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Temperature shocks and the cost of equity capital: Implications for climate change perceptions[☆]

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A B S T R A C T

Financial market information can provide an objective assessment of losses anticipated from temperature changes. In an APT model in which temperature shocks are a systematic risk factor, 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 uncertainty about temperature changes are 0.22 percent, implying a present value loss of 7.92 percent of wealth. These costs represent a new channel that may contribute to cost of climate change assessment.

1. Introduction

We examine to what extent temperature shocks affect the cost of equity.[1] If temperature fluctuations are uncertain and systematically affect cash flows, temperature shocks could represent a priced Arbitrage Pricing Theory (APT) risk factor, resulting in increases in expected returns. Higher expected returns mean a higher cost of capital to firms, which can have a profound and adverse impact on economic growth (Henry, 2003).[2] To study empirically whether temperature shocks are a priced APT factor, we follow the empirical asset-pricing literature (e.g. Vassalou, 2003; Kapadia, 2011). We find that the average cost of equity capital is 0.22 percentage points higher on an annual basis due to temperature shocks. Based on Henry's (2003) finding of an approximate one-to-one relationship between the cost of capital and GDP per capita growth our results imply that temperature shocks cause a 0.22 percentage point reduction in the growth rate of U.S. GDP per capita. This estimate is statistically and economically significant.[3]

A rapidly growing new climate-economy literature has drawn on exogenous temperature shocks to identify causal effects of high temperatures on production at both micro and macro levels,

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[1] Our investigation is motivated by substantial uncertainty in temperature variation, which can be illustrated by the Intergovernmental Panel on Climate Change (IPCC)'s widely quoted estimates for the increase in the global mean temperature. IPCC's 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 vast: from 0.3 °C to 4.8 °C (IPCC, 2014).

[2] 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 perceptions of the distribution of future temperatures, on systematic risk and the economy-wide cost of capital.

[3] To put the number in perspective, the aggregate economic costs of mitigating secular increases in temperature (designed to limit climate change to below 2°C by the end of the 21st century relative to pre-industrial levels) only amount to an annualized reduction of per capita consumption growth of 0.04 to 0.14 percentage points (IPCC, 2014).

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thereby uncovering widespread cash flow effects of temperature shocks. For instance, Fisher, Hanemann, Roberts, and Schlenker (2012) find a negative impact of high temperatures on U.S. agriculture. Graff Zivin and Neidell (2014) show that temperature increases at the higher end of the distribution reduce labor productivity in sectors with high exposure to weather 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 high temperatures affect labor productivity (Seppänen, Fisk, and Lei, 2006). Dell, Jones and Olken (2012) in a world sample find that temperature increases reduce not only levels but also growth rates of real GDP, particularly in developing countries.[4] We contribute to the new climate-economy literature by investigating if temperature shocks also have discount-rate effects.

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 this paper identifies a specific mechanism through which temperature shocks impact growth. Temperature shocks have not only cash-flow but also discount-rate effects, 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).

In a contemporaneous paper, Bansal, Kiku, and Ochoa (2015) develop a long-run risks model focusing on temperature-induced disasters, and find that temperature shocks have a negative impact on asset prices. There are two major differences between Bansal, Kiku, and Ochoa (2015) and the present paper. First, the underlying temperature-economy linkages are different. While temperature-induced disasters drive the negative impact of temperature variation in Bansal, Kiku, and Ochoa (2015), the impact in the present paper is the result of high temperatures emphasized by the new climate-economy literature. For instance, high temperatures without disasters could still reduce labor productivity and supply (Graff Zivin and Neidell, 2014), which may help explain the negative effects of temperature shocks in earlier years when temperature-induced disasters were insignificant. Second and more importantly, the perspectives differ. Bansal, Kiku, and Ochoa (2015) do not disentangle the cash-flow and discount-rate effects. Given that cash-flow effects of temperature variation are well documented in the new climate-economy literature, we focus here on identifying the discount-rate effect of temperature shocks.

The remainder of the paper is organized as follows: Section 2 states three testable hypotheses and briefly discusses the data. Section 3 presents the tracking portfolio approach of constructing the temperature shock factor. Section 4 provides estimates of the loadings and the premium on the temperature shock factor. Section 5 investigates specifically the quantitative impact of temperature shocks on the cost of equity capital. Section 6 discusses further empirical results, and Section 7 concludes with a discussion of implications and a brief summary.

[4] Earlier studies also document a 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.

2. Hypotheses and data

Temperature shocks essentially act as a systematic negative productivity shock in the context of Balvers and Huang (2007). Since temperature shocks negatively affect most firms (i.e. the factor loadings on the temperature shock factor are generally negative), the risk premium must be negative to ensure that riskier assets have higher average returns.

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

Temperature shocks may have an uneven impact. In particular, some sectors are more vulnerable: *Agriculture, forestry, fishing, and hunting; mining; construction; transportation; and manufacturing*, because these sectors have high exposure to climate (Graff Zivin and Neidell, 2014). Furthermore, Quiggin and Horowitz (2003) emphasize adjustment costs to temperature changes. 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 more vulnerable. Along this line, *small firms* should be more sensitive to temperature shocks, because they may lack resources to adjust. 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 factor and, accordingly, higher required returns and costs of capital.

Hypothesis 2. *Industries or firms that are more vulnerable to temperature shocks have higher loadings (in absolute value) on the temperature shock factor.*

If suspicions of climate change have intensified in recent decades, the aggregate importance of temperature shocks ought to have risen. Bansal, Kiku, and Ochoa (2015) substantiate that negative elasticity of asset prices to temperature fluctuations has been increasing over time, which motivates us to test the following hypothesis.

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

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, because the required temperature and financial-market data are available for the U.S. and are uniformly accurate. The portfolio returns and Fama-French factor data are from Kenneth French's website. The macro variables data are from the Federal Reserve Bank of St. Louis. The temperature is the U.S. average temperature series obtained from the National Climatic Data Center. In addition, we merge CRSP and Compustat to construct a variety of equity portfolios for empirical testing.

3. Economic tracking portfolios: a non-structural approach

To infer the news concerning future temperature variation contained in current stock returns, we employ the economic tracking portfolio approach proposed by Breeden, Gibbons, and Litzenberger (1989) and Lamont (2001) and previously applied by Vassalou (2003) and Kapadia (2011). This statistical approach allows us to estimate the risk premium of temperature shocks without imposing a particular model of asset pricing.

3.1. Primary specification

Our simple time-series model is essentially the daily temperature model of Campbell and Diebold (2005) amended to deal with monthly observations and to avoid seasonal adjustment :[5]

$$T_{t+12} = c + at + \tau_{t+12}, \tag{1}$$

where T_{t+12} is the average temperature from month $t+1$ to $t+12$, t is the deterministic time trend, and τ_{t+12} captures effects of all other variables (emissions, climate policy, etc.). Tautologically, we can separate T_{t+12} into a previously expected component, a news component, and noise,

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

where the news component is $\Delta E_t(T_{t+12}) \equiv E_t(T_{t+12}) - E_{t-1}(T_{t+12})$, which is contained in the temperature observation in month t, and the noise component is $\omega_{t+12} \equiv \tau_{t+12} - E_t(\tau_{t+12})$.[6]

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

$$\Delta E_t(T_{t+12}) = b[R_t - E_{t-1}(R_t)] + \eta_t, \tag{3}$$

where $R_t - E_{t-1}(R_t)$ represents a column vector of unexpected excess returns, with R_t a column vector of excess returns of the basis assets in month t (i.e., returns net of the risk free rate), and η_t the component of news that is orthogonal to the unexpected excess returns of the basis assets.

