Temperature Shocks and the Cost of Equity Capital: Implications for Climate Change Perceptions*

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Abstract

Financial market information can provide an objective assessment of losses anticipated from climate change. In a Merton-type asset pricing model, with asset prices affected by perceived changes in investment opportunities due to climate change, the risk premium is significantly negative, loadings for most assets are negative, and asset portfolios in more vulnerable industries have stronger negative loadings on a temperature shock factor. Weighted average increases in the cost of equity capital attributed to climate change are 0.22 percent, implying a present value loss of 7.92 percent of wealth. These costs complement previous estimates of the cost of climate change.

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1. Introduction

In the last few years, a rapidly growing new climate-economy literature uses exogenous temperature shocks to identify causal effects of temperature on industries and the economy as a whole.[1] For instance, Fisher, Hanemann, Roberts, and Schlenker (2012) find a negative impact of temperature increases on US agriculture. Graff Zivin and Neidell (2014) show that temperature increases at the higher end of the distribution reduce labor productivity in industries with high exposure to climate such as agriculture, forestry, fishing, and hunting; mining; construction; transportation and utilities; and manufacturing. Cachon, Gallino, and Olivares (2012) find that high temperatures reduce productivity and automobile production at the plant level. There is also experimental evidence that temperature affects labor productivity (e.g., Seppänen, Fisk, and Lei. 2006). Dell, Jones and Olken (2012) in a world sample find that temperature increases reduce not only income levels but also growth rates, particularly in developing countries.[2]

It has also been known for at least a century that the climate (the stochastic distribution of temperatures) changes over time, in part depending on carbon dioxide concentration and therefore fossil fuel burning. For instance, Agassiz (1840) found indications of glacial movements in Europe. Tyndall (1865) identified qualitatively a greenhouse effect and suggested that variation in carbon dioxide concentration might be partly responsible for past climate

[1] Temperature variation over time within a given spatial area is substantial. For instance, from 1953 to 2014, the difference between the maximum and minimum annual average temperatures in the US is 2.44 °C (the standard deviation is 0.92 °C). Thus, the max-min temperature variation in the US is almost three times the increase in the global temperature from 1880 to 2012 which is estimated to be 0.85 °C by the Intergovernmental Panel on Climate Change (IPCC), and consistent with the increase in the global temperature projected at the end of the 21st century under all but one scenario analyzed by IPCC (IPCC, 2014). In a panel of 125 countries from 1950 to 2003, Dell, Jones and Olken (2012) find that the max-min temperature variation within a country averages 2.2 °C, ranging between 1.3 °C and 3.4 °C for 95 percent of countries.

[2] Earlier studies also document negative cross-sectional relationship between temperature and income per capita (e.g., Nordhaus, 2006; Dell, Jones and Olken, 2009). See Dell, Jones and Olken (2014) for an excellent review of the new climate-economy literature.

changes. Arrhenius (1896) explicitly calculated that a doubling of carbon dioxide concentration could lead to a 5.7 °C increase in average global temperature. Callender (1938) suggested that burning of fossil fuel could produce increases in atmospheric carbon dioxide, and Keeling (1960) provided specific evidence that fossil fuel burning since the industrial revolution had increased the concentration of atmospheric carbon dioxide. Subsequent research in 1970s and 1980s drew public attention to the climate change issue and led to the formation of the Intergovernmental Panel on Climate Change (IPCC) in 1988.[3] Despite scientific research spanning more than 100 years, considerable uncertainty remains about the magnitude of climate change (the uncertainty stemming in part from doubt about global climate policy). The IPCC's widely-quoted estimates for the increase in the global mean temperature exemplify this uncertainty: its range for the possible increase of global mean surface temperature by the end of the 21st century (2081–2100) relative to the 1986–2005 period is from 0.3°C to 4.8°C (see IPCC, 2014).

These two strands of research provide the following empirical features regarding temperature realizations: (1) broad negative effects of temperature changes on labor productivity, particular industries, and the economy as a whole; and (2) the distribution of temperatures varies stochastically over time, leading to inherent uncertainty about climate change. From (1) temperature shocks have a substantial causal impact on economy-wide productivity; and from (2) temperature shocks affect the perceived direction and magnitude of climate change (because unexpected temperature realizations from a Bayesian perspective lead individuals to revise their perceptions of the current climate and of potential climate-changing policy reactions), it follows that the aggregate climate perception as it changes over time in response to temperature shock realizations may be viewed as a Merton (1973) state variable influencing economy-wide

[3] See Bolin (2007) for an excellent overview of the history of the Intergovernmental Panel on Climate Change.

investment opportunities. In an intertemporal world a perceived shift in the temperature distribution represents a risk outcome with systematic economic repercussions to which different firms are exposed to different degrees. In the Merton view temperature shocks should accordingly be priced as a risk factor, influencing the cross-section of expected returns. Firms whose cash flows are negatively affected by positive temperature shocks (i.e., temperature increases) have to compensate investors by higher expected returns to induce investors to hold their risky assets (because these firms generate lower returns when, at the same time, overall investment opportunities deteriorate). Higher expected returns mean a higher cost of capital to firms, which can have a profound and adverse impact on capital investment, innovation, and economic growth (e.g., Henry, 2003).[4]

We combine time series and cross-sectional information to identify the role of temperature shocks (associated with uncertain climate change) in financial markets, hence contributing to the climate-change literature along two dimensions. First, focusing on economic outcomes such as GDP per capita, the new climate-economy literature is able to identify the causal effects of temperature shocks, but does so at a particular horizon. Consequently, short-run impacts are obtained without a clear view of how these impacts aggregate over time. One problem is for instance that the longer-run effects fail to include adaptation along the lines of Mendelsohn, Nordhaus, and Shaw (1994). In contrast, we emphasize stock returns, which reflect

[4] Kamstra, Kramer and Levi (2003) examine how temperature affects human mood and investor behavior, but not from the climate change perspective. Fankhauser and Tol (2005) study the impact of climate change on capital accumulation, but not from the cost of capital perspective. Brunner (2002) analyzes the effects of the El Niño weather cycle on commodity prices and economic activity but does not consider the cost of capital. Previous finance literature has examined the interaction between weather and financial markets. For instance, Roll (1984) and Fleming et al. (2006) study how weather-related information affects, respectively, mean returns and return variances in particular weather-sensitive markets, and Hirshleifer and Shumway (2003) consider how weather impinges on returns by affecting trader attitudes. These studies focus on higher-frequency (daily) weather events and subsequent return realizations. Our paper focuses on a very different aspect of the interaction between weather and financial markets: the impact of lower-frequency (monthly) weather events, relating to changing expectations about climate change, on systematic risk and the economy-wide cost of capital.

the capitalized sum of immediate and future impacts and properly incorporate such additional effects as anticipated future adaptation (at least as these effects are viewed by the aggregate of market participants). Thus, our focus on asset returns allows a natural aggregation of the impacts at various horizons.

Second, the extant literature on the economic impact of climate change has emphasized the future effect of an *abrupt* change in climate to occur around 2100. Prominent examples are the work of Mendelsohn et al. (2000) and Nordhaus and Boyer (2000) examining and aggregating the output losses by sector; and the work of Nordhaus (2006) identifying aggregate output losses with a reduced-form cross-sectional approach, occurring once temperatures increase by at least 2.5 to 3.0 °C. However, if the temperature distribution associated with uncertain climate change is a Merton (1973) state variable, a risk premium is added to firms' costs of capital (which depend on the product of a firm's exposure to temperature shocks, and the aggregate risk premium on temperature shocks), which can adversely affect investment and economic growth. This cost of capital channel matters even if climate changes gradually, and supplements the extant literature.

To examine empirically whether the temperature distribution is a priced Merton (1973) state variable, we follow the empirical asset pricing literature (e.g. Vassalou, 2003; Kapadia, 2011). Specifically, we first use the tracking portfolio approach of Lamont (2001) to construct the temperature shock factor, as the news in the temperature realization leading to changing expectations regarding future temperature change; then we employ the standard time-series and cross-sectional regression methodology to estimate the loadings and risk premium associated with this factor; finally we calculate the economy-wide impact of temperature shocks on the cost of equity capital by multiplying the temperature shock risk premium by the weighted average loading on this factor.

We find that the average cost of equity capital is 0.22 percentage points higher on an annual basis due to temperature shocks associated with uncertain climate change. Since an approximate one-to-one relationship tends to hold between the cost of capital and GDP per capita growth (Henry, 2003), our results directly imply that temperature shocks cause a 0.22 percentage point reduction in the growth rate of US GDP per capita. This estimate is not only statistically but also economically significant. To put the number in perspective, the aggregate economic costs of mitigation (designed to limit climate change to below 2 °C by the end of the 21st century relative to pre-industrial levels) amount to an annualized reduction of per capita consumption growth of 0.04 percentage point, lowering it to 0.14 percentage points (IPCC, 2014). The aggregate damage impact measured via the financial channel considers the effect of higher cost of equity capital on asset prices. Cumulating in effect the short-run through long-run impacts, the present-value loss is estimated to equal 7.92 percent of wealth.

