Is the Positive Correlation Between Beta and Return Consistent Across Countries and Over Time?

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Abstract

Antoniou et al. (2016) introduced investor sentiment into the analysis of the beta-return relationship, to examine the linear upward-sloping relationship predicted by the Capital Asset Pricing Model (CAPM). Their U.S.-focused study showed low beta stocks outperform high beta stocks during optimistic periods and the reverse during pessimistic periods. The purpose of our research is to extend this analysis globally, to explore the impact of temperature and latitude on investor sentiment, beta, and stock returns. We created Temperature-Beta portfolios, dividing the sample into warm-climate and cool-climate countries. Our findings reveal that globally, beta-sorted portfolios show a smaller, statistically insignificant performance gap between low and high-beta stocks, differing from U.S.-based models. When we analyzed the impact of latitude and separated countries into warm-climate and cool-climate groups, the significant influence of beta on stock returns was less evident, suggesting limited effects of beta, investor sentiment, and latitude on global portfolios. However, considering temperature, we found a nonlinear relationship with stock returns: during moderate temperatures and optimism, stocks had lower returns, whereas during extreme temperatures and pessimism, stocks had higher returns. Incorporating latitude, the expected significant impact of beta on stock returns was not pronounced. In this research, we found the beta and return relationship for the global portfolio. High temperatures boosted stock returns in warm-climate countries during optimistic periods, while low temperatures negatively affected stock returns in cool-climate countries during pessimistic periods. These findings demonstrate the complex interplay between temperature, investor sentiment, and stock returns across different global climates. These findings underscore the complex interplay of temperature, investor sentiment, and stock returns across different global climates.

Keywords: Stock Returns; Temperature-Beta; Latitude; Portfolio; Investor Sentiment
JEL Classification: G12, G41

1. Introduction

The Capital Asset Pricing Model (CAPM), developed by Sharpe (1964) and Lintner (1965), suggests that the required return on a stock investment is linearly correlated with its corresponding systematic risk, known as the asset's beta. However, Fama and French (1992) found no relation between expected returns and beta, challenging the applicability of the CAPM. In a subsequent study, Antoniou *et al.* (2016) introduced the concept of investor sentiment into the analysis of beta and stock returns, demonstrating that the beta-return relationship can exist under certain conditions. They incorporated pessimistic and optimistic sentiment measures by using Baker and Wurgler's (2006) index (BW) and discovered that the standard CAPM only holds for U.S. stocks during pessimistic periods. Specifically, during optimistic periods, noise traders tend to invest heavily in risky stocks, causing them to become overpriced and subsequently underperform. This optimism-driven effect can weaken the positive beta-return relationship. In contrast, noise investors tend to stay away from the market during pessimistic periods, allowing the standard CAPM to remain applicable. However, it's important to note that this result appears to be limited to U.S. data. This favorable result may not hold when extended to global data, as demonstrated in Section 6.

One potential reason for this inconsistency could be the influence of other geographical factors that can potentially affect stock returns and investor sentiment on a global scale. We propose that such factors include latitude and weather conditions. In particular, we present evidence that, beyond investor sentiment, temperature, a direct indicator of weather, plays a significant role in global stock returns (Huang *et al*., 2023; Huang and Sugianto, 2024) and the relationship between beta and returns on a global scale.

Research on the interplay between temperatures and stock performance has a rich history dating back to the early 20th century. Numerous studies have delved into the impact of temperature on stock returns, including works by Cao and Wei (2005), Chuang *et al.* (2006), Silva and Almeida (2011), Brahmana *et al.* (2012), Kathiravan *et al.* (2018), Andrikopoulos *et al.* (2019), Sugianto and Huang (2020), Yan *et al.* (2022), and Makridis and Schloetzer (2022).

Cao and Wei (2005) employed temperature as a tool to explore its influence on stock returns across various countries. Their findings revealed a linearly negative correlation between stock market returns and temperature. They observed that lower temperatures were associated with better stock market returns, possibly due to a prevalence of aggressive risk-taking behavior. Conversely, higher temperatures appeared to result in lower stock market returns due to the dominance of investor apathy over aggression.

Numerous studies conducted worldwide have presented diverse findings when compared to Cao and Wei (2005). Chuang *et al.* (2006), Kathiravan *et al.* (2018), Yan *et al.* (2022), and Makridis and Schloetzer (2022) observed that temperature exerted a significant and negative impact on the stock markets of several countries; Spain, Taiwan, Sri Lanka, China, and the United States. In contrast, Silva and Almeida (2011) reported that lower temperatures were associated with higher returns in Portugal's stock market index. Brahmana *et al.* (2012), however, concluded that temperature had no discernible influence on market returns in the Australian and Indonesian stock exchanges. Furthermore, Andrikopoulos *et al.*

(2019) found that temperature did not significantly affect stock returns in the US and UK market indices. In a broader context, Sugianto and Huang (2020) discovered significant positive effects of temperature on returns across stock market indices in various countries. The variability in results can be attributed to geographic location and the specific models employed in these studies.

Most previous studies in the area of weather-return relationships have often assumed a linear relationship between weather conditions and stock returns. However, as demonstrated by Boduch and Fincher (2009), the World Health Organization (1990), and Huang *et al.* (2023), the impact of weather, especially temperature, on human activities is likely to be nonlinear. Human comfort typically falls within a specific temperature range, beyond which temperatures can become uncomfortable. The range of comfortable temperatures for human beings typically falls between 9°C and 26°C. Extreme temperatures, whether uncomfortably hot or cold, tend to influence investor behavior more than moderate temperatures substantially.

Huang *et al.* (2023) introduced a nuanced perspective, demonstrating that the relationship between stock returns and temperatures is nonlinear and contingent on regional factors. Their research revealed that investors from warm-climate countries with tropical or subtropical climates tended to achieve higher returns during hot temperatures (greater than 23°C). On the other hand, investors from cool-climate countries with temperate or polar climates experienced enhanced returns during periods of cold weather (lower than 11°C).

No matter whether temperature has a linear or non-linear impact on stock returns, all the above studies use temperature to proxy investment sentiment to investigate the direct impact on stock returns. One main problem associated with these studies is that the potential interaction between weather and investor sentiment is ignored.

Only Goetzmann *et al.* (2015) delved into the impact of deseasonalized cloud cover on investor sentiment, measured by the buy-sell imbalance at the investor level. Their study, conducted using data from the United States, revealed that weather conditions influence institutional investors' perceptions of market mispricing. They established that lower levels of deseasonalized cloud cover, indicative of investor optimism, were negatively associated with overpricing. According to Goetzmann *et al.* (2015), weather significantly affects investor sentiment, likely influencing the beta-return relationship. However, it's important to note that Goetzmann *et al.* (2015) did not explore the influence of investor sentiment on stock returns.

Therefore, this paper has a dual objective. Firstly, we strive to confirm the reliability and endurance of the beta-return relationship across diverse countries and varying time frames. Secondly, we endeavor to explore whether temperature and latitude influence alterations in the beta-return relationship.

Previous studies by Huang and Sugianto (2024a) and Huang *et al.* (2023) have investigated the link between temperature and stock returns, focusing mainly on individual stocks rather than portfolios. Our research aims to enhance this methodology by incorporating a temperature-beta portfolio and investor sentiment indicators. Detailed information on the temperature-beta portfolio can be found in Section 4. Additionally, we include beta in our analysis to examine its relationship with returns. This study also seeks to demonstrate the consistency of beta as a predictor for global portfolios. By expanding the scope from individual stocks to a broader portfolio analysis, we hope to provide a more comprehensive understanding of these relationships. Ultimately, our goal is to validate beta's reliability in the context of international markets.

2. Latitude and Weather Risk

In international markets, we believe that factors such as geographic location and climate play a significant role in influencing the beta-return relationship. Geographic location can be assessed through the latitude of a country. Climate, in this context, is essentially captured by the concept of weather risk. Weather risk refers to the potential impact that variations in weather conditions can have on financial markets.

Firstly, the relationship between beta and returns in international markets is likely influenced by latitude. VandeVliert and Van Lange (2019) found that people tend to become less aggressive as they move from the equator toward the north poles. They observed differences in attitudes and behaviors related to aggression and self-control between individuals in the northern and southern parts of the northern hemisphere. If the latitude affects how aggressively investors take risks, the influence of temperature on returns, whether straightforward or complex, is likely to be shaped by these geographical distinctions. It's important to examine how weather might negatively affect stock performance carefully. This is crucial for investors to make well-informed decisions about their trading or investment strategies and to create effective risk-control measures. To achieve success in this area, it's essential to fully understand how weather risks impact investor behavior.

Second, the impact of weather began with psychological studies that posited a connection between temperature levels and human responses. Allen and Fisher (1978) and Pilcher *et al.* (2002) suggested that humans are influenced by both high and low temperatures. Additionally, Wyndham (1969) conducted research that highlighted behavioral changes in response to extreme heat. He observed that individuals tend to become more prone to hysteria and apathy during periods of extreme heat. Supporting these findings, researchers such as Howarth and Hoffman (1984), Baron and Ransberger (1978), Schneider *et al.* (1980), Palamerek and Rule (1980), and Bell (1981) concluded that aggression levels tend to rise at higher temperatures. Cunningham (1979) observed that individuals are less inclined to provide assistance in conditions of extreme heat or cold. However, these investigations did not explicitly identify the specific temperature thresholds that induce such reactions.

In other literature, critical temperature thresholds have been identified as triggers for distinct human behaviors. Boduch and Fincher (2009) and the World Health Organization (1990) noted that the comfort zone for humans typically falls within the range of 18–24°C (64–75°F) indoors and 15–25°C (59–77°F) in work environments. Lane (2011) suggested that 18°C (64°F) is suitable for healthy individuals, 16°C (60.8°F) for those with respiratory problems and allergies, and at least 20°C (68°F) for very young or elderly individuals, as well as those who are ill or disabled. Temperatures outside of these ranges can lead to discomfort and potential health issues.

The effect of latitude and temperatures have been investigated by Huang *et al.* (2023). They found that investors from warm-climate countries with tropical or subtropical climates tended to achieve higher returns during hot temperatures (greater than 23°C). On the other hand, investors from cool-climate countries with temperate or polar climates experienced enhanced returns during periods of cold weather (lower than 11°C). Huang and Sugianto (2024b) also found that countries situated further from the equator experience less intense effects from hot temperatures compared to those closer to the equator. Additionally, the further a country is from the Greenwich Meridian, the more pronounced the impact of global warming sentiment is on investors.

In conclusion, countries located at different latitudes experience diverse climate patterns, resulting in unique market conditions. These variations can affect investor behavior and sentiment, thereby influencing the beta-return relationship. By factoring in geographic location and climate, we aim to gain deeper insights into how these elements impact stock return dynamics in international markets. This method acknowledges the complexity of global financial markets and strives to offer a more detailed understanding of the underlying mechanisms at work.

3. Investor Sentiment

The significant influence of investors' psychological behavior on the stock market has been extensively documented in the literature (Daniel, Hirshleifer, and Subrahmanyam, 1998; Mehra and Sah, 2002; Wallace, 2010). According to the behavioral finance hypothesis, individuals occasionally make irrational decisions in the stock market, such as buying and selling stocks, because they tend to give greater importance to recent information while downplaying past experiences (De Bondt and Thaler, 1985). This irrationality, stemming from investors' emotions, mood swings, and sentiment (Mehra and Sah, 2002), can result in mispricing and bias in stock prices (Daniel *et al*., 1998). As Thaler (1999) argued in his paper, cognitive biases, such as investor overreaction, can lead to predictable mispricing of traded stocks. These arguments challenge the efficient market hypothesis, which posits that returns cannot be predicted, and also cast doubt on the claim of the Capital Asset Pricing Model (CAPM) that returns and beta are positively correlated.

In one of the earliest studies, Delong *et al.* (1990), in their theoretical study, claimed that investors are subject to sentiment, and many investors do not follow economists' advice to buy and hold the portfolio. They split investors into two types: rational individuals who are not swayed by sentiment, and irrational ones who are influenced by it. These two groups of investors compete with each other and play a role in determining market prices.