Assume that the basis asset excess returns in month t are a linear function of Z^E_{t-1}, a vector of conditioning *economic* variables known at t-1, and that τ_{t+12} is a linear function of both Z^E_{t-1} and Z^C_{t-1}, the latter a vector of conditioning *climate* variables known at t-1. Therefore, $E_{t-1}(R_t) = d\,Z^E_{t-1}$ and $E_{t-1}(\tau_{t+12}) = f\,Z^E_{t-1} + g\,Z^C_{t-1}$. Then we have from Eqs. (1), (2), and (3) that $T_{t+12} = [c + at + fZ^E_{t-1} + gZ^C_{t-1}] + [b\,(R_t - d\,Z^E_{t-1}) + \eta_t] + \omega_{t+12}$, which provides:

Primary Specification

$$T_{t+12} = c + a\,t + e\,Z^E_{t-1} + gZ^C_{t-1} + bR_t + \varepsilon_{t+12}, \tag{4}$$

with $e \equiv -b\,d + f$ and $\varepsilon_{t+12} \equiv \eta_t + \omega_{t+12}$. Note that while we consider temperatures based on annual averages, which sidesteps seasonal issues, we continue to utilize the additional information in monthly control variables and returns to measure coefficients more precisely.

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

The unconditional mean of the tracking portfolio returns $b\,E(R_t)$ represents the factor risk premium (see Lamont, 2001, Vassalou, 2003, and Kapadia, 2011), which is in our application the factor risk premium of the temperature shock factor. The intuition is that the estimated coefficients b represent basis asset loadings on the temperature variation news. The portfolio with weights b on the basis assets has a mean excess return $b\,E(R_t)$ that reflects the risk due to temperature news and can be interpreted as the risk premium on the temperature shock factor. If temperature variation impacts are generally adverse (e.g., Dell, Jones and Olken, 2014), we expect to see a negative premium: since the loadings on the temperature shock factor should normally be negative, and to compensate for 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 follow Vassalou (2003) and use the six Fama-French size and book-to-market (BM) portfolios as the basis assets. To obtain the economic conditioning variables – the Z^E_{t-1} in Eq. (4) – we again follow Vassalou (2003) and use macro variables known to predict equity returns. They are the risk-free rate (RF), the term premium (TERM) (the 10-year government bonds rate from the St. Louis Federal Reserve Bank minus the risk-free rate), and the default premium (DEF) (the yield difference between BAA and AAA bonds from the St. Louis Fed). We use the lagged average temperature over the past year (i.e., from t - 12 to t - 1) as the single climate control variable in Z^C_{t-1}.

The primary specification in Table 1 presents the construction and diagnostic tests of the tracking portfolios for the temperature shock factor based on Eq. (4) with the six Fama-French size-value portfolios as the basis assets and the macro variables used by Vassalou (2003) as conditioning variables. Because we use overlapping data, the t-ratios are obtained from Newey-West HAC standard errors with the bandwidth (lag parameter) set equal to 24.[7]

All results are for 1953:5 - 2014:5 (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 T_{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 as expected: Growth firms may potentially benefit from temperature variation 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 temperature variation (by, for instance, relocating production). Conform the ability of larger firms to adapt more easily to temperature fluctuations, the portfolios of large companies show no significant sensitivity to temperature shocks. The chi-square test in Panel A rejects at the 5% level the hypothesis that the coefficients on the basis assets are jointly zero, indicating that these 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 -4.26. This provides direct support for Hypothesis 1, that the risk premium on temperature variation is significantly negative. The result is not dependent on the choice of a particular asset-pricing model. Fig. 1 shows raw average temperatures and the derived temperature shock factor series (the tracking portfolio returns) from 1953 through 2014.

3.2. Alternative specifications

We consider three alternative approaches for constructing the temperature shock factor in order to evaluate the robustness of our results.

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

[6] Our approach is agnostic about the extent to which unanticipated temperature shocks signal changes in climate. In the Web Appendix we show that five-year average temperature shocks in the U.S. are highly persistent in the period 1950-2014 with a coefficient of 0.70 (whereas this coefficient is 0.17 in the period from 1895-1950). This persistence may merely be indicative of temporary warming/cooling trends rather than permanent changes in climate. The importance of temperature shocks, however, definitely extends beyond the current period. Our approach isolates the changes in value of firms resulting from the temperature shocks, thus providing a discounted sum of the market-perceived impacts over time irrespective of whether these reflect transitory trends or permanent climate change.

[7] The bandwidth exceeds the data overlap interval as suggested by Sun, Phillips, and Jin (2008). Following Bekaert and Hoerova (2014) we set the bandwidth equal to Max[3, 2*horizon] which is 24 in the case with annual horizon.

Table 1
Tracking Portfolios and Diagnostic Tests.

The tracking portfolio regression results are in Panel A. All results are for the 1953:5 - 2014:5 period using overlapping data. While the dependent variable for PRIMARY and ALT1 is T_{t+12} (the average annual temperature from t+1 to t+12), that for ALT2 is $TGRTH_{t+12}$ (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-value 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. To adjust for the autocorrelation in errors resulting from the overlapping temperature shock data, Newey-West heteroskedasticity and autocorrelation corrected standard errors are obtained employing a bandwidth of 24 months.

Panel A. Tracking Portfolio Regressions								
PRIMARY			ALT1			ALT2		
	Coeff	t-ratio		Coeff	t-ratio		Coeff	t-ratio
SL_t	0.023	1.91	SL_t	0.026	2.13	SL_t	0.092	2.90
SM_t	0.001	0.04	SM_t	0.002	0.07	SM_t	−0.102	−1.70
SH_t	−0.046	−2.09	SH_t	−0.049	−2.23	SH_t	−0.034	−0.65
BL_t	0.005	0.32	BL_t	0.003	0.19	BL_t	−0.019	−0.59
BM_t	0.017	0.91	BM_t	0.013	0.70	BM_t	0.100	2.47
BH_t	0.001	0.07	BH_t	0.003	0.22	BH_t	−0.053	−1.36
			$LCMLG_t$	0.020	1.32			
			$LGMRF_t$	0.018	1.69			
Constant	45.375	9.16	Constant	45.648	8.98	Constant	−0.135	−0.35
RF_{t-1}	−0.629	−1.30	RF_{t-1}	−0.644	−1.32	RF_{t-1}	0.916	1.01
DEF_{t-1}	−0.088	−0.39	DEF_{t-1}	−0.100	−0.44	DEF_{t-1}	−0.248	−0.69
$TERM_{t-1}$	−0.120	−1.12	$TERM_{t-1}$	−0.124	−1.16	$TERM_{t-1}$	0.099	0.41
t	0.002	4.28	t	0.002	4.24	$TGRTH_{t-12}$	−0.383	−6.16
T_{t-12}	0.111	1.12	T_{t-12}	0.106	1.04			
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	0.03		χ^2 p-value	0.02	
Panel B. The means of the Tracking Portfolio Returns								
Mean	−0.02	−4.26	Mean	−0.02	−4.15	Mean	−0.07	−5.54

3.2.1. Alternative specification 1

We apply here the recent approach of Kapadia (2011) instead of Vassalou (2003) for choosing the basis assets and conditioning variables used in the tracking portfolio approach.

$$T_{t+12} = c + a\,t + eZ^E_{t-1} + gZ^C_{t-1} + bR_t + \varepsilon_{t+12}, \tag{4a}$$

where T_{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-value portfolios and the excess return of long-term corporate bonds over long-term government bonds (LCMLG) from Ibbotson Associates (2014) as well as the excess return of long-term government bonds over the risk free rate (LGMRF); $Z^E_{t-1}= (RF_{t-1}, DEF_{t-1}, TERM_{t-1})'$, represents as before, respectively, the lagged one-month T-Bill rate, the lagged default risk premium, and the lagged term premium; Z^C_{t-1} is again the lagged average temperature from t-12 to t-1. The temperature shock factor is the tracking portfolio return, $TSF_t = bR_t$.