Our results have important implications for climate change research. The extant climate change literature relies on a "damage function" to incorporate the effects of climate change on economic outcomes. The typical specification allows temperature variation to affect the level but not the growth rate of output (Dell, Jones and Olken, 2014), which is inconsistent with the empirical evidence in the new climate-economy literature. Dell, Jones and Olken (2014) accordingly call for research to help understand the mechanisms underlying the temperature-growth relationship. The evidence in our paper identifies a specific mechanism through which temperature shocks impact productivity growth. Temperature shocks influence not only goods and resource markets but also financial markets, and a large literature pioneered by Bagehot

(1873) and Schumpeter (1911) shows theoretically and empirically that the cost of capital affects capital accumulation as well as innovation and productivity (e.g., King and Levine, 1993).

The remainder of the paper is organized as follows: Section 2 discusses in detail the theoretical perspective, and states three testable hypotheses, as well as presenting the appropriate expression for calculating welfare losses associated with temperature shocks. Section 3 briefly discusses the data. Section 4 presents the tracking portfolio approach that not only helps us construct the temperature shock factor but also allows us to test the first hypothesis in a non-structural fashion. Section 5 provides quantitative results in a structural context – applying the two-pass regression methodology to the standard asset-pricing models. Section 6 investigates specifically the quantitative impact of temperature shocks on the cost of equity capital, and Section 7 concludes the paper with a brief summary.

2. Theoretical Perspective and Hypotheses

The Merton (1973) model provides a general perspective on the risk factors explaining average asset returns. It implies that excess returns are determined by the systematic risk of an asset, which in turn depends on the asset's sensitivity to both market returns and aggregate changes in investment opportunities. Application of the Merton model is not straightforward because it provides no specifics about how to characterize aggregate changes in investment opportunities. Of the two most popular asset-pricing models, the Sharpe-Lintner CAPM ignores the possibility of investment opportunity shifts, and the Fama-French (1996) Three-Factor model empirically captures investment opportunity shifts by means of value and size factors.

Provided that temperature shocks may signal persistent changes in climate they are associated with important perceived changes in aggregate investment opportunities. They represent risk factor realizations which change the state variables that summarize investment opportunities. This risk should be priced as a hedging factor in the context of the Merton model, or directly as a productivity shock in the context of Balvers and Huang (2007). The tracking portfolio approach that we apply does not require we specify the actual stochastic process by which climate perceptions change. It is appropriate if the climate changes abruptly or gradually. A simple two-state example presuming an abrupt climate change could be that either the climate is unchanged or a hotter climate prevails. Realizations of high temperatures increase the Bayesian probability that the hotter climate state is in effect. Even in this scenario, an unexpectedly hot period raises the (subjective) probability of the hotter climate state, worsening (perceived) investment opportunities.

We accordingly postulate that temperature shocks associated with climate change represent a priced Merton factor and check empirically if the implications of this view are confirmed by the data. The following hypotheses derive more or less directly from this postulate and will be the target of our empirical analysis in the following sections.

HYPOTHESIS 1. *The temperature shock factor has a significant and negative risk premium.*

If the risk factor is priced, it should have a statistically and economically significant risk premium. Assets with returns that have positive correlation with temperature shocks (positive loadings on the temperature shock factor) constitute a *hedge* against adverse shocks to investment opportunities, thus requiring lower average returns. Since the presumption is that most firms are negatively affected by (positive) temperature shocks (i.e. the factor loadings on the temperature shock factor are generally negative), most assets enhance temperature shock risk rather than hedge against it. The risk premium must be negative [5] to ensure that riskier assets have higher average returns – a decrease in future investment opportunities is added on top of the initial temperature shock; and firms whose returns are affected more are accordingly riskier.

Temperature shocks may have an uneven impact. In particular, particular industries are more vulnerable: *Agriculture, forestry, fishing, and hunting; mining; construction; transportation; and manufacturing*, because these industries have high exposure to climate (Graff Zivin and Neidell, 2014). Furthermore, Quiggin and Horowitz (2003) emphasize adjustment costs to climate change. They argue that costs of adjustment arise if capital stocks: (i) are dependent on climate for their optimal location; and (ii) depreciate more slowly than is required to permit easy adjustment to a changing climate. Thus, firms with capital in place, *value firms*, should be vulnerable too. Along this line, *small firms* should be sensitive to temperature shocks associated with uncertain climate change, because they may lack resources to adjust or to adapt. If temperature shocks are truly a risk factor, the industries or firms that are more sensitive to temperature shocks should have higher loadings (in absolute value) on the temperature shock factor and, accordingly, higher required returns and costs of capital.

HYPOTHESIS 2. *Industries or firms that are considered to be more vulnerable to temperature shocks associated with uncertain climate change have higher loadings (in absolute value) on the temperature shock factor.*

[5] There is no real significance to the negative sign of the risk premium. If we defined temperature shocks with the opposite sign (as an unexpected *decrease* in temperature), the loadings would be usually positive, and the risk premium would be positive, leading to equivalent cost of capital implications.

The perception of the likelihood of climate change has increased over the last several decades and this can be taken to imply that changes in weather patterns may be increasingly thought to be attributable to climate change and hence more persistent, implying a larger impact.

> **HYPOTHESIS 3.** *The impact of the temperature shock factor on the average cost of equity capital increases over time.*

To address these three hypotheses with some accuracy we ask a rather narrower question than the question of whether temperature shocks associated with climate change affect the cost of capital. For reasons of implementation we ask: *How does news about changes in average U.S. temperatures affect the cost of capital for U.S. equities?* Our belief is that by focusing on a case for which we have accurate data and a clearly defined set of questions, we can begin to obtain insights and ideas that are more generally applicable to the global case.

A related objective is to provide a detached assessment of possible costs of climate change. Roll (1984) shows that financial markets may be more reliable indicators of future events influencing cash flows than the pronouncements of specialized forecasters: orange juice futures prices have forecasting power for weather conditions (involving frost) beyond the forecasts of the National Weather Service. Since the scientific literature is not definitive concerning the magnitude of the welfare effects of climate change, the observable financial market impact of climate change, likewise, may provide an objective measure of the collective perception of some of the economic impacts of climate change. Thus, as an implication, contingent on confirmation of the above hypotheses, we can formulate a measure for the losses stemming from temperature shocks' effect on the cost of equity capital.

Proposition.

(A) *The aggregate change in the cost of equity capital due to the temperature shock factor equals the product of the value-weighted average temperature shock beta and the temperature shock risk premium.*

(B) *The aggregate losses in average shareholder value can be approximated by the product of the average change in the cost of equity capital and the average price-dividend ratio.*

Part (B) of the proposition follows from a Gordon growth model approximation for equity value and by differentiating equity value with respect to the cost of capital.

3. Data

Dictated by data availability, our sample period starts in April 1953 and ends in May 2015. In terms of location, we limit ourselves to the United States. Whereas climate change is a world-wide phenomenon, there are complicated distribution issues that we are not prepared to address. Additionally, the required weather and financial-market data are available for the U.S. and are uniformly accurate – in particular, climate measures, macro and risk factor data, and industry-specific equity portfolio returns. The portfolio returns and Fama-French factor data are from Kenneth French's website.[6] The macro variables data are from the Federal Reserve Bank of St. Louis. The temperature time series is the US average temperature series obtained from the National Climatic Data Center.

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

4. Economic Tracking Portfolios: A Non-Structural Approach

Asset returns are driven by changing information, 'news', about future cash flows and discount rates. What matters for our purposes is the news concerning future temperature variation contained in the current observation. We could use a structural model to estimate the news concerning future temperature variation. But doing so results in a joint test of the validity of the model for what constitutes news and the validity of our hypothesis that temperature shocks matter for financial markets. To circumvent this issue, we use the economic tracking portfolio approach proposed by Breeden, Gibbons, and Litzenberger (1989) and Lamont (2001), and previously applied by Vassalou (2003) and Kapadia (2011). Importantly, this statistical approach allows us to estimate the risk premium of temperature shocks without imposing a particular model of asset pricing.

