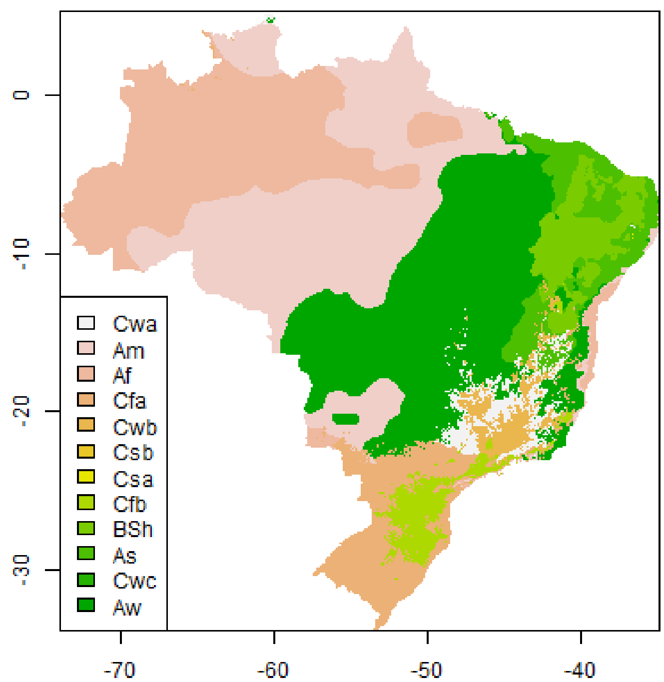
(B) Spatial Mesh

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

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 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.



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

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.

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

	Mean	SD	0.025quant	0.5quant	0.975quant	Mode
Fixed effects						
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
Random effects						
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

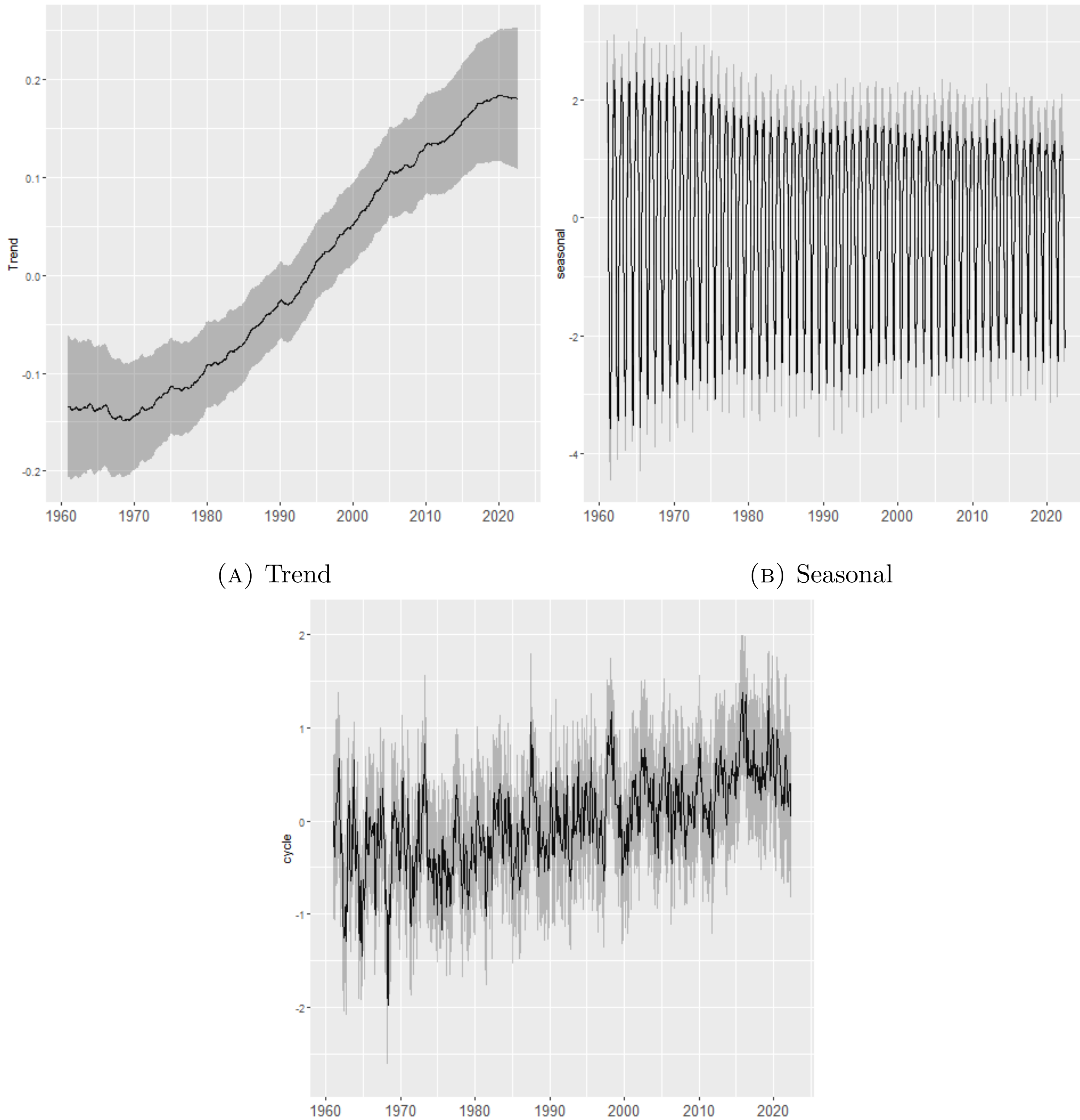
Note - Prec. indicates the precision (inverse of the variance of each latent component). The parameters for the cycle component as represented by the first and second partial autocorrelations (PACF1 and PACF1). See Eq. 3 for the definition of the parameters of the spatial covariance function. Parameters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

