# Global Warming Asset Pricing

Mihir Tirodkar

Doctoral candidate

University of Auckland

Faculty of Business and Economics

M.Tirodkar@auckland.ac.nz

**Abstract**

This study considers the implications of long-term temperature risk in U.S. equity markets. Using an estimate of low frequency temperature shocks I find a negative time trend for average industry temperature betas, suggesting that temperature shocks have had greater consequences on industry returns over time. However, I find no evidence for the existence of a cross-sectional temperature risk premium. Furthermore, industry temperature betas do not predict abnormal returns generated by the 2015 Paris Agreement, and firm temperature betas do not correlate with self-disclosed exposures to environmental risk. Trading strategies also reveal that a long-short temperature portfolio does not generate significantly negative abnormal returns. Results provide no evidence of priced temperature risk in U.S. markets. I attribute the lack of results to both the long time horizons of climate change induced disasters, and investor diversification options.

## 1. Introduction

Climate change is a growing economic concern due to the expected consequences of the environment on economic variables including output, employment and productivity. This research adds financial market considerations to the climate change discussion through examining the explanatory power of temperature as a risk factor in the cross-section of U.S. equity returns. Temperature change is a core driver of aggregate climate change phenomenon and is the main climate variable examined in this study. I focus on the impact of low frequency temperature shocks on equities. The main contribution of this study is testing the hypothesis of a priced temperature risk factor in financial markets with an approach that is consistent with the asset pricing literature. I take a consumption-based pricing approach motivated by disaster pricing models and test for the existence of a negative price of temperature risk. Temperature rise is strongly linked to climate disaster events that will ultimately reduce consumption. Assets that are expected to perform poorly in states of high temperatures and low consumption are less attractive; I therefore test whether investors have empirically required a premium for stocks with negative temperature loadings.

I create a low frequency temperature shock variable by transforming raw U.S. temperature data and use it to proxy shocks to expectations of long-term temperature trends. I estimate the sensitivities of U.S. industry equity returns to low frequency temperature shocks and find that on average, industry temperature betas have been decreasing with time over the sample. However, I find no evidence of interaction between temperature betas and low frequency temperature levels themselves, revealing that the negative temperature beta time trend is driven by an unknown factor. The main empirical tests estimate the cross-sectional temperature risk premium that is required by investors as compensation for temperature risk. I focus on the period post 1988; this date is chosen to coincide with the establishment of the Intergovernmental Panel on Climate Change[1] and is set as the cut-off

[1] The IPCC was established in 1988 by the World Meteorological Organization. The IPCC has issued a series of Assessment Reports that highlight the causes and consequences of climate change, and have increased climate awareness. The First Assessment Report was produced in 1990.

date from which climate change awareness rapidly increased.[2] Results provide no evidence of a low frequency temperature risk priced into U.S. stock returns.

Additional tests conducted on temperature betas include an event study on the 2015 Paris Agreement and temperature beta correlations with firm specific environmental disclosures. Industry temperature betas cannot predict the outcomes of the Paris Agreement, nor does firm exposure to temperature correlate with firm disclosure to total climate risk. Traditional portfolio tests are also employed to test the relation between returns and temperature risk. I create portfolios based on temperature sensitivity to test for a trading anomaly and to serve as a robustness check for main results. Neither equal nor value-weighted portfolios are found to generate significant returns on average in accordance with the hypothesised temperature risk, nor are portfolio alphas significant once control risk factors are included in a regression. These results again provide no evidence of a temperature risk premium.

I reconcile the lack of evidence of a temperature risk factor with two plausible reasons. The first is the very long time horizons of climate related disasters. If climate disasters are expected to occur in the distant future, discounted losses are likely to be minute. Secondly, if temperature exposure is diversifiable then temperature risk is not systematic, and exposure will not generate a premium.

## 2. Literature review

I examine the price of risk associated with temperature change using a consumption-based pricing approach.[3] I review the literature by first examining a study conducted by Bansal, Kiku, & Ochoa (2016), and then consider the relation between consumption, disasters and temperature. Lastly I provide examples of some interactions between temperature and industry returns.

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[2] James E. Hansen of NASA also gave testimony to Congress in 1988 that largely raised climate change awareness.

[3] In the setting $R = \beta * \gamma$ when excess returns R are a function of temperature sensitivity $\beta$, the price of temperature risk is $\gamma$. The temperature factor risk premium is equivalent to the price of temperature risk and the two terms are used interchangeably.

Bansal et al. (2016) find evidence of equity market sensitivity to long-run changes in temperature trends, and a negative price of temperature risk. I conduct tests for the same relationship, albeit with differences in assumptions, models and data. Bansal et al. (2016) use first order differences in long-term temperature averages as a proxy for temperature risk. I argue that the first order differences are largely predictable. Predictable changes in low frequency trends are unlikely to create systematic risk; else investors could earn arbitrage profits on average by taking opposite positions in positive and negative temperature sensitive securities, given the existence of a temperature risk premium. Bansal et al. (2016) also do not control for popular risk factors in the literature, use a yearly frequency of data, and estimate betas in a time series without allowing for dynamic temperature betas. Their regressions may therefore suffer from omitted variable bias in the explanatory variables, or measurement bias due to the low frequency of returns and through not accounting for dynamic exposures to temperature risk. Following their rationale I hypothesise a negative price of temperature risk; however I augment their modelling approach.

### 2.1. Temperature and consumption

Campbell (2003) states that assets that are expected to perform better in states of poor consumption will be in greater demand, and investors are willing to pay higher prices or equivalently receive lower average returns as compensation. Campbell (2003) argues that investors will attempt to smooth consumption through time, and value the equity premium as the covariance between stock excess returns and consumption growth multiplied by investor risk aversion. Models that estimate the equity premium will only equilibrate with observed premiums if unreasonable risk aversion parameters are introduced. Temperature effects are estimated to shock growth rates (Bansal & Ochoa, 2011), which may explain a portion of the equity premium puzzle.

Bansal & Ochoa (2011) find that rising temperature levels impact world GDP growth negatively. Rising global temperature trends deteriorate aggregate growth and may lead to states of low consumption. Bansal & Ochoa (2011) also show that temperature betas contain information about differences in cross-country risk premiums. Global temperature rise has negative impacts on economic growth that is stronger for countries that are closer to the equator; market correlations to temperature shocks are found to vary between countries based on geography. This supports evidence presented by Dell, Jones & Olken (2009) who find that temperature has a negative relationship with cross-sectional income at both the international and domestic levels. Additionally, Dell, Jones & Olken (2012) reveal that growth is negatively affected when poorer countries have unusually hotter years, and is correlated with decreased investments and increased political instability. Aggregate investors value returns more in poorer states and therefore place a negative price on the covariance of equity returns and the temperature.

### 2.2. Disaster risk

Disasters are states in which GDP and consumption fall sharply (Barro & Jin, 2011). The disaster asset pricing literature primarily focuses on economic and wartime disasters such as the Great Depression, the World Wars, and disease epidemics; however I consider the consequences of long-term climate change which includes hurricane intensification, sea level rise, ocean acidification (Jaffe & Kerr, 2015) along with extreme conditions such as storms, droughts and frosts (Schaeffer et al., 2012) that will reduce consumption. Pricing of both actual and potential disaster events are of importance, as asset prices are set ex-ante on forward looking expectations of future states (Berkman, Jacobsen, & Lee, 2011). The unmanageable events of Nordhaus (2013) are examples of disastrous climate change events that will negatively shock consumption and production in the long and very long-run. Van Aalst (2006) finds that higher temperature levels are expected to result in more frequent natural disasters. Tail event probabilities for rare climate disaster reduce future consumption and should be priced into equity returns (Rietz, 1988); equities that are more susceptible to natural disaster related costs should generate greater returns on average for incorporating climate disaster risk.

Disaster asset pricing provides a potential solution to the equity premium puzzle which is also grounded on consumption-based asset pricing theory. Disaster models incorporate the demands of risk-averse investors who are also averse to extreme losses that may be incurred due to disastrous events. Even if next period disasters do not actually occur ex-post, equity owners must be compensated with a premium for ex-ante exposure. Rietz (1988) finds that given reasonable estimates of risk aversion and investor impatience, an Arrow-Debreu approach that accounts for probabilities of market crashes can explain high equity premiums and low risk free rates. Similarly, Barro (2006) calibrates a model to estimate an average probability of disasters that reduce GDP per capita by between 15 and 64 percent that provides an explanation for low interest rates in the U.S. during major wars. Copeland & Zhu (2007) however argue that rare disaster risk is diversifiable to the extent that correlations between international disasters are less than perfect. Extending their argument to climate change, if climate disaster exposures are diversifiable between countries or industries then the effect on required rates of return will be constrained. The Rietz-Barro hypothesis is further limited by the assumption of constant probability of disaster. Disaster probabilities may alternatively be modelled as a dynamic variable that adjusts based on investor expectations of future states, and varies in both the cross-section and time series (Gabaix, 2012). Variation in the cross-section and time series of natural disaster sensitivity is likely to exist due to heterogeneous relationships between industry and temperature trends. The next period probability of extreme climate disasters is conditional on the current temperature levels (Van Aalst, 2006), and the risk to cash flows is distributed unequally amongst industries (Schaeffer et al., 2012). Models that allow for variable rare disaster risk also allow for volatile asset prices and time-varying risk premiums. Berkman et al. (2011) empirically test this approach by creating an index on perceptions of time-varying political disaster probabilities, and find evidence in the cross-section for priced crisis risk; industries that are more sensitive to rare crises are found to yield higher returns on average. Bansal et al. (2016) additionally find that the price of temperature risk has both a constant component and a time-varying component. Their results indicate that the temperature risk premium is dynamic, and depends on the temperature level in the current state. Following their findings, I allow for moving temperature betas and also include tests for a time-varying temperature risk premium. Incorporating dynamic estimates of temperature betas and risk premiums in models accounts for industry adaptation effects and time-varying probabilities of future state natural disaster.

In summary, returns which are correlated with low frequency temperature shocks are risky to the extent they cannot be diversified and therefore require a risk premium. Assets which are expected to perform well in states where consumption is relatively low due to temperature related natural disasters must on average generate lower returns in the cross-section, ceteris paribus. This leads to a hypothesised negative temperature risk premium. If higher temperatures are expected to correlate with worse states of consumption, assets that have positive sensitivities to temperature should have negative temperature risk premiums in equilibrium (Campbell, 2003). Alternatively, assets that perform poorly when temperature levels are high and consumption is low are a relatively unattractive investment to investors and require a premium in returns.

### 2.3. Industry consequences of temperature rise

Through channels of demand and supply, climate change winners and losers emerge in the cross-section within both the aggregate U.S. economy and industry subsets. Industry sensitivity to temperature effects is not constant in the sample. Variation in the consequences of temperature change amongst industries provides information on the temperature risk premium in the main tests. Industries have fundamentally different exposures to both temperature and aggregate climate change. I argue that the aggregate impacts of temperature at the industry level become complicated through various channels, and provide a few examples within the agriculture and energy industries.