Numerous studies have explored the impact of investor sentiment on stock market returns, employing various methodologies and considering a wide range of factors and conditions. For instance, in an early study, Shleifer and Vishny (1997) linked investor sentiment to arbitrage. They noted that rational investors are less aggressive compared to irrational ones, which makes attempts to drive prices towards fundamentals and away from the influence of sentimental investors a risky and potentially costly endeavor. Other studies, such as those by Ritter (1984) and Ljungqvist and Wilhelm (2003), focused on investor sentiment in Initial Public Offerings (IPOs). They discovered that start-up companies tend to experience higher initial returns on their IPOs compared to well-established, mature, and profitable offerings. During economic crises, researchers like Asness *et al.* (2000) and Chan *et al.* (2000) applied the concept of investor sentiment to investigate the impact of the stock market bubble in 2000. They found that prior to the market crash, the high valuations of growth stocks were difficult to rationalize based on anticipated earnings growth.

Some studies developed the link between investor sentiment and investor confidence. Daniel, Hirshleifer, and Subrahmanyam (1998) studied the effect of overconfidence. They proved that investors are overconfident because they overweight their private information and ignore publicly available information. As a result, investors overreact to private information and underreact to public information. Boyle *et al.* (2004) showed that investors' confidence and willingness to invest in risky assets increase during festive occasions and in good sentiment.

Recent studies have further developed investor sentiment indicators, expanded sample data, and applied more comprehensive models. A key literature on investor sentiment that we adopt is Baker and Wurgler (2006, 2007). They used cross-section analysis to examine the relationship between investor sentiment and stock returns. Their samples included U.S. stock market data and considered six investor sentiment indicators: (1) CEFD, the average difference between the net asset values (NAV) of closed-end stock fund shares and their market prices; (2) TURN, the natural log of the raw turnover ratio, detrended by the 5-year moving average; (3) NIPO, the number of IPOs; (4) RIPO, the average first-day returns of initial public offerings; (5) S, the share of equity issues in total equity and debt issues, which may capture sentiment dividend premium; (6) PD−ND, the log difference of the average market-to-book ratios of payers and nonpayers. These components were combined to create a single index (BW), which has been adopted by many recent papers to develop sentiment as a proxy in various research topics in finance. By including these investor sentiment indicators and applying them to a broader sample encompassing multiple countries, our paper breaks new ground in the field, offering a more comprehensive investigation.

Our research is motivated by the idea that climate, particularly global warming, can influence human behavior, especially the behavior of financial market participants. Extreme weather conditions also impact financial sentiment, often causing investors to overreact. This overreaction, during extreme weather events, can significantly amplify projection bias and affect financial markets and stock returns. Therefore, examining the influence of a critical global warming factor becomes intriguing. By incorporating investor sentiment indicators into our model in conjunction with climate factors, our paper is among the first to combine investor sentiment studies with climate-related factors. As a result, we find that our model is more robust than previous ones.

This paper aims to investigate the relationship between global warming, investor sentiment, beta, and stock returns. Additionally, we expand our sample to include 25 countries; including developed countries from Fama and French (2012) and emerging markets of international market data.

4. Temperature-Beta Portfolio

Bower (1981, 1991), Arkes *et al.* (1988), Wright and Bower (1992), Johnson and Tversky (1983) have all documented that sentiment refers to a mental attitude, which can be either positive or negative. Positive sentiment is associated with excessively optimistic attitudes, while negative sentiment is linked to overly pessimistic attitudes. Antoniou *et al.* (2016) also discovered that investor sentiment plays a significant role in the relationship between beta and stock returns. They found that noise traders tend to be more bullish about high beta stocks when sentiment is positive, whereas investor behavior appears to align more closely with rationality during negative periods. They also concluded that beta is positively priced when the standard Capital Asset Pricing Model (CAPM) holds during pessimistic periods. Therefore, grouping the portfolio by sentiment and beta is a crucial step in the portfolio formation process.

Similar to Antoniou *et al.* (2016), we utilize Baker and Wurgler's (2006) index (BW) in our basic analysis to measure sentiment. We orthogonalize this index with respect to several macro factors. Additionally, we follow Antoniou *et al.* (2016) in completing the methodology proposed by Fama and MacBeth (1973) by incorporating the sentiment factor into beta portfolios. This allows us to examine variations in stock returns across beta portfolios. Our procedure begins with the calculation of beta using the basic methodology of Fama and MacBeth (1973). To determine decile breakpoints, we sort all stocks in each country by pre-ranking betas for individual equities, accounting for beta variance. We use the available 24-60 monthly returns to calculate these pre-ranking betas. This process helps us establish beta breakpoints for each size decile using all stocks in each country. Thus, we create 5 size-beta portfolios through this method. We also apply this process to form portfolios for the world, warm-climate, and cool-climate countries.

Subsequently, we employ the Fama and MacBeth (1973) methodology to conduct regressions on the returns for post-formation betas and control variables for each month, denoted as t. We believe that Fama and MacBeth (1973) model is a more reliable predictor of beta stock formation and its impact on stock returns.

As previously mentioned, various studies, including Chuang *et al.* (2006), Silva and Almeida (2011), Brahmana *et al.* (2012), Kathiravan *et al.* (2018), Andrikopoulos *et al.* (2019), Sugianto and Huang (2020), Yan *et al.* (2022), and Makridis and Schloetzer (2022), have demonstrated that temperature significantly influences stock returns by affecting investor sentiment. Therefore, we propose to include temperature as an additional indicator for portfolio formation alongside beta. We use the methodology employed by Antoniou *et al.* (2016), which follows the beta portfolio formation process outlined by Fama and French (1992). However, our approach introduces an additional dimension by categorizing the samples into five quintiles based on temperature.[1] The process initiates with beta estimation, specifically in June of year t, where all firms are sorted by temperature to establish quintile breakpoints.

Utilizing these breakpoints, we assign all firms in the sample for year t to five temperature portfolios. To account for beta variation unrelated to temperature, each temperature quintile is further subdivided into five portfolios based on pre-ranking betas for individual stocks. These pre-ranking betas are computed using 24–60 monthly returns (as available) concluding in June of year t. We set beta breakpoints for each temperature quintile, resulting in 25 temperature-beta portfolios.

Following the categorization of firms into temperature-beta portfolios in June, we calculate the equally weighted returns for these portfolios from July of year t until June of year t+1. This process yields 100 time series of returns, one for each temperature-beta portfolio, spanning our entire sample period. Post-formation betas are estimated using the returns of these portfolios, employing the CRSP value-weighted return as a proxy for the market portfolio. Similar to Fama and French (1992), pre- and post-ranking betas are computed as the sum of slopes in the regression of returns on the current and lagged market return.

5. Hypothesis and Research Design

5.1. Primary Examination of CAPM's Validity.

One main goal of this study is to confirm if the beta-return relationship remains consistent and enduring across various countries and over time. In our initial analysis, we evaluate the applicability of the Capital Asset Pricing Model (CAPM) for each country, breaking down our first analysis into three key steps:

Step 1. Examination of CAPM's Upward Slope: In this step, we investigate the upward slope of CAPM beta (β) coefficient under the assumption of linearity in each country. The goal is to confirm that beta coefficient is greater than 0 for each country.

$$\text{The } beta > 0 \text{ for each country}$$

Step 2. Reevaluation under Different Investor Sentiment to examine the result of Antoniou *et al.* (2016): Following the first step, we reexamine our findings under varying investor sentiment. We aim to verify that beta coefficient is greater than 0 under pessimistic periods

[1] In the beginning, we do not divide the portfolios by size to accommodate beta variations unrelated to size. Nevertheless, we will incorporate this aspect in our robustness testing.

and less than 0 under optimistic periods for each country. And that the difference between the slopes under pessimistic (beta) and optimistic (gamma) periods is not equal to 0.

$$beta > 0 \text{ for each country}$$
$$beta - gamma \neq 0$$

Where beta is the slope of β under pessimistic periods, gamma is the slope of γ under optimistic periods.

Step 3. Aggregating Country Data: In this step, we consolidate data from all countries, adopting a methodology similar to Fama and French (1993). We employ an F-test to assess whether beta is greater than 0 across the entire dataset.

$$F\text{-}test \text{ for } beta > 0$$

By following these steps, our aim is to confirm the consistency of the beta-return relationship globally and comprehend its behavior in diverse circumstances. However, in Section 6, we discovered that the outcomes of the Capital Asset Pricing Model (CAPM) are not valid. To improve our results, we divided the sample countries into two groups based on latitude—categorized as tropical and non-tropical, and warm and cool-climate. Additionally, we segmented our samples into different time periods: two sub-periods (1973-1996; 1997-2020), three sub-periods (1973-1988; 1989-2004; 2005-2020), and five sub-periods (1970s, 1980s, 1990s, 2000s, 2010s). After this segmentation, we reevaluated whether $\beta > 0$. If the latitude split yields meaningful results, we can conclude that latitude might be a contributing factor. Additionally, we explore the possibility that temperature influences the results. To test this, we split the samples by temperature and assess whether it can account for the observed trends.

5.2. Temperature-Beta Portfolio Model

As discussed in Section 1, previous research has predominantly focused on examining the relationship between investor sentiment and stock returns, assuming a linear association. However, under extreme weather conditions, emotions tend to fluctuate more significantly, potentially leading to greater projection bias. This heightened projection bias could have a more pronounced impact on the stock market and stock returns. In such extreme conditions, the link between investor sentiment and stock returns is likely to be nonlinear (Huang *et al.*, 2023). People tend to become more emotional when faced with extremely high or low temperatures, which can influence their investment behavior and stock performance. Furthermore, extreme temperatures may induce more pronounced price movements or trading volume in the stock market.

In addition to forming temperature-beta portfolios, we will also segment sentiment into two conditions: positive and negative sentiment, following the approach of Antoniou *et al.*

(2016). The calculation of sentiment indicators will be based on Baker and Wurgler (2006, 2007) methodology. However, since we are examining data from 25 sample countries, some of the six sentiment indicator proxies originally proposed by Baker and Wurgler may not be available. In such cases, we will replace them with four proxies that are readily accessible and represent major macroeconomic influences: 1. Turnover: The five-year moving average detrended by the natural log of the raw turnover ratio. 2. CC (Consumer Confidence): The consumer confidence index, suggested by Corredor *et al.* (2013). 3. NIPO: the number of IPOs. 4. RIPO: the average first-day returns of initial public offerings

We will then create a sentiment-changes index to investigate return co-movement patterns associated with changes in sentiment. The levels index will essentially comprise the first principal component of the four proxies, while the changes index will consist of the first principal component of changes in the four proxies. The methodology used by Baker and Wurgler (2006, 2007) will be applied to generate positive and negative sentiment indicators, which will be used for segmenting our portfolio samples.

Anderson and Bushman (2002) found that high temperatures play a significant role in triggering an increase in aggressive thoughts, physiological arousal, and a surge in angry feelings that contribute to violent behavior. Prudkov and Rodina (2019) extended this understanding, suggesting that aggression and violence can be viewed as outcomes resulting from the accumulation of depressive mood states induced by cold temperatures during the winter. Both hot and cold temperatures have the potential to induce aggression, and when these temperatures reach extremes, the fluctuation in people's emotions becomes more pronounced, leading to a greater projection bias. In such conditions, the relationship between weather and stock returns is more likely to exhibit nonlinearity. Studies by Huang *et al.* (2023) and Cao and Wei (2005) have indicated that extreme temperatures can make individuals more aggressive in their investment behavior.

Extreme temperatures, whether extremely high or low, have a notable effect on the emotional responses in individuals. These emotional reactions, in turn, wield a substantial influence on investment decisions and, consequently, play a pivotal role in shaping the performance of stocks. Moreover, the impact of extreme temperature conditions extends beyond individual sentiments to affect the overall dynamics of the stock market. Such conditions often give rise to more pronounced price fluctuations and heightened trading activity.

Dahmene *et al.* (2021) demonstrated that heightened optimism results in stock prices being overvalued, while Balasuriya *et al.* (2010) found that financial optimism leads to increased risk-taking, manifesting in the selection of riskier portfolios and higher levels of borrowing. During periods of extreme heat, optimistic investors are inclined towards more aggressive risk-taking. In contrast, Mansour *et al.* (2008) observed that pessimistic investors tend to be risk-averse, potentially due to an inclination to exaggerate negative experiences or maintain defensively low expectations. This suggests that extreme heat might mitigate aggressive risk-taking among pessimistic investors. Conversely, depression induced by cold temperatures can intensify aggressiveness, especially when coupled with pessimism. This interplay of mood and weather contributes to a nonlinear relationship between temperature and stock returns. Utilizing winner and loser stock portfolios, as suggested by De Bondt and Thaler (1985), acts as a measure of excessively optimistic and pessimistic risk-taking. De Bondt and Thaler (1985) highlighted that prior optimism or pessimism significantly influences the subsequent performance of stocks in investors' portfolios.