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

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 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.

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



(A) Trend (B) Seasonal

(C) Cycle

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

absence of transactions in the portfolio on that date, and is linked to lower liquidity and the number of companies in some sectors.

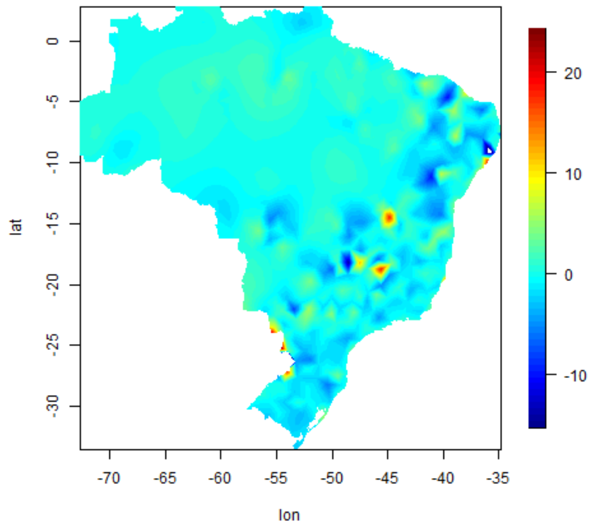


FIGURE 5. Posterior Mean of Spatial Random Effect

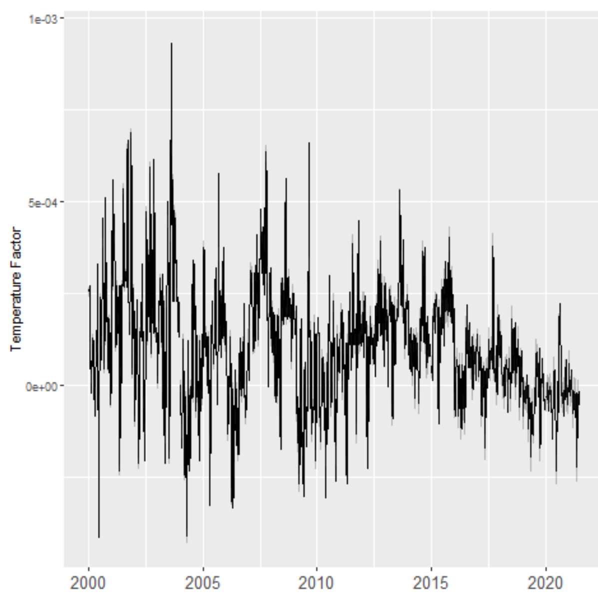


FIGURE 6. Posterior Distribution of Temperature Risk Factor - $\mu_t - \mu_{t-1}$

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

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

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.