Schaeffer et al. (2012) summarise the consequences of climate change on various industries. They argue that agricultural considerations of temperature rise include the long-term effects on precipitation, evapotranspiration and the reproduction rates of pests, all of which are expected to worsen the cash flows to the industry. The increasing probability of tail events that include droughts, frosts and floods are also material considerations. However, higher $CO_2$ levels can positively improve the photosynthesis of crops (Schaeffer et al., 2012). As each crop category has an ideal temperature range in which productivity is maximised, gradual increases in temperature are likely to have parabolic relationships with crop output. Using data on climate variables and farmland prices Mendelsohn, Nordhaus, & Shaw (1994) find further relationships between agricultural activities and environmental effects. Through their models on the agriculture industry, they reveal that the major grain groups are most negatively sensitive to temperature increases but represented less than 16% of the American farm market. The impact of warmer temperatures may alternatively improve returns of some agricultural produce. The cumulative impact on the agriculture industry is therefore dependent on the underlying temperature level as well as the composition of the industry.

Climate change relationships with the energy and utility sector are also nonconstant at the industry level. Within the energy and utilities sector Schaeffer et al. (2012) further break down the sub-industries of hydropower, wind power, biofuels, solar energy, marine energy, oil, gas and coal into their resource endowments, energy supply and energy distributions supply chains. Even at this relatively broad level, the matrix of variables in the entire industry is quite large, and it is immediately obvious that climate variables have heterogeneous effects on each sub-industry. For example, solar energy generation is dependent on atmospheric water vapour content, cloud characteristics and atmospheric transmissivity. Climate change therefore has differing implications on solar energy generation at the country level; positive impacts are reported in south-eastern Europe, while negative impacts are noted in Canada as a result of decreasing solar radiation (Schaeffer et al., 2012). With rising temperatures, energy demand is also found to increase for cooling and decrease for heating. Total energy demand for temperature control follows a parabolic function in relation to temperature levels. Similar nonlinear structures are also found in the demand for motors, engines and water. Schaeffer et al. (2012) find that rising temperatures are found to increase the demand for vehicular air conditioning, leading to an increase in demand for fuel and efficient automotives. Demand-side implications for the energy sector are influenced by regional effects; for example, rising temperature levels in tropical climates would more likely increase cooling energy demand while colder regions would see reductions in heating energy demand.

## 3. Data

### 3.1. Low frequency temperature shock

The primary aim of this research is to estimate the market price of risk associated with exposure to temperature change factors. The alternative hypothesis is the existence of a negative temperature risk premium that compensates for exposure to long-term temperature risk. I first create a proxy for a low frequency temperature shock that is used in the various asset pricing models that follow.

I focus on shocks to long-term temperature trends as a subset of total climate change risk. Raw temperature data consists of U.S. temperature observations in degrees Fahrenheit that are obtained from the National Oceanic and Atmospheric Administration (NOAA).[4] The NOAA data is made up of average monthly temperature observations for the contiguous 48 states. Low frequency temperature shock data requires a transformation of raw temperature data into a new variable that estimates the differences in temperature trends between observations and investor expectations. I create a low frequency temperature shock variable by forecasting low frequency temperature with the Cochrane-Orcutt procedure, subtract it from observed low frequency temperature levels, and label it *Temp*. First a 5 year moving average is calculated for U.S. temperatures, representing low frequency temperature levels. The moving average is not biased by monthly seasonality and has a smoother time trend than raw temperature data, however it is non-stationary.

$$MA_t = \alpha + \beta^{time} * t + \varepsilon_t \tag{1}$$

I estimate the linear time trend and intercept parameters $\beta^{time}$ and $\alpha$ in an ordinary regression in which the moving average MA is regressed against the time variable *t*. The monthly residuals $\varepsilon_t$ are stored. Autocorrelation in the moving average time series provide information that can improve forecasting precision. Autocorrelated components in the moving average are removed with the

[4] Temperature data is sourced from URL https://www.ncdc.noaa.gov/cag/time-series/us. Monthly data for the observed average temperature in degrees Fahrenheit is retrieved for the period January 1895 to April 2017. No base period is subtracted from raw data and thus temperature data is not a meteorological temperature anomaly. Data has however been adjusted to remove artificial effects created by instrument changes, station relocation, urbanisation and observer practice changes, and data may differ from official observations located elsewhere.

following Cochrane-Orcutt iterative forecasting procedure.[5] Residual autocorrelations with up to 12 month lagged residuals are plotted using the partial autocorrelation function (PACF), from which AR(1) errors are assumed. The results are illustrated in the PACF plot in figure 1. The correlation estimate of residuals with lagged residuals is plotted with a 95% confidence band. The residuals and 1 month lagged residuals show almost perfect positive correlation. The correlation between residuals and 2, 3 and 6 month lagged residuals is negative and significant at the 5% level, however for simplicity in my model I ignore these marginal values and correct only for the 1 month lag.

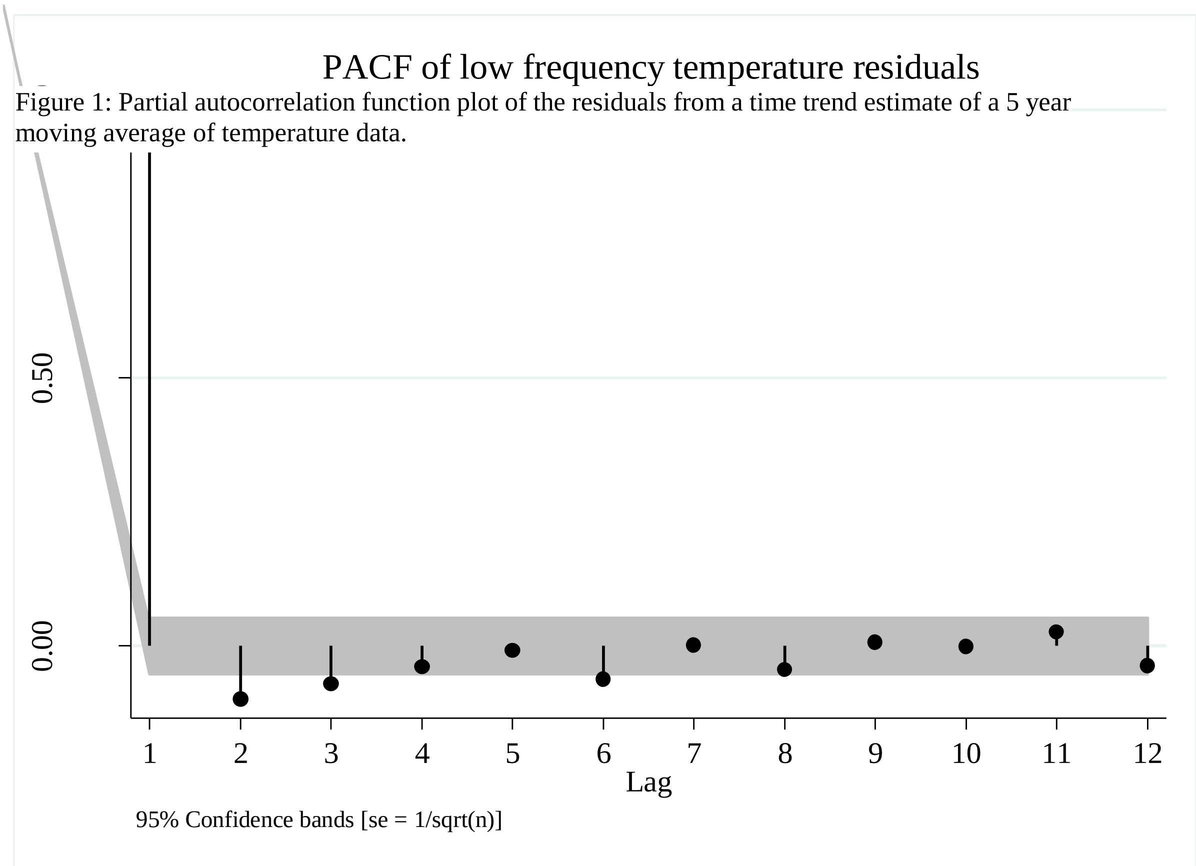



Figure 1: Partial autocorrelation function plot of the residuals from a time trend estimate of a 5 year moving average of temperature data.

$$\varepsilon_t = \rho * \varepsilon_{t-1} + \delta_t \qquad (2)$$

The residuals are used in a linear regression with no intercept against one month lagged residual values, and the slope estimate ρ is stored.

[5] The Cochrane-Orcutt iterative forecasting procedure is applied to data that have serial autocorrelation in the error term. The procedure estimates autocorrelation in the error term of a time series and adjusts the estimates of time series intercepts and slope coefficients; forecasts can then be made more accurately. See Ibbotson & Jaffe (1975) or Chordia, Roll, & Subrahmanyam (2002) for examples of application.

$$MA_t^* = MA_t - \rho * MA_{t-1} \tag{3}$$

$$T^* = t - \rho * (t - 1) \tag{4}$$

The lagged moving average multiplied by the estimated autoregressive component ρ is then subtracted from the current moving average figure to create an adjusted moving average, $MA^*$. The time variable is similarly transformed.

$$MA_t^* = \alpha^{co} + \beta^{co} * T^* + \varepsilon_t^{co} \tag{5}$$

The adjusted moving average is regressed against the adjusted time value to estimate the Cochrane-Orcutt intercept and slope, $\alpha^{co}$ and $\beta^{co}$.

$$MA_t - ( \alpha^{co}/(1 - \rho) + \beta^{co} * t ) = \eta_t \tag{6}$$

The estimated time trend slope and intercept effects are removed from the observed moving average data in order to calculate the adjusted error term $\eta_t$ for each month.

$$F_t = MA_t^* + \rho * \eta_{t-1} \tag{7}$$

A forecast for the next moving average is created, $F_t$, by adding back the auto-correlated portion of the lagged error term, equal to $\rho * \eta_{t-1}$. I assume that the forecasted value is the expectation for low frequency temperature levels set by investors.

$$Temp_t = MA_t - F_t \tag{8}$$

Finally, the difference between the observed moving average and the forecasted moving average is calculated and stored as *Temp*. *Temp* is used as a proxy for low frequency temperature shocks.

Conceptually this transformation of raw temperature values into the *Temp* variable represents a proxy for shocks to 5 year temperature averages after adjusting for autocorrelation. I assume investor expectations are removed through the data transformation. *Temp* is thus a proxy for both unanticipated and exogenous low frequency temperature shocks.

Bansal et al. (2016) use first order differences in the moving average of temperature to proxy for low frequency temperature shocks; however, first order differences are not entirely representative of shocks to investor expectations. First order differences may be predictable if the temperature time trend can be accurately estimated and therefore are not representative of temperature *risk*. I use a different approach by proxying investor expectations with Cochrane-Orcutt forecasts. *Temp* is thus of a smaller magnitude on average than the first order differences of Bansal et al. (2016) as low frequency temperature forecasts are more accurate than standard OLS predictions, and are subtracted from observed levels. This approach creates a more appropriate explanatory risk variable than first order differences in moving averages.