3.2.2. Alternative specification 2

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. Estimate the following model over the entire sample:

$$TGRTH_{t+12} = c + eZ^E_{t-1} + gZ^C_{t-1} + bR_t + \varepsilon_{t+12}, \tag{4b}$$

where $TGRTH_{t+12} = 100 \times \log(T_{t+1,t+12}/T_{t-11,t})$ is the log difference in the average annual temperature. The variables are the same as in the benchmark specification: $R_t=(SL_t, SM_t, SH_t, BL_t, BM_t, BH_t)'$; $Z^E_{t-1} = (RF_{t-1}, DEF_{t-1}, TERM_{t-1})'$; Z^C_{t-1} is the lagged growth rate in the average temperature; and the temperature shock factor is the tracking portfolio return $TSF_t = bR_t$.

3.2.3. Alternative specification 3

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. Estimate the following model in a rolling fashion (for each month s we estimate for the months s-120 to s-1) to avoid using future information; generate an error term e_s using the 10 years of data preceding month s so that for each month only the residual for the last month of the following regression is utilized to serve as the unexpected temperature change:

$$T^m_t = C + A\cdot t + \sum_{i=1}^{11} S_i \cdot seasonal_i + \sum_{i=1}^{n} L_i T^m_{t-i} + e_t, \tag{4c}$$

where T^m_t represents the monthly temperature, t is the deterministic time trend, $seasonal_i$ is the seasonal dummy variable for month i. The lag length is selected by the Schwartz-Bayes Criterion. Then we calculate the expected temperature based on the estimated parameters. The temperature shock factor is the unexpected change in the monthly temperature, $TSF^*_t = e_t$ (the asterisk indicates that the temperature shock factor is not a tradable asset in this case).

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.

4. Standard asset pricing models: structural approaches

The tracking portfolio approach of Lamont (2001) in Section 3 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 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,

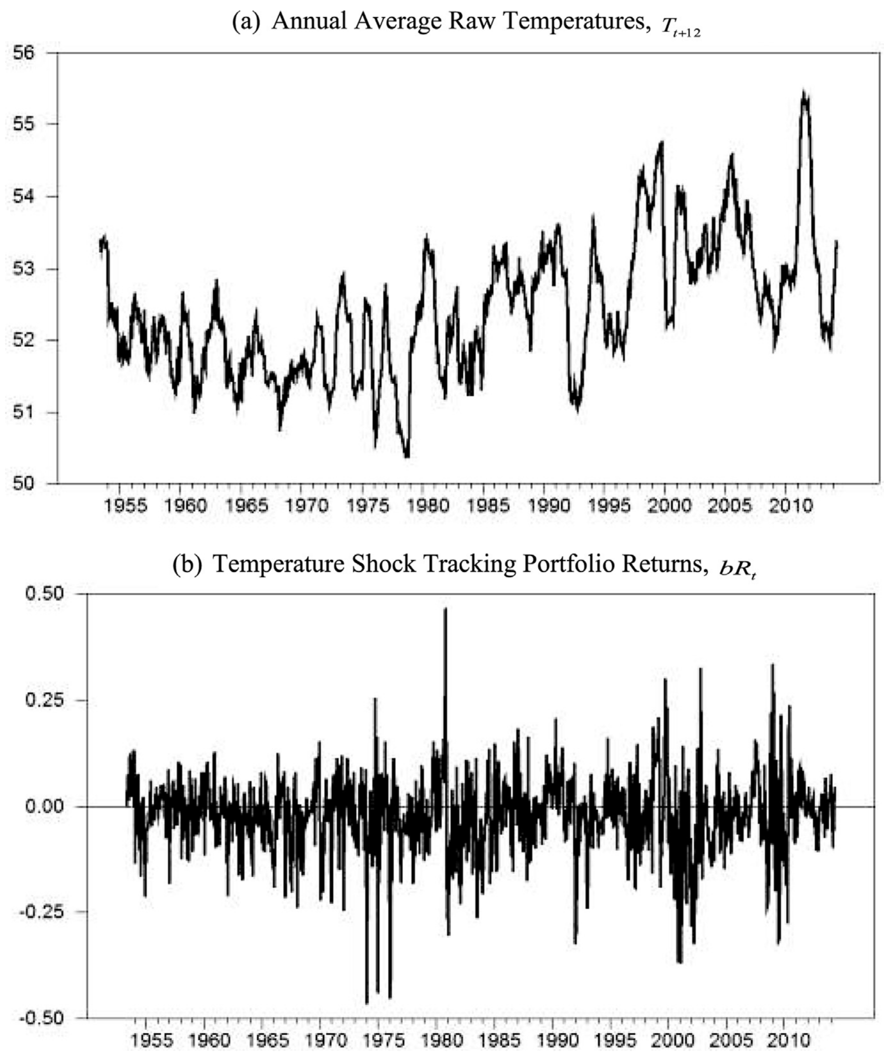

Fig. 1. Temperatures and the Temperature Shock Factor.
Fig. 1a shows the average raw temperatures over the next one year in degrees Fahrenheit. Fig. 1b displays the temperature shock factor series, the temperature shock factor mimicking portfolio returns based on Eq. (4).

and to identify the aggregate quantitative impact on the cost of equity capital and how this impact changes over time, to address Hypothesis 3.

For our asset-pricing specifications, we take the Fama and French (1996) three-factor model and the Sharpe-Lintner CAPM. These are the most common systematic risk models. The temperature shock factor is added to these specifications as an additional factor. 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 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 et al. (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 empirical asset-pricing 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-economy literature has predictions for how different industries should be affected. We thus use 55 size-value and industry portfolios (25 size-value portfolios plus 30 industry portfolios) as our test assets, instead of just 25 size-value portfolios.

Since temperature variation is a systematic risk, 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 ro-

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

Panel A summarizes time-series regressions to explain monthly excess returns on 55 size-value 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-value 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 models are:

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

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

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

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

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 from Eq. (4).

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}	p bootstrap
CAPM	Constant	0.85	3.92	3.88	
	MKT	−0.12	−0.42	−0.42	[0.48]
	R^2	−0.01			
FF	Constant	0.96	4.45	4.37	
	MKT	−0.30	−1.13	−1.11	[0.41]
	SMB	0.11	1.02	1.02	[0.44]
	HML	0.19	1.79	1.78	[0.43]
	R^2	0.20			
CAPM+TSF	Constant	0.81	3.66	3.64	
	MKT	−0.15	−0.57	−0.56	[0.47]
	TSF	*−0.01*	*−2.74*	*−2.72*	*[0.04]*
	R^2	0.27			
FF+TSF	Constant	0.92	4.25	4.15	
	MKT	−0.25	−0.94	−0.92	[0.43]
	SMB	0.13	1.16	1.16	[0.42]
	HML	0.21	1.97	1.96	[0.40]
	TSF	*−0.02*	*−3.28*	*−3.20*	*[0.02]*
	R^2	0.34			

bustly significant and in the ballpark of the mean return of the temperature shock factor for the primary specification reported in Table 1 which is −0.02 percent. We confirm Hypothesis 1.[8] Table 3 shows the alternative specifications perform similarly as the primary specification, further corroborating Hypothesis 1: the temperature shock risk premium is significantly negative, although only marginally so for ALT3.