In view of these noteworthy observations, another primary objective of this study is to delve into two pivotal hypotheses related to temperature-beta portfolios. We want to prove the influence of temperatures on stock returns under different investor sentiments. Drawing on insights from the research conducted by Huang *et al.* (2023) and recognizing the significance of investor sentiment in this context, we aim to contribute a nuanced understanding of the interplay between extreme temperatures and stock market dynamics.

Considering the supporting evidence gathered thus far and the preliminary findings outlined in the subsequent section (Section 6), we have formulated two hypotheses that form the crux of our investigation. These hypotheses are crafted to shed light on the intricate relationship between temperature conditions and beta portfolios. They will serve as the foundation for our subsequent analysis and discussions, enhancing our comprehension of the multifaceted connections between weather extremes, investor sentiment, and stock market behaviors.

From above supporting evidences and the preliminary results we found in the next section, Section 6, we constructed first hypothesis as follows:

H1. *In periods characterized by normal temperatures and optimism, stocks are expected to generate lower returns. Conversely, during times of extreme temperatures and pessimism, stocks are anticipated to yield higher returns.*

In addition of investor sentiment, Antoniou *et al.* (2016) introduced the concept of investor sentiment into the analysis of beta and stock returns, showing that the beta-return relationship can manifest under specific conditions. Bower (1981, 1991), Arkes et al. (1988), Wright and Bower (1992), and Johnson and Tversky (1983) have all noted that sentiment reflects a mental outlook, which can be either positive or negative. Positive sentiment is tied to overly optimistic views, whereas negative sentiment is connected to excessively pessimistic attitudes. By using Baker and Wurgler's (2006) sentiment index, they found that the traditional CAPM holds true for U.S. stocks only during pessimistic periods. During optimistic times, noise traders tend to overinvest in high-risk stocks, leading to their overpricing and subsequent underperformance, thereby weakening the positive beta-return relationship. Conversely, in pessimistic periods, noise traders generally avoid the market, allowing the standard CAPM to apply effectively.

Dahmene *et al.* (2021) demonstrated that increased optimism can lead to stock prices being overvalued, while Balasuriya et al. (2010) found that financial optimism encourages greater risk-taking, including selecting riskier portfolios and higher borrowing levels. During extreme heat, optimistic investors tend to engage in more aggressive risk-taking. Conversely, Mansour et al. (2008) noted that pessimistic investors are generally risk-averse, possibly due to a tendency to exaggerate negative experiences or maintain low expectations. This suggests that extreme heat might reduce aggressive risk-taking among pessimistic investors, whereas cold temperatures can increase aggressiveness, particularly when combined with pessimism. This interaction between mood and weather contributes to a nonlinear relationship between temperature and stock returns. Utilizing winner and loser stock portfolios, as suggested by De Bondt and Thaler (1985), helps measure excessively optimistic and pessimistic risk-taking, indicating that prior optimism or pessimism significantly impacts the future performance of stocks in investors' portfolios.

Furthermore, Van Lange *et al.* (2017) discovered that individuals in different latitudes exhibited distinct lifestyles and levels of aggression. Van de Vliert and Van Lange (2019) found that latitude significantly influenced investors' aggressive risk-taking, with aggression diminishing as investors resided farther away from the equator toward the north pole. In their study, Huang *et al.* (2023) identified an investment strategy wherein investors could achieve exceptionally high returns by purchasing winner stocks from warm-climate countries and selling loser stocks from cool-climate countries during extremely hot weather conditions. The impact of extremely hot temperatures on stock returns was more pronounced in warm-climate countries than in cool-climate countries, while the effect of extremely cold temperatures was stronger in cool-climate countries. They concluded that under the influence of extreme temperatures, investors tended to adopt aggressive investment behavior and exhibit a propensity for risk-taking, contingent on whether they were located in a warm-climate or cool-climate country. The predictive power of beta in forecasting stock returns is predominantly applicable to countries with cool climates. In contrast, the global portfolio and countries with warm climates are anticipated to display statistically insignificant relationships between beta and stock returns. This categorization into cool-climate and warm-climate groups aligns with the impact of latitude as proposed by Huang *et al.* (2023). Therefore, we can construct our second hypothesis as follows:

H2. *For warm-climate countries, the upward-sloping relationship between beta and return is more significant under pessimism rather than under optimism under high temperatures. In contrast, for cool-climate countries, the downward-sloping relationship between beta and return is more apparent under pessimism rather than under optimism under low temperatures.*

We use a regression model separately for different conditions to assess how temperature affects investor sentiment in both optimistic and pessimistic periods. We categorize the monthly temperature data in each country or region into three groups: high, medium, and low. The high temperature group includes the top 30% of temperatures, the medium group covers the middle 40%, and the low group consists of the bottom 30%. We then apply our regression model to each of these temperature groups to analyze the data.

$$R_i = a + beta\,\beta + c\ln[ME] + d\ln[BM] + e\,Ret1 + f\,Ret6 + g\,Ret12 \tag{1}$$

Where β is the stock beta, *ln[ME]* is natural log of stock market equity, and *ln[B/M]* is natural log of book to market ratio. The return of stock i in month t − 1 is indicated as *Ret1*; *Ret6* is cumulative return of stock i in the six months prior to month t − 1; and *Ret12* is the cumulative return of stock i in the six months prior to month t − 7. This model is based on the approach used by Antoniou *et al.* (2016).

Following the approach outlined by Huang *et al.* (2023), we also categorize our sample into two distinct groups: Group 1, comprising warm-climate countries (latitude 0–40), and Group 2, consisting of cool-climate countries (latitude 40–90). The classification is based on the Koppen Climate Classification, which divides the world into four climate regions: tropical (latitude 0–23.5), subtropical (latitude 23.5–40), temperate (latitude 40–60.5), and polar (latitude 60.5–90). Notably, Huang *et al.* (2023) condensed this into two regions by merging countries with a tropical or subtropical climate into the warm-climate category (latitude 0–40) and those with a temperate or polar climate into the cool-climate category (latitude 40–90).

The findings from Huang *et al.* (2023) indicate that investors experienced higher returns in both extremely hot and cold temperatures compared to comfortable temperatures. Their analysis reveals that elevated temperatures correlated with increased returns specifically for investors hailing from warm-climate countries with a tropical or subtropical climate. Conversely, lower temperatures were associated with higher returns exclusively for investors originating from cool-climate countries with a temperate or polar climate. This underscores the necessity of bifurcating the sample countries into two groups based on climate regions for a more nuanced understanding of the temperature-return relationship.

6. Data

The MSCI Developed Markets Index encompasses 23 developed countries and 25 emerging markets. However, due to constraints in data availability, certain countries were excluded owing to the absence of temperature data and investor sentiment indicators. Norway, Hungary, Belgium, Egypt, India, Taiwan, and Hong Kong lack temperature data. After removing these 7 countries from the initial 48, we assessed the availability of investor sentiment data. It was observed that New Zealand, Singapore, Malaysia, Thailand, Philippines, Chile, Colombia, Peru, Czech Republic, Pakistan, Qatar, Saudi Arabia, Kuwait, South Africa, Turkey, and the UAE did not have sentiment data. Consequently, our final dataset comprises 25 countries across four regions: (i) North America, including the United States and Canada; (ii) Europe; (iii) Japan; and (iv) the Asia Pacific.

To uphold the integrity and reliability of our dataset, we meticulously adhered to the data screening and enhancement protocols articulated by Corredor *et al.* (2013) and Ince and Porter (2006). This comprehensive process entailed several key steps:

1. Removal of Padded Zero Returns: We systematically eliminated any artificially appended zero returns that often appeared at the conclusion of delisted companies' data records.
2. Minimum Data Length Requirement: Stocks with less than 24 months of return data were excluded from our analysis.
3. Price Threshold: Entries with a stock price lower than US$1 were also omitted from our dataset, ensuring the data's quality and applicability to our research goals.
4. Treatment of Outliers: Similar to the methodology adopted by Corredor *et al.* (2013) and Ince and Porter (2006), we identified and pruned outliers from our dataset. This involved discarding monthly returns that fell below the 5^{th} percentile and those that exceeded the 95^{th} percentile.
5. Exclusion of Financial Firms: In order to maintain the dataset's relevance to our research objectives, we opted to exclude all entries pertaining to financial firms.
6. Exclusion of Inapplicable Entries: Foreign firms, listings not categorized as equity, and firms lacking market equity were promptly removed from our dataset to ensure its coherence.
7. Adjustment for Specific Entity Types: To further enhance the dataset's suitability, we made specific exclusions and adjustments. This included removing Global Depositary Receipts (GDRs), cross-listed firms, and multinational corporations, in line with the methodology advanced by Griffin *et al.* (2010).

To investigate the relationships between investor sentiment, stock beta, returns, and temperatures, we integrated various datasets. The first dataset comprises monthly average temperature data collected from weather stations, which can be downloaded from the National Climatic Data Center of the National Oceanic and Atmospheric Administration (www.ncdc.noaa.gov). The second dataset encompasses financial data, including monthly stock prices for calculating monthly stock returns, obtained from Thomson Reuters Data Stream. Additional financial data, such as trading volume, shares outstanding (used to calculate the turnover ratio), market equity, and book-to-market ratio, were sourced from the S&P Capital IQ database.

Following the methodology employed by Huang and Sugianto (2024a), we undertook a process to align the zip codes of individual firms from the S&P Capital IQ database with the geographical coordinates, specifically latitude and longitude, of the respective weather stations located near each firm's headquarters. This methodology is consistent with recent studies such as Pankratz *et al.* (2019), Hugon and Law (2019), and Pérez-González and Yun (2013), although it's important to note that these studies primarily focused on data from the United States.

To facilitate this merging process, we acquired zip codes and geographic coordinates for various global locations from two sources: GeoNames (http://www.geonames.org/) and the Geodata International database provided by Killet GeoSoftware Inc. (https://www.killetsoft.de/p_igda_e.htm). This allowed us to combine the two datasets, effectively linking each individual firm to its corresponding weather reporting station.

The merging procedure encompassed several distinct steps. To commence, we amalgamated the Geodata International dataset with the temperature dataset. A key consideration was the dissimilarity in the level of detail pertaining to geographical coordinates within these datasets. To address this, we opted to round the latitude and longitude values to a single decimal place. This adjustment provided an approximate accuracy of 0.1°, equating to a geographical span of approximately 11.1 kilometers for each weather station. In essence, this refinement delineated the coverage area of each weather station as an 11.1x11.1 square kilometer zone. Subsequent to this adjustment, we proceeded to merge this amalgamated dataset with the accounting data. This fusion was achieved through a matching process predicated on zip or postal codes, a technique akin to that outlined by Huang and Sugianto (2024a). Specifically, the two datasets were harmonized by aligning individual entries based on their respective zip or postal codes.

In our final sample, we included a total of 113,295 stocks spanning from the beginning year to year 2020. The breakdown of the number of stocks in each country is provided in Table 1.

Table 1 List the number of stocks, latitude, and temperature of each country.