Table 1: Summary statistics for *Temp*, the variable used to proxy for low frequency temperature shocks.

| | | | Temp | | | | |
|---|---|---|---|---|---|---|---|
| Date range | N | Mean | Median | Min | Max | Std Dev | Skewness |
| January 1900 - April 2017 | 1,408 | 0.000 | 0.000 | -0.209 | 0.180 | 0.049 | -0.008 |

Due to the moving average transformation the first 5 years of the raw NOAA data are lost when creating the *Temp* variable. On average the unexpected monthly temperature innovation is 0 degrees Fahrenheit. There is only weak negative skew in the *Temp* data, and the mean and median are approximately equal. The data has monthly frequency and spans over a century. I illustrate the 5 year moving average temperature, forecasted temperature and *Temp* data in figures 2 and 3. The Cochrane-Orcutt forecasts track observed low frequency temperature levels very closely, thus shocks to temperature expectations are of low magnitudes. As time trends have been removed from *Temp* there is no predictable pattern in the data.[6]

[6] Using a Dickey-Fuller test I reject the null hypothesis that *Temp* has a unit root at the 1% level. *Temp* is therefore a stationary time series. The Durbin-Watson test also fails to detect autocorrelation in *Temp* data.

Figure 2: A time series of observed low frequency temperature levels and forecasts generated with the Cochrane-Orcutt procedure. Low frequency temperature observations are created with a 5 year moving average of observed temperatures. The difference between observed values and forecasts are stored as a low frequency temperature shock, *Temp*.

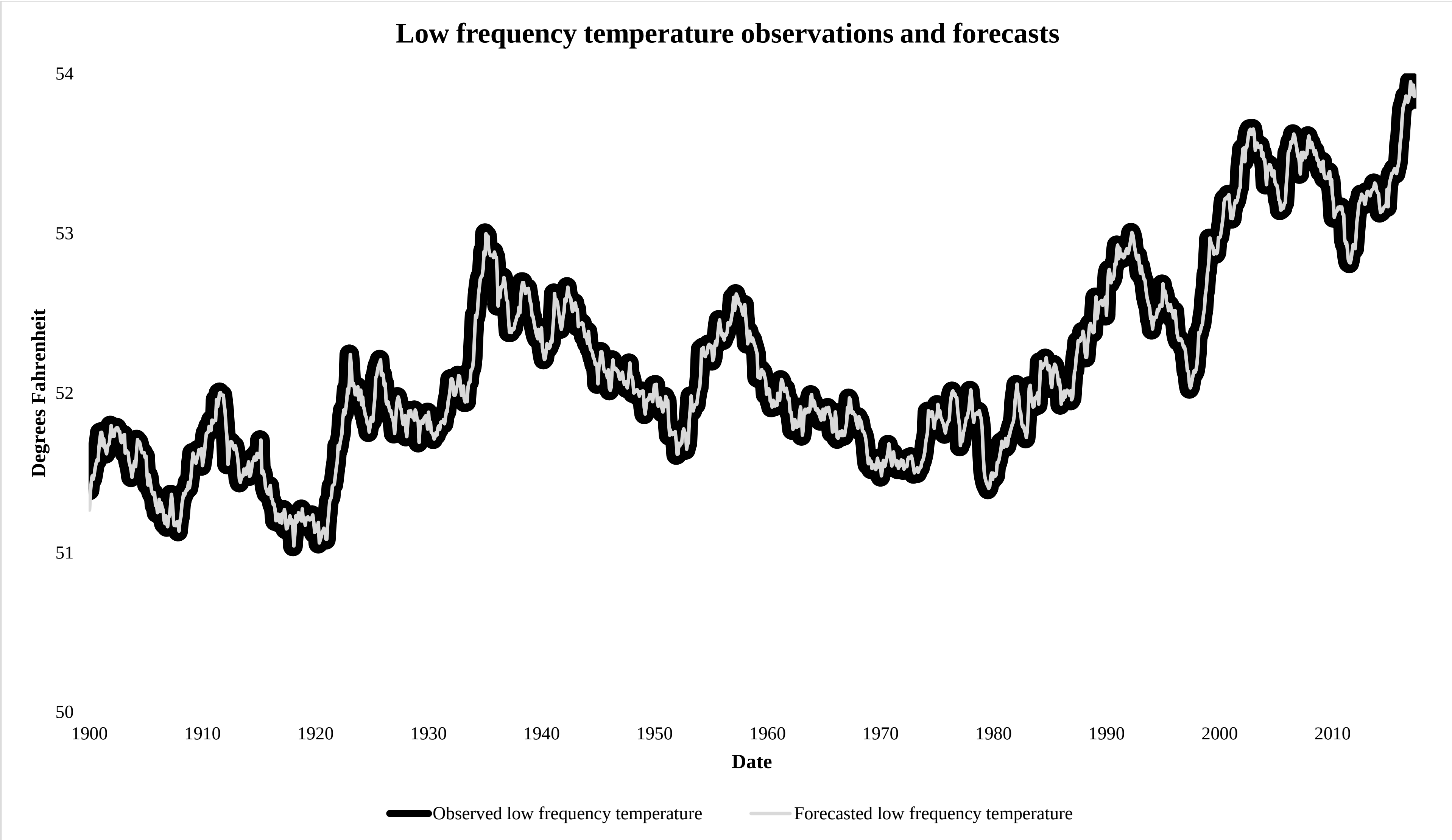
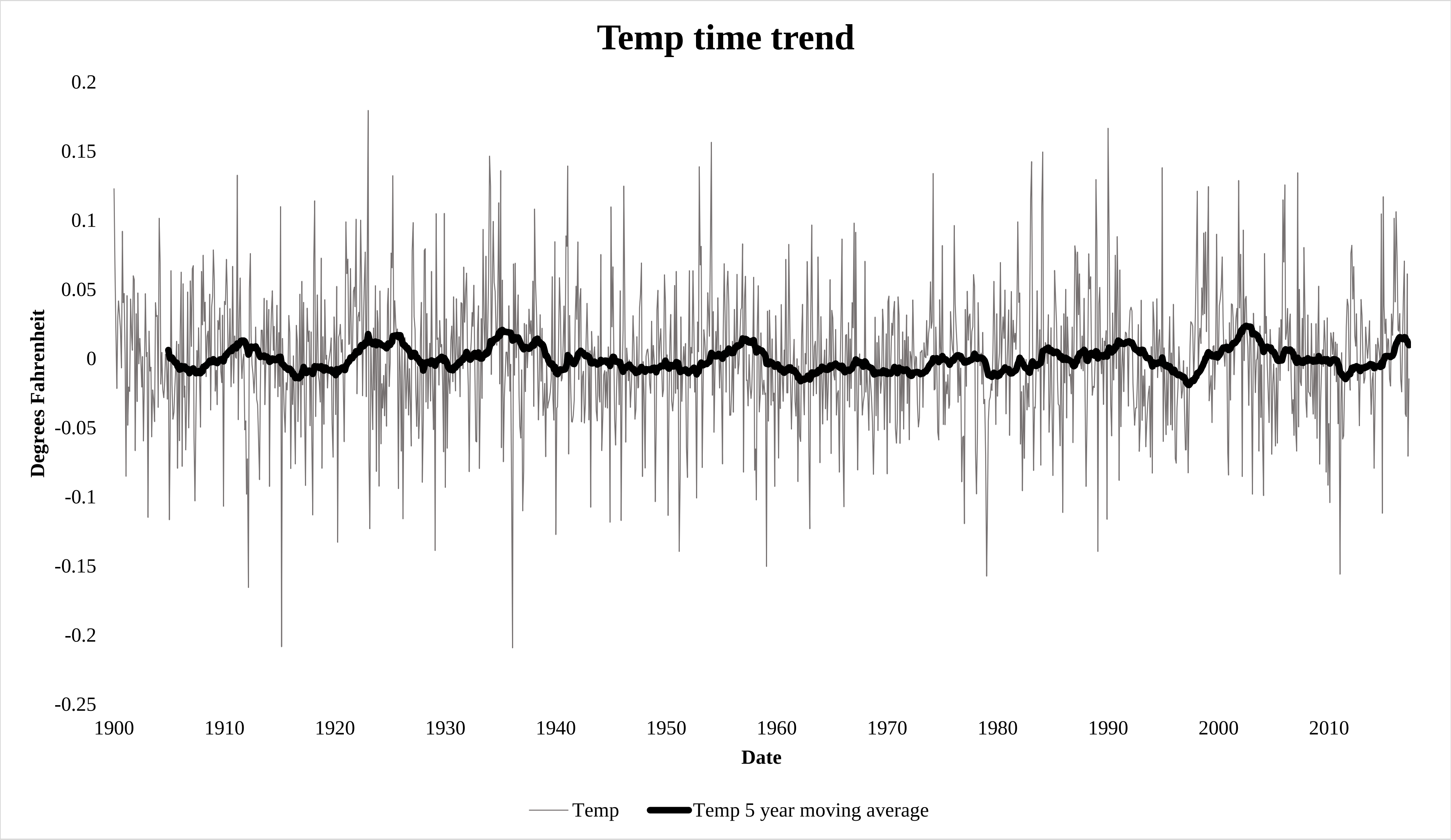


Figure 3: A time series of *Temp*, the shocks to low frequency temperature expectations. The 5 year moving average of the *Temp* innovation is plotted in bold.



## 3.2. Returns and control risk factors

I obtain monthly and daily returns for the Fama-French 49 industry value weighted portfolios (Fama & French, 1997).[7] For portfolio tests I use monthly realised returns on U.S. equities.[8] I use monthly data on control risk factors which consists of the U.S. relevant market risk premium, SMB, HML, RMW, CMA and MOM portfolio returns along with the risk free rate proxy.[9] The Fama-French 5-factors data dates back to 1963, while the momentum factor begins from 1927. Data for the Hou, Xue and Zhang q-factors (Hou, Xue, & Zhang, 2014) are also obtained.[10] Control factor models therefore include the CAPM, the Fama-French 3-factor and 5-factor models (Fama & French, 2016), the Carhart 4 factor model (Carhart, 1997) and the HXZ q-factor model. All data on returns are in percentage format.

In table 2 I present the correlations in the data between control risk factors and *Temp* shocks. Correlations are weak and indicate that the *Temp* variable is orthogonal to the control risk factors. Note that though the Fama-French market factor is almost perfectly collinear with the HXZ market factor, minor variation exists due to construction methods.

[7] Industry portfolio returns were sourced from Kenneth R. French's data library. Daily returns on industry portfolios are used in the event study.

[8] Monthly realised return data for equities are obtained from the CRSP database. I exclude returns on non-domestic equities. I follow Shumway (1997) in correcting for delisting biases. If delisting returns in the panel data have a delisting stock code of 500, 520, between 551 and 573 inclusive, 574, 580 or 584, returns have been set at a value of -30%; while a missing delisting return with an available delisting code has returns set to -100%. Microcaps also are excluded for the equal-weighted portfolio. The microcap exclusion process involves dropping stocks with market capitalisations in the lowest decile in each month. Microcaps are given immaterial weights in value-weighted portfolios and therefore do not need to be excluded.

[9] MKT, SMB, HML, RMW, CMA, MOM and the risk free rate data were sourced from Kenneth R. French’s data library. I also obtain daily frequency data for the Carhart 4-factors to use in the event study.

[10] I thank Lu Zhang for returns data on the q-factor portfolios.