5. Temperature shocks and the cost of equity capital

5.1. Sensitivity to temperature shocks

To estimate the impact of temperature shocks 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

[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

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

Panel A summarizes time-series regressions to explain monthly excess returns on 55 size-value 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 results with 55 size-value 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 temperature shock factor specifications for ALT1, ALT2, and ALT3 are from Eqs. (4a), (4b), and (4c), respectively. Since the temperature shock factor for ALT3 is not a return, alphas and GRS statistic are meaningless and are not reported for this case.

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	N.A.	0.66	N.A.

Panel B: Cross-sectional regression summary statistics

		γ	t_{EIV}	t_{MIS}	p bootstrap
ALT1	Constant	0.83	3.75	3.73	
	MKT	−0.17	−0.62	−0.62	[0.45]
	TSF	−0.01	−2.72	−2.70	[0.06]
	R^2	0.27			
ALT2	Constant	0.73	3.29	3.26	
	MKT	−0.07	−0.25	−0.25	[0.48]
	TSF	−0.03	−2.45	−2.42	[0.02]
	R^2	0.23			
ALT3	Constant	0.71	3.05	2.99	
	MKT	0.00	−0.01	−0.01	[0.51]
	TSF*	−0.80	−1.92	−1.50	[0.06]
	R^2	0.07			

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 more sensitive to temperature shocks. The results in Table 4 are broadly consistent with this conjecture, confirming Hypothesis 2, as we discuss next.[9]

5.1.1. Industry portfolios

The results for the 30 Fama-French 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 Graff Zivin and Neidell (2014) suggest; Food Products (Food), Coal (Coal), Utilities (Util), and four Manufacturing industries [Beer & Liquor (Beer), Tobacco Products (Smoke), Consumer Goods (Hshld), and Electrical Equipment (ElcEq)] also have negative sensitivity to the temperature shock factor, although not significant.

lower, and (2) the significance of the risk premia, for the temperature shock factor in particular, is higher.

[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.

Table 4
Factor loadings of 55 size-value 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 with 12 lags) t-statistics for 55 size-value 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; construction; mining; and transportation and utilities; and manufacturing), while "Low" consists of the 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. For the temperature factor we use the primary temperature factor TSF_t obtained from Eq. (4)
To test Hypothesis 2 formally for the size-value portfolios, in Panel B we also form equal-weighted portfolios to and use the primary temperature factor TSF_t obtained from Eq. (4) . "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	0.35	0.96	**−6.18**	0.88
	(4.98)	(38.93)	(−4.65)	
Low	0.47	1.02	**−1.37**	0.91
	(6.60)	(47.60)	(−1.68)	
High - Low	−0.11	−0.05	**−4.81**	0.08
	(−1.27)	(−2.20)	(−3.40)	

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)	

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 a 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 only five industries, 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 temperature fluctuations as this increases demand for its product.

To test Hypothesis 2 formally with the industry portfolios, we create two equal-weighted portfolios. "High" includes the high-exposure sectors identified by Graff Zivin and Neidell (2014) (specifically: agriculture, forestry, fishing, and hunting; construction; mining; and transportation and utilities; and manufacturing), while "Low" consists of the remaining sectors. The loadings on the temperature shock factor for “High” and “Low” capture the average sensitivities of the high-exposure and low-exposure sectors, respectively. Consequently, the loading on the temperature shock factor for “High – Low” picks up the sensitivity difference between the high- and low-exposure sectors. The time-series regressions for “High”, “Low” and “High – Low” are reported at the bottom of Panel A. The average loading on the temperature shock factor for the high-exposure sectors is −6.18 (t=−4.65), while that for the low-exposure sectors is −1.37 (t=−1.68). The sensitivity difference is −4.81 with a HAC-robust (Newey-West with 12 lags) t-statistic of −3.40. Thus, Hypothesis 2 is significantly supported for the 30 industry portfolios.[10]

5.1.2. Size and value 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.

5.2. Impact on the cost of equity

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. We use the market value weights and loadings of the 55 industry- and size-value sorted portfolios. The weight is obtained by dividing the market value of each portfolio by the sum of the market values of the 55 portfolios. The loadings on the alternative versions of TSF are obtained as in Table 4 from the time series regressions of portfolio returns on the appropriate factors for each model. The weighted averages of the loadings are multiplied by the risk premium (γ from Table 2 for the primary specification CAPM+TSF model, and Table 3 for the alternative TSF specifications) to find the average impact measure. Note that the step of multiplying the risk premium by the loadings is necessary because there is nothing in our approach that requires loadings to sum to one (as for market returns) or to zero (as for some factor mimicking portfolios).[11]

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 TSF 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.

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 impact difference 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 a significant impact in both periods with a substantially larger impact in 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 Fig. 2. These 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 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 Panel E of Fig. 2 shows, the standard deviation of temperature (30-year moving average of U.S.

[10] A more direct test, instead of obtaining loadings from the mimicking portfolio for temperature shocks – our primary specification of TSF from Eq. (4) – obtains loadings straight from the temperature shocks – alternative specification 3 (TSF* from Eq. 4c). As shown in the Web Appendix, the loadings of the sectors identified by Graff Zivin and Neidell (2014) *a priori* as having the highest exposure to weather, have (equal-weighted) average loading of -4.52 to the temperature shocks measured based on Eq. (4c) whereas the remaining sectors have only slightly negative loading on these temperature shocks of -0.17. The difference is -4.35, which is marginally insignificant (bootstrapping p-value of 0.11 in a one-tailed test). The support for Hypothesis 2 is weaker here due to higher standard errors. This occurs because the raw temperature shocks contain less focused information about economically relevant future weather implications than is captured by the mimicking temperature factor portfolios. The weaker results illustrate the advantage of using tracking portfolios rather than raw temperature shocks.

[11] The value-weighted average loadings present a proper market average (for the US stock market). Whereas, roughly, each firm is represented twice (once in the industries and once in the value-size sorted portfolios) the computation requires the value weights of the 55 portfolios to sum to one so that each firm's market value is accurately reflected.

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 factor risk premium (from Table 3) by the weighted average loading on this factor. We use the market value weights and loadings of the 55 industry and size-value sorted portfolios. The weight is obtained by dividing the market value of each portfolio by the sum of the market values of the 55 portfolios. The loadings on the alternative versions of TSF are obtained as in Table 4. Panel A shows the value-weighted impact for the entire sample period.
Following Cooper, Gutierrez and Hameed (2004), we estimate in Panel B 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. Since our first observation is in 1953:4, the first estimate is for 1983:4. It uses the construction of the TSF and loadings on this factor for the period 1953:4–1983:3 and multiplies the value-weighted loadings by the TSF realization for 1983:4 to obtain $\text{IMPACT}_{1983:4}$. We then roll everything forward by a month to find $\text{IMPACT}_{1983:5}$, etc. D_{83-98} is equal to 1 for all months in the period 1983–1998 and zero otherwise, and D_{99-14} is equal to 1 for 1999–2014 and zero otherwise. The mean impact in 1983–1998 is i_{83-98}, while that in 1999–2014 is i_{99-14}. 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_{83-98}	0.11	14.16	0.11	15.13	0.17	20.8	−0.01	−1.76
i_{99-14}	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*

annual temperatures) displays a similar pattern as the time series of impact estimates in Panels A-D, and has started to decline after 2004. (2) The ability of firms to handle temperature fluctuations 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. (3) 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 over the full data period.