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

	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

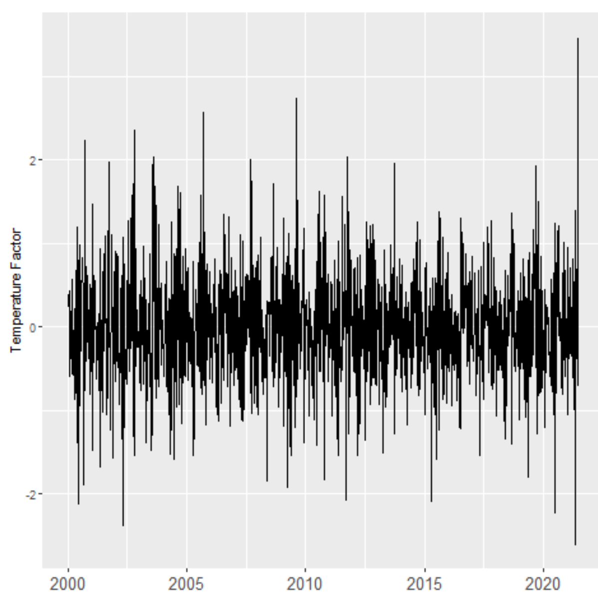


Figure 7. Alternative Temperature Factor - First Difference of average weekly temperature

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, 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.

	S1	S2	S3	S4	S5	S6	S7	S8	S9
(Intercept)	0.002^{***}	0.000	-0.002^{*}	0.001	0.002^{**}	-0.001	0.000	-0.002	-0.002^{*}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Rm_minus_Rf	0.613^{***}	0.715^{***}	1.011^{***}	0.462^{***}	0.568^{***}	0.817^{***}	0.659^{***}	0.806^{***}	0.811^{***}
	(0.018)	(0.017)	(0.033)	(0.069)	(0.029)	(0.038)	(0.015)	(0.032)	(0.041)
SMB	0.151^{***}	0.285^{***}	0.298^{***}	0.119	0.183^{***}	0.842^{***}	0.349^{***}	0.411^{***}	0.641^{***}
	(0.040)	(0.037)	(0.074)	(0.159)	(0.064)	(0.086)	(0.034)	(0.071)	(0.092)
HML	0.160^{***}	-0.038	0.134^{**}	-0.480^{***}	0.081^{*}	0.028	0.036	-0.107^{**}	-0.054
	(0.028)	(0.026)	(0.052)	(0.110)	(0.045)	(0.060)	(0.024)	(0.050)	(0.065)
WML	-0.009	-0.026	-0.013	-0.065	-0.006	-0.049	0.042^{**}	0.059	0.029
	(0.023)	(0.021)	(0.041)	(0.089)	(0.036)	(0.048)	(0.019)	(0.040)	(0.051)
IML	0.098^{**}	-0.009	-0.060	0.260	0.040	-0.085	0.082^{**}	0.008	0.068
	(0.041)	(0.037)	(0.074)	(0.164)	(0.065)	(0.086)	(0.035)	(0.071)	(0.092)
Temp.	0.001	-0.000	0.000	-0.006^{*}	-0.001	-0.001	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(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

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

	S10	S11	S12	S13	S14	S15	S16	S17	S18
(Intercept)	-0.002^{***}	0.001	-0.000	0.001^{*}	0.001	-0.002	-0.001	-0.002	0.005^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Rm_minus_Rf	0.747^{***}	0.752^{***}	0.722^{***}	0.768^{***}	0.729^{***}	0.983^{***}	0.886^{***}	0.722^{***}	0.856^{***}
	(0.025)	(0.045)	(0.035)	(0.024)	(0.130)	(0.063)	(0.086)	(0.078)	(0.102)
SMB	0.305^{***}	0.623^{***}	0.427^{***}	0.349^{***}	0.468	0.867^{***}	0.510^{**}	0.884^{***}	0.095
	(0.056)	(0.104)	(0.085)	(0.053)	(0.311)	(0.158)	(0.211)	(0.196)	(0.241)
HML	-0.062	-0.263^{***}	-0.455^{***}	-0.174^{***}	0.189	-0.471^{***}	-0.186	-0.108	-0.132
	(0.040)	(0.073)	(0.058)	(0.038)	(0.209)	(0.105)	(0.143)	(0.129)	(0.164)
WML	-0.045	0.068	-0.030	0.053^{*}	0.274^{*}	0.202^{**}	-0.150	0.029	-0.144
	(0.031)	(0.057)	(0.044)	(0.030)	(0.160)	(0.079)	(0.109)	(0.098)	(0.124)
IML	0.117^{**}	-0.100	0.135	0.224^{***}	-0.041	0.217	0.131	0.164	0.691^{***}
	(0.056)	(0.106)	(0.091)	(0.054)	(0.336)	(0.171)	(0.227)	(0.213)	(0.260)
Temp.	-0.000	0.001	0.002	0.002^{**}	-0.008	0.000	0.002	0.001	-0.003
	(0.001)	(0.002)	(0.001)	(0.001)	(0.005)	(0.003)	(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