4.1. A Statistical Model of Temperature Variation News

We follow Campbell and Diebold (2005) and take a simple time series approach to modeling and forecasting temperature.[7] Our time-series model is the daily temperature model of Campbell and Diebold (2005) amended to deal with monthly observations. We include a linear time trend and 11 monthly seasonal dummies for our monthly temperature data. That is,

$$T_t = C + A \cdot trend_t + \sum_{i=1}^{11} S_i \cdot seasonal_i + error_t \ , \tag{1a}$$

with T_t representing the average temperature in month *t,* and *error*$_t$ representing the effects of all other variables. Defining $CT_{t+12} = (\sum_{i=1}^{12} T_{t+i})/12$ as the average temperature over the next year, we have

[7] See also Harvey (1989), Seater (1993), and Visser and Molenaar (1995).

$$CT_{t+12} = c + a \cdot trend_t + e_{t+12} \ , \tag{1b}$$

where $c = C + (\sum_{i=1}^{12} iA + \sum_{i=1}^{11} S_i)/12$, $a = A$, and $e_{t+12} = (\sum_{i=1}^{12} error_{t+i})/12$, captures the effects of all other variables between t+1 and t+12. Therefore,

$$E_{t-1}(CT_{t+12}) = c + a \cdot trend_t + E_{t-1}(e_{t+12}) \tag{1c}$$

Now define $\Delta E_t(CT_{t+12}) = E_t(CT_{t+12}) - E_{t-1}(CT_{t+12})$ as the news component in the temperature observation in month *t*. Then we have the tautology

$$CT_{t+12} \equiv E_{t-1}(CT_{t+12}) + \Delta E_t(CT_{t+12}) + \omega_{t+12} \ , \tag{2}$$

which decomposes the annual temperature at the end of the following year in a previously expected component, a news component, and noise, with noise $\omega_{t+12} \equiv e_{t+12} - E_t(e_{t+12})$.

4.2. An Economic Tracking Portfolio for Climate Change

If temperature variation matters for asset pricing, innovations in excess returns of base assets reflect innovations in expectations about future temperature variation. That is,

$$\Delta E_t(CT_{t+12}) = b\tilde{R}_t + \eta_t \ , \tag{3}$$

where $\tilde{R}_t$ represents a column vector of unexpected returns $\tilde{R}_t = R_t - E_{t-1}(R_t)$, with R_t a column vector of excess returns of base assets in month *t*, and η_t the component of news that is orthogonal to the unexpected returns of the base assets.

Assume that the base asset return in month *t* is a linear function of Z_{t-1}, a vector of conditioning economic variables known at period *t-1*, and that e_{t+12} is a linear function of Z_{t-1}, and $Z^{/}_{t-1}$ a vector of conditioning climate variables known at period *t-1*. That is,

$E_{t-1}(R_t) = d \cdot Z_{t-1}$ and $E_{t-1}(e_{t+12}) = f \cdot Z_{t-1} + g \cdot Z^{/}_{t-1}$. Then we have from equations (1b), (2), and (3) that

$$CT_{t+12} = E_{t-1}(CT_{t+12}) + \Delta E_t(CT_{t+12}) + \omega_{t+12}$$

$$= c + a \cdot trend_t + fZ_{t-1} + gZ^{/}_{t-1} + b(R_t - dZ_{t-1}) + \eta_t + \omega_{t+12}.$$

This provides our *Primary Specification*:

$$CT_{t+12} = c + a \cdot trend_t + gZ^{/}_{t-1} + bR_t + eZ_{t-1} + \varepsilon_{t+12} \quad , \qquad (4)$$

with $e = - bd + f$, and $\varepsilon_{t+12} = \eta_t + \omega_{t+12}$.

Tracking portfolio returns are defined here as the ‘factor mimicking’ portfolios of excess returns, bR_t. The OLS regression given by equation (4) can be used to estimate the portfolio weights b so as to obtain bR_t. The tracking portfolio return that traces the changes in expectations regarding temperature variation, the *temperature shock factor*, is thus $TSF_t = bR_t$.

The unconditional mean of the tracking portfolio returns $bE(R_t)$ represents the factor risk premium (see Lamont, 2001, Vassalou, 2003, and Kapadia, 2011); in our application the factor risk premium of the temperature shock factor. The intuition is that the estimated coefficients b represent base asset loadings on the temperature variation news. The portfolio with weights b on the base assets has a mean excess return $bE(R_t)$ that reflects the risk due to temperature variation news and can be interpreted as the risk premium on the temperature shock factor. If temperature variation is economically important, the risk premium associated with temperature shocks should be significantly different from zero. Furthermore, if temperature-variation impacts are generally adverse (e.g., Dell, Jones and Olken, 2014), we expect to see a negative premium: because the loadings on the temperature shock factor should normally be negative and to compensate for the additional risk the equilibrium return should be higher, which, with negative loadings, can only be achieved by a negative risk premium.

Following the tracking portfolio literature, we focus on news concerning next year's temperature variation. In our primary specification we largely follow Vassalou (2003) and use the six Fama-French size and book-to-market (BM) portfolios as the base assets. To obtain the conditioning variables – the Z_{t-1} in equation (4) – we again largely follow Vassalou (2003) and use macro variables known to predict equity returns. They are the risk-free rate (RF), the term premium (TERM) (the difference between the 10-year government bonds rate from the Federal Reserve Bank - St. Louis and the risk-free rate), and the default premium (DEF) (the yield difference between BAA and AAA bonds from the Federal Reserve Bank - St. Louis). We use the lagged average temperature over the past one year (i.e. from *t* - 12 to *t* - 1) as the single temperature control variable in $Z_{t-1}^{/}$

4.3. Tracking Portfolio Properties

The primary specification in Table 1 presents the construction and diagnostic tests of the temperature shock factor tracking portfolios based on equations (4) with the six Fama-French size-BM portfolios as the base assets and the macro variables used also by Vassalou (2003) as conditioning variables. The t-ratios are obtained from Newey-West HAC standard errors with the lag parameter set equal to 12.

All results are for 1953:5 - 2014:5 (note that we lose 1953:4 because we employ a one-month lagged term premium and our term premium data start in 1953:4. We also lose the 2014:6-2015:5 period which is required for the final sample point of CT_{t+12}). The coefficient estimates in Panel A indicate that SL (small growth firms) and SH (small value firms) have significant tracking ability, positive and negative, respectively, for future temperature changes. The signs and significance of these coefficients are consistent with our expectations: Growth firms may potentially benefit from climate change as they do not yet have their capital in place (SL coefficient > 0). Value firms face adjustment costs, as implied by Quiggin and Horowitz (2003), since their capital is already in place (SH coefficient < 0). The impact is particularly significant for small companies because small companies generally lack resources to adapt to climate change (by, for instance, relocating their production). Conform the ability of larger firms to adapt more easily to climate change, the portfolios of mid-range and large companies show no significant sensitivity to climate change. The chi-square test in Panel A rejects at the 5% level the hypothesis that the coefficients on the base assets are jointly zero, indicating that the base assets have significant tracking ability.

Panel B provides the mean of the tracking portfolio return, which is -0.02 percent per month with a t-statistic of -4.44. This provides direct support for Hypothesis 1, that the risk premium on temperature variation associated with uncertain climate change is significantly negative. Note that the result is not dependent on the choice of a particular asset pricing model. Figure 1 shows raw average temperatures and the derived temperature shock factor series (the tracking portfolio returns) from 1953 through 2014.

4.4 Alternative Specifications

We consider three alternative approaches for constructing the temperature shock factor in order to evaluate the robustness of our results. First, we apply the more recent approach of Kapedia (2011) instead of Vassalou (2003) for choosing the basis assets and conditioning variables used in the tracking portfolio approach.

Alternative Specification 1

$$CT_{t+12} = c + a \cdot trend_t + gZ_{t-1}^{/} + bR_t + eZ_{t-1} + \varepsilon_{t+12} \qquad (4a)$$

where CT_{t+12} represents the average annual temperature from t+1 to t+12; R_t = (SL$_t$, SM$_t$, SH$_t$, BL$_t$, BM$_t$, BH$_t$, LCMLG$_t$, LGMRF$_t$)' represents excess returns of the Fama-French size-BM portfolios and the excess return of long-term corporate bonds over long-term government bonds (LCMLG) from Ibbotson Stocks, Bonds, Bills & Inflation Yearbook (2014) as well as the excess return of long-term government bonds over the risk free rate (LGMRF); Z_{t-1} = (RF$_{t-1}$, DEF$_{t-1}$,TERM$_{t-1}$)', represents respectively, the lagged one-month T-Bill rate, the lagged default risk premium, and the lagged term premium; $Z_{t-1}^{/}$ is the lagged average temperature from t-12 to t-1. The temperature shock factor is the tracking portfolio return $TSF_t = bR_t$.

Second, we avoid the specifics of the temperature trend model of Campbell and Diebold (2005) by assuming instead a stochastic trend model of temperature with unknown drift term to identify the tracking portfolio.

Alternative Specification 2

Estimate the following model over the entire sample:

$$CTGRTH_{t+12} = c + gZ_{t-1}^{/} + bR_t + eZ_{t-1} + \varepsilon_{t+12}, \qquad (4b)$$

where $CTGRTH_{t+12}$ = 100×log(CT$_{t+1,t+12}$/CT$_{t-11,t}$), the log difference in the average annual temperature. As in the benchmark specification R_t = (SL$_t$, SM$_t$, SH$_t$, BL$_t$, BM$_t$, BH$_t$)' represents excess returns: the Fama-French size-BM portfolios net of the one-month T-Bill rate; and Z_{t-1} = (RF$_{t-1}$, DEF$_{t-1}$.,TERM$_{t-1}$)', represents respectively, the lagged one-month T-Bill rate, the lagged default risk premium, and the lagged term premium; $Z_{t-1}^{/}$ is the lagged growth rate in the average temperature. The temperature shock factor is the tracking portfolio return $TSF_t = bR_t$.