6. Further discussion and robustness checks

6.1. Industry portfolios as basis assets

In this paper, we follow Vassalou (2003) and use the six Fama-French size and book-to-market (BM) portfolios as the basis assets to construct the temperature shock tracking portfolio. However, as Lewellen, Nagel, and Shanken (2010) imply, because size and BM portfolios have a strong factor structure, a factor with spurious correlation with the size and book-to-market factors could seem to carry a significant risk premium in standard asset-pricing tests. Lewellen, Nagel, and Shanken (2010) suggest taking into account industry portfolios. In our case, previous studies (e.g., Graff Zivin and Neidell, 2014) also suggest that particular sectors (e.g., construction, transportation, and manufacturing) are more vulnerable to temperature shocks. However, we should not expect climate sensitivity to be homogenous within an industry, because as we have pointed out size and value also matter. For instance, although temperature shocks affect labor supply and productivity, a large manufacturing firm (or a firm with less capital in place), relative to a small firm (or a firm with more capital in place), may be better able to mitigate the effects of temperature shocks by, for instance, installing more effective/advanced cooling systems. Thus, it may be more informative to use industry-size-value sorted portfolios, instead of just industry portfolios, to construct the temperature shock tracking portfolio.

To avoid employing too many basis assets we adopt the Fama-French five-industry classification.[12] For each of the five industries we use only the small-firm portfolios (small firms are more sensitive to climate changes) and distinguish between low-value and high-value firms (firms with fewer assets in place adjust more easily than those with more assets in place). In all we parsimoniously employ 10 industry-size-value portfolios (SL and SH in each industry) as the basis assets to construct the temperature shock tracking portfolio, and report the results in Panel A of Table 6.[13] Multicollinearity among even this diverse and relatively small group of 10 basis assets makes it difficult to interpret individual coefficients. However, the chi-square test cannot reject at the 5% level the hypothesis that the coefficients on the basis assets are jointly zero, indicating that the basis assets jointly have significant tracking ability. Furthermore, the mean return of the tracking portfolio is −0.03 with a t-statistic of −4.27, which is close to that based on the primary specification (i.e., using six size and BM portfolios as basis assets).

We repeat the time-series as well as cross-sectional tests with the newly constructed temperature shock tracking portfolio (TSF10), and report the results in Panels B and C of Table 6. The time-series tests show that not only do many of the test assets have significant exposure to the temperature shock factor, but also their exposure is consistent with the predictions of the climate-economy literature. For instance, value (high-BM) portfolios are

[12] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The industries are Cnsmr (Consumer Durables, NonDurables, Wholesale, Retail, and Some Services – Laundries, Repair Shops), Manuf (Manufacturing, Energy, and Utilities), HiTec (Business Equipment, Telephone and Television Transmission), Hlth (Healthcare, Medical Equipment, and Drugs), and Other (Other, Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance).

[13] As shown in the Web Appendix, employing only the five industry portfolios as the basis assets provides no significant tracking ability. In addition, we find considerable within-industry heterogeneity along the size and value dimensions. Nevertheless, holding size and BM constant, industry sensitivities differ substantially, indicating that temperature shocks are not merely relevant as spuriously related to size and BM.

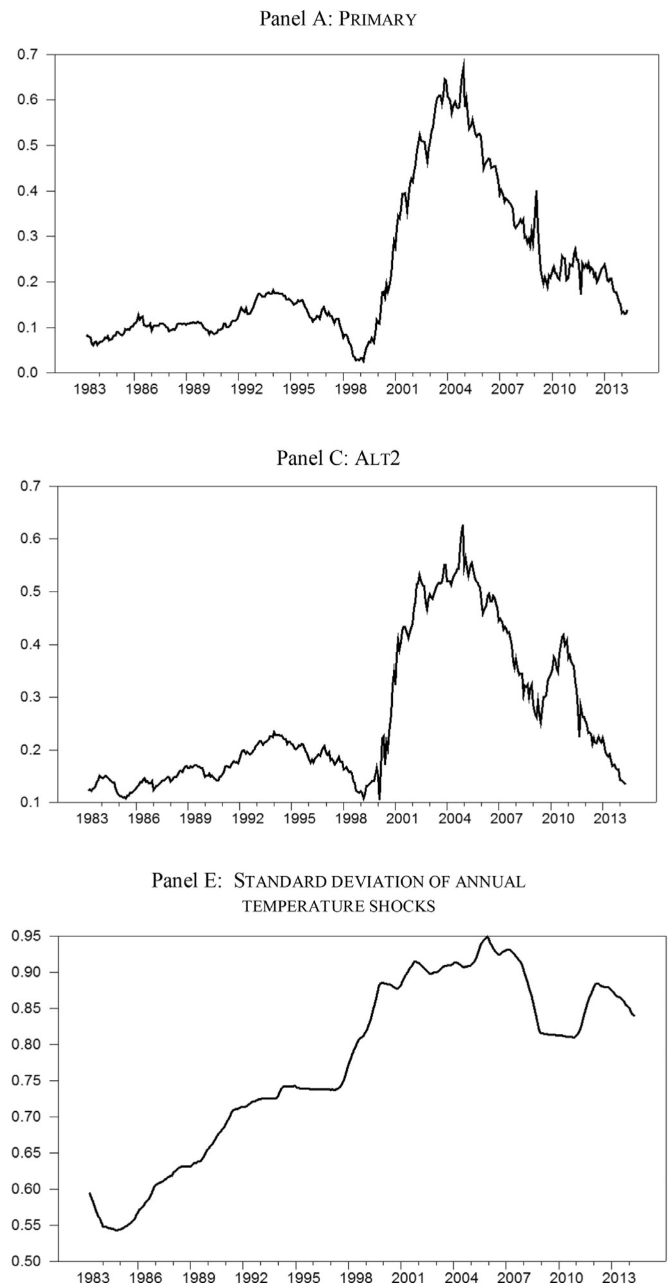

Fig. 2. Rolling Impact Estimates of the Temperature Shock Factor.
The impact is estimated for the entire sample using 30 years of preceding data for each estimate. Accordingly, the first period starts in 1983:4. We update the estimates each month by dropping the earliest observation and adding the latest observation. The mimicking factor (TSF) portfolio weights and the loadings on the mimicking factors are estimated using the 30 years of data preceding the data point. The value-weighted loadings are then multiplied by the TSF realization for the data point to obtain the impact estimate for that month.
In Panels A-D PRIMARY represents our main specification given the basis asset and conditioning variable choices of Vassalou (2003) based on Eq. (4); ALT1 represents an alternative specification given the basis asset and conditioning variable choices of Kapadia (2011) based on Eq. (4a); ALT2 represents our alternative specification with the temperature growth rate as the temperature shock factor (Eq. 4b); ALT3 directly uses the temperature surprise as the temperature shock factor (Eq. 4c). Panel E shows the 30-year rolling average standard deviation of annual U.S. temperatures.

negatively affected by temperature shocks. The cross-sectional test reveals that the temperature shock factor carries a significantly negative premium even in the presence of the market factor.