	Country	Number of stocks	Beginning year	Latitude			
				Center	Bottom	Top	Diff
Panel A:							
1	Australia	7,591	1974	-27.732	-43.003	-12.461	30.542
2	Brazil	934	1994	-21.150	-52.950	10.650	63.600
3	Indonesia	1,176	2001	-2.500	-11.000	6.000	17.000
4	Mexico	791	2001	23.500	14.000	33.000	19.000
5	Japan	19,465	1982	36.205	20.000	45.000	25.000
6	China	6,802	1991	35.288	18.243	52.333	34.090
7	United States	17,515	1973	37.090	19.501	64.857	45.356
8	Korea	3,559	1998	38.000	33.000	43.000	10.000
9	Greece	3,353	1988	39.074	35.012	41.503	6.491
10	Portugal	80	1988	39.400	32.633	42.079	9.446
11	Spain	2,841	1987	40.417	27.000	44.000	17.000
12	Italy	4,648	1973	41.872	36.717	46.996	10.279
13	France	1,712	1973	46.228	41.591	51.035	9.444
14	Switzerland	955	1973	46.818	45.832	47.697	1.865
15	Austria	1,658	1977	48.210	46.527	48.817	2.290
16	Germany	1,193	1973	51.166	47.407	54.908	7.501
17	Poland	1,677	2001	52.044	49.298	54.790	5.492
18	Netherlands	1,514	1973	52.370	50.771	53.359	2.588

19	Ireland	2,558	1974	53.142	51.587	55.133	3.547
20	United Kingdom	5,130	1974	53.550	50.103	60.155	10.051
21	Denmark	3,335	1974	55.676	54.769	57.721	2.952
22	Canada	13,608	1973	56.130	42.000	83.000	41.000
23	Russia	1,013	1998	56.487	41.284	71.690	30.406
24	Sweden	2,375	1995	60.128	55.375	67.856	12.481
25	Finland	6,093	1987	61.924	59.833	68.906	9.073
	World	113,295	1973	45.000	0.000	90.000	90.000

Panel B:

	Country	Temperature (°F)					
		Min	Average	Max	Diff (Max-Min)	Upper L_{temp}	Lower H_{temp}
1	Australia	48.5	65.4	92.5	44.0	58.5	68.0
2	Brazil	63.0	74.6	87.0	24.0	70.0	76.0
3	Indonesia	77.0	83.6	87.0	10.0	81.0	84.0
4	Mexico	52.0	63.9	93.1	41.1	61.0	75.0
5	Japan	33.0	63.4	93.0	60.0	49.0	69.0
6	China	19.0	58.6	86.0	67.0	38.0	69.0
7	United States	10.0	56.5	91.0	81.0	41.0	63.0
8	Korea	12.0	57.8	84.0	72.0	41.0	67.0
9	Greece	38.0	67.1	91.0	53.0	58.0	71.0
10	Portugal	42.0	63.9	89.0	47.0	56.0	67.5
11	Spain	28.0	60.3	90.0	62.0	47.0	65.0
12	Italy	34.0	64.7	95.0	61.0	54.0	69.0
13	France	24.0	54.3	87.0	63.0	46.0	58.0
14	Switzerland	11.0	52.9	85.0	74.0	40.5	58.0
15	Austria	12.0	54.3	85.0	73.0	41.0	60.0
16	Germany	8.5	51.7	85.5	77.0	39.0	57.0
17	Poland	8.0	50.4	75.0	67.0	37.0	58.0
18	Netherlands	15.0	52.2	81.0	66.0	43.0	57.0
19	Ireland	32.0	51.1	66.0	34.0	46.0	54.0
20	United Kingdom	12.0	46.4	70.0	58.0	39.0	50.0
21	Denmark	21.5	50.8	80.0	58.5	40.5	55.5
22	Canada	0.0	50.7	87.5	87.5	34.0	58.0
23	Russia	12.0	46.3	78.0	66.0	31.0	53.0
24	Sweden	4.5	48.1	78.5	74.0	34.5	54.5
25	Finland	-9.5	45.5	77.5	87.0	32.0	51.5
	World	-9.5	59.7	95.0	104.5	31.0	50.0

Note: the period of the data is from the beginning year to year 2020

Our analysis uncovers an inherent imbalance in the total number of firms across different countries within our sample. This imbalance is particularly pronounced, with a disproportionately large representation of firms from the United States and Japan compared to other nations. Conversely, some countries are represented by relatively small samples of firms. This uneven distribution of countries in our dataset raises questions regarding the generalizability of our findings to all global firms. To address this issue, we employ a portfolio-based approach aimed at mitigating the impact of the unequal number of observations from each country. The methodology for forming Beta-sorted portfolios closely aligns with the procedure outlined by Antoniou *et al.* (2016).

Fama and French (1992) previously noted that the relationship between beta and returns appeared rather flat. Subsequently, Antoniou *et al.* (2016) introduced sentiment indicators into their analysis. They found that in the United States, during optimistic sentiment periods, low beta stocks outperformed high beta stocks in terms of average monthly returns. This phenomenon was attributed to noise traders overvaluing high beta stocks when experiencing optimism. Conversely, during pessimistic sentiment periods, the average monthly return of these portfolios suggested that stock returns increased with beta, aligning with the predictions of the Capital Asset Pricing Model (CAPM).

Table 1, Panel A highlights the latitude variations for each country. Countries like Brazil, China, the United States, and Canada cover large areas, resulting in a significant latitude range exceeding 30 degrees. In Panel B, however, Brazil shows a small temperature variation of less than 30°F due to its tropical and subtropical location. Similarly, Australia, Indonesia, and Mexico, situated in warm climates, also exhibit minimal temperature differences. Interestingly, Ireland, despite being in a cooler climate, has a small temperature variation because of its small size and mild temperate oceanic climate.

Adopting a comparable methodology, we implement Beta-sorted portfolios in our analysis across the 25 countries in our sample. Figure 1 visually presents the returns of Beta-sorted portfolios for each country. Notably, not all countries conform to the anticipated pattern. Among the 25 nations, certain countries, including Australia, Brazil, Indonesia, Mexico, Korea, Greece, and Austria, yielded results that deviated from the expected return patterns for both optimistic and pessimistic investors. Within these nations, the average monthly return during optimistic sentiment months indicated an increase in stock returns with beta, while during pessimistic sentiment months, stock returns appeared to decrease with beta. These findings marked a reversal compared to the results reported by Antoniou *et al.* (2016). Additionally, in some countries like Korea, Greece, Spain, Italy, Ireland, Denmark, Canada, and Finland, the disparity in stock returns between beta groups was less pronounced in one or both of the optimistic and pessimistic scenarios.

The study conducted by Antoniou *et al.* (2016) has yielded valuable insights into the predictive capacity of beta regarding stock returns. Their results highlight that beta's effectiveness as a predictor is more prominent in countries characterized by cooler climates. This implies that in regions where temperatures tend to be lower, beta's impact on stock performance becomes more apparent.

However, when we broaden our scope to encompass the global portfolio and countries with warmer climates, the dynamics between beta and stock returns are expected to take on a different complexion. The rationale behind this expectation lies in the fact that extreme weather conditions, particularly those associated with the latitude, climate, and temperature. The warmer climates can significantly impact investor sentiment and behavior. As such, it is reasonable to anticipate that in these regions, beta's role in shaping stock returns may deviate from the patterns observed in cooler climates.

In essence, this leads us to the hypothesis that beta's predictive power may wane or exhibit distinct characteristics in countries characterized by warmer climates. The interplay between temperature, investor sentiment, and beta could potentially yield unique insights into how stock markets operate in regions where extreme weather conditions are more prevalent. Consequently, our study aims to shed light on these nuanced relationships within a global context, taking into account the diverse temperature ranges across different countries.

7. Result and discussion

7.1. Preliminary Analysis

As shown in Figure 1, our analysis involves ranking equities based on their pre-formation betas and then grouping them into deciles within each country. We calculate the monthly returns of these portfolios using a value-weighted approach. The results, summarized in Table 2, present the monthly time-series averages of these value-weighted returns for the beta portfolios.

To distinguish between optimistic and pessimistic time periods, we use the method described in the previous section. We then calculate the average monthly returns for these periods separately. Unlike Antoniou et al. (2016), who focused solely on beta portfolios in the U.S. market, our study extends this analysis to beta portfolios across 25 markets.

Our findings reveal that globally, beta-sorted portfolios show a smaller performance gap between low and high beta stocks, and this difference is not statistically significant. Additionally, we do not observe a pattern similar to the Capital Asset Pricing Model (CAPM), as illustrated in Figure 2, indicating that beta-based classifications do not apply to the global portfolio.

This highlights a key distinction: Fama and French's (1993) and Fama and MacBeth's (1973) models are primarily relevant to the U.S. stock market. In contrast, Antoniou et al.'s (2016) study was limited to specific temperature conditions in a particular region. Our research, however, covers a wide range of countries worldwide, each with different temperature ranges.

Table 2 Each country and world beta coefficient of Beta-sorted portfolios in all, pessimistic, and optimistic sentiment.

In this table, we implement the three steps outlined in Section 5.1 to assess the validity of CAPM.

Step 1. Examination of CAPM's Upward Slope.

Step 2. Reevaluation under Different Investor Sentiment.

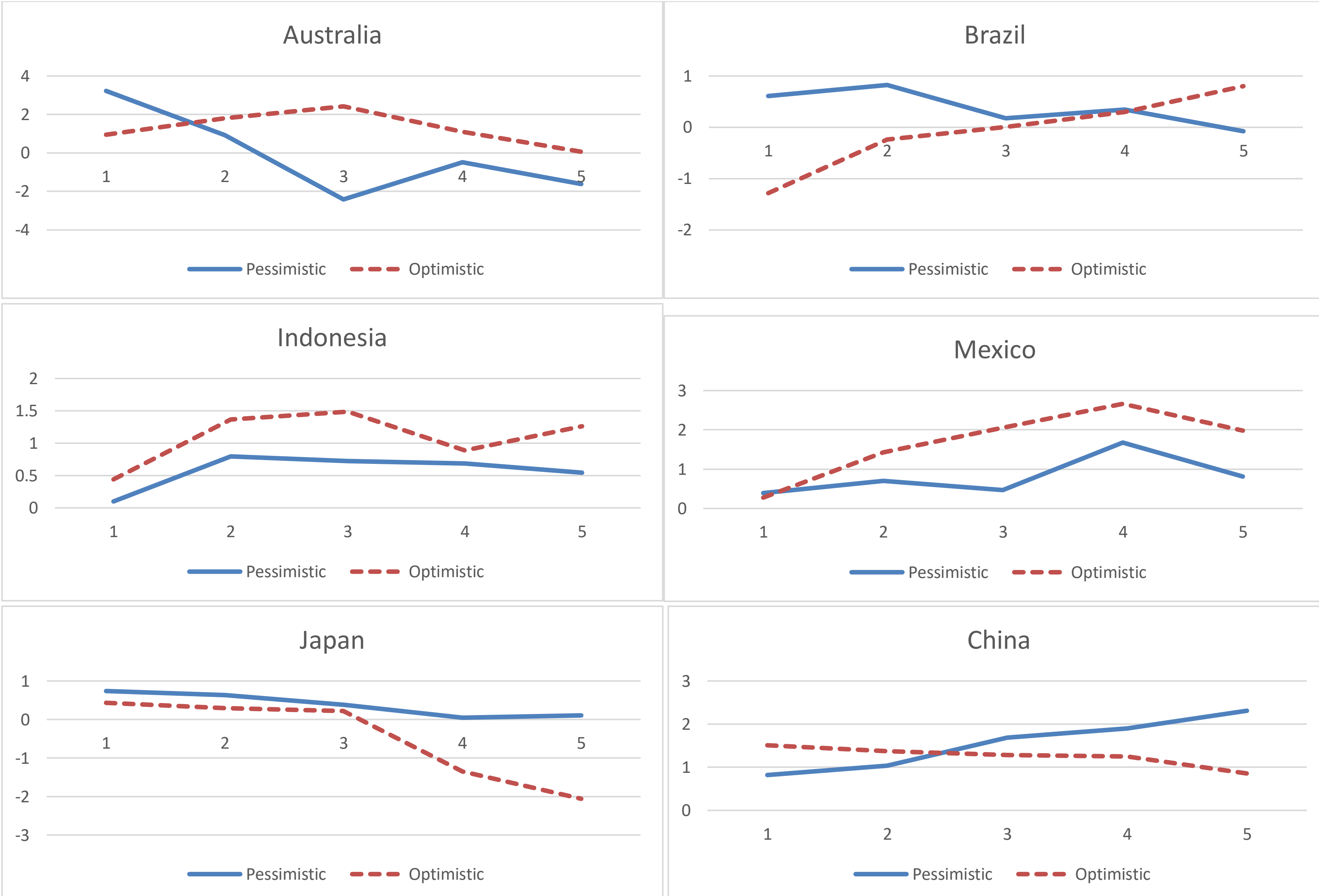
Step 3. Aggregating Country Data.

The values in parentheses indicate the corresponding p-values.