Third, we avoid the tracking portfolio approach altogether in favor of a standard two-pass approach with specific risk corrections based on the CAPM and the Fama-French three-factor model, using unexpected temperature changes as the temperature shock factor.

Alternative Specification 3

Estimate the following model with the 10 years of data preceding a particular month (say January 1970):

$$T_t = C + A \cdot trend_t + \sum_{i=1}^{11} S_i \cdot seasonal_i + \sum_{i=1}^{n} L_i T_{t-i} + e_t \tag{4c}$$

where T_t represents the monthly temperature, and the lag length is selected by the Schwartz-Bayes Criterion. Then, calculate the expected temperature in January 1970 based on the estimated parameters. The temperature shock factor is the unexpected change in the monthly temperature, $TSF_t = e_t$.

The specifics of the tracking portfolios generated by the first and second robustness approaches (ALT1 and ALT2) are in Table 1 (the third approach does not use a tracking portfolio). Panel B in this table illustrates that the mean tracking portfolio return continues to be robustly significantly negative for the alternative set of basis assets and the different trend specification for temperatures.

5. Standard Asset Pricing Models: Structural Approaches

The tracking portfolio approach of Lamont (2001) in Section 4 estimates the risk premium of the temperature shock factor without specifying an equilibrium asset-pricing model. In this section, we supplement these results by estimating the risk premium of temperature shocks associated with uncertain climate change within the standard multi-factor models. This approach enables us to obtain the sensitivities to the temperature shock factor of particular industries/firms, to address Hypothesis 2, and to identify the aggregate quantitative impact on the cost of equity capital and how the impact changes over time, to address Hypothesis 3.

5.1. The Empirical Model

For our asset-pricing specifications we take the Fama-French (1996) three-factor model and the Sharpe-Lintner CAPM. These are the most common systematic risk models. Both can be viewed as special cases of the Merton (1973) model. The temperature shock factor is added to these specifications as an additional factor affecting investment opportunities over time (the only factor affecting investment opportunities in the Sharpe-Lintner CAPM case).

If temperature-shock impacts are adverse we expect to find negative loadings for typical firms or portfolios and a negative risk premium to compensate for the additional risk (the equilibrium return should be higher; with negative loadings this can only be achieved with a negative risk premium). The impact of temperature shocks on the average cost of capital can naturally be measured by the product of the premium and the average loading of assets on the temperature shock factor.

We use the Black-Jensen-Scholes (1972) / Fama-MacBeth (1973) two-pass methodology – estimating factor sensitivities in the first pass, and using these to obtain risk premia in the second pass – with standard refinements: the Shanken (1992) correction to obtain errors-in-variables-robust standard errors, accounting for the fact that factor sensitivities are estimated, and the Shanken and Zhou (2007) correction to generate misspecification-robust standard errors.

Lewellen, Nagel and Shanken (2010) argue that using as test assets only size–BM portfolios, as is common in the literature, can be highly misleading due to the strong factor structure of these portfolios. They propose to expand the set of test assets to include other portfolios, such as industry portfolios. Including industry portfolios is particularly attractive for our research since the climate change literature has predictions for how different industries should be affected. We therefore use 55 size-BM and industry portfolios (25 size-BM portfolios and 30 industry portfolios) as our test assets instead of just 25 size-BM portfolios.

5.2. Empirical Results

Since temperature variation, insofar as it leads to an updated distribution of future temperatures, represents a systematic risk, affecting investment opportunities in the economy, we expect to see that the temperature shock factor is priced and that its premium is negative. The results based on the primary specification for constructing the temperature shock factor are reported in Table 2. The first-pass results for each of the four models: CAPM, the Fama-French model (FF), the CAPM plus the temperature shock factor (CAPM+TSF), and the Fama-French model plus the temperature shock factor (FF+TSF) are similar. In each case the GRS test rejects the model. The second-pass results reveal that the risk premium for the temperature shock factor is significantly negative as predicted. The model has a higher average cross-sectional R-square when the temperature shock factor is included in the Fama-MacBeth regressions. The premium estimates of -0.01 percent (CAPM plus TSF) and -0.02 percent (FF plus TSF) are robustly significant and in the ballpark of the mean return of the temperature shock factor based on the primary specification reported in Table 1 which is -0.02 percent. We confirm Hypothesis 1.[8]

Table 3 shows that the alternative specifications perform similarly as the primary

[8] The second-pass results in Tables 2 and 3 are based on OLS. The GLS results are available from the authors. They are different only in that (1) the R-squares are lower; (2) the significance of the risk premia, for the temperature shock factor in particular, is higher.

specification, further corroborating Hypothesis 1: the temperature shock risk premium is significantly negative, although only marginally so for ALT3.

6. Temperature Shocks and the Cost of Equity Capital

6.1. Estimation

To estimate the impact of temperature shocks associated with uncertain climate change on the cost of capital, we report the factor loadings for industry as well as size and BM portfolios in Table 4 for the 1953:5 to 2014:5 sample period. The significant loadings on the temperature shock factor (at the 5% level for two-sided tests) are in boldface. We discuss these loadings to gauge the support for Hypothesis 2. As we indicated earlier, temperature shocks may have an uneven impact. In particular, industries/firms with high exposure to climate or with high adjustment costs should be very sensitive to temperature shocks associated with uncertain climate change. The results in Table 4 are broadly consistent with this conjecture, confirming Hypothesis 2, as we discuss next.[9]

Industry Portfolios

The results for 30 industry portfolios are presented in Panel A of Table 4. Overall, 18 out of 30 industry portfolios have statistically significant negative loadings on the temperature shock factor. Construction (Cnstr), Mining (Mines), Transportation (Trans), and nine Manufacturing industries (i.e., Printing and Publishing (Books), Apparel (Clths), Chemicals (Chems), Textiles (Txtls), Steel Works (Steel), Fabricated Products and Machinery (FabPr), Automobiles (Autos), Aircraft, ships, and railroad equipment (Carry), and Business Supplies and Shipping Containers (Paper)) have significantly negative sensitivity, because they have high exposure to climate as

[9] We only present the loadings on the temperature shock factor for the primary specification. The loadings for alternative specifications 1 and 2 are very similar to the loadings for the primary specification. For alternative specification 3 the loadings have lower, but still positive, correlation with those of the primary specification.

Graff Zivin and Neidell (2014) suggest; Coal (coal), Petroleum and Natural Gas (Oil), and five Manufacturing industries (i.e., Food Products (Food), Beer & Liquor (Beer), Tobacco Products (Smoke), Consumer Goods (Hshld), and Electrical Equipment (ElcEq)) also have negative sensitivity to the temperature shock factor, although not statistically significant.

Recreation (Games), Wholesale (Whlsl), Retail (Rtail), and Tourism (Meals) are significantly negatively affected by temperature shocks, possibly because temperature shocks affect time allocation (for instance, Graff Zivin and Neidell (2014) find that temperature increases reduce time allocated to outdoor leisure); Banking, Insurance, Real Estate, Trading (Fin) has negative loading on the temperature shock factor, which may reflect the negative impacts of temperature shocks on the real economy.

The loadings on the temperature shock factor are positive for five of the industries only, with three of these significant: Health (Hlth), Services (Servs), and Business Equipment (BusEq). The health industry has a small demand elasticity, and therefore may provide a good hedge against negative supply shocks. Services have few long-lived capital assets. Business Equipment may benefit from adjustment due to climate change as this increases demand for its product.

To formally test Hypothesis 2 with the industry portfolios, we create two equal-weighted portfolios. "High" includes the high-exposure industries identified by Graff Zivin and Neidell (2014) (specifically: agriculture, forestry, fishing, and hunting; mining; construction; transportation; and manufacturing), while "Low" consists of all remaining industries. The loadings on the temperature shock factor for "High" and "Low" capture the average sensitivities of the high-exposure and low-exposure industries, respectively. Consequently, the loading on the temperature shock factor for "High – Low" picks up the sensitivity difference between the high- and low-exposure industries. The time-series regressions for "High", "Low" and "High – Low" are reported at the bottom of Panel A. The average loading on the temperature factor for the high-exposure industries is -6.04 (t = -6.26), while that for the low-exposure industries is -3.01 (t = -3.54). The sensitivity difference is -3.03 with a HAC-robust (Newey-West) t-statistic of -2.97. Thus, Hypothesis 2 is significantly supported for the 30 industry portfolios.