6.2. Bootstrapping simulation

In evaluating the significance of the risk premia in Panel C of Table 6 we consider errors-in-variables robust (Shanken, 1992) and misspecification-robust (Shanken and Zhou, 2007) standard errors.[14] Jiang, Kan, and Zhan (2015) demonstrate that, even with these corrections, ignoring estimation error in factor mimicking portfolio weights can lead to an underestimation of the standard errors of the estimated risk premia corresponding to these portfolios. To gauge if our results are robust to the estimation errors of the (factor mimicking) tracking portfolio, we carry out bootstrapping simulations for all instances involving tracking portfolios.

[14] The GMM-based standard errors employed in, among others, Vassalou (2003) and Aretz, Bartram, and Pope (2010) also adjust for errors in variables.

Table 6
Time-series and cross-sectional tests with the tracking portfolio based on 10 industry portfolios.

We use 10 industry-size-value portfolios (SL and SH for each portfolio in the Fama-French five-industry classification) as the basis assets to construct the temperature shock tracking portfolio TSF10. Panel A provides the tracking portfolio coefficients on each portfolio, Newey-West standard errors are based on 24 lags. Panels B and C present the time-series and cross-sectional tests with TSF10 replacing TSF. Significance is evaluated by t-values based on the Shanken correction (EIV), the Shanken-Zhou correction (MIS), and a bootstrapping procedure p-value.

Panel A: Tracking portfolio regression

	Cnsmr		Manuf		HiTec		Hlth		Other	
	SL_t	SH_t	SL_t	SH_t	SL_t	SH_t	SL_t	SH_t	SL_t	SH_t
Coeff	0.011	0.024	0.007	−0.016	0.016	−0.027	0.006	0.003	−0.005	−0.026
t-ratio	0.53	1.42	0.38	−1.03	1.07	−2.90	0.58	0.63	−0.27	−2.15
	Constant	RF_{t-1}	DEF_{t-1}	$TERM_{t-1}$	Trend	CT_{t-12}	Adj-R^2	χ^2 p-value		Mean
Coeff	51.464	0.109	−0.176	−0.123	0.004	−0.036	0.40	0.01		−0.03
t-ratio	10.09	0.22	−0.75	−1.20	6.47	−0.36				−4.27

Panel B: Factor loadings of 55 size-value and Industry Portfolios

Industry portfolios					Size and BM portfolios					
	Alpha	MKT	TSF	R^2	Size	BM	Alpha	MKT	TSF	R^2
Food	0.31	0.70	−0.74	0.50		Growth	−0.46	1.40	4.65	0.65
Beer	0.30	0.76	−1.43	0.41		2	0.16	1.19	0.10	0.63
Smoke	0.61	0.67	−1.91	0.23	Small	3	0.17	1.06	−3.19	0.67
Games	0.05	1.30	0.58	0.68		4	0.30	0.98	**−5.74**	0.66
Books	−0.06	1.05	−1.88	0.69		Value	0.32	1.06	**−8.15**	0.65
Hshld	0.04	0.81	−0.03	0.59		Growth	−0.08	1.37	**6.71**	0.77
Clths	0.11	1.11	−0.06	0.56		2	0.12	1.15	0.10	0.76
Hlth	0.34	0.81	**4.29**	0.58	2	3	0.25	1.03	**−3.85**	0.76
Chems	0.03	1.05	−1.94	0.69		4	0.21	0.99	**−6.67**	0.75
Txtls	0.03	1.14	−0.10	0.48		Value	0.13	1.09	**−9.72**	0.72
Cnstr	−0.18	1.18	**−4.56**	0.75		Growth	0.02	1.30	**6.83**	0.81
Steel	−0.45	1.32	**−5.55**	0.62		2	0.17	1.11	−0.87	0.83
FabPr	−0.06	1.23	−0.54	0.76	3	3	0.15	0.98	**−4.57**	0.80
ElcEq	0.13	1.23	−0.62	0.75		4	0.14	0.95	**−7.24**	0.78
Autos	−0.20	1.14	−2.07	0.53		Value	0.26	1.01	**−10.17**	0.74
Carry	0.14	1.10	**−4.48**	0.62		Growth	0.12	1.22	**5.16**	0.86
Mines	−0.13	0.94	−3.49	0.30		2	0.01	1.08	−1.30	0.87
Coal	−0.10	1.20	**−8.11**	0.27	4	3	0.05	1.03	**−4.73**	0.82
Oil	0.20	0.79	**−4.16**	0.43		4	0.09	0.93	**−7.30**	0.81
Util	0.04	0.51	**−6.70**	0.37		Value	0.06	1.02	**−8.65**	0.75
Telcm	0.20	0.79	0.80	0.57		Growth	0.06	0.99	**3.94**	0.90
Servs	0.13	1.30	**5.40**	0.81		2	0.08	0.94	−1.46	0.87
BusEq	−0.05	1.29	**3.83**	0.70	Big	3	−0.03	0.88	**−3.19**	0.80
Paper	0.02	0.94	−1.92	0.68		4	−0.03	0.82	**−6.14**	0.74
Trans	−0.03	1.03	**−2.57**	0.67		Value	−0.01	0.87	**−7.21**	0.64
Whlsl	0.07	1.02	−0.11	0.74						
Rtail	0.22	1.00	**3.70**	0.67						
Meals	0.13	1.02	0.48	0.59						
Fin	−0.14	1.06	**−5.70**	0.78						
Other	−0.31	1.08	−1.77	0.71						

Panel C: Risk premium estimates

	γ	t_{EIV}	t_{MIS}	$p_{bootstrap}$
Constant	0.68	2.38	2.35	
MKT	−0.06	−0.16	−0.16	[0.48]
TSF10	−0.02	−2.05	−2.01	[0.03]
R^2	0.27			

We randomly permute the time index for the market index returns (MKT) and the Temperature observations jointly. Then we run the tracking portfolio regression to create the TSF from Eq. (4). Subsequently, we find the loadings on MKT and TSF, and then the risk premia from the second pass cross-sectional regression on the mean returns of the 55 portfolios. We repeat this for 1000 random permutations of the time index for MKT and Temperature to generate the distribution of the estimated risk premia under the null hypothesis that the risk premia are zero. Panel C in Table 6 indicates that, with the 10 industry-size-value portfolios as basis assets, only 32 of the thousand simulations generate a TSF risk premium smaller than the obtained risk premium of −0.02. Thus, the one-sided p-value is 0.03 for the TSF risk premium (compared to $p = 0.02$ for the errors-in-variables and misspecification-robust approaches).

A similar bootstrapping procedure for the significance of the risk premia for the primary specification is conducted for Table 2 and for the alternative specifications in Table 3. The risk premia remain significant for the primary specification in Table 2 ($p = 0.04$ for the CAPM+TSF and $p = 0.02$ for the CAPM+FF). Results for the alternative TSF specifications in Table 3 are similar as those implied by the regular t-statistics except for Alt1 for which the results are no longer significant at the 5 percent level, with $p = 0.06$.

6.3. Tracking portfolio regressions with alternative horizons

Since it is not clear a priori how far ahead financial markets can forecast temperatures, we run a number of tracking portfolio regressions in which we use the: contemporaneous temper-

Table 7
Robustness checks with the tracking portfolio.