Country	$R_i = a + beta\,\beta$			$R_i = a + beta\,\beta + c\ln[ME] + d\ln[BM] + e\,Ret1 + f\,Ret6 + g\,Ret12$			F-test	
	All	Pessimistic	Optimistic	All	Pessimistic	Optimistic	Pessimistic - Optimistic	F-statistic
1 Australia	0.4841	0.1932	1.098	0.928	2.4024	0.5187	0.0922	1.39
	[0.8648]	[0.7767]	[0.0001]	[0.7314]	[0.3146]	[0.1459]	[0.017]	[0.0002]
2 Brazil	1.6952	1.7995	0.4899	1.9133	1.8738	0.215	-0.0156	1.28
	[0.0089]	[0.0106]	[0.595]	[0.002]	[0.007]	[0.2482]	[0.6456]	[0.0228]
3 Indonesia	0.5571	-0.083	0.8766	0.4175	-0.0251	0.9822	-0.1508	1.18
	[0.265]	[0.8464]	[0.4463]	[0.4249]	[0.9561]	[0.4008]	[0.0006]	[0.208]
4 Mexico	0.0786	-0.737	0.4735	0.0882	-0.3719	0.4914	0.1339	1
	[0.166]	[0.1721]	[0.4787]	[0.002]	[0.5051]	[0.4909]	[0.0001]	[0.9725]
5 Japan	1.3636	1.1712	-0.2421	0.9661	1.1911	-0.5674	-0.0138	1.11
	[0.0003]	[0.0183]	[0.7344]	[0.0001]	[0.0349]	[0.0482]	[0.4699]	[0.1523]
6 China	-2.7949	-4.776	2.7962	-5.0894	-3.3355	0.4761	-0.0817	1.34
	[0.0001]	[0.0056]	[0.1244]	[0.0001]	[0.0555]	[0.8005]	[0.0039]	[0.0209]
7 United States	0.2949	1.4173	-0.309	0.4251	1.0325	-0.5636	-0.0037	1.07
	[0.7453]	[0.0037]	[0.041]	[0.3774]	[0.0096]	[0.0067]	[0.8732]	[0.3638]
8 Korea	0.1919	-0.0279	5.4854	0.5779	0.7066	6.785	0.066	1.83
	[0.7414]	[0.954]	[0.1003]	[0.3265]	[0.1523]	[0.1159]	[0.1944]	[0.0009]
9 Greece	-0.3114	-3.8936	1.1439	-0.3202	-1.6056	-0.2568	-0.0105	1.24
	[0.8043]	[0.0282]	[0.5674]	[0.0879]	[0.4024]	[0.9004]	[0.7212]	[0.0876]
10 Portugal	0.7988	0.7977	-1.3293	0.3815	1.6331	-2.7635	0.0787	1.93
	[0.4882]	[0.4481]	[0.6252]	[0.7503]	[0.1668]	[0.4314]	[0.1235]	[0.0002]
11 Spain	0.3693	-0.3377	1.9367	0.1698	-0.8774	1.2038	0.024	1.45
	[0.5946]	[0.7612]	[0.1932]	[0.8354]	[0.4699]	[0.4391]	[0.1945]	[0.0001]
12 Italy	0.9317	1.4617	0.3268	0.9937	1.3406	-0.5629	0.0118	1.26

	[0.1941]	[0.0985]	[0.7683]	[0.0349]	[0.1377]	[0.6309]	[0.759]	[0.0224]
13 France	-0.2518	1.077	-0.5461	0.6252	1.4743	-0.4321	0.042	1.09
	[0.6528]	[0.0912]	[0.4883]	[0.0978]	[0.1144]	[0.7069]	[0.012]	[0.217]
14 Switzerland	0.8059	0.2521	1.6647	1.6	0.9339	2.6649	0.1796	1.35
	[0.0771]	[0.6631]	[0.0428]	[0.5653]	[0.4592]	[0.1809]	[0.0001]	[0.0019]
15 Austria	1.1055	0.9663	2.8282	0.6424	3.468	-1.6355	0.0533	1.09
	[0.9207]	[0.4733]	[0.0768]	[0.7188]	[0.0979]	[0.6235]	[0.0032]	[0.3823]
16 Germany	0.1232	0.0167	-1.6388	1.7993	1.3595	-0.8788	-0.0003	1.09
	[0.8455]	[0.9766]	[0.1336]	[0.0507]	[0.1958]	[0.6119]	[0.9854]	[0.3015]
17 Poland	0.145	1.4891	-0.2992	0.7543	-1.3691	-0.0842	0.0048	1.5
	[0.8373]	[0.4342]	[0.6894]	[0.3554]	[0.4752]	[0.9152]	[0.9312]	[0.0145]
18 Netherlands	0.8703	1.3667	1.2963	-1.4767	1.2488	-1.668	0.0677	1.15
	[0.0578]	[0.0725]	[0.0531]	[0.2189]	[0.2602]	[0.4783]	[0.0297]	[0.1126]
19 Ireland	0.2668	2.2572	-4.3224	1.8901	1.6466	-6.9329	0.0599	2.38
	[0.0004]	[0.5042]	[0.1487]	[0.3417]	[0.6568]	[0.0076]	[0.0853]	[0.0001]
20 United Kingdom	-0.0431	0.3508	-0.1827	1.5715	3.3282	-0.2287	0.0088	1.2
	[0.8948]	[0.5625]	[0.6076]	[0.0282]	[0.004]	[0.7086]	[0.6558]	[0.0062]
21 Denmark	0.0766	1.6253	-0.0498	-0.2756		-1.0837	0.0804	240.57
	[0.3343]	[0.4479]	[0.2194]	[0.883]		[0.2148]	[0.8934]	[0.0001]
22 Canada	0.3059	1.1009	0.1434	0.018	0.351	-0.7503	-0.0082	1.1
	[0.3112]	[0.0237]	[0.7432]	[0.9687]	[0.5245]	[0.5935]	[0.7392]	[0.171]
23 Russia	1.3356	1.7106	-1.4583	2.6774	1.6951	-3.0208	0.0085	1.02
	[0.0629]	[0.1287]	[0.3743]	[0.0152]	[0.2783]	[0.2271]	[0.9023]	[0.9371]
24 Sweden	0.1319	3.5853	-1.338	0.4075	0.257	-4.1249	-0.0233	1.13
	[0.9458]	[0.1027]	[0.5994]	[0.9359]	[0.9339]	[0.3338]	[0.6413]	[0.5234]
25 Finland	-0.1276	2.017	-1.2723	-1.0444	4.0078	-2.7466	0.0049	1.09
	[0.9277]	[0.3748]	[0.5903]	[0.6481]	[0.2158]	[0.6508]	[0.8353]	[0.4605]
World	0.0377	0.0028	-0.0342	0.0885	0.25	0.1517	0.3268	64.731
	[0.4692]	[0.9853]	[0.237]	[0.5401]	[0.1842]	[0.4466]	[0.0001]	[0.0001]
World (Pooled)	0.0026	0.2052	0.0369	0.0758	0.2963	-0.0223	0.3584	65.729
	[0.9608]	[0.2201]	[0.2007]	[0.6239]	[0.1572]	[0.9165]	[0.0001]	[0.0001]

Figure 1 Each country returns of Beta-sorted portfolios in pessimistic and optimistic sentiment.




United States
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France
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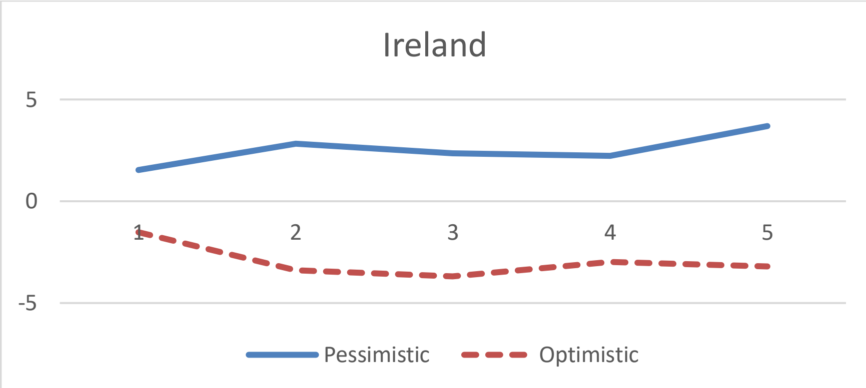
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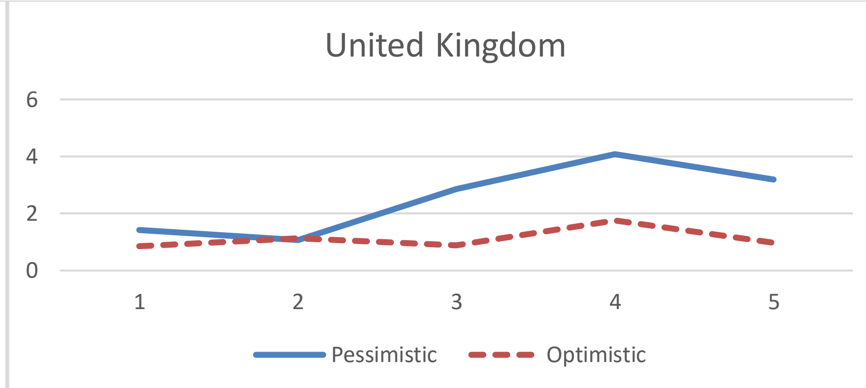
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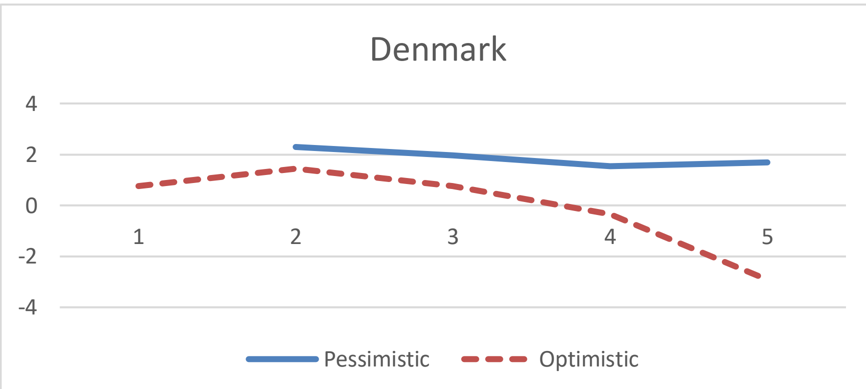
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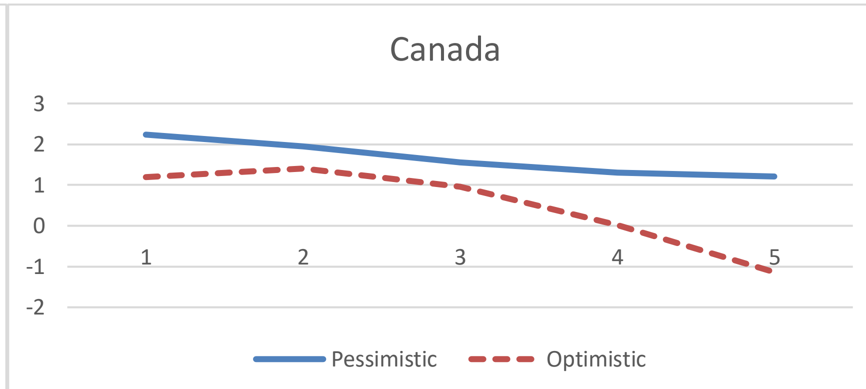
Canada
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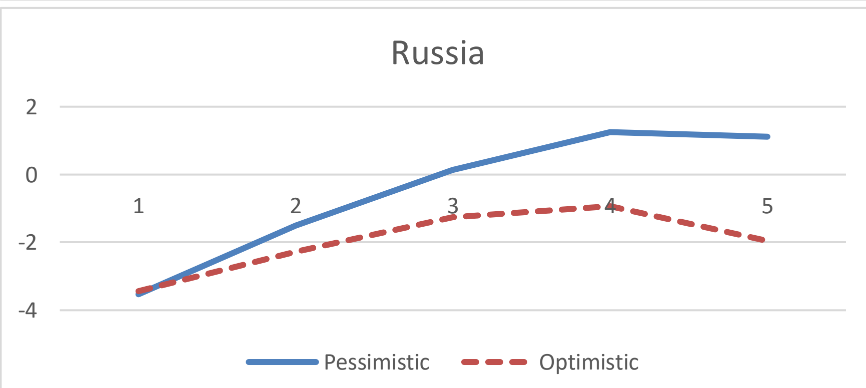
Pessimistic
Optimistic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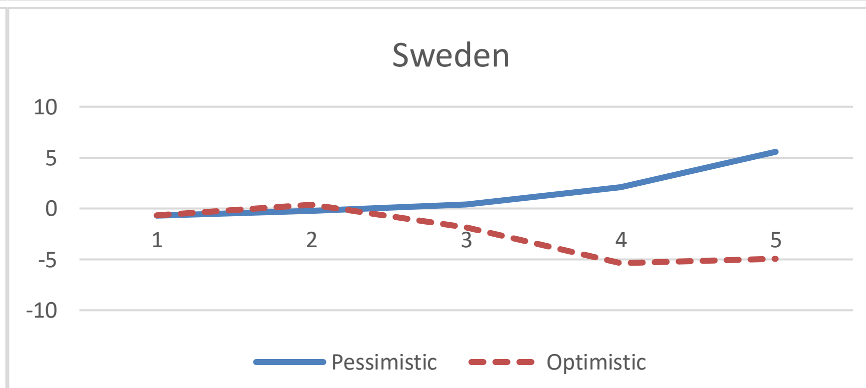
Sweden
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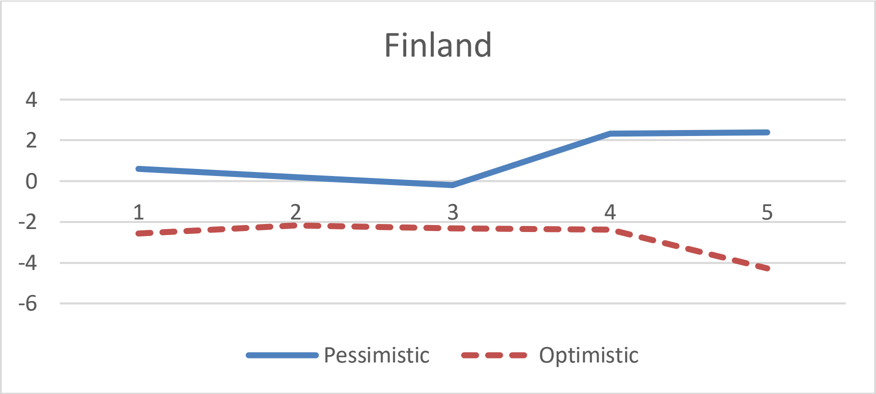
Optimistic