Size and BM Portfolios

For the size- and value-sorted portfolios the conjectures are that: (1) value firms, which tend to have long-lived capital assets, are more sensitive to the temperature shock factor than growth firms, and (2) smaller firms, which may have less resources to adapt or to adjust, are more sensitive to the temperature shock factor than larger firms. The results for the 25 size- and BM-sorted portfolios in Panel B of Table 4 are consistent with these conjectures. For instance, the temperature shock sensitivities of the small-value portfolio and the small-growth portfolio are, respectively, -27.15 and -6.73, suggesting that value firms are more sensitive to temperature shocks; similarly, the temperature shock loadings of the small-value portfolios and the large-value portfolio are, respectively, -27.15 and -12.77, implying that small firms are more vulnerable to temperature shocks.

To test Hypothesis 2 formally for the size and BM portfolios, we again form equal-weighted portfolios to capture the average sensitivities of different types of stocks. "Small" consists of the five small-capitalization portfolios, and "Big" includes the five large-capitalization portfolios; "Value" contains the five value portfolios, and "Growth" comprises the five growth portfolios. "Small – Big" picks up the difference between small and big stocks, and "Value – Growth" does the same for value and growth stocks. The time-series regressions for the returns of these portfolios are reported at the bottom of Panel B. The average loading on the temperature factor for small stocks is -16.89 (t = -10.38), while for large stocks it is -2.80 (t = -

3.17). The sensitivity difference between small and big stocks is -14.09 with a HAC-robust t-statistic of -6.51. The average loading on the temperature factor for value stocks is -21.40 (t = -29.29), while that for growth stocks is 1.64 (t =1.40). The sensitivity difference between value and growth stocks is -23.04 with a HAC-robust t-statistic of -18.06. Thus, Hypothesis 2 is also strongly supported for the 25 size and BM portfolios.

6.2. Average Impact Estimates

The economy-wide average impact on the cost of equity capital is obtained by multiplying the temperature shock risk premium by the weighted average loading on this factor. Panel A of Table 5 shows the total value-weighted impact. Using the CAPM plus TSF risk model the impact (the risk premium times the average temperature shock loading) is economically significant and has the same order of magnitude for each of the alternative specifications. Numerically, the weighted average annual increase in the cost of equity capital from temperature shocks is 0.22 percent in the Primary specification, 0.23 percent for ALT1, 0.26 percent for ALT2, and 0.18 percent for ALT3.

6.3. Time Path of the Impact

To discover if Hypothesis 3 can be confirmed we repeat the above exercise with rolling samples to find whether the impact of temperature shocks has increased from an early part of the test period to a later part. The risk premium at each time is estimated with 30 years of data to obtain meaningful estimates. As our earliest observation for the term premium is 1953 the test period starts in 1983. We update estimates monthly by dropping the earliest observation and adding the latest observation. Panel B of Table 5 shows the average impact based on the rolling estimates over two evenly divided sub-periods: 1983-1998 and 1999-2014. To properly evaluate the significance of the difference in impact in the two subsample periods we use the approach of Cooper, Gutierrez, and Hameed (2004) which provides appropriate standard errors.

In the primary specification the average temperature shock impact in period 1983-1998 is a significantly positive 0.11 percent. The impact in the more recent period 1999-2014 is also significantly positive, but three times as large at 0.33 percent. The difference is clearly significantly positive. The results for the three alternative specifications are qualitatively identical, also showing significant impact in both periods that is substantially larger for the second period.

The significant difference for the two intervals nominally confirms Hypothesis 3. To obtain more information about the path of the temperature shock impact over time, we present the specific time paths of the impact in Figure 2 which are quite consistent for the various specifications. A closer look at the time path of the impacts over time illustrates that the issues are not as simple as hypothesized. The evidence further confirms that temperature variation associated with uncertain climate change matters for asset pricing and that its impact is significantly positive and, until recently, has been growing over time as is consistent with Hypotheses 1 and 3. However, the impact estimate appears to decrease after 2004, which is not consistent with Hypothesis 3. There are plausible explanations for the unexpected decrease in the impact estimate after 2004 that are consistent with the perspective of climate change risk. In particular: (1) The risk premium on the temperature shock factor may have declined because of reduced temperature risk. Indeed, as shown in Panel E of Figure 2, the standard deviation of temperature displays a similar pattern as the time series of impact estimates in Panel A-D, and has started to decline after 2004. (2) Learning about climate change may have stabilized in recent years, implying that particular temperature shocks carry less of a revision in the perceptions of the rate and magnitude of climate change. (3) The ability of firms to handle climate change threats has improved as trading in weather derivatives has taken off dramatically since the turn of the century and adaptation may have been substantial in recent years. (4) It is naturally also possible that the time series after 2004 is too short to pick up a reliable trend, in contrast to our simple sample split, which did support Hypothesis 3 using our full data period.

6.4. Implications

A convenient means of capitalizing the *one-period* impact to account for the *long run* present value costs of temperature shocks is to use the Gordon growth model approximation arising when we equate asset prices with the expected net present value of future dividends, and proxy the associated variables by setting the dynamic paths of dividends, dividend growth, and costs of capital equal to their averages. Aggregate stock market values can then be expressed as $P = D/(R - G)$, in which P is the current stock market price index, D the end-of-period expected dividends (considered a constant proportion of GDP), G the average anticipated growth rate of dividends, and R the average cost of equity capital. We are then able to draw the following conclusions by placing our results in the context of the existing literature:

(1) The estimated cost of climate change measured in units of a *permanent* future decreases in GDP, established in the previous literature, varies from around 0.2% to 1.0% (Stern, 2007) to 2.0% to 3.5% per 1 degree Celsius increase in temperature (Choinière and Horowitz, 2006) and a maximum of 3.75% (Heal and Kriström, 2002). Even though these estimates deal with permanent changes in GDP the *present value* of the cost, assuming that dividends remain a constant proportion of GDP and even if the changes occur without delay, is simply the equivalent

percent change in stock market value: the Gordon growth equation implies that $\%\Delta P = \%\Delta D$, so the present value of the cost also varies between 0.2% and 3.75%.

(2) Henry (2003) finds an approximate one-to-one relationship between the cost of capital and GDP *growth*. This is consistent with the Gordon growth perspective in which the impact of a change in the cost of capital is equivalent to the impact of an opposite change in the growth rate of dividends or output: $\%\Delta P / \Delta R = -\%\Delta P / \Delta G$. Accordingly, the stock market wealth impact of the 0.22 percent increase in the cost of equity capital (based on the full-sample primary specification) is equivalent to that of a 0.22 percent reduction in the growth rate of dividends or GDP. Since the aggregate economic costs of mitigation are an annualized reduction of consumption growth by 0.04 to 0.14 percentage (IPCC, 2014), the impact of climate change on the cost of equity capital alone is of higher magnitude than the total policy cost, allowing room to contemplate more aggressive climate-change mitigation policies.

(3) The Gordon growth approximation also implies that $\%\Delta P = -(P / D)\Delta R$. If we set *P/D* (the price-dividend ratio) equal to 36, which is its average value over our sample period from March 1953 to December 2014 (see Robert Shiller's website) then the present value of the cost of temperature shocks associated with climate change is 36 x 0.22% = 7.92%. This negative impact in isolation is of similar magnitude as the cost of mitigating climate change based on the IPCC estimate range, which is 1 to 4% in 2030, 2 to 6% in 2050 and 3 to 11% in 2100 (IPCC, 2014).

6.5. Perspectives

To put our estimate of a 7.92 percent loss due to global warming in the perspective of previous estimates, consider that:

First, the literature has considered mainly the specific present value costs of permanent losses in GDP due to abrupt climate change in future years, and, more recently, the costs of losses in GDP related to extreme weather resulting from gradual climate changes. However, the uncertainty about temperatures adds substantially to the overall costs and shows up in the higher cost of equity capital which previous studies have ignored in this context. Thus our result amounts to adding an additional present value cost of climate change of larger magnitude to previously identified costs.

Second, our estimate of a 7.92% loss presumes that the change in the cost of equity capital is permanent. Our rolling regression results for the impact show how dangerous this assumption is – clearly the impact changes substantially over time and may have decreased in recent years. However, we have taken conservatively the *average* impact. While it is certainly possible that the cost of equity capital attributable to climate change may continue to decrease over time, it may also increase over time, and there is little reason to assume that uncertainty about climate change is diminishing in the near future.

Third, it is not clear how representative the United States stock market values are of the world. Developed economies experience higher losses due to the adjustment costs of capital and so the costs for the United States may overestimate those for the world. A further implicit assumption is that the stock market losses are representative for losses in the overall economy. It is possible for example that certain sectors of the economy are over- or under-represented in the stock market or that there are distribution effects within sectors. For instance, farmers may suffer from climate change but this need not lower profit margins in the food industry.

Fourth, our estimates do not take into consideration time variation in the sensitivities to the temperature shock factor. Industries with larger increases in the cost of equity capital may shrink over time as investment in these industries falls, causing the value-weighted loadings to move closer to zero. On the other hand, such reduction in investment lowers growth, an indirect effect that we have not yet incorporated in the damage impact calculation.

Fifth, the total present value loss of 7.92% is based on the standard discounting paradigm. Other social discounting perspectives, such as zero discounting or Dietz and Asheim's (2012) sustainable discounting, would typically generate a larger loss and motivate stronger abatement efforts.