Table 2: Correlation matrix between explanatory risk variables. Correlation between temperature anomalies and risk factors is weak, suggesting orthogonal effects and a low chance of collinearity problems in tests. Correlation coefficients significant at the 5% level are in bold.

| | Temp | MKT (FF) | SMB | HML | MOM | RMW | CMA | MKT (HXZ) | ME | I/A | ROE |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Temp | 1 | | | | | | | | | | |
| MKT (FF) | 0.017 | 1 | | | | | | | | | |
| SMB | 0.006 | **0.275** | 1 | | | | | | | | |
| HML | -0.025 | **-0.259** | **-0.079** | 1 | | | | | | | |
| MOM | -0.027 | **-0.133** | -0.023 | **-0.185** | 1 | | | | | | |
| RMW | -0.014 | **-0.233** | **-0.353** | 0.074 | **0.109** | 1 | | | | | |
| CMA | -0.033 | **-0.385** | **-0.100** | **0.692** | -0.012 | -0.037 | 1 | | | | |
| MKT (HXZ) | 0.013 | **0.999** | **0.277** | **-0.274** | **-0.143** | **-0.244** | **-0.399** | 1 | | | |
| ME | -0.004 | **0.261** | **0.974** | -0.048 | -0.015 | **-0.376** | -0.055 | **0.267** | 1 | | |
| I/A | -0.048 | **-0.385** | **-0.188** | **0.676** | 0.029 | **0.095** | **0.911** | **-0.386** | **-0.147** | 1 | |
| ROE | 0.003 | **-0.197** | **-0.367** | **-0.137** | **0.500** | **0.668** | **-0.090** | **-0.208** | **-0.311** | 0.036 | 1 |

### 3.3. Firm specific climate disclosure

For secondary tests on climate sensitivity, I obtain a firm specific variable that provides a measure of firm exposure to aggregate climate risk.[11] Sourced from sustainability disclosures on Ceres, the climate disclosure variable is found in 10-K filings following the SEC ruling stating material information regarding climate risks should be included in reports.[12] Prior to mandated disclosure, less than 24% of companies included any discussion of climate risk in their 10-K's, while within this sample period 56% of companies find material climate risk in need of disclosure (Berkman, Jona, Lim, & Soderstrom, 2017); hence the sample size is limited to 4 years. Through a textual analysis of material climate risk exposures on 10-K filings from 2010 onwards, a raw climate risk score is generated. Developed by the Ceres-CookESG, the RawScore variable is used as a proxy for firm specific climate risk. RawScore is an output of the language used as well as the length of climate disclosure in firm's 10-K reports but does not distinguish between the differing types of climate risk. Table 3 summary statistics reveal that RawScore is positively skewed as there is large variation between industry averages.

Table 3: Summary statistics for RawScore, raw values of self-disclosed environmental exposure extracted from firm 10-K reports.

| | | | RawScore | | | | |
|---|---|---|---|---|---|---|---|
| Date range | N | Mean | Median | Min | Max | Std Dev | skewness |
| January 2011 - January 2014 | 5,561 | 20.402 | 2.000 | 0.000 | 961 | 50.900 | 6.145 |

## 4. Average industry temperature exposure over time

I initially test temperature betas over time. I employ the Fama-French 49 industry value weighted portfolios as test assets. I choose industry portfolios in order to reduce asset idiosyncratic risk and to

[11] I thank Henk Berkman for access to the environmental disclosure data.
[12] See SEC (2010) for full guidelines on required environmental disclosure.

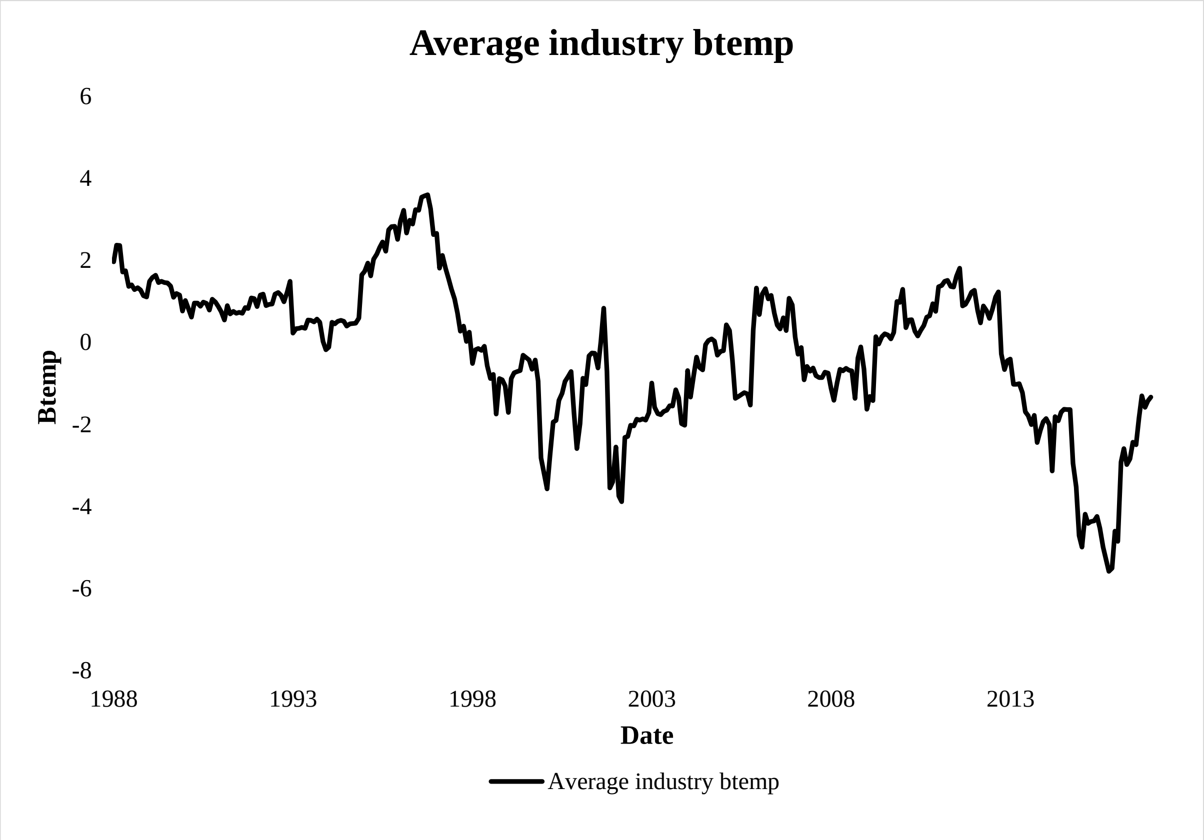
estimate the varying consequences of temperature levels at the industry level. Popular benchmark models such as the Fama-French factors do a poor job of explaining cross-sectional variance in industry portfolios (Berkman et al., 2011). I test whether *Temp* adds explanatory power in asset pricing models. I first create estimates for industry temperature betas by conducting the following time series regression for each industry.

$$R_t = \alpha_t + \beta_t^{temp} * temp_t + \beta_t^{mkt} * MKT_t + \beta_t^{smb} * SMB_t + \beta_t^{hml} * HML_t + \beta_t^{mom} * MOM_t + \varepsilon_t \qquad (9)$$

Industry returns $R_t$ are regressed on *Temp* while controlling for the Carhart 4-factors in a 60 month rolling window regression.[13] Rolling windows provide dynamic estimates of exposure to all risk factors employed in the regression. Assets that have returns with less than 30 prior periods are set to missing. I average the industry temperature betas $\beta_t^{temp}$ for each month from 1988 onwards. This procedure generates an equal-weighted measure that is representative of the average industry exposure to temperature. I plot average industry temperature betas in figure 4.

Figure 4: An illustration of estimated average industry temperature betas Btemp over the sample period. The average industry temperature betas are non-stationary with a negative time trend.

[13] I choose 60 month rolling windows following the methodology of other research in this area. See Petkova & Zhang (2005), Berkman et al. (2011), and Franzoni (2002) for examples.




Average industry temperature betas are non-stationary and are decreasing over the sample. I fit a linear time trend of the average industry temperature betas with the following regression.

$$\beta_t^{temp} = \alpha + \gamma^{\beta t\text{-}1} * \beta_{t\text{-}1}^{temp} + \gamma^{time} * t + \varepsilon_t \qquad (10)$$

Estimated average industry temperature betas $\beta_t^{temp}$ are regressed against lagged betas[14] $\beta_{t-1}^{temp}$ and time *t*, from which a lagged effect $\gamma^{\beta t-1}$, time trend $\gamma^{time}$, intercept $\alpha$ and errors $\varepsilon_t$ are estimated. Standard errors are adjusted for Newey-West 5 month lags.[15] The time trend $\gamma^{time}$ is interpreted as the average drift in sensitivities to long-term temperature innovations. I present the fitted yearly time trend in table 4. I also conduct the same regression for each of the 49 industries to highlight industry specific temperature beta time trends over the sample period, presented in table 5.

[14] A PACF function with 12 lags on average industry temperature betas reveals strong autocorrelation in the series with only the first lag.

[15] Following the literature I set the lag equal to $4(T/100)^a$ where T = 348 time periods and a = 4/25 using the quadratic spectral kernel. The output equals 4.88, which I round up to 5.

Table 4: Estimated average temperature beta yearly time trend and constant values. P-values are Newey-West adjusted with 5 month lags. P-values in bold denote significance at the 10% level.

**Average industry temperature beta time trend**

| Parameter | Coefficient | P-value |
|---|---|---|
| Lagged effect | 0.943 | **[0.000]** |
| Time trend | -0.006 | **[0.039]** |
| Intercept | 0.068 | [0.117] |

There is an estimated negative time trend for the average industry temperature beta after adjusting for autocorrelation in the data. Every year the average industry temperature beta estimates decrease by 0.006. With 29 years in the sample, the time effect eventually becomes stronger than the intercept and moves the temperature beta into negative territory. Low frequency temperature shocks therefore decrease returns for the average industry more over time. A negative beta trend is intuitive; with growing average temperature levels over time the marginal impact of temperature shocks are also likely to be larger. Average industry returns are expected to have a stronger negative exposure to low frequency temperature shocks as underlying temperature levels rise.

Table 5: Estimated individual industry temperature beta yearly time trends. P-values are Newey-West adjusted with 5 month lags. Estimates in bold denote significance at the 10% level.