Finland
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Pessimistic
Optimistic

In addition to our analysis, we also conduct a test involving the global portfolio. Illustrated in Figure 2, the beta-sorted portfolios on a global scale reveal a narrower performance gap between low and high beta stocks, and notably, this difference lacks statistical significance. The returns associated with each beta category also demonstrate an apparent indifference. This observation brings attention to a pivotal distinction: the models presented by Fama and French (1993) and Fama and MacBeth (1973) are designed exclusively for the U.S. stock portfolio. Moreover, the study by Antoniou *et al.* (2016), which exclusively considers beta and investor sentiment factors. The necessity for reevaluation becomes apparent as we broaden our study, encompassing a diverse array of countries worldwide, each characterized by different latitudes and distinct temperature ranges.

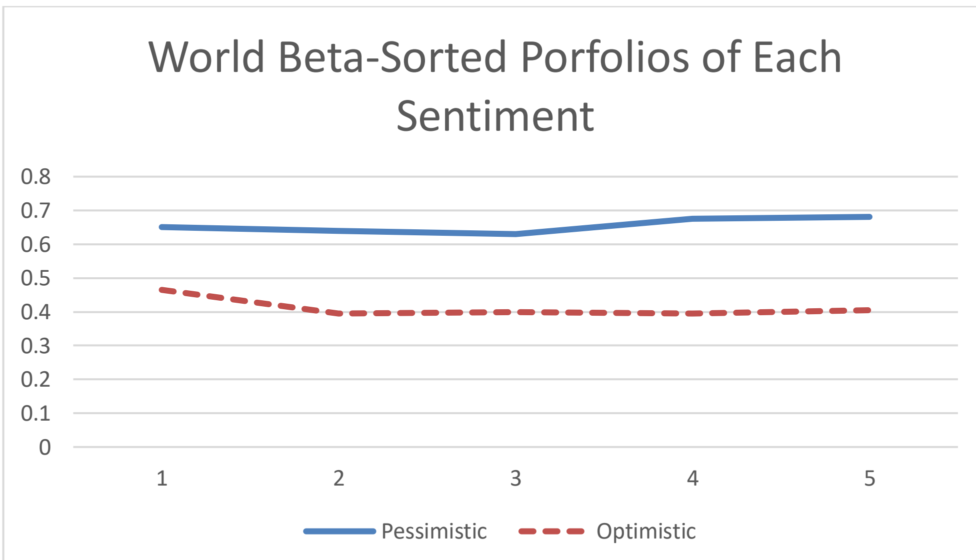

Figure 2 The comparison between returns of world Beta-sorted portfolios.

7.2. Temperature-Beta Portfolio Model

In our follow-up analysis, we divided our sample into two groups: warm-climate countries with latitudes below 40 degrees and cool-climate countries with latitudes above 40 degrees. This division is based on the methodology used by Huang *et al.* (2023) and reflects our observation of varying results in sub-tropical and temperate countries like Italy, Spain, Portugal, Greece, Germany, and the Netherlands. We then created beta portfolios for each group using the same approach as before, with the results shown in Table 3.

Table 3 displays the regression outcomes for each climate group and the global beta coefficients of Beta-sorted portfolios under all sentiment conditions—pessimistic and optimistic. In the United States, there is a positive and significant relationship between stock beta and returns during pessimistic investor moods, but this relationship turns negative and significant during optimistic periods. This finding aligns with Antoniou *et al.* (2016). However, for the global data and the cool-climate group, no significant results were found. For the warm-climate group, a positive and significant relationship only appeared during optimistic investor sentiment. This suggests that the effects of beta and investor sentiment are not significant when using global data and are primarily applicable to the U.S. market.

In this study, we also considered the impact of different time periods on our results. To ensure robustness, we divided our samples into two sub-periods as shown in Table 4 and into three sub-periods as shown in Table 5, suspecting that the results we obtained earlier might have been influenced by the entire time span of our data.

By separating the samples into different categories, based on latitude and time periods, we want to confirm the consistency of the beta-return relationship globally and comprehend its behavior in diverse circumstances. After this segmentation, we reevaluated whether $\beta > 0$. If the latitude split yields meaningful results, we found that latitude is an important factor. Additionally, we explore the possibility that temperature influences the results.

Table 4 reveals findings consistent with those in Table 3 for the United States across both sub-periods. However, for global, warm-climate, and cool-climate countries, the results become insignificant in the first sub-period from 1973 to 1996 (Panel A). In the second sub-period from 1997 to 2020 (Panel B), only warm-climate countries during periods of optimistic investor sentiment show a positive and significant relationship.

When we further divided the data into three sub-periods, as presented in Table 5, we observed an improvement for warm-climate countries in the period from 1989 to 2004 (Panel B), which displayed positive and significant results. However, the earlier period from 1973 to 1988 (Panel A) and the later period from 2005 to 2020 (Panel C) did not show any significant results, except for the United States market.

Overall, Tables 3 to 5 demonstrate that the expected significant impact of beta on stock returns is not as pronounced as anticipated. This suggests that the effects of beta, investor sentiment, and latitude do not have a substantial influence on global portfolios.

Table 3 Each climate group and world beta coefficient of Beta-sorted portfolios in all, pessimistic, and optimistic sentiment.

In this table, we implement the three steps outlined in Section 5.1 to assess the validity of CAPM.

Step 1. Examination of CAPM's Upward Slope.

Step 2. Reevaluation under Different Investor Sentiment.

Step 3. Aggregating Country Data.

The values in parentheses indicate the corresponding p-values.

		$R_i = a + beta\,\beta$			$R_i = a + beta\,\beta + c\ln[ME] + d\ln[BM] + e\,Ret1 + f\,Ret6 + g\,Ret12$	
Group	All	Pessimistic	Optimistic	All	Pessimistic	Optimistic
World	0.0377	0.0028	-0.0342	0.0885	0.25	0.1517
	[0.4692]	[0.9853]	[0.237]	[0.5401]	[0.1842]	[0.4466]
United States	0.2949	1.4173	-0.309	0.4251	1.0325	-0.5636

	[0.7453]	[0.0037]	[0.041]	[0.3774]	[0.0096]	[0.0067]
Warm-climate	0.4184	-0.0208	0.5617	0.05	0.2783	0.742
	[0.0063]	[0.9236]	[0.0117]	[0.7834]	[0.2343]	[0.007]
Cool-climate	-0.0094	-0.0171	-0.0429	-0.3485	0.0552	-0.1422
	[0.8692]	[0.9367]	[0.1608]	[0.1574]	[0.868]	[0.6472]

Table 4 Two Sub-periods: Each climate group and world beta coefficient of Beta-sorted portfolios in all, pessimistic, and optimistic sentiment.

In this table, we implement the three steps outlined in Section 5.1 to assess the validity of CAPM.

Step 1. Examination of CAPM's Upward Slope.

Step 2. Reevaluation under Different Investor Sentiment.

Step 3. Aggregating Country Data.

The values in parentheses indicate the corresponding *p*-values.

	$R_i = a + beta\,\beta$			$R_i = a + beta\,\beta + c\ln[ME] + d\ln[BM] + e\,Ret1 + f\,Ret6 + g\,Ret12$		
Group	All	Pessimistic	Optimistic	All	Pessimistic	Optimistic
Panel A: Year 1973-1996						
World	0.3328	-0.0814	-0.2921	0.3768	-0.0688	-0.3455
	[0.1051]	[0.7981]	[0.3539]	[0.1951]	[0.8981]	[0.3888]
United States	0.8816	1.5655	-0.2654	0.8744	1.2455	-0.2564
	[0.0298]	[0.0833]	[0.0492]	[0.1458]	[0.0023]	[0.0343]
Warm-climate	0.3983	0.1227	-0.4039	0.6663	0.3267	-0.4111
	[0.2472]	[0.8726]	[0.4845]	[0.2982]	[0.8566]	[0.4466]
Cool-climate	0.2812	-0.1538	-0.2242	0.2452	-0.248	-0.234
	[0.27]	[0.6604]	[0.5479]	[0.2788]	[0.9664]	[0.6779]
Panel B: Year 1997-2020						
World	0.0245	0.0168	-0.0333	-0.0822	0.25	0.1517
	[0.6602]	[0.921]	[0.2741]	[0.5686]	[0.1842]	[0.4466]
United States	0.1153	1.318	-0.9649	0.4824	1.0325	-0.5636
	[0.7458]	[0.0502]	[0.0013]	[0.3163]	[0.0096]	[0.0674]
Warm-climate	0.4198	-0.0531	0.7389	0.05	0.2783	0.742
	[0.0122]	[0.814]	[0.0024]	[0.7834]	[0.2343]	[0.007]
Cool-climate	-0.0175	-0.0047	-0.0425	-0.3485	0.0552	-0.1422
	[0.779]	[0.9857]	[0.1995]	[0.1574]	[0.868]	[0.6472]

Table 5 Three Sub-periods: Each climate group and world beta coefficient of Beta-sorted portfolios in all, pessimistic, and optimistic sentiment.

In this table, we implement the three steps outlined in Section 5.1 to assess the validity of CAPM.

Step 1. Examination of CAPM's Upward Slope.

Step 2. Reevaluation under Different Investor Sentiment.

Step 3. Aggregating Country Data.

The values in parentheses indicate the corresponding *p*-values.