Lastly, we do in effect equate the cost of climate change with the cost of climate uncertainty and thus ignore the potentially substantial costs directly related to known trends, such as the secular increase in temperature.

6.6. Uncertainty about regulation

One potential explanation for the sensitivity of particular industries to our temperature shock measure is that the indicator has little intrinsic economic importance for climate change (either because it is a statistical illusion, has only minor economic impact, or is too remote to affect current present values) but that markets fear the political pressures arising from common perceptions of a climate change threat that may lead to untoward regulation hurting business profits. This 'untoward regulation' line of reasoning implies that those industries which are most vulnerable to regulation designed to reduce man-made climate change would be the most sensitive to the temperature change factor. A prospective regulatory impact generally entails rationing or taxation of carbon-dioxide emissions. Hence the prediction is that industries that are the most sensitive to the temperature change factor are those industries that have the highest share of carbon dioxide emissions.

Schipper (2006) provides data on carbon-dioxide emissions in U.S. manufacturing. Manufacturing accounts for around 84 percent of energy-related carbon dioxide emissions. The Petroleum, Chemicals, and Primary Metals industries have the highest carbon dioxide emissions, together generating more than half of these emissions. However, as is apparent from Table 4, Oil (Petroleum and Natural Gas), Chems (Chemicals), and Mines (Precious Metals, Non-Metallic, and Industrial Metal Mining) do not have particularly large negative sensitivities to the temperature shock factor. Furthermore, many of the industries in Table 4 with strong negative exposures to the temperature shock factor are non-manufacturing industries such as Finance, Retail, and Meals, with obviously low carbon-dioxide emissions. These observations do not support the 'untoward regulation' explanation.

7. Conclusion

The severity of impact and even the existence of climate change are heavily debated. On one end of the debate are the 'environmentalists' who care deeply about the negative long-run impact of climate change and may be tempted to under appreciate the economic sacrifices required to combat man-made climate change; on the other end are the 'industrialists' who may be owners of capital and overly occupied with the costs necessary to implement policies of fighting climate change. The controversy makes it difficult to obtain an unbiased measure of even the perceived costs of climate change. Financial markets may be helpful in uncovering true perceptions. When investing in financial assets, individuals – irrespective of their background or political convictions – have an incentive not to 'put their money where their mouth is' but to put their money where their true beliefs are. Asset prices provide objective measures of perceived value. We attempt to exploit the information embedded in asset price reactions to news about temperature changes associated with climate change to infer an objective measure of perceived costs of climate change.

Although the extant literature on climate changes emphasizes an abrupt change in climate to occur around 2100, a gradual climate change viewpoint is consistent with scientific research spanning more than 100 years. Our approach ties into the gradual-climate-change perspective and stresses the higher cost of equity capital that arises from uncertainty about the extent of climate change. The costs of climate change that we derive, therefore, are a complement to the costs found in the earlier work and we should add it to previous damage impact estimates in order to obtain a more comprehensive cost total.

While we may draw inferences about the broad question of what financial markets in general can tell us about climate change, we obtain a more reliable answer to a narrower question: How do US equity markets react to news about average US temperature changes? Working in the context of the Merton (1973) asset pricing model, we hypothesize that *(i)* a significant risk premium exists on a temperature shock factor, *(ii)* its impact on the cost of equity capital, at least until recently, has been increasing over time, and *(iii)* loadings at the industry level on this factor are generally negative and more so for industries that are considered to be more sensitive to climate change.

On the whole we are able to confirm the hypotheses and infer, taking the average risk premium, that the cross-sectional average cost of equity capital is 0.22 percentage points higher on an annual basis due to climate change. Thus, markets expect that, due to temperature shocks associated with uncertainty climate change, potential projects will on average have a 0.22 percentage points lower return. The implied costs of climate change amount to a point estimate of a 7.92 percent loss in value – larger than, and adding to, the majority of previous estimates.

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Figure 1a. Annual Average Raw Temperatures, CT_{t+12}

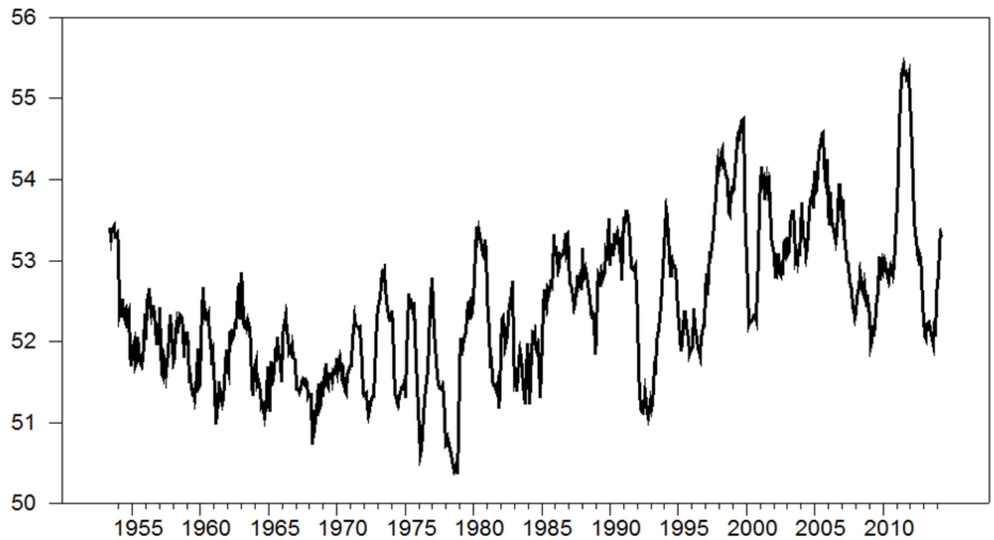

Figure 1b. Temperature Shock Tracking Portfolio Returns, bR_t

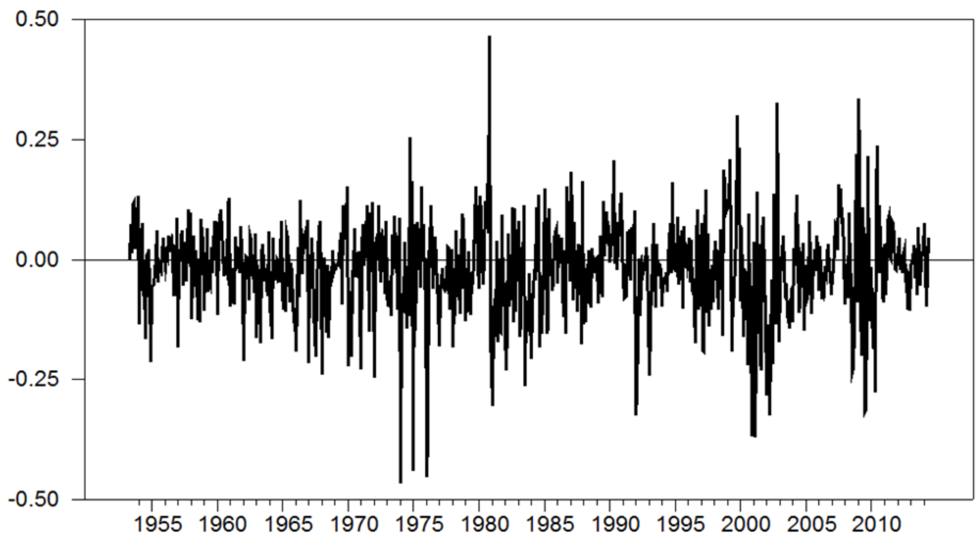

Figure 1. Temperatures and the Temperature Shock Factor.

Figure 1a shows the average raw temperatures over the next one year in degrees Fahrenheit. Figure 2b displays the temperature shock factor series, the temperature shock factor mimicking portfolio returns.