**Individual industry temperature beta time trends**

| Industry | Time trend | Industry | Time trend | Industry | Time trend |
|---|---|---|---|---|---|
| Agric | 0.017 | Cnstr | **-0.042** | Hardw | **-0.035** |
| Food | -0.008 | Steel | -0.014 | Softw | **-0.024** |
| Soda | 0.013 | FabPr | 0.011 | Chips | **-0.023** |
| Beer | 0.009 | Mach | -0.011 | LabEq | 0.009 |
| Smoke | 0.017 | ElcEQ | 0.007 | Paper | -0.006 |
| Toys | 0.008 | Autos | **-0.032** | Boxes | -0.007 |
| Fun | **-0.026** | Aero | -0.006 | Trans | 0.002 |

| | | | | | |
|---|---|---|---|---|---|
| Books | **-0.027** | Ships | -0.026 | Whlsl | -0.006 |
| Hshld | 0.008 | Guns | -0.009 | Rtail | 0.009 |
| Clths | -0.020 | Gold | -0.002 | Meals | 0.000 |
| Hlth | **0.034** | Mines | -0.003 | Banks | 0.001 |
| MedEq | -0.011 | Coal | -0.031 | Insur | 0.001 |
| Drugs | -0.009 | Oil | 0.008 | RlEst | -0.012 |
| Chems | 0.004 | Util | 0.010 | Fin | 0.020 |
| Rubbr | 0.008 | Telcm | **0.023** | Other | **0.049** |
| Txtls | -0.023 | PerSv | **-0.032** | | |
| BldMt | **0.015** | BusSv | **0.011** | | |

The individual industry temperature beta trends are also interesting. Industry specific temperature beta time trends are largely consistent with expectations. For example, the temperature betas for construction, hardware and autos decline over the sample period, whereas the exposure of safe havens such as gold and real estate are unaffected. Healthcare has had an increasing temperature beta trend. These results highlight the changes in specific industry exposures to temperature trends. I also test the relation between average industry temperature betas and the underlying low frequency temperature level itself.

$$\Delta\beta_t^{temp} = \mu + \pi * \Delta MA_t + \eta_t \tag{11}$$

The first order differences in average industry temperature betas $\Delta\beta_t^{temp}$ are regressed against the first order differences in the 5 year moving average temperature, $\Delta MA_t$.[16] The model provides estimates of the intercept $\mu$, the slope parameter $\pi$ and the error term $\eta_t$. If the hypothesised relation

[16] I use first order differences to avoid spurious regression results from using the non-stationary $\beta^{temp}$ and MA variables. Using Dickey-Fuller tests on $\Delta\beta^{temp}$ and $\Delta$MA I reject the null hypothesis of unit roots in the transformed data at the 1% level. The result of the Durbin-Watson test also does not indicate autocorrelation in the error terms.

between average industry temperature betas and base temperature levels is true, a negative value for $\pi$ is expected.

Table 6: Estimated relationship between first order differences in average industry temperature betas and a 5 year moving average. P-values are Newey-West adjusted with 5 month lags. P-values in bold denote significance at the 10% level.

**Average temperature beta relation with low frequency temperature**

| Parameter | Coefficient | P-value |
|---|---|---|
| $\pi$ | 0.709 | [0.382] |
| $\mu$ | -0.013 | [0.573] |

Results provide no evidence of a negative relation between temperature levels and average industry temperature betas.[17] Estimates are not consistent with expectations of rising climate related costs in the future. Average industry temperature betas are found to fall over time; however the trend is not correlated with temperature change itself. Results are unexpected and suggest industry temperature sensitivities are likely driven by some unspecified confounding variable.

## 5. Main Results

### 5.1. Two-way clustered regressions

I use a two-way clustered regression model to estimate the temperature risk premium. The approach follows two stages; in the first stage I estimate industry return sensitivities to *Temp*, then in the second stage I conduct a pooled panel regression of industry returns on estimated betas. In the first stage, I conduct the following rolling window regression for each portfolio *i*.

$$R_t = \alpha_t + \beta_t^{temp} * temp_t + \boldsymbol{\beta_t^{cont}} * \boldsymbol{cont_t} + \varepsilon_t \tag{12}$$

Excess industry portfolio returns $R_t$ are regressed against the low frequency temperature innovation $temp_t$ and a vector of control risk factors $\mathbf{cont_t}$ in a 60 month rolling window time series regression. For each portfolio *i* during month *t*, $\alpha_t$ is the regression constant and $\varepsilon_t$ is the error term.

[17] In unreported results, I find no evidence of a relation between average industry temperature betas and temperature levels even when interaction effects between $\Delta MA_t$ and $MA_t$ are specified. Similar non-results are obtained when considering the relation between first order differences in average temperature betas and lagged temperature levels.

$\beta_t^{temp}$ and $\boldsymbol{\beta_t^{cont}}$ are the estimated factor loadings of the temperature shock and control risk factors respectively and are stored for the second stage. Estimated sensitivities to temperature innovations vary dependent on the benchmark control risk factors used to estimate betas. Observations prior to 1988 are then excluded; with this reduced sample I conduct the second stage pooled panel regression.

$$R_{i,t} = \mu + \gamma^{temp} * \beta_{i,t-1}^{temp} + \boldsymbol{\gamma^{cont}} * \boldsymbol{\beta_{i,t-1}^{cont}} + \eta_{i,t} \tag{13}$$

Portfolio returns $R_{i,t}$ are regressed against the lagged beta estimates $\beta_{i,t-1}^{temp}$ and $\boldsymbol{\beta_{i,t-1}^{cont}}$ in a two-way clustered pooled panel regression following the findings of Petersen (2009). The model adjusts standard errors for clustering on both industry and time dimensions. $\eta_{i,t}$ captures the error term of the two-way clustered regression, while $\gamma^{temp}$ is the estimated temperature risk premium and $\boldsymbol{\gamma^{cont}}$ is the estimated vector of premiums for control factor risk. I repeat the entire two-stage approach separately for each of the 5 control risk factor models.[18] Table 7 presents the results of the two-way clustered regressions.

[18] Control risk factor models are the CAPM, Fama-French 3-factors, Carhart 4-factors, Fama-French 5-factors and the Hou-Xue-Zhang q-factors.

Table 7: Regression results with firm and time clusters in a pooled panel setting. Industry portfolios are used as test asset. Monthly returns are regressed against control risk and temperature loadings to estimate the corresponding risk premiums. P-values are based on two-way clustered standard errors and are shown in brackets below estimates. P-values in bold denote significance at the 10% level.

**49 Industry two-way clustered regression results**

| | CAPM | FF 3 | Carhart | FF 5 | HXZ |
|---|---|---|---|---|---|
| Constant | 0.553 | 0.563 | 0.732 | 0.852 | 0.751 |
| | **[0.042]** | **[0.022]** | **[0.001]** | **[0.001]** | **[0.005]** |
| Temp | -0.005 | -0.002 | 0.000 | 0.001 | -0.002 |
| | [0.297] | [0.635] | [0.981] | [0.893] | [0.764] |
| MKT | 0.171 | 0.131 | -0.040 | -0.163 | -0.048 |
| | [0.593] | [0.682] | [0.895] | [0.624] | [0.879] |
| SMB | | 0.112 | 0.217 | 0.175 | |
| | | [0.476] | [0.148] | [0.217] | |
| HML | | 0.094 | 0.010 | 0.061 | |
| | | [0.640] | [0.961] | [0.762] | |
| MOM | | | 0.113 | | |
| | | | [0.740] | | |
| RMW | | | | 0.090 | |
| | | | | [0.561] | |
| CMA | | | | -0.049 | |
| | | | | [0.711] | |
| ME | | | | | 0.109 |
| | | | | | [0.520] |
| I/A | | | | | 0.129 |
| | | | | | [0.346] |
| ROE | | | | | -0.044 |
| | | | | | [0.789] |

Results of the two-way clustered regression do not provide any evidence of a cross-sectional temperature risk premium. The low frequency temperature shock is estimated to have a negative premium in accordance with the disaster pricing hypothesis; however estimates are not significant at the 10% level in any test. The estimated temperature risk premium is much smaller than premium estimates for control risk factors due to the low average magnitude of the *Temp* variable. A majority of the total equity premium is captured by the regression constant, as opposed to sensitivity to *Temp* or to the control risk factors.

The two-way clustered regression estimates a constant temperature risk premium across the panel data. I additionally test whether using a more recent sample generates a significant estimate of the temperature risk premium. I reduce the sample into the sub-period 2000 – 2017 and again conduct the two-way clustered regressions controlling for the Carhart 4-factors. In this reduced sample I estimate a temperature risk premium of 0.003 with an insignificant p-value of 0.371. Again, there is no evidence of a temperature risk premium in the U.S. equity market. Though climate awareness has grown in this period, estimates of the temperature risk premium are not significant. These results do not conform to expectations of an increasing price of temperature risk.

### 5.2. Time-varying temperature risk premium

I use the Fama-Macbeth methodology to test for temperature risk premiums (Fama & MacBeth, 1973). The Fama-Macbeth approach allows for time-varying estimations of the temperature risk premium, also serves as a robustness check. I again use the Fama-French 49 industry value weighted portfolios in a two-stage regression approach. In the first stage I calculate temperature betas for each of the *i* portfolios in a rolling window regression.

$$R_t = \alpha_t + \beta_t^{temp} * temp_t + \boldsymbol{\beta_t^{cont}} * \boldsymbol{cont_t} + \varepsilon_t \tag{14}$$

I calculate industry portfolio temperature betas by regressing excess portfolio returns $R_t$ on $temp_t$ and the control risk factors $\mathbf{cont_t}$ in the first stage 60 month rolling window regression, in the same manner as the two-way clustered regressions. After the first stage procedure I again reduce the sample period to observations from 1988 onwards. I then conduct the following second stage cross-sectional regressions at each time period *t*.

$$R_i = \mu + \gamma^{temp} * \beta_{i,t-1}^{temp} + \boldsymbol{\gamma}^{\boldsymbol{cont}} * \boldsymbol{\beta}_{\boldsymbol{i,t-1}}^{\boldsymbol{cont}} + \eta_{i,t} \qquad (15)$$

The estimated betas from the first stage are stored and used in the second stage cross-sectional regressions. In contrast to the single pooled panel regression conducted at the second stage for the two-way clustered regression, in the Fama-Macbeth approach regressions are conducted for each time period. Excess returns are regressed against 1 month lagged $\beta^{temp}$ and $\boldsymbol{\beta}^{\mathbf{cont}}$ variables in each monthly cross-section to obtain a risk premium estimate for each risk factor, labelled as $\gamma_t^{temp}$ and $\boldsymbol{\gamma}_{\mathbf{t}}^{\mathbf{cont}}$ respectively. $\mu_t$ captures the constant risk premium term in the model, while $\eta_{i,t}$ are the error terms.

The resulting estimated risk premium for the temperature factor and control factors, $\gamma_t^{temp}$ and $\boldsymbol{\gamma}_{\mathbf{t}}^{\mathbf{cont}}$, are then averaged throughout the time series with Newey-West standard error corrections for 5 month lags. The entire two-step procedure is conducted separately using each of the 5 control risk models. Results are presented in table 8.

Table 8: Second stage Fama-Macbeth results using monthly *Temp* data as a proxy of temperature innovations and industry portfolios as test assets. Results are the time series averages of risk premiums of temperature risk and control risk factors. Fama-Macbeth tests are run with CAPM, FF 3-factor, 5-factor, Carhart 4-factor and HXZ q-factor models for robustness. P-values calculated from Newey-West adjusted standard errors with 5 month lags are shown in brackets below estimates. P-values in bold denote significance at the 10% level.