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 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.

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

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 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 information for risk analysis (Patterson et al. (2020)). Previous models that test the effects of

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

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 asset-level 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 proposed to investigate whether the markets price temperature shocks effects on industries stock. To do so, an augmented Fama-French five-factor model is proposed with a temperature risk factor alongside the other five common factors of the model. The literature reports a wide range of effects throughout the economic activity that might affect the stock prices, while few studies cover these effects.

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

In addition, we relied on a spatio-temporal model to create a temperature risk factor carrying geospatial information. The advancements in spatial engineering enable the development of climate-based financial models carrying asset-level data, enriching the analyzed information. Climate literature shows the importance of geolocation of climate events (Nordhaus (2013)).

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. In addition, future research can investigate mechanisms that can efficiently mitigate the effects of temperature shocks on the stock market.

References

Alvares, C., J. Stape, P. Sentelhas, J. Gonçalves, and G. Sparovek (2013). Köppen's climate classification map for Brazil. *Meteorologische Zeitschrift 22*(6), 711–728.

Aniskin, N. and C. N. Trong (2018). The thermal stress of roller-compacted concrete dams during construction. In *MATEC Web of Conferences*, Volume 196, pp. 04059. EDP Sciences.

Baer, W. (2001). *Brazilian Economy, The: Growth and Development: Growth and Development*. ABC-CLIO.

Balvers, R., D. Du, and X. Zhao (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking & Finance 77*, 18–34.

Bansal, R., M. Ochoa, and D. Kiku (2017). Climate change and growth risks. Technical report, National Bureau of Economic Research.

Bender, J., T. A. Bridges, and K. Shah (2019). Reinventing climate investing: building equity portfolios for climate risk mitigation and adaptation. *Journal of Sustainable Finance & Investment 9*(3), 191–213.

Bianchi, D., M. Büchner, and A. Tamoni (2021). Bond risk premiums with machine learning. *The Review of Financial Studies 34*(2), 1046–1089.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Global non-linear effect of temperature on economic production. *Nature 527*(7577), 235–239.

Caldecott, B., L. Kruitwagen, M. McCarten, X. Zhou, D. Lunsford, O. Marchand, P. Hadjikyriakou, V. Bickel, T. Sachs, and N. Bohn (2018). Climate risk analysis from space:

remote sensing, machine learning, and the future of measuring climate-related risk. Technical report, University of Oxford.

Chen, N., R. Roll, and S. Ross (1986). Economic forces and the stock market. *The Journal of Business 59*, 383–403.

Chinowsky, P., C. Hayles, A. Schweikert, N. Strzepek, K. Strzepek, and C. A. Schlosser (2011). Climate change: comparative impact on developing and developed countries. *The Engineering Project Organization Journal 1*(1), 67–80.

Clark, P. K. (1987). The cyclical component of U.S. economic activity. *The Quarterly Journal of Economics 102*(4), 797–814.

Connor, G., L. R. Goldberg, and R. A. Korajczyk (2010). *Portfolio Risk Analysis*. Princeton University Press.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Donovan, G. H., P. A. Champ, and D. T. Butry (2007). Wildfire risk and housing prices: a case study from Colorado Springs. *Land Economics 83*(2), 217–233.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *The Journal of Finance 47*(2), 427–465.

Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116*(1), 1–22.

Gordon, A. (1991). Global warming as a manifestation of a random walk. *Journal of Climate 4*(6), 589–597.