We run a number of tracking portfolio regressions, in which we use the contemporaneous temperature, one-quarter ahead average temperature (i.e., from $t+1$ to $t+3$), two-quarter ahead average temperature (i.e., from $t+1$ to $t+6$), three-quarter ahead average temperature (i.e., from $t+1$ to $t+9$), and four-quarter ahead average temperature (i.e., from $t+1$ to $t+12$) as the dependent variable. To remove the seasonality in monthly temperatures, we follow Bansal, Kiku, and Ochoa (2015) and use temperature anomalies, defined relative to the 1951–1980 average. The basis assets are six size-value portfolios in Panel A, and 10 industry-size and BM portfolios in Panel B. T-statistics use Newey-West standard errors with lag (bandwidth) determined as max [3, 2*horizon] following Bekaert and Hoerova (2014), where the horizon equals the number of months in the forecast interval.

Panel A: Tracking portfolio regressions with alternative forecast horizons based on six size-value portfolios

	Contemporaneous		1-quarter ahead		2-quarter ahead		3-quarter ahead		4-quarter ahead	
	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
SL_t	0.016	0.35	0.051	1.71	0.041	1.90	0.039	2.51	0.023	1.91
SM_t	−0.098	−1.05	−0.078	−1.37	−0.012	−0.29	−0.019	−0.56	0.001	0.04
SH_t	0.093	1.35	0.019	0.40	−0.051	−1.48	−0.039	−1.41	−0.046	−2.09
BL_t	0.080	1.86	0.053	1.83	0.011	0.51	0.003	0.22	0.005	0.32
BM_t	−0.115	−2.15	−0.042	−1.08	−0.007	−0.23	0.005	0.26	0.017	0.91
BH_t	0.033	0.72	−0.001	−0.02	0.013	0.61	0.002	0.14	0.001	0.07
Constant	−0.644	−2.24	−0.727	−2.39	−0.739	−2.18	−0.716	−2.19	−0.757	−2.43
RF_{t-1}	−1.060	−2.20	−1.233	−2.47	−0.883	−1.71	−0.640	−1.27	−0.629	−1.30
DEF_{t-1}	0.220	1.00	0.199	0.78	0.007	0.03	−0.073	−0.31	−0.088	−0.39
$TERM_{t-1}$	−0.230	−1.83	−0.254	−2.31	−0.170	−1.56	−0.122	−1.14	−0.120	−1.12
t	0.002	3.72	0.003	5.24	0.003	4.36	0.002	3.95	0.002	4.28
T_{t-h}	0.250	2.13	0.053	1.07	0.041	0.56	0.115	1.23	0.111	1.12
Adj-R^2	0.08		0.17		0.23		0.31		0.38	
χ^2 p-value	0.20		0.10		0.28		0.13		0.05	
Mean	0.01	1.53	−0.02	−2.43	−0.03	−4.57	−0.03	−5.11	−0.02	−4.26

Panel B: Tracking portfolio regressions with alternative forecast horizons based on 10 industry portfolios

	Contemporaneous		1-quarter ahead		2-quarter ahead		3-quarter ahead		4-quarter ahead	
	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
Cnsmr SL_t	−0.020	−0.58	−0.040	−1.35	−0.020	−0.86	−0.010	−0.45	0.011	0.53
Cnsmr SH_t	−0.031	−0.82	0.033	1.19	0.027	1.02	0.032	1.49	0.024	1.42
Manuf SL_t	−0.038	−1.06	−0.004	−0.14	0.006	0.26	0.009	0.46	0.007	0.38
Manuf SH_t	−0.013	−0.28	−0.056	−1.79	−0.039	−1.60	−0.030	−1.54	−0.016	−1.03
HiTec SL_t	0.025	0.72	0.069	2.92	0.056	2.92	0.033	1.87	0.016	1.07
HiTec SH_t	0.015	0.60	−0.019	−1.02	−0.033	−2.45	−0.030	−2.74	−0.027	−2.90
Hlth SL_t	0.021	0.96	0.006	0.43	0.008	0.84	0.012	1.38	0.006	0.58
Hlth SH_t	−0.024	−1.39	−0.004	−0.46	−0.002	−0.26	−0.002	−0.25	0.003	0.63
Other SL_t	−0.011	−0.24	−0.016	−0.60	−0.024	−1.13	−0.013	−0.70	−0.005	−0.27
Other SH_t	0.090	2.05	0.023	0.91	0.006	0.29	−0.015	−0.98	−0.026	−2.15
Constant	−1.691	−3.10	−1.901	−3.07	−2.105	−3.82	−2.179	−4.54	−2.292	−4.86
RF_{t-1}	−0.636	−1.36	−0.643	−1.14	−0.218	−0.40	0.093	0.18	0.109	0.22
DEF_{t-1}	0.232	1.14	0.183	0.70	−0.034	−0.14	−0.145	−0.59	−0.176	−0.75
$TERM_{t-1}$	−0.232	−2.04	−0.268	−2.35	−0.191	−1.73	−0.124	−1.17	−0.123	−1.20
t	0.003	4.91	0.004	5.37	0.004	5.80	0.004	5.85	0.004	6.47
T_{t-h}	0.210	3.68	0.013	0.23	−0.049	−0.68	−0.002	−0.02	−0.036	−0.36
Adj-R^2	0.12		0.17		0.25		0.33		0.40	
χ^2 p-value	0.26		0.04		0.04		0.04		0.01	
Mean	0.03	1.65	−0.03	−2.06	−0.04	−3.95	−0.04	−3.92	−0.03	−3.91

ature, one-quarter-ahead, two-quarter-ahead, three-quarter-ahead, and four-quarter-ahead average temperature as the dependent variable. To remove the seasonality in monthly temperatures, we follow Bansal, Kiku, and Ochoa (2015) and use temperature anomalies, defined relative to the 1951–1980 monthly averages. The results for both the six size-value and the 10 industry-size-value portfolios as basis assets are presented in Panels A and B of Table 7, respectively. First, the contemporaneous temperature does not significantly affect basis asset returns, as the chi-square test cannot reject at the 5% level the hypothesis that the coefficients on the basis asset returns are jointly zero. Second, the financial markets can forecast future temperatures, and the adjusted R^2 increases with the forecasting horizon. The adjusted R^2 rises from 17% for the one-quarter horizon to 38% (six basis assets case) or 40% (10 basis assets case) for the one-year horizon. This result echoes Roll (1984) who 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. The evidence thus justifies our tracking portfolio specification.

6.4. Global temperatures

Should global temperatures affect U.S. asset returns? Provisionally, the answer is No, invoking the recent climate-economy literature which emphasizes "local" effects of temperature. (For instance, Graff Zivin and Neidell 2014, find that temperatures affect labor supply within a county. That is, a high temperature in a county reduces the labor supply in that county, because "[*h*]igh temperatures cause discomfort, fatigue, and even cognitive impairment", p. 1). Global temperatures, accordingly, may not impact U.S. asset returns. To test this conjecture, we obtain the global temperature anomalies data from the National Climatic Data Center. The "anomalies" are defined as the temperature minus the average temperature over the 1951–1980 period, seasonally adjusted. Fig. 3 plots the global and U.S. temperature anomalies. The general trends are similar, but there is considerable difference between U.S. and global temperatures. For instance, the lead article in The Economist of November 28-December 4 2015 notes that the global temperature was the highest in 2014 since NASA temperature recording began in 1880, but the U.S. temperature was not particularly high in that year.