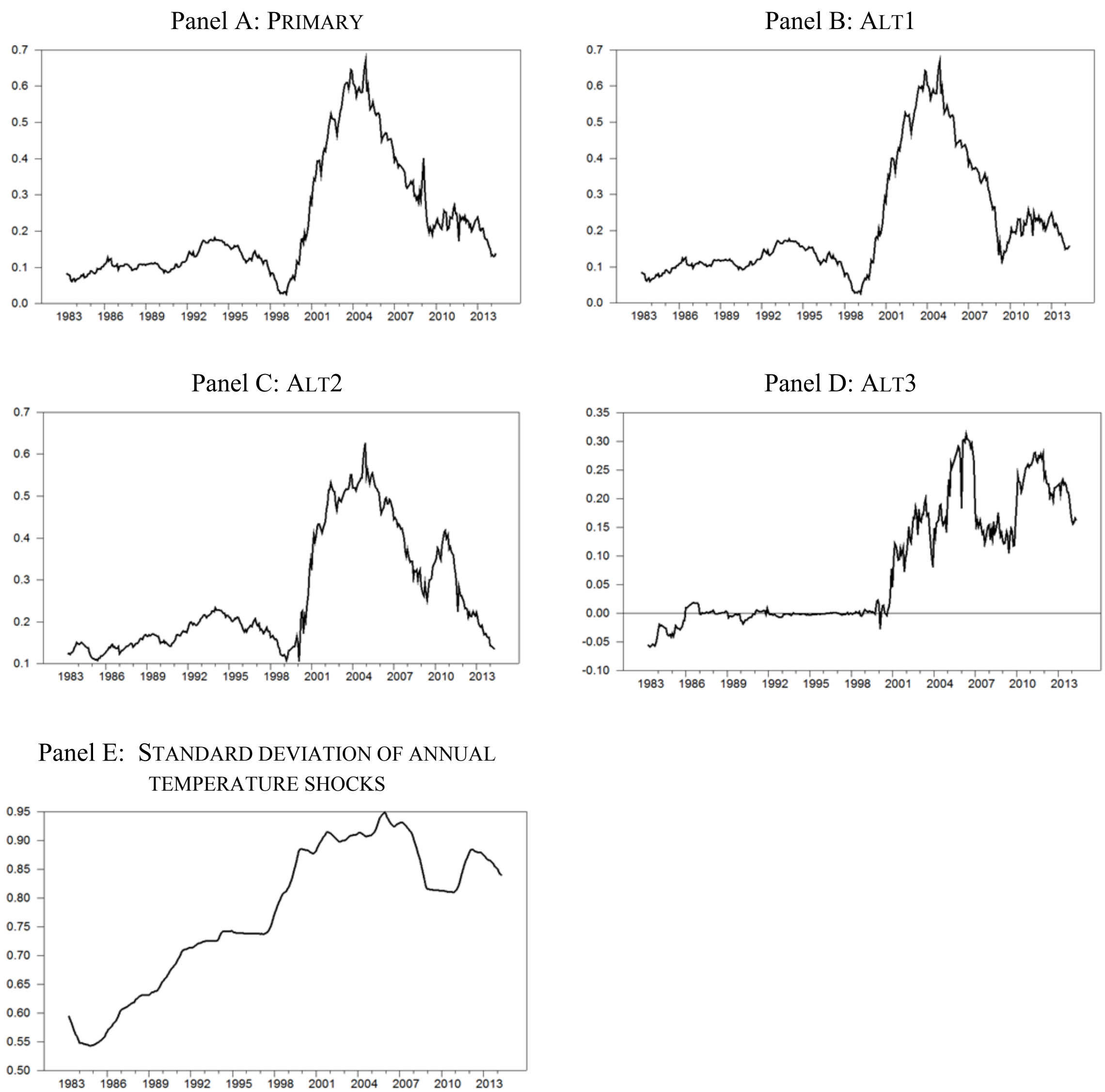

Figure 2. Rolling Impact Estimates of the Temperature Shock Factor.

The impact is estimated for the entire sample using 30 years of data for each estimate. Accordingly, the first period starts in 1983:4. We update the estimates each month by dropping the earliest observation and adding the latest observation.

PRIMARY represents our main specification given the base asset and conditioning variable choices of Vassalou (2003); ALT1 represents an alternative specification given the base asset and conditioning variable choices of Kapedia (2011); ALT2 represents our alternative specification with the temperature growth rate as the temperature shock factor; ALT3 directly uses the temperature surprise as the temperature shock factor.

Table 1. Tracking Portfolios and Diagnostic Tests

The tracking portfolio regression results are in Panel A. While the dependent variable for PRIMARY and ALT1 is CT_{t+12} (the average annual temperature from t+1 to t+12), that for ALT2 is $CTGRTH_{t+12}$ (the temperature growth rate). SL_t, SM_t, SH_t, BL_t, BM_t, BH_t, $LCMLG_t$, and $LGMRF_t$ are excess returns: the Fama-French size-BM portfolios net of the one-month T-Bill rate, the corporate bond rate minus the long-term government bond rate, and the long-term government bond rate minus the T-Bill rate; RF_{t-1}, DEF_{t-1}-, and $TERM_{t-1}$ represent, respectively, the lagged one-month T-Bill rate, the lagged default risk premium, and the lagged term premium. Panel B presents for each specification the average return on the zero-investment portfolio with the weights given by the coefficient estimates in Panel A.

Panel A. Tracking Portfolio Regressions

	PRIMARY			ALT1			ALT2	
	Coeff	t-ratio		Coeff	t-ratio		Coeff	t-ratio
SL_t	0.023	1.73	SL_t	0.026	1.90	SL_t	0.092	2.74
SM_t	0.001	0.04	SM_t	0.002	0.07	SM_t	-0.102	-1.63
SH_t	-0.046	-2.20	SH_t	-0.049	-2.33	SH_t	-0.034	-0.68
BL_t	0.005	0.32	BL_t	0.003	0.18	BL_t	-0.019	-0.57
BM_t	0.017	0.98	BM_t	0.013	0.75	BM_t	0.100	2.55
BH_t	0.001	0.07	BH_t	0.003	0.21	BH_t	-0.053	-1.43
			$LCMLG_t$	0.020	1.24			
			$LGMRF_t$	0.018	1.68			
Constant	45.375	9.42	Constant	45.648	9.25	Constant	-0.135	-0.33
RF_t	-0.629	-1.36	RF_t	-0.644	-1.38	RF_t	0.916	1.00
DEF_{t-1}	-0.088	-0.42	DEF_{t-1}	-0.100	-0.47	DEF_{t-1}	-0.248	-0.68
$TERM_{t-1}$	-0.120	-1.17	$TERM_{t-1}$	-0.124	-1.21	$TERM_{t-1}$	0.099	0.44
Trend	0.002	4.59	Trend	0.002	4.53	$CTGRTH_{t-12}$	-0.383	-5.29
CT_{t-12}	0.111	1.16	CT_{t-12}	0.106	1.08			
Adj-R^2	0.38		Adj-R^2	0.38		Adj-R^2	0.16	
χ^2 p-value	0.05		χ^2 p-value	0.04		χ^2 p-value	0.02	

Panel B. The means of the Tracking Portfolio Returns

Mean	-0.02	-4.44	Mean	-0.02	-4.16	Mean	-0.07	-5.48

Table 2. Summary statistics of time-series and cross-sectional regressions for 55 size-BM and industry portfolios under the primary specification

Panel A summarizes time-series regressions to explain monthly excess returns on 55 size-BM and industry portfolios. Panel A provides the average absolute value of the intercepts (|Alpha|), the average adjusted R^2 (AVG R^2), and the GRS F-test statistic (GRS). Panel B reports the Fama and MacBeth (1973) two-pass OLS regressions with 55 size-BM and industry portfolios as the test assets. γ is the estimated risk premium associated with each factor. t_{EIV} and t_{MIS} are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R^2. The four models are:

CAPM: $r_{it} = \alpha_i + m_i MKT_t + \varepsilon_{it}$

FF: $r_{it} = \alpha_i + m_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{it}$

CAPM+TSF: $r_{it} = \alpha_i + m_i MKT_t + f_i TSF_t + \varepsilon_{it}$

FF+TSF: $r_{it} = \alpha_i + m_i MKT_t + s_i SMB_t + h_i HML_t + f_i TSF_t + \varepsilon_{it}$.

where r_{it} is the excess return on asset i in period t, and MKT_t is the excess market return, SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks, and TSF_t is the tracking portfolio returns of changes in expectations about temperature changes.

Panel A: Time-series regression summary statistics

	|Alpha|	AVG R^2	GRS
CAPM	0.19	0.66	3.58*
FF	0.15	0.75	3.13*
CAPM+TSF	0.17	0.70	2.81*
FF+TSF	0.14	0.76	2.72*

Panel B: Cross-sectional regression summary statistics

		γ	t_{EIV}	t_{MIS}
CAPM	Constant	0.85	3.92	3.88
	MKT	-0.12	-0.42	-0.42
	R^2	-0.01		
FF	Constant	0.96	4.45	4.37
	MKT	-0.30	-1.13	-1.11
	SMB	0.11	1.02	1.02
	HML	0.19	1.79	1.78
	R^2	0.20		
CAPM+TSF	Constant	0.81	3.66	3.64
	MKT	-0.15	-0.57	-0.56
	TSF	*-0.01*	*-2.74*	*-2.72*
	R^2	0.27		
FF+TSF	Constant	0.92	4.25	4.15
	MKT	-0.25	-0.94	-0.92
	SMB	0.13	1.16	1.16
	HML	0.21	1.97	1.96
	TSF	*-0.02*	*-3.28*	*-3.20*
	R^2	0.34		

Table 3. Summary statistics of time-series and cross-sectional regressions for 55 size-BM and industry portfolios under the alternative specifications

Panel A summarizes time-series regressions to explain monthly excess returns on 55 size-BM and industry portfolios. Panel A provides the average absolute value of the intercepts (|Alpha|), the average adjusted R^2 (AVG R^2), and the GRS F-test statistic (GRS). Panel B reports the Fama and MacBeth (1973) two-pass OLS regressions with 55 size-BM and industry portfolios as the test assets. γ is the estimated risk premium associated with each factor. t_{EIV} and t_{MIS} are the Shanken (1992) errors-in-variables robust t-ratio and the Shanken and Zhou (2007) misspecification robust t-ratio, respectively. We also report the OLS cross-sectional adjusted R^2.