Graff Zivin, J. and M. Neidell (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics 32*(1), 1–26.

Grassi, S., E. Hillebrand, and D. Ventosa-Santaularia (2013). The statistical relation of sea-level and temperature revisited. *Dynamics of Atmospheres and Oceans 64*, 1–9.

Gregory, R. P. (2021). The pricing of global temperature shocks in the cost of equity capital. *Journal of International Financial Markets, Institutions and Money 72*, 101319.

Hamududu, B. and A. Killingtveit (2017). Assessing climate change impacts on global hydropower. In *Climate Change and the Future of Sustainability*, pp. 109–132. Apple Academic Press.

Hong, H., G. A. Karolyi, and J. A. Scheinkman (2020). Climate finance. *The Review of Financial Studies 33*(3), 1011–1023.

Hong, H., F. W. Li, and J. Xu (2019). Climate risks and market efficiency. *Journal of Econometrics 208*(1), 265–281.

Jacobson, M. Z. (2009). Review of solutions to global warming, air pollution, and energy security. *Energy & Environmental Science 2*(2), 148–173.

Kaswan, A. (2019). 'carbon pricing: Essential but insufficient'. Technical report, Center for Progressive Reform, July.

Krainski, E. T., V. Gómez-Rubio, H. Bakka, A. Lenzi, D. Castro-Camilo, D. Simpson, F. Lindgren, and H. Rue (2021). *Advanced Spatial Modeling with Stochastic Partial Differential Equations Using R and INLA*. Chapman & Hall/CRC Press.

Laurini, M. P. (2019). A spatio-temporal approach to estimate patterns of climate change. *Environmetrics 30*(1), e2542.

Lindgren, F., H. Rue, and J. Lindström (2011). An explicit link between Gaussian fields and Gaussian Markov random fields: The stochastic partial differential equation approach. *Journal of the Royal Statistical Society: Series B (Statistical Methodology) 73*(4), 423–498.

Lobell, D. B., U. L. C. Baldos, and T. W. Hertel (2013). Climate adaptation as mitigation: the case of agricultural investments. *Environmental Research Letters 8*(1), 015012.

Musiela, M. and M. Rutkowski (2008). *Martingale Methods in Financial Modelling*. Springer.

Nordhaus, W. (2013). *The climate casino: Risk, uncertainty, and economics for a warming world*. Yale University Press.

Pao, H.-T. and H.-C. Fu (2013). Renewable energy, non-renewable energy and economic growth in Brazil. *Renewable and Sustainable Energy Reviews 25*, 381–392.

Patterson, D. J., Y. Ariel, B. Burks, E. M. Gratcheva, J. S. Hosking, N. Klein, L. Protopopova, E. E. T. Ruiz, S. Schmitt, B. Shackelton, et al. (2020). Spatial finance: Challenges and opportunities in a changing world. Technical report, World Bank.

Proietti, T. and E. Hillebrand (2017). Seasonal changes in central England temperature. *Journal of Royal Statistical Association - Series A 180*(3), 769–791.

Pryor, S. C. and R. Barthelmie (2010). Climate change impacts on wind energy: A review. *Renewable and Sustainable Energy Reviews 14*(1), 430–437.

Quiggin, J. and J. Horowitz (2003). Costs of adjustment to climate change. *Australian Journal of Agricultural and Resource Economics 47*(4), 429–446.

Ross, S. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory 13*, 341–360.

Rue, H., S. Martino, and N. Chopin (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society: Series B (Statistical Methodology) 71*(2), 319–392.

Salinas, C. X. and J. Mendieta (2013). Mitigation and adaptation investments for desertification and climate change: an assessment of the socioeconomic return. *Mitigation and Adaptation Strategies for Global Change 18*, 659–672.

Valente, F. and M. Laurini (2022). Urban climate change: A statistical analysis for são paulo. *Urban Climate 41*, 101077.

Yavuzturk, C., K. Ksaibati, and A. Chiasson (2005). Assessment of temperature fluctuations in asphalt pavements due to thermal environmental conditions using a two-dimensional, transient finite-difference approach. *Journal of Materials in Civil Engineering 17*(4), 465–475.

Zhang, P., O. Deschenes, K. Meng, and J. Zhang (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. *Journal of Environmental Economics and Management 88*, 1–17.