	$R_i = a + beta\,\beta$			$R_i = a + beta\,\beta + c\ln[ME] + d\ln[BM] + e\,Ret1 + f\,Ret6 + g\,Ret12$		
Group	All	Pessimistic	Optimistic	All	Pessimistic	Optimistic
Panel A: Year 1973-1988						
World	0.3332	-1.1212	-0.7685	0.1982	-1.4312	-0.4885
	[0.6265]	[0.3549]	[0.337]	[0.8755]	[0.5449]	[0.3456]

United States	0.1456	0.2734	-0.2929	0.1654	0.1211	-0.1999
	[0.9662]	[0.8029]	[0.6833]	[0.4562]	[0.9876]	[0.8775]
Warm-climate	0.1983	0.1007	-0.2909	0.1654	0.1211	-0.1999
	[0.2982]	[0.8996]	[0.5875]	[0.4562]	[0.9876]	[0.8775]
Cool-climate	0.3559	-1.3718	-0.7685	0.2959	-1.0918	-0.6893
	[0.6018]	[0.2454]	[0.337]	[0.6018]	[0.1994]	[0.6049]
Panel B: Year 1989-2004						
World	0.0735	0.3147	-0.0353	-0.1013	0.8589	-0.1902
	[0.2248]	[0.2336]	[0.253]	[0.8272]	[0.1362]	[0.6079]
United States	0.1551	1.9241	-0.2603	0.6979	1.3791	-0.471
	[0.7186]	[0.0783]	[0.005]	[0.7846]	[0.0089]	[0.0185]
Warm-climate	1.5317	1.1247	0.7771	0.4249	1.5212	0.7313
	[0.0001]	[0.03]	[0.0158]	[0.6034]	[0.1178]	[0.2644]
Cool-climate	0.0027	0.0731	-0.0421	-0.6564	0.2511	-0.5498
	[0.9662]	[0.8117]	[0.1901]	[0.2834]	[0.7417]	[0.2526]
Panel C: Year 2005-2020						
World	-0.246	-0.13	-0.13	-0.0999	0.1345	-0.0947
	[0.0801]	[0.4855]	[0.4855]	[0.5027]	[0.5019]	[0.6995]
United States	0.0275	1.0869	-0.8059	0.4297	1.1654	-0.988
	[0.9435]	[0.0867]	[0.0576]	[0.359]	[0.0787]	[0.0637]
Warm-climate	-0.1939	-0.2148	-0.2148	0.04	0.1709	0.3157
	[0.2737]	[0.3686]	[0.3686]	[0.8251]	[0.48]	[0.3074]
Cool-climate	-0.4084	-0.1416	-0.1416	-0.3985	0.0156	-0.5549
	[0.0886]	[0.6571]	[0.6571]	[0.1449]	[0.967]	[0.2223]

Table 6 highlights the differences in returns for Beta-sorted portfolios across various country groups. Our analysis did not find a significant difference in returns between high beta and low beta stocks. Additionally, the differences in returns between pessimistic and optimistic sentiment periods within each beta group were also insignificant. This indicates that latitude and sentiment do not significantly impact global portfolio returns. Consequently, we can conclude that beta fails to predict stock returns in the global sample.

In our quest for more robust results, we enhance the beta-sorted portfolio by introducing an additional factor: temperature. We categorize temperature into five quintiles and classify the lowest three deciles as the low-temperature group, the middle four deciles as the medium-temperature group, and the highest three deciles as the high-temperature group. Much like Table 6, we stratify our sample based on sentiment conditions and examine the differences in stock returns through the lens of temperature-beta portfolios. Table 7 illustrates these differences for [Pess, H_{temp} - Opt, H_{temp}], [Pess, H_{temp} - Opt, L_{temp}], [Pess, L_{temp} - Opt, L_{temp}], and [Pess, L_{temp} - Opt, H_{temp}].

The results furnish a more compelling narrative: the discrepancies emerge primarily in the combination of high-low temperature portfolios and optimistic-pessimistic sentiment conditions. This pattern is further elucidated in Figure 3 for the world portfolio. By employing temperature in conjunction with specific investor sentiment conditions, we demonstrate that under low temperatures and pessimistic conditions, stock returns align with the traditional CAPM model, whereas under high temperatures and optimistic conditions, stock returns exhibit a negative slope.

Moreover, Table 7 underscores the robustness of our findings, indicating strong significance differences between each temperature-beta portfolio in both the world, warm-climate, and cool-climate countries across various combinations of temperature and sentiment. Notably, we identify significant differences between low temperatures in pessimistic markets and high temperatures in optimistic markets [Pess, L_{temp} - Opt, H_{temp}]. Specifically, cold temperatures in pessimistic markets correspond to higher returns, while hot temperatures in optimistic markets yield lower returns. In light of these findings, we assert that temperature emerges as a more potent predictor of stock returns. In conclusion, temperature establishes a compelling relationship between beta and returns, augmenting the influence of investor sentiment as a formidable factor impacting stock returns.

Table 6 The difference between returns of each group Beta-sorted portfolios.

Country		Lowβ	1	2	3	Highβ	Highβ - Lowβ
World	All	0.39	0.33	0.48	0.63	0.88	0.49
	Pessimistic	0.05	0.20	0.36	0.53	0.85	0.8
	Optimistic	0.33	0.62	0.71	0.81	0.95	0.62
	Diff: Pess - Opt	-0.28	-0.42	-0.35	-0.28	-0.1	
United States	All	0.19	0.40	0.57	0.75	1.01	0.82
	Pessimistic	0.18	0.40	0.58	0.75	1.01	0.83
	Optimistic	0.22	0.43	0.59	0.73	0.14	-0.08
	Diff: Pess - Opt	-0.04	-0.03	-0.01	0.02	0.87	
Warm-climate	All	0.00	0.15	0.38	0.49	0.58	0.58
	Pessimistic	-0.09	0.06	0.23	0.38	0.52	0.61
	Optimistic	0.05	-0.19	0.37	0.38	0.49	0.44
	Diff: Pess - Opt	-0.14	0.25	-0.14	0	0.03	
Cool-climate	All	0.22	0.41	0.53	0.70	0.96	0.74
	Pessimistic	0.13	0.29	0.42	0.65	0.95	0.82
	Optimistic	0.40	0.67	0.78	0.91	1.06	0.66
	Diff: Pess - Opt	-0.27	-0.38	-0.36	-0.26	-0.11	

Note: The each group beta-sorted portfolios' average returns are shown in this table. Fama and MacBeth (1973) betas are used to prerank all stocks in each country and divide them into 5 portfolios. These preranking betas are calculated using 24–60 monthly returns (as available). We obtain value-weighted monthly returns for these portfolios of month t. With respect to macroeconomic variables, Baker and Wurgler's (2006) annual index, which measures sentiment, is orthogonalized. If the sentiment index is positive (negative) in month t-1, then we classify all observations in month t as being optimistic (pessimistic). The average portfolio returns and spreads for optimistic and pessimistic months are then calculated separately. Our sample spans from the beginning year to year 2020. The difference of each beta group is represented by the coefficient and ***, **, and * which denote significance at the 1%, 5%, and 10% level, respectively.

Table 7 The difference between returns of Temperature-Beta-sorted portfolios in each sentiment and temperature group.

Country		Temp	Lowβ	1	2	3	Highβ	Highβ - Lowβ	Temp
World	Pessimistic	L_{Temp}	1.09	0.43	0.23	0.24	-0.10	-1.19*	36.35
		H_{Temp}	0.73	1.01	1.59	1.17	1.39	0.66	79.98
	Optimistic	L_{Temp}	1.42	0.55	0.51	0.60	1.16	-0.26	36.61
		H_{Temp}	0.62	0.99	1.66	1.80	1.99	1.37*	78.28
	Diff:	Pess,H_{temp} - Opt, H_{temp}	0.11	0.02	-0.07	-0.63	-0.60		1.70
		Pess,H_{temp} - Opt, L_{temp}	-0.68*	0.45*	1.08**	0.56*	0.23*		43.38
		Pess,L_{temp} - Opt, L_{temp}	-0.33	-0.12	-0.28	-0.36	-1.26**		-0.25
		Pess,L_{temp} - Opt, H_{temp}	0.47	-0.56*	-1.43**	-1.56**	-2.09***		-41.93
United States	Pessimistic	L_{Temp}	1.59	0.99	0.68	0.43	0.03	-1.56*	34.43
		H_{Temp}	2.71	2.84	2.50	1.98	2.94	0.23	78.20
	Optimistic	L_{Temp}	0.41	0.61	0.57	0.32	1.29	0.88	29.36
		H_{Temp}	2.56	2.87	3.10	2.37	2.77	0.21	75.91
	Diff:	Pess,H_{temp} - Opt, H_{temp}	0.15	-0.03	-0.6	-0.39	0.17		2.29
		Pess,H_{temp} - Opt, L_{temp}	2.3	2.24**	1.93**	1.66**	1.65**		48.84
		Pess,L_{temp} - Opt, L_{temp}	1.18	0.38**	0.11	0.11	-1.26*		5.07
		Pess,L_{temp} - Opt, H_{temp}	-0.97	-1.88**	-2.42***	-1.94*	-2.74***		-41.48
Warm-climate	Pessimistic	L_{Temp}	-0.23	0.29	0.14	-0.26	-0.74	-0.51	43.89
		H_{Temp}	-1.40	-0.67	1.07	1.77	1.97	3.37***	82.08
	Optimistic	L_{Temp}	0.55	-0.11	0.33	-0.22	0.25	-0.29	44.41
		H_{Temp}	1.27	1.14	1.32	1.47	0.47	-0.80*	80.75
	Diff:	Pess,H_{temp} - Opt, H_{temp}	-2.67	-1.82	-0.25	0.3	1.5		1.33
		Pess,H_{temp} - Opt, L_{temp}	-1.94*	-0.56	0.75	2***	1.71**		37.66
		Pess,L_{temp} - Opt, L_{temp}	-0.78	0.41**	-0.19	-0.04	-1		-0.53
		Pess,L_{temp} - Opt, H_{temp}	-1.5	-0.85	-1.18*	-1.73**	-1.21**		-36.86
Cool-climate	Pessimistic	L_{Temp}	0.54	0.63	0.82	0.75	0.35	-0.19	32.70
		H_{Temp}	1.93	1.68	1.82	1.35	1.78	-0.14	79.00
	Optimistic	L_{Temp}	2.16	1.18	1.09	1.42	1.67	-0.49	34.32
		H_{Temp}	0.41	1.24	2.13	2.71	1.98	1.57**	77.35
	Diff:	Pess,H_{temp} - Opt, H_{temp}	1.52	0.44	-0.31	-1.37	-0.2*		1.65
		Pess,H_{temp} - Opt, L_{temp}	-0.24	0.5**	0.73**	-0.08***	0.11		44.68
		Pess,L_{temp} - Opt, L_{temp}	-1.63	-0.55	-0.27	-0.68	-1.32		-1.62
		Pess,L_{temp} - Opt, H_{temp}	0.13	-0.61***	-1.31***	-1.97***	-1.64***		-44.65
Cool - Warm	Diff:	Pess L_{Temp} - Opt H_{Temp}	-0.73	-0.51	-0.51	-0.73	-0.12**		-48.05

Note: The each group beta-sorted portfolios' average returns are shown in this table. Fama and MacBeth (1973) three-factor betas are used to prerank all stocks in each country and divide them into 5 portfolios. We also sort the temperature into 10 deciles and classify the lowest 3-decile as low temperature group, middle 4-decile as medium temperature group, and the highest 3-decile as high temperature group These preranking betas are calculated using 24–60 monthly returns (as available). We obtain value-weighted monthly returns for these portfolios of month t. With respect to macroeconomic variables, Baker and Wurgler's (2006) annual index, which measures sentiment, is orthogonalized. If the sentiment index is positive (negative) in month t-1, then we classify all observations in month t as being optimistic (pessimistic). The average portfolio returns and spreads for optimistic and pessimistic months are then calculated separately. Our sample spans from the beginning year to year 2020. The difference of each beta group is represented by the coefficient and ***, **, and * which denote significance at the 1%, 5%, and 10% level, respectively.