Panel A: Time-series regression summary statistics

	|Alpha|	AVG R^2	GRS
ALT1	0.16	0.69	2.93*
ALT2	0.15	0.69	2.86*
ALT3	0.19	0.66	3.57*

Panel B: Cross-sectional regression summary statistics

		γ	t_{EIV}	t_{MIS}
ALT1	Constant	0.83	3.75	3.73
	MKT	-0.17	-0.62	-0.62
	TSF	*-0.01*	*-2.72*	*-2.70*
	R^2	0.27		
ALT2	Constant	0.73	3.29	3.26
	MKT	-0.07	-0.25	-0.25
	TSF	*-0.03*	*-2.45*	*-2.42*
	R^2	0.23		
ALT3	Constant	0.71	3.05	2.99
	MKT	0.00	-0.01	-0.01
	TSF	*-0.80*	*-1.92*	*-1.50*
	R^2	0.07		

Table 4. Factor loadings of 55 size-BM and Industry Portfolios

The factor loadings of the portfolios are inferred from:

$$r_{it} = \alpha_i + m_i MKT_t + f_i TSF_t + \varepsilon_{it}$$

where r_{it} is the excess return on asset *i* in period *t*, MKT_t, TSF_t are the excess returns on the market and the temperature shock factor. The β 's are the associated factor loadings, and ε_{it} is the disturbance. To save space, we do not report the associated HAC-robust (Newey-West) t-statistics for 55 size-BM and industry portfolios. The significant factor loadings at the 5% level of significance are in bold.

To formally test Hypothesis 2 with the industry portfolios, we create two equal-weighted portfolios. "High" includes the high-exposure industries identified by Graff Zivin and Neidell (2014) (specifically: agriculture, forestry, fishing, and hunting; mining; construction; transportation; and manufacturing), while "Low" consists of all remaining industries. The loadings on the temperature shock factor for "High" and "Low" capture the average sensitivities of the high-exposure and low-exposure industries, respectively. Consequently, the loading on the temperature shock factor for "High – Low" picks up the sensitivity difference between the high- and low-exposure industries.

To test Hypothesis 2 formally for the size-BM portfolios, we also form equal-weighted portfolios to capture the average sensitivities of different types of stocks. "Small" consists of the five small-capitalization portfolios, and "Big" includes the five large-capitalization portfolios; "Value" contains the five value portfolios, and "Growth" comprises the five growth portfolios. "Small – Big" picks up the difference between small and big stocks, and "Value – Growth" does the same for value and growth stocks.

Panel A: Industry portfolios

	Alpha	MKT	TSF	R^2
Food	0.24	0.73	-2.83	0.55
Beer	0.20	0.78	-4.11	0.44
Smoke	0.50	0.69	-4.28	0.25
Games	-0.17	1.33	**-9.65**	0.66
Books	-0.17	1.09	**-7.87**	0.69
Hshld	0.15	0.84	-0.74	0.60
Clths	-0.25	1.13	**-12.73**	0.62
Hlth	0.45	0.84	**5.69**	0.59
Chems	-0.11	1.07	**-4.46**	0.71
Txtls	-0.53	1.21	**-24.02**	0.62
Cnstr	-0.33	1.22	**-11.07**	0.80
Steel	-0.54	1.34	**-9.97**	0.65
FabPr	-0.17	1.22	**-5.27**	0.78
ElcEq	0.09	1.22	-1.61	0.73
Autos	-0.38	1.18	**-13.12**	0.59
Carry	-0.02	1.14	**-7.96**	0.60
Mines	-0.19	0.97	**-7.46**	0.33
Coal	0.14	1.17	-5.42	0.28
Oil	0.32	0.81	2.16	0.46
Util	0.15	0.56	-3.31	0.38
Telcm	0.16	0.75	1.87	0.55
Servs	0.19	1.22	**5.64**	0.72
BusEq	0.18	1.26	**6.88**	0.71
Paper	-0.06	0.99	**-4.93**	0.72
Trans	-0.24	1.10	**-10.01**	0.70
Whlsl	-0.11	1.08	**-6.82**	0.72
Rtail	0.04	1.00	**-3.78**	0.67
Meals	0.00	1.08	**-7.97**	0.58
Fin	-0.16	1.09	**-7.25**	0.78
Other	-0.28	1.10	**-4.72**	0.69
High	0.34	1.04	**-6.04**	0.92
	(5.14)	(53.88)	(-6.26)	
Low	0.39	1.05	**-3.01**	0.90
	(5.23)	(43.55)	(-3.54)	
High - Low	-0.06	-0.01	**-3.03**	0.03
	(-0.66)	(-0.34)	(-2.97)	

Panel B: Size and BM portfolios

Size	BM	Alpha	MKT	TSF	R^2
	Growth	-0.65	1.41	**-6.73**	0.61
	2	-0.20	1.26	**-13.08**	0.67
Small	3	-0.19	1.13	**-16.84**	0.74
	4	-0.03	1.09	**-20.60**	0.79
	Value	-0.10	1.17	**-27.15**	0.84
	Growth	-0.31	1.36	0.56	0.73
	2	-0.14	1.19	**-9.78**	0.79
2	3	0.00	1.10	**-14.57**	0.83
	4	-0.08	1.08	**-18.98**	0.87
	Value	-0.20	1.21	**-26.27**	0.89
	Growth	-0.13	1.28	2.50	0.79
	2	-0.01	1.12	**-7.61**	0.84
3	3	-0.04	1.05	**-11.87**	0.86
	4	0.00	1.03	**-15.94**	0.87
	Value	-0.07	1.11	**-22.65**	0.87
	Growth	0.05	1.18	**5.12**	0.86
	2	-0.08	1.08	**-4.51**	0.88
4	3	0.00	1.06	**-9.12**	0.86
	4	-0.01	1.01	**-13.20**	0.86
	Value	-0.16	1.12	**-18.11**	0.82
	Growth	0.12	0.97	**6.80**	0.91
	2	0.06	0.93	1.04	0.88
Big	3	0.09	0.88	-0.95	0.79
	4	-0.06	0.88	**-8.08**	0.76
	Value	-0.14	0.96	**-12.77**	0.69
Small		0.14	1.21	**-16.89**	0.75
		(1.04)	(36.12)	(-10.38)	
Big		0.39	0.92	**-2.80**	0.92
		(6.66)	(49.95)	(-3.17)	
Small - Big		-0.25	0.29	**-14.09**	0.17
		(-1.50)	(6.45)	(-6.51)	
Value		0.24	1.11	**-21.40**	0.93
		(3.85)	(53.29)	(-29.29)	
Growth		0.19	1.24	1.64	0.84
		(1.85)	(47.00)	(1.40)	
Value - Growth		0.05	-0.13	**-23.04**	0.57
		(0.57)	(-4.57)	(-18.06)	

Table 5. Value-weighted Annual Impact (%) Estimates

The economy-wide average impact on the cost of equity capital is obtained by multiplying the temperature shock risk premium by the weighted average loading on this factor. Panel A shows the total value-weighted impact for the entire sample period.

Following Cooper, Gutierrez and Hameed (2004), we estimate the impact of the temperature shock factor in two sub-sample periods with the following regression:

$$\text{IMPACT}_t = i_{83-98} D_{83-98} + i_{99-14} D_{99-14} + e_t$$

where $IMPACT_t$ is the impact in month t estimated based on 30-year rolling samples, $D_{83\text{-}98}$ is equal to 1 for the period 1983-1998 and zero otherwise, and $D_{99\text{-}14}$ is equal to 1 for 1999-2014 and zero otherwise. The mean impact in 1983-1998 is $i_{83\text{-}98}$, while that in 1999-2014 is $i_{99\text{-}14}$. To test whether the mean impacts are equal, we run the following regression:

$$\text{IMPACT}_t = a + i_{Difference} \; D_{99-14} + e_t$$

The impact difference is $i_{Difference}$. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12. The subsample results are presented in Panel B.

Panel A: The Impact of the temperature shock factor in the entire sample period

	PRIMARY	ALT1	ALT2	ALT3
Impact	0.22	0.23	0.26	0.18

Panel B: The Impact of the temperature shock factor in two sub-sample periods

	PRIMARY		ALT1		ALT2		ALT3	
	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
$i_{83\text{-}96}$	0.11	14.16	0.11	15.13	0.17	20.8	-0.01	-1.76
$i_{97\text{-}10}$	0.33	8.11	0.33	7.79	0.36	10.53	0.17	8.22
$i_{Difference}$	0.22	*5.32*	0.21	*5.03*	0.19	*5.50*	0.17	*8.38*