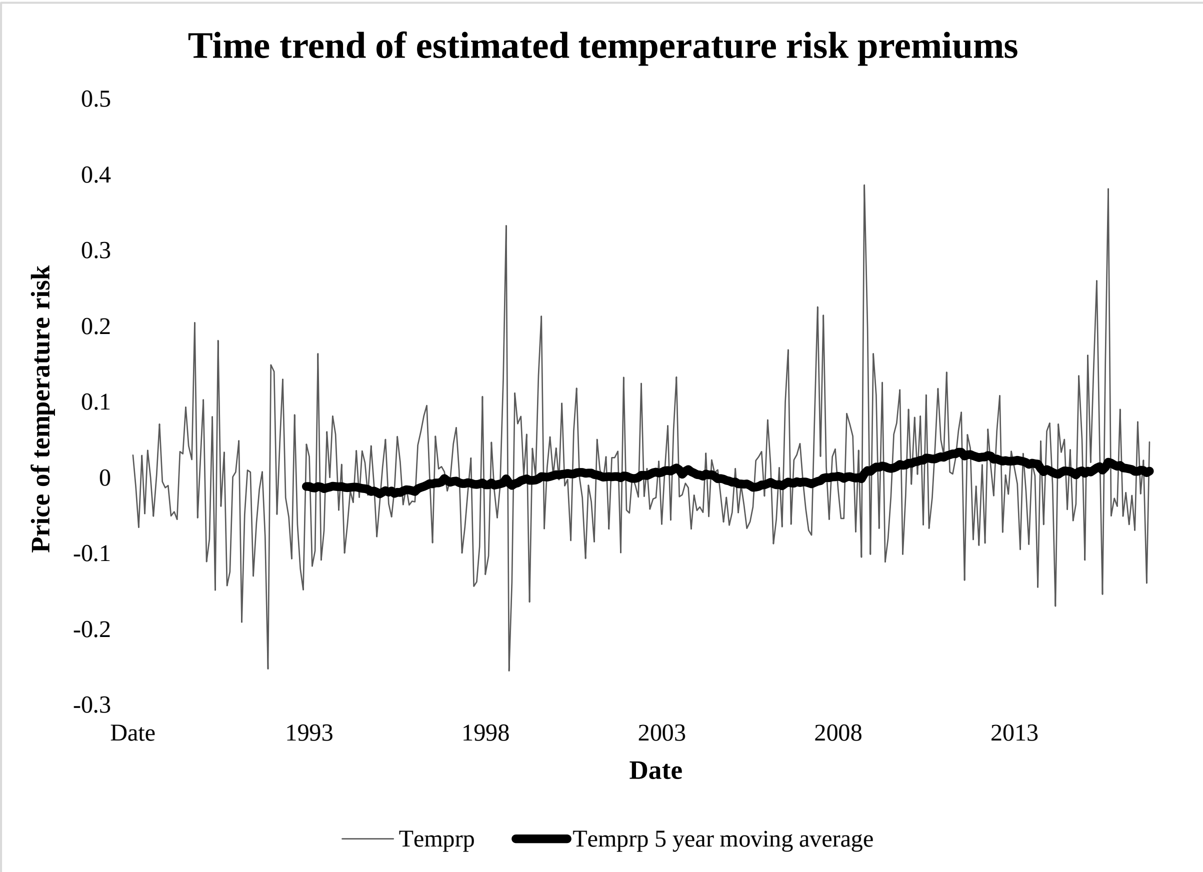
**49 Industry Fama-Macbeth results**

| | CAPM | FF 3 | Carhart | FF 5 | HXZ |
|---|---|---|---|---|---|
| Constant | 0.355 | 0.341 | 0.332 | 0.418 | 0.334 |
| | [0.183] | [0.136] | [0.147] | **[0.059]** | [0.164] |
| Temp | -0.002 | 0.002 | 0.003 | 0.001 | 0.003 |
| | [0.675] | [0.592] | [0.466] | [0.767] | [0.567] |
| MKT | 0.340 | 0.310 | 0.327 | 0.258 | 0.337 |
| | [0.303] | [0.308] | [0.300] | [0.368] | [0.274] |
| SMB | | 0.042 | 0.092 | -0.014 | |
| | | [0.775] | [0.527] | [0.927] | |
| HML | | 0.312 | 0.267 | 0.270 | |
| | | **[0.097]** | [0.153] | [0.136] | |
| MOM | | | 0.301 | | |
| | | | [0.276] | | |
| RMW | | | | 0.099 | |
| | | | | [0.434] | |
| CMA | | | | 0.053 | |
| | | | | [0.731] | |
| ME | | | | | 0.095 |
| | | | | | [0.532] |
| I/A | | | | | 0.102 |
| | | | | | [0.497] |
| ROE | | | | | 0.141 |
| | | | | | [0.361] |

The Fama-Macbeth approach is not as robust as the two-way clustered regression (Petersen, 2009), however results generated from both approaches provide no evidence of a temperature risk premium. Fama-Macbeth results do not show a significant average temperature risk premium across the sample for low frequency innovations in temperature. Many of the control risk variables do not show significance in estimates for average risk premiums either.

I illustrate the Fama-Macbeth estimated temperature risk premium time trend controlling for the Carhart 4-factor model in figure 5 by plotting cross-sectional estimates of temperature risk premiums from 1988 to 2017.

Figure 5: Monthly cross-sectional estimates of the temperature risk premium temprp, estimated using the *Temp* variable and controlling for the Carhart 4-factors. A 5 year moving average is plotted with the darker thicker line.




Contrary to a priori expectations of increasing climate awareness, temperature risk premiums have no strong trend through the time series, and are largely volatile. In the time series we see large volatilities in estimates of temperature risk premiums while the smoothed 5 year moving average seems relatively stationary. There is a slight upwards trend in the late 2000's, however this movement is in the opposite direction to the hypothesis and does not last. In accordance to the negative relation between temperature and consumption, there is no evidence of the hypothesised negative trend in the temperature risk premium. I test the time trend of the temperature risk premium with the following regression.

$$Temprp_t = \alpha + \beta^t * \mathrm{t} + \varepsilon_t \qquad (16)$$

The estimated temperature risk premiums $Temprp_t$ are regressed against time $t$ in order to estimate a time trend $\beta^t$.[19] The constant and error terms are captured by $\alpha$ and $\varepsilon_t$ respectively.

Table 9: Estimated time trend of the temperature risk premium, calculated using the Carhart 4-factor model. Newey-West adjusted p-values with 5 month lags are displayed below estimates in brackets. P-values in bold denote significance at the 10% level.

**Temperature risk premium time trend**

| Intercept | Time trend |
|---|---|
| -0.01319 | 0.00009 |
| [0.124] | **[0.044]** |

I find no evidence of an economically significant time trend in temperature risk premiums. The constant estimate is negative but is not significant. I perform another regression to test whether temperature risk premiums have shifted in recent decades.

$$Temprp_t = \alpha + \beta^{2000} * D_t^{2000} + \beta^{2010} * D_t^{2010} + \varepsilon_t \qquad (17)$$

Estimates of the temperature risk premium $Temprp_t$ are regressed against 2 time dummies $D^{2000}$ and $D^{2010}$ which are activated during the 2000's and 2010's respectively. The constant temperature risk premium $\alpha$ and decadal dummy effects $\beta^{2000}$ and $\beta^{2010}$ are presented in table 10.

[19] The results of the Durbin-Watson test on cross-sectional temperature risk premium estimates indicate no autocorrelation in the time trend errors.

Table 10: Decadal dummy coefficients of the temperature risk premium, calculated using the Carhart 4-factor model. Newey-West adjusted p-values with 5 month lags are displayed below estimates in brackets. P-values in bold denote significance at the 10% level.

| Temperature risk premium with decadal effects | | |
|---|---|---|
| Constant | 2000's Dummy | 2010's Dummy |
| -0.005 | 0.012 | 0.019 |
| [0.422] | [0.228] | [0.106] |

I find no evidence of negative decadal effects in estimated temperature risk premiums. Neither of the dummy coefficients are estimated with significance, and are of the opposite sign. Results do not provide evidence for either a negative time trend for temperature risk premiums over the sample or average decadal effects in the last two decades.

## 6. Additional temperature beta tests

### 6.1. Event study

I use event study methodology to examine the relationship between industry temperature beta estimates and the impacts of environmental regulation. The event study is conducted using the United Nations Framework Convention on Climate Change Paris Agreement, adopted by the U.S. on the 12$^{th}$ of December 2015. Alternative events are available, such as the Kyoto Protocol, the Copenhagen Accord or various physical climate phenomena, however the Paris Agreement is chosen for its recent occurrence and unexpected outcomes.[20] I test whether the outcomes of the event on industry returns are linked to industry exposure to temperature risk. The event study serves as an external validity test of industry temperature betas and provides evidence that they largely make sense. The event is expected to have a greater impact on the returns for temperature sensitive industries through regulatory channels.

[20] See "Deal done" (2015) for examples of the unexpected outcomes of the Paris Agreement.

Industry sensitivities to low frequency temperature risk are used to form expectations on the event abnormal return variation between industries. I group industries based on estimates of sensitivities to the low frequency temperature shock variable. I calculate industry temperature betas for each industry using the following 60 period rolling window regression for each industry.

$$R_t = \alpha_t + \beta_t^{temp} * temp_t + \beta_t^{mkt} * MKT_t + \beta_t^{smb} * SMB_t + \beta_t^{hml} * HML_t + \beta_t^{mom} * MOM_t + \varepsilon_t \qquad (18)$$

The industry monthly excess portfolio returns $R_t$ are regressed against the *Temp* variable and the control Carhart 4-factors. I store the resulting industry $\beta_t^{temp}$ estimates that fall within an approximate 3 year period prior to the event, which ranges from the 1st of January 2013 to the 30th of November 2015. I then average the monthly $\beta_t^{temp}$ estimates over the three years for each industry to generate an ex-ante average temperature exposure. Industries with positive betas are expected to benefit from expectations of increasing temperature, and suffer when temperatures are expected to fall. As the Paris Agreement is supposed to limit future temperature rise, I group industries with positive average temperature betas as 'expected losers', and negative average temperature betas as 'expected winners'.

Daily value-weighted industry returns are used to estimate the event impact on U.S. industries. The measurement period is set as the year prior to the event, spanning from the 30th of November 2014, to the 31st of December 2015. A dummy variable is set to equal 1 on both the 11th and 14th of December 2015.[21] The following Newey-West regression with is run with 5 day lags for each industry to estimate coefficients for the dummy variable.[22]

$$R_t = \alpha + \beta^D * D_t + \beta^{mkt} * MKT_t + \beta^{smb} * SMB_t + \beta^{hml} * HML_t + \beta^{mom} * MOM_t + \varepsilon_t \qquad (19)$$

$R_t$ is the daily excess realised return for a particular industry, α is the estimated constant and $\varepsilon_t$ is the error term in the regression. I control for the daily returns on the Carhart 4-factor control model. The variable $D_t$ is the event dummy variable, while $\beta^D$ is the estimated coefficient for the abnormal

[21] I follow the dummy variable abnormal return estimation approach of Binder (1998). The 12th and 13th of December 2015 fell on a Saturday and Sunday and have no returns data. Activating the dummy variable over the 11th and the 14th allows for any leaked information or delayed reaction impacts to be captured and is a conservative approach.

[22] There are 274 time periods (weekends have no data), which rounds up to a 5 day lag based on prior Newey-West lag specifications.

returns when the variable is turned on. The event dummy coefficient estimates the average daily abnormal return generated around the event. This regression is run for each of the 49 industry portfolios. Abnormal return estimates are displayed for the 49 industries along with average temperature beta estimates in tables 11 and 12.

Table 11: Results of the Paris Climate Agreement on the predicted loser portfolios of the Fama-French 49 industries. Industry average temperature betas are shown along with daily abnormal returns that are captured by the dummy coefficient. P-values are Newey-West adjusted for 5 day lags and are shown in brackets below estimations. P-values in bold denote significance at the 10% level.