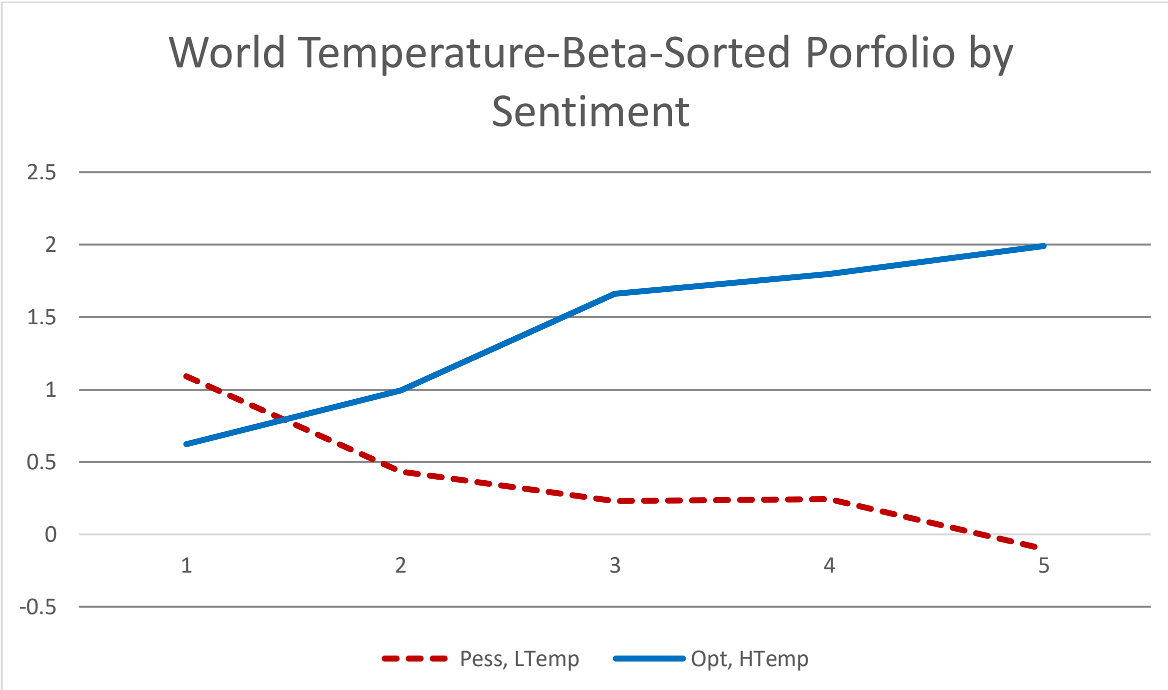

Figure 3 The comparison between returns of world Temperature-Beta-sorted portfolios by sentiment.

Building on the insights from Tables 6 and 7, we conducted a similar regression analysis by incorporating temperature groups. The definitions for these temperature groups are detailed in Sections 5.2, 7.2, and the notes accompanying Table 7. We divided the temperature distribution into three categories: low temperature (L_{temp}), medium temperature (M_{temp}), and high temperature (H_{temp}).

The regression results presented in Table 8a reveal that, in warm-climate countries, the relationship between temperature and stock returns is significantly positive for the medium and high temperature groups during periods of optimistic investor sentiment (Panel B). However, during periods of pessimistic and mixed investor sentiment, these results are not significant. Conversely, in cool-climate countries, the relationship is significantly negative for the low temperature group during pessimistic investor sentiment. This significant effect is also evident in the global portfolio, particularly within the low temperature group.

We also performed a sensitivity analysis, as we previously identified the period from 1989 to 2004 as the most significant time window. The results of this analysis are displayed in Table 8b. The regression results in Table 8b mirror those in Table 8a but with more pronounced significance. Again, in warm-climate countries, the temperature relationship with stock returns is significantly positive for the medium and high temperature groups during optimistic investor sentiment (Panel B), whereas the results remain insignificant during pessimistic and mixed sentiment periods. In cool-climate countries, the relationship is significantly negative for the low temperature group during pessimistic investor sentiment, and this significant effect is also observed in the global portfolio, especially within the low temperature group.

Our findings demonstrate that the relationship between temperature and stock returns is nonlinear. More specifically, high temperatures correlate with significantly positive stock returns for investors in warm-climate countries during optimistic periods. Conversely, low temperatures correlate with significantly negative stock returns for investors in cool-climate countries during pessimistic periods. These results underscore the importance of considering temperature variations when analyzing stock returns across different climate regions and investor sentiment conditions.

Table 8a CAPM Regression of Temperature-Beta-sorted portfolios in each sentiment and temperature group.

In this table, we implement the three steps outlined in Section 5.1 to assess the validity of CAPM.

Step 1. Examination of CAPM's Upward Slope.

Step 2. Reevaluation under Different Investor Sentiment.

Step 3. Aggregating Country Data.

The values in parentheses indicate the corresponding p-values.

	$R_i = a + beta\,\beta$			$R_i = a + beta\,\beta + c\ln[ME] + d\ln[BM] + e\,Ret1 + f\,Ret6 + g\,Ret12$		
Panel A. All						
Group:	L_{temp}	M_{temp}	H_{temp}	L_{temp}	M_{temp}	H_{temp}
World	-0.0405	0.228	0.7542	-0.2943	0.1181	0.0616
	[0.4577]	[0.2573]	[0.0001]	[0.1718]	[0.6637]	[0.8211]
United States	0.0928	0.0949	0.0949	0.4928	0.4824	0.5019
	[0.7453]	[0.7453]	[0.7453]	[0.3163]	[0.3163]	[0.3163]
Warm-climate	0.4136	0.4988	0.3754	-0.053	0.1958	0.1257
	[0.1151]	[0.0629]	[0.1525]	[0.8602]	[0.5481]	[0.6905]
Cool-climate	-0.0614	0.1061	1.0487	-0.6423	0.0148	-0.2113
	[0.2748]	[0.7288]	[0.0004]	[0.0431]	[0.9766]	[0.7029]
Panel B. Optimistic						
Group:	L_{temp}	M_{temp}	H_{temp}	L_{temp}	M_{temp}	H_{temp}
World	-0.046	0.6389	0.292	-0.2358	0.7528	0.1177
	[0.1081]	[0.0281]	[0.2716]	[0.449]	[0.051]	[0.7363]
United States	0.319	0.309	0.309	-0.5829	-0.5636	0.5636
	[0.4095]	[0.4095]	[0.041]	[0.6742]	[0.6742]	[0.0428]
Warm-climate	-0.818	1.3473	1.0671	-0.5112	1.4743	1.2458
	[0.0369]	[0.0309]	[0.0065]	[0.2768]	[0.019]	[0.0095]
Cool-climate	-0.0423	0.1522	-0.4118	-0.0197	0.316	-0.803
	[0.1579]	[0.74]	[0.2574]	[0.9649]	[0.6523]	[0.1475]
Panel C. Pessimistic						
Group:	L_{temp}	M_{temp}	H_{temp}	L_{temp}	M_{temp}	H_{temp}
World	-0.5151	0.6115	0.0754	-0.2975	0.7322	0.6154
	[0.0268]	[0.0358]	[0.7805]	[0.0291]	[0.0443]	[0.0764]
United States	-0.2626	0.4173	0.4173	-0.0325	-0.0325	-0.0339

	[0.0397]	[0.3705]	[0.3705]	[0.0955]	[0.9557]	[0.9557]
Warm-climate	-0.2243	0.3242	-0.0746	-0.0046	0.7362	0.2462
	[0.5137]	[0.4242]	[0.846]	[0.9902]	[0.0944]	[0.5475]
Cool-climate	-0.7644	0.9418	0.0551	-0.4737	0.5421	0.8463
	[0.0168]	[0.0295]	[0.8884]	[0.0286]	[0.4222]	[0.2332]

Table 8b CAPM Regression of Temperature-Beta-sorted portfolios in each sentiment and temperature group from year 1989 to 2004.

In this table, we implement the three steps outlined in Section 5.1 to assess the validity of CAPM.

Step 1. Examination of CAPM's Upward Slope.

Step 2. Reevaluation under Different Investor Sentiment.

Step 3. Aggregating Country Data.

The values in parentheses indicate the corresponding *p*-values.

Panel A. All						
Group	L_{temp}	M_{temp}	H_{temp}	L_{temp}	M_{temp}	H_{temp}
World	-0.0129	0.3119	1.713	-0.5841	-0.2394	0.8403
	[0.8339]	[0.3292]	[0.0001]	[0.3848]	[0.771]	[0.0394]
United States	0.1551	0.1551	0.1551	0.6979	0.6979	0.6979
	[0.7186]	[0.7186]	[0.7186]	[0.7846]	[0.7846]	[0.7846]
Warm-climate	1.7571	1.1831	1.6033	-0.7501	0.4785	2.0186
	[0.0007]	[0.0219]	[0.0006]	[0.5775]	[0.0175]	[0.0064]
Cool-climate	-0.0427	-0.0903	1.6942	-0.8503	-0.7849	0.1879
	[0.0488]	[0.8255]	[0.0001]	[0.3039]	[0.4704]	[0.9033]
Panel B. Optimistic						
Group	L_{temp}	M_{temp}	H_{temp}	L_{temp}	M_{temp}	H_{temp}
World	-0.0448	0.8074	0.4346	-0.2128	0.9013	-0.6843
	[0.1416]	[0.0447]	[0.2177]	[0.6981]	[0.2467]	[0.3164]
United States	-0.2603	-0.1893	0.2523	-2.471	-2.5637	2.486
	[0.0501]	[0.0201]	[0.5012]	[0.0185]	[0.0752]	[0.0192]
Warm-climate	-0.6306	1.4939	1.1802	-0.3545	0.3627	1.5028
	[0.2882]	[0.0033]	[0.0412]	[0.7739]	[0.7158]	[0.0203]
Cool-climate	-0.0436	0.2332	-0.1214	-0.187	1.2291	1.481
	[0.1688]	[0.705]	[0.7858]	[0.7786]	[0.3428]	[0.0906]
Panel C. Pessimistic						
Group	L_{temp}	M_{temp}	H_{temp}	L_{temp}	M_{temp}	H_{temp}
World	-0.2245	0.8413	0.4218	-0.5865	0.8071	2.9731
	[0.5956]	[0.1094]	[0.3382]	[0.5281]	[0.3861]	[0.0109]
United States	1.9241	1.8611	2.9434	0.3791	0.2891	1.2111
	[0.0783]	[0.0799]	[0.0183]	[0.8946]	[0.0595]	[0.0235]
Warm-climate	0.9392	0.0203	1.9173	0.3048	2.1216	3.3693
	[0.2488]	[0.9829]	[0.0407]	[0.8497]	[0.1161]	[0.1148]
Cool-climate	-0.5662	1.0508	-0.0075	-1.2334	0.1368	2.5962
	[0.0452]	[0.0941]	[0.988]	[0.0309]	[0.9143]	[0.0925]

8. Conclusion

Antoniou *et al.* (2016) introduced the concept of investor sentiment into the analysis of correlation between beta and stock returns in order to resolve the puzzle of the linear beta-return relationship predicted by the traditional Capital Asset Pricing Model (CAPM), developed by Sharpe (1964) and Lintner (1965). Their U.S.-focused study found that, during optimistic sentiment periods, low beta stocks outperformed high beta stocks in terms of average monthly returns. Conversely, during pessimistic sentiment periods, the average monthly return of these portfolios indicated that stock returns increased with beta, aligning with the predictions of CAPM. Nevertheless, we aim to demonstrate that the linear beta-return relationship, particularly under pessimistic sentiment, is limited to certain countries within our sample. Additionally, the use of a portfolio beta may no longer be applicable when extending the analysis to include international markets and, potentially, different time periods.

Based of our findings, our study reveals that globally, beta-sorted portfolios exhibit a smaller performance gap between low and high beta stocks, which is not statistically significant. This indicates that beta-based classifications do not apply to the global portfolio, diverging from patterns observed in the U.S. market as per Fama and French's (1993) and Fama and MacBeth's (1973) models. While Antoniou et al.'s (2016) study was confined to specific temperature conditions within a particular region, our research spans a diverse array of countries with varying temperature ranges. When incorporating latitude and separating countries into warm-climate and cool-climate groups, the anticipated significant impact of beta on stock returns was not as pronounced, suggesting that beta, investor sentiment, and latitude have limited influence on global portfolios. However, by factoring in temperature, we found a nonlinear relationship between temperature and stock returns. We found during the normal temperatures and optimism, stocks are expected to generate lower returns. Conversely, during times of extreme temperatures and pessimism, stocks are anticipated to yield higher returns.

High temperatures positively affected stock returns in warm-climate countries during optimistic periods, while low temperatures negatively impacted stock returns in cool-climate countries during pessimistic periods. Thus, we proved our hypothesis that for warm-climate countries, the upward-sloping relationship between beta and return is more significant under pessimism rather than under optimism under high temperatures. In contrast, for cool-climate countries, the downward-sloping relationship between beta and return is more apparent under pessimism rather than under optimism under low temperatures. These findings highlight the nuanced and complex interplay between temperature, investor sentiment, and stock returns across different global climates.

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