**Paris agreement event study: expected losers**

| Industry | Beta | Dummy | Industry | Beta | Dummy |
|---|---|---|---|---|---|
| Agric | 12.918 | -0.465 | Util | 0.047 | 0.114 |
| | | **[0.000]** | | | [0.577] |
| Beer | 6.582 | -0.189 | Telcm | 5.600 | -0.519 |
| | | [0.499] | | | **[0.000]** |
| Smoke | 7.536 | 0.191 | BusSv | 3.237 | -0.129 |
| | | [0.164] | | | **[0.001]** |
| Toys | 2.305 | 1.600 | Hardw | 0.834 | 0.102 |
| | | **[0.000]** | | | [0.529] |
| Hshld | 1.104 | 0.303 | Softw | 2.917 | 0.278 |
| | | [0.126] | | | **[0.051]** |
| Hlth | 1.639 | -1.163 | Paper | 0.314 | 0.090 |
| | | **[0.017]** | | | [0.282] |
| Drugs | 3.465 | 0.148 | Trans | 0.718 | -0.241 |
| | | [0.128] | | | [0.123] |
| Chems | 0.359 | -1.163 | Meals | 0.148 | -0.399 |
| | | **[0.000]** | | | **[0.020]** |
| FabPr | 6.100 | 0.744 | Banks | 7.320 | 0.278 |
| | | [0.197] | | | **[0.000]** |
| Ships | 4.524 | 0.333 | Fin | 5.838 | -0.855 |
| | | **[0.025]** | | | **[0.000]** |
| Gold | 5.524 | -1.239 | | | |
| | | [0.174] | | | |

Table 12: Results of the Paris Climate Agreement on the predicted winner portfolios of the Fama-French 49 industries. Industry average temperature betas are shown along with daily abnormal returns that are captured by the dummy coefficient. P-values are Newey-West adjusted for 5 day lags and are shown in brackets below estimations. P-values in bold denote significance at the 10% level.

**Paris agreement event study: expected winners**

| Industry | Beta | Dummy | Industry | Beta | Dummy |
|---|---|---|---|---|---|
| Food | -7.664 | -0.041 | Aero | -7.229 | -0.086 |
| | | [0.689] | | | [0.814] |
| Soda | -12.545 | 0.090 | Guns | -9.638 | -0.167 |
| | | [0.306] | | | [0.705] |
| Fun | -5.626 | -0.151 | Mines | -0.772 | 0.539 |
| | | [0.354] | | | **[0.028]** |
| Books | -11.125 | -0.695 | Coal | -48.829 | -0.941 |
| | | **[0.000]** | | | [0.319] |
| Clths | -6.316 | 0.257 | Oil | -8.093 | 0.618 |
| | | [0.151] | | | [0.363] |
| MedEq | -2.105 | 0.232 | PerSv | -17.160 | -0.307 |
| | | [0.196] | | | **[0.000]** |
| Rubbr | -1.714 | 0.353 | Chips | -11.386 | -0.317 |
| | | **[0.013]** | | | [0.334] |
| Txtls | -13.195 | 0.148 | LabEq | -2.111 | 0.101 |
| | | [0.422] | | | **[0.052]** |
| BldMt | -0.779 | 0.412 | Boxes | -8.203 | -0.198 |
| | | **[0.033]** | | | [0.786] |
| Cnstr | -2.413 | 0.067 | Whlsl | -5.317 | 0.225 |
| | | [0.828] | | | [0.254] |
| Steel | -13.140 | 0.404 | Rtail | -0.070 | 0.267 |
| | | [0.299] | | | **[0.059]** |
| Mach | -6.228 | 0.512 | Insur | -4.846 | -0.172 |
| | | **[0.004]** | | | [0.586] |
| ElcEQ | -3.446 | 0.663 | RlEst | -3.096 | -0.585 |
| | | **[0.000]** | | | **[0.006]** |
| Autos | -4.930 | -0.410 | Other | -0.228 | 0.265 |
| | | **[0.020]** | | | [0.104] |

I present the summarised outcomes in table 13. Out of all 49 industries, only 26 expectations were met, of which only 14 had significant abnormal return estimates.

Table 13: A summary of the winners and losers, grouped by temperature betas, from the Paris Agreement event study. Presented are a count of the number of industries in both groups, along with a count of the number of industries that have expectations met and a count of the number of expectations that are met with significant estimates at the 10% level.

**Event study summary**

| Winners | | Losers | | Total |
|---|---|---|---|---|
| Count | 28 | Count | 21 | 49 |
| Expected outcomes | 16 | Expected outcomes | 10 | 26 |
| Significant and expected estimate | 7 | Significant and expected estimate | 7 | 14 |

If industry groupings based on temperature beta are unrelated to the event outcome, the cumulative probability for 26 or more successfully predicted outcomes out of 49 is 0.388.[23] This means that the observed correct 26 industry predictions are likely due to chance acting alone. The significance levels decline more if only significant predicted outcomes are considered successful predictions. As expectations of industry impacts were set based on average temperature betas, findings therefore do not provide evidence of a relationship between industry exposure to temperature and the abnormal returns generated around the Paris Agreement. The estimated event impact on industries such as Fun, Coal and Hshld also illustrate how outcomes did not follow expectations based solely on industry temperature betas. Additionally, the grouping of industries such as coal and oil as winners is not intuitive. Non-significant results from using industry temperature exposure as the basis of predictions indicate that the Paris Agreement had impacts on industry returns that are not directly related to temperature sensitivity. This seems plausible; shocks in industry expected cash flows and risks are channelled through regulatory uncertainties (Wellington & Sauer, 2005) or industry exposure to other climate phenomena; the temperature variable is only a subset of aggregate climate

[23] The cumulative probability of observed results under the null hypothesis is calculated by randomly distributing the 49 industries into one of the two groups with equal probability. The cumulative binomial probability of 26 or more successful predictions out of 49 is 0.388. This probability is insignificant in a one-tailed hypothesis test.

change and does not provide the full picture. Overall results are unable to show that industry exposure to temperature is linked to the abnormal returns generated by the 2015 Paris Agreement.

### 6.2. Climate disclosure tests

I conduct tests on estimated temperature sensitivities using a firm specific measure of overall environmental exposure, a proxy for overall climate risk. Tests examine whether firms that disclose climate risk on their 10-K filings also have temperature sensitive equity returns. I use a subsample of CRSP equity data based on firms that have climate disclosures. I calculate equity temperature sensitivity with a 60 period rolling window regression and control for the Carhart 4-factors. I keep estimated temperature betas for the financial years 2011 – 2014.

$$R_t = \alpha_t + \beta_t^{temp} * temp_t + \beta_t^{mkt} * MKT_t + \beta_t^{smb} * SMB_t + \beta_t^{hml} * HML_t + \beta_t^{mom} * MOM_t + \varepsilon_t \qquad (20)$$

I average temperature betas $\beta_t^{temp}$ for each of the 4 years for each firm, and perform a pooled panel regression with time clusters. The RawScore variable is regressed against yearly average temperature beta estimates in the panel as follows.

$$RawScore_{i,t} = \mu + \pi * \beta_{i,t}^{temp} + \eta_{i,t} \qquad (21)$$

The regression estimates the relation between equity temperature betas and self-disclosed aggregate climate risk $\pi$. The intercept and error term of this regression are captured by $\mu$ and $\eta_{i,t}$ respectively. I present the results in table 14.

Table 14: Estimated intercepts and slope coefficients for the RawScore regression. P-values are based on heteroscedasticity-consistent standard errors with clustering on time. P-values in bold denote significance at the 10% level.

**Climate disclosure tests**

| Variable | Coefficient | P-value |
|---|---|---|
| $\pi$ | -0.024 | [0.680] |
| $\mu$ | 20.246 | **[0.000]** |

I find no evidence of a relationship between climate disclosures and estimated temperature sensitivities for both absolute values and deviations.[24] Results indicate that either the temperature variable is immaterial when calculating firm specific environmental sensitivity, or more likely, that firms do not consider their stocks temperature sensitivities when disclosing environmental risk. Temperature sensitivities are calculated with equity data, while the RawScore variable consists of expected sensitivities of business activity to climate change. Though equity prices are a function of business activity, they are also influenced by investor expectations and sentiment; due to these differences equity loadings on temperature may not translate exactly to firm climate risk disclosures.

## 7. Portfolio tests

I implement a long-short portfolio strategy and create a tradeable temperature hedge portfolio to test for a priced *Temp* factor. I create both equal-weighted and value-weighted portfolios based on return sensitivity to the *Temp* variable. I combine monthly equity excess returns data with the 5 control risk factor models and *Temp* in the time series. I begin the portfolio creation process by creating temperature beta estimates for individual equities.

$$R_t = \alpha_t + \beta_t^{temp} * temp_t + \boldsymbol{\beta_t^{cont}} * \boldsymbol{cont_t} + \varepsilon_t \qquad (22)$$

The beta estimation methodology follows the same process as the first stage regressions in temperature risk premium tests but instead uses individual equities as test assets. I regress excess equity returns against the temperature variable and control risk factors in the 60 month rolling window first stage regressions; from which coefficients formed with less than 30 prior periods are dropped. After the beta estimation the sample is reduced to observations from 1988 onwards. In each month I generate portfolio breakpoints based on the deciles of NYSE lagged temperature betas. Stocks are sorted into one of the ten temperature portfolios at each month in time. I calculate the ex-post monthly returns of each portfolio, and implement a long-short portfolio strategy by subtracting the returns of

[24] In unreported results, I also find no evidence of a relation between industry temperature betas and environmental disclosure at the industry level using the Fama-French 49 industries, nor is there evidence of a relation between firm temperature betas and environmental disclosure when variables are standardized by year and industry.

the lowest temperature decile portfolio from the highest temperature decile portfolio, labelling the resulting portfolio HMLtemp. If a risk premium exists for temperature risk then the HMLtemp portfolio should generate negative returns on average and in excess of the benchmark. I test for abnormal returns using the following regression.

$$R_t = \alpha + \boldsymbol{\beta}^{cont} * \textbf{cont}_t + \varepsilon_t \qquad (23)$$

The returns of the HMLtemp portfolio $R_t$ are used in a time series regression against the control risk factors $\textbf{cont}_t$ with Newey-West adjustments with 5 month lags. The estimated sensitivity to control risk factors is captured in the vector $\boldsymbol{\beta}^{cont}$, with an estimated intercept α and error terms $\varepsilon_t$. The intercept parameter estimate is interpreted as the HMLtemp portfolio abnormal returns, which is expected to reflect the priced temperature risk factor in an efficient market setting. I repeat the portfolio formation process and test for abnormal returns using all 5 benchmarks factors[25] with both equal and value-weights for robustness. Table 15 and 16 present the average returns, abnormal returns and factor sensitivities for the equal and value-weighted portfolios respectively.

[25] As estimated temperature betas are dependent on the benchmark model employed in the first stage regressions, portfolio composition will also vary, effectively creating different portfolios based on each set of control risk factors. Each column in the output tables is a different portfolio that is sorted on estimations of temperature sensitivities controlling for one of the 5 benchmark factor models, from which the tabulated estimates for portfolio sensitivities and abnormal returns are again calculated using the same benchmark.

Table 15: Equal-weighted HMLtemp portfolio regression results. The average monthly portfolio return is shown in the first row. Coefficients shown are the estimated sensitivities of the HMLtemp portfolio to control risk factors. Portfolio alphas are shown in the second row, significantly negative alphas would support the alternative hypothesis. Newey-West p-values generated with 5 month lags are reported in brackets below estimates. P-values in bold denote significance at the 10% level.

**Equal-weighted HMLtemp portfolio results**

| | CAPM | FF 3 | Carhart | FF 5 | HXZ |
|---|---|---|---|---|---|
| Avg. | 0.090 | 0.117 | 0.119 | 0.099 | 0.095 |
| | [0.490] | [0.315] | [0.324] | [0.387] | [0.411] |
| Alpha | 0.049 | 0.179 | 0.151 | 0.109 | 0.240 |
| | [0.732] | [0.115] | [0.234] | [0.396] | **[0.070]** |
| MKT | 0.063 | -0.007 | 0.014 | 0.017 | -0.033 |
| | [0.276] | [0.789] | [0.605] | [0.600] | [0.363] |
| SMB | | 0.014 | 0.026 | -0.084 | |
| | | [0.780] | [0.615] | **[0.056]** | |
| HML | | -0.243 | -0.217 | -0.211 | |
| | | **[0.000]** | **[0.004]** | **[0.000]** | |
| MOM | | | 0.015 | | |
| | | | [0.806] | | |
| RMW | | | | 0.032 | |
| | | | | [0.640] | |
| CMA | | | | 0.127 | |
| | | | | [0.204] | |
| ME | | | | | -0.037 |
| | | | | | [0.548] |
| I/A | | | | | -0.198 |
| | | | | | **[0.034]** |
| ROE | | | | | -0.102 |
| | | | | | **[0.067]** |
| N | 347 | 347 | 347 | 347 | 335 |
| Adj. $R^2$ | 0.008 | 0.110 | 0.096 | 0.057 | 0.037 |

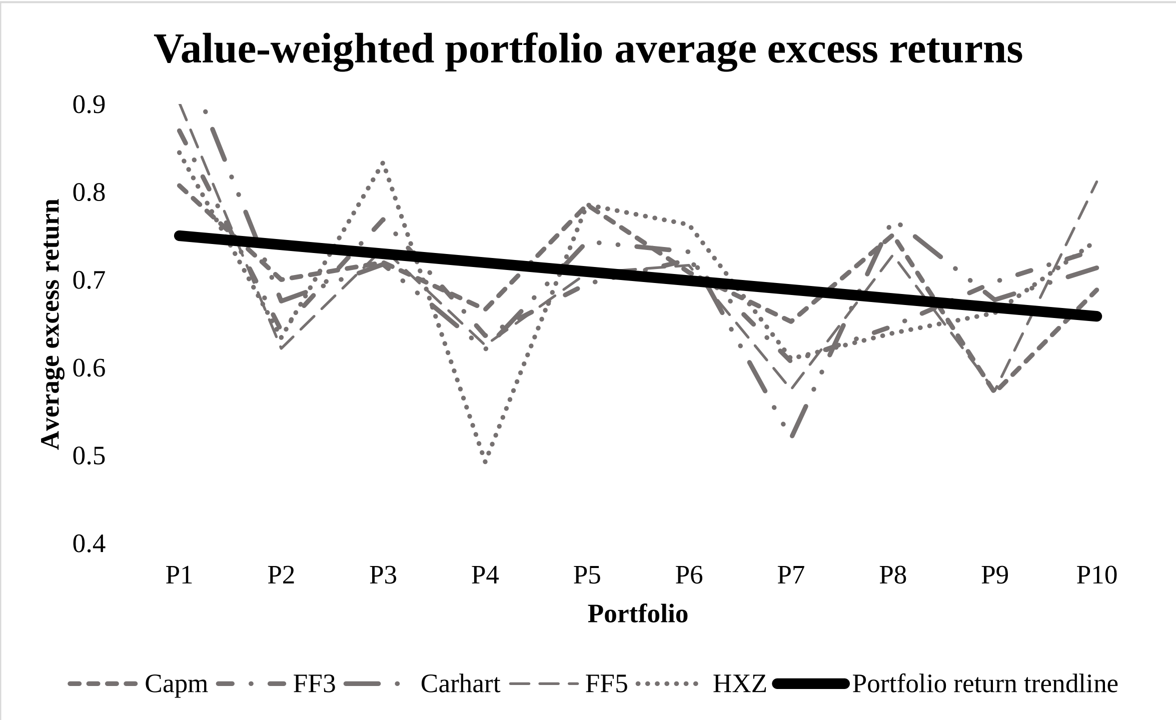
Table 16: Value-weighted HMLtemp portfolio regression results. The average monthly portfolio return is shown in the first row. Coefficients shown are the estimated sensitivities of the HMLtemp portfolio to control risk factors. Portfolio alphas are shown in the second row, significantly negative alphas would support the alternative hypothesis. Newey-West p-values generated with 5 month lags are reported in brackets below estimates. P-values in bold denote significance at the 10% level.

**Value-weighted HMLtemp portfolio results**

| | CAPM | FF 3 | Carhart | FF 5 | HXZ |
|---|---|---|---|---|---|
| Avg. | -0.119 | -0.136 | -0.253 | -0.090 | -0.100 |
| | [0.594] | [0.412] | [0.139] | [0.563] | [0.574] |
| Alpha | -0.250 | -0.170 | -0.382 | -0.094 | -0.178 |
| | [0.272] | [0.283] | **[0.034]** | [0.608] | [0.480] |
| MKT | 0.200 | 0.130 | 0.152 | 0.030 | 0.052 |
| | **[0.002]** | **[0.005]** | **[0.010]** | [0.614] | [0.433] |
| SMB | | -0.048 | -0.062 | -0.069 | |
| | | [0.497] | [0.361] | [0.243] | |
| HML | | -0.171 | -0.081 | -0.158 | |
| | | **[0.071]** | [0.386] | [0.115] | |
| MOM | | | 0.108 | | |
| | | | [0.147] | | |
| RMW | | | | 0.032 | |
| | | | | [0.724] | |
| CMA | | | | 0.091 | |
| | | | | [0.618] | |
| ME | | | | | -0.034 |
| | | | | | [0.671] |
| I/A | | | | | -0.215 |
| | | | | | [0.146] |
| ROE | | | | | 0.279 |
| | | | | | **[0.018]** |
| N | 347 | 347 | 347 | 347 | 335 |
| Adj. $R^2$ | 0.042 | 0.043 | 0.047 | 0.003 | 0.043 |

Average portfolio returns are not significantly negative for either the equal or value-weighted portfolios. If the negative risk premium expectations for temperature sensitive returns are true, the HMLtemp portfolio should generate negative alphas on average that are unexplainable by loadings on the control risk factors.  Results show very weak evidence of HMLtemp abnormal returns.[26] The value-weighted HMLtemp portfolio strategy has only one significant negative alpha at the 5% level when benchmarked against the Carhart 4-factor model. The equal-weighted portfolios surprisingly have a positive alpha significant at the 10% level. Returns of the equal-weighted portfolios are negatively driven by the HML factor, however the value-weighted portfolios have positive loadings on the market factor. The SMB factor does not explain much of the returns of the HMLtemp portfolios. This is interesting, as it indicates that there is no relation between size and firm exposure to low frequency temperature shocks. Figure 6 illustrates the average excess returns for the decile temperature portfolios generated with all 5 benchmark models. The average excess return structure of the decile portfolios do not follow a monotonically negative trend as expected under the hypothesis of a negative temperature risk premium. Decile portfolios formed with HXZ q-factors have the most erratic average excess return trend. Though an average negative relationship is evident, it is not monotonic and is noisy. Results overall do not provide any evidence of a priced *Temp* factor.

Figure 6: Average portfolio excess returns of decile portfolios formed on temperature shocks and all 5 control risk factors, and an average trendline. Higher portfolio numbers have greater average temperature sensitivity, while lower portfolio numbers have lower average temperature sensitivity.




[26] Results would further weaken if transaction costs are accounted for.

## 8. Discussion

I find no evidence of a cross-sectional temperature risk factor. This is inconsistent with the hypothesis developed using consumption and disaster pricing theory. I reconcile the lack of results with two explanations.

The first explanation is the very long time horizon in which climate change disasters are expected to take place. The greatest unmanageable climate disasters of Nordhaus (2013) are more likely to take place in the distant future. Costs and consumption losses that are incurred through these scenarios may not be large once discounted to present values. Pindyck (2007) reveals how the very long time horizons of climate change and policy response lead to minimal present value cash flows. Dasgupta (2008) states that the consequences of climate change are on both intragenerational and intergenerational welfare. Dasgupta (2008) points out that the considerations behind saving for our children or grandchildren, who are the real losers of climate change outcomes, are not the same as saving for personal future consumption. Investors may not place value the consumption of later generations. Alternatively, technology may improve at a rate which prevents the full scope of long-term climate change from occurring. Expectations of technology innovations counteract expectations of the future costs of climate change, to an extent. The implications of these factors may result in non-priced climate risk.

The second possibility is the diversification options at the investor, firm and country level. Extending the argument of Copeland & Zhu (2007), if investors are able to diversify away their exposure to temperature shocks then there should not be a priced temperature risk factor in equilibrium. Diversification can also occur at the country level. If cross-country correlation to climate disasters is less than perfect, global investors are able to reduce portfolio exposure to temperature. Firms and industries also have dynamic capabilities. Businesses that can adapt to changing environmental factors benefit from built-in real option values (Trigeorgis, 1993) that constrain the negative outcomes driven by temperature rise. Mendelsohn et al. (1994) illustrate how, in rising temperatures, farmers will be able to reallocate their production efforts to varying outputs. If the impacts of the manageable activities of Nordhaus (2013) constitute a large portion of total climate change costs, the total risk involved is minimised through diversification. If temperature risk is not a systematic risk, there will be no equilibrium price for it.

## 9. Conclusion

Overall I find no evidence of the existence of a temperature risk factor in U.S. equity markets. Low frequency temperature risk is a subset of total climate risk, and has complex impacts on economic variables. Results do not suggest that exposure to low frequency temperature risk is correlated with higher excess returns in U.S. equity markets.

I transform temperature data to create a low frequency temperature shock proxy, and calculate the temperature exposures for industry portfolios, and find a decreasing time trend for both the average and many individual industries. I find no evidence to support a hypothesised negative risk premium for the temperature factor. I find that the risk premium is not significantly negative even in recent periods, contrary to expectations of increasing investor awareness of climate risk. Cross-sectional estimates of the temperature risk premium are calculated using the Fama-Macbeth approach, and are used in the time series to test whether premiums have increased with global temperatures. I find no evidence for either a linear time trend in temperature risk premium, or decadal dummy effects. I create portfolios sorted by temperature betas but find no evidence that portfolios with higher temperature loadings are outperformed by portfolios formed with lower temperature loadings. Neither the equal nor value-weighted HMLtemp long-short portfolios provide sufficient evidence of negative returns on average or in excess of control risk factors. I finally test the implications of temperature betas using an event study and firm specific climate variable. Results surprisingly indicate that industry temperature betas cannot predict the outcomes of the Paris Agreement, nor do firm temperature betas explain firm exposure to climate risk. Further study could take a global outlook and estimate the impacts in different countries, or include additional climate variables in tests to improve estimates of environmental impacts on financial markets.

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