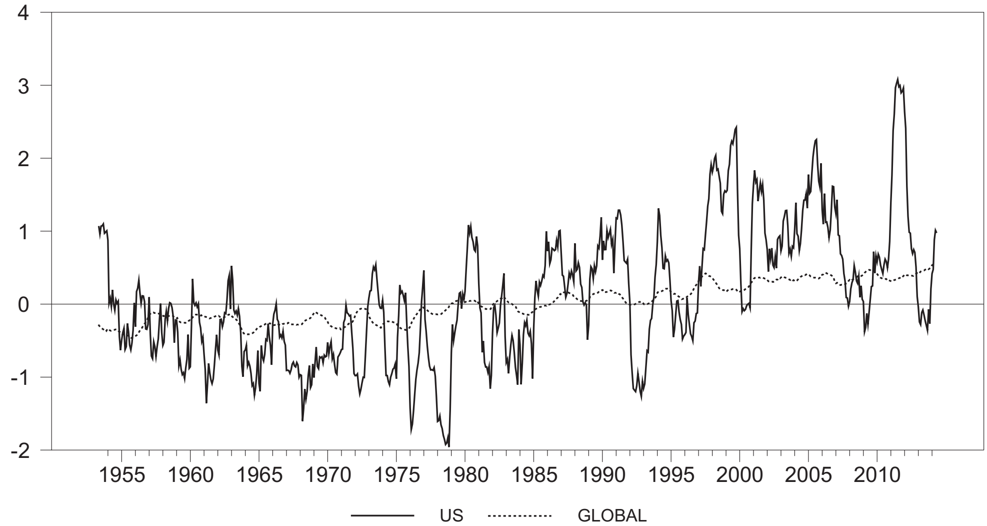

Fig. 3. U.S. and global temperature anomalies.
Fig. 3 plots the global and U.S. temperature anomalies. The source is the global temperature anomalies data from the National Climatic Data Center. The anomalies are defined as the temperature minus the average temperature over the 1951–1980 period, seasonally adjusted.

Table 8
Global temperatures, SMB, and HML.
We report the tracking portfolio regressions for the global temperature in Panel A. The dependent variable in all cases is T_{t+12}, the average annual global temperature from t+ 1 to t+ 12. SL_t, SM_t, SH_t, BL_t, BM_t, and BH_t are excess returns: the Fama-French size-value portfolios net of the one-month 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. *t* is the deterministic time trend. Cnsmr: Consumer Durables, NonDurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops); Manuf: Manufacturing, Energy, and Utilities; HiTec: Business Equipment, Telephone and Television Transmission; Hlth: Healthcare, Medical Equipment, and Drugs; Other: Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance. To adjust for the autororrelation in errors resulting from the overlapping temperature shock data, Newey-West standard errors are obtained to calculate the t-ratios employing a bandwidth of 24 months.
We separately regress SMB and HML on the temperature shock factor, and report the results in Panel B.

Panel A: Global temperature tracking portfolio regressions

	Coeff	t-ratio		Coeff	t-ratio
SL_t	−0.002	−0.95	Cnsmr SL_t	−0.002	−1.25
SM_t	0.002	0.41	Cnsmr SH_t	0.004	2.10
SH_t	0.001	0.41	Manuf SL_t	0.001	0.42
BL_t	0.001	0.60	Manuf SH_t	−0.002	−0.94
BM_t	0.003	1.59	HiTec SL_t	0.001	0.71
BH_t	−0.005	−2.55	HiTec SH_t	−0.002	−1.62
			Hlth SL_t	0.000	0.08
			Hlth SH_t	0.001	1.06
			Other SL_t	0.000	0.22
			Other SH_t	0.000	−0.10
Constant	−0.543	−6.63	Constant	−0.960	−8.37
RF_{t-1}	−0.137	−2.79	RF_{t-1}	0.007	0.11
DEF_{t-1}	0.025	0.93	DEF_{t-1}	0.003	0.11
$TERM_{t-1}$	−0.023	−2.05	$TERM_{t-1}$	−0.013	−1.00
t	0.001	7.90	t	0.001	9.25
T_{t-12}	0.249	2.89	T_{t-12}	0.008	0.08
Adj-R^2	0.89		Adj-R^2	0.88	
χ^2 p-value	0.27		χ^2 p-value	0.19	

Panel B: SMB, HML, and TSF

	TSF based on six size-value basis assets			TSF based on 10 industry-size-value basis assets		
	Constant	TSF	Adj-R^2	Constant	TSF10	Adj-R^2
SMB	0.00	−8.62	0.09	0.24	−0.43	−0.00
	(0.03)	(−5.25)		(1.58)	(−0.25)	
HML	−0.07	−20.81	0.61	0.01	−11.42	0.29
	(−1.17)	(−18.56)		(0.06)	(−10.10)	

If the global temperature affects U.S. financial markets, U.S. asset returns should reflect innovations in expectations about future global temperature variation. That is, our (U.S.-based) basis assets should have significant ability to track future global temperature fluctuations. We report the corresponding tracking portfolio regressions in Panel A of Table 8. For robustness, we explore both sets of basis assets. From the chi-square test we cannot reject the hypothesis that the coefficients are jointly zero at the 5% level, regardless of which set of basis assets we use, indicating that the (U.S.-specific) basis assets do not track global temperatures.

Table 9
Climate sensitivity in high and low temperature-variation states.

We retrieve state-level temperature data from the National Climatic Data Center, and rank the U.S. states according to the standard deviation of the state-level temperature from 1953 to 2015. We define the 10 states with the highest standard deviation of temperatures as high temperature-variation states (H), and the 10 states with the lowest standard deviation of temperatures as low temperature-variation states (L). We run time-series regressions to examine if firms in high temperature-variation states are more negatively affected by the temperature shock factor, relative to similar firms (in terms of size-value or industry) in low temperature-variation states. Section "Industry portfolios" present the results for five industry portfolios, those for the size-value portfolios are shown in Section "Size-value portfolios". Standard t-statistics are presented in parentheses.

Industry portfolios		Alpha	MKT	TSF	R^2	Size-value portfolios		Alpha	MKT	TSF	R^2
Cnsmr	H	−0.12	0.94	−6.67	0.74	SL	H	−0.18	1.28	−7.46	0.77
		(−1.05)	(25.86)	(−3.72)				(−1.23)	(36.93)	(−5.17)	
	L	0.07	0.98	−4.21	0.77		L	−0.28	1.44	−1.88	0.72
		(0.60)	(24.68)	(−2.58)				(−1.40)	(27.12)	(−0.72)	
	H-L	−0.19	−0.04	−2.46	0.01		H-L	0.10	−0.16	−5.58	0.10
		(−1.68)	(−1.36)	(−1.96)				(0.71)	(−3.58)	(−3.04)	
Manuf	H	−0.06	0.97	−5.14	0.79	SM	H	−0.05	1.05	−13.81	0.85
		(−0.54)	(26.65)	(−2.68)				(−0.53)	(35.31)	(−11.89)	
	L	0.14	0.79	−0.00	0.68		L	−0.04	1.23	−14.73	0.81
		(1.44)	(23.97)	(−0.00)				(−0.25)	(32.99)	(−8.36)	
	H-L	−0.20	0.17	−5.13	0.08		H-L	−0.02	−0.18	0.92	0.11
		(−1.60)	(3.79)	(−3.24)				(−0.15)	(−6.18)	(0.68)	
HiTec	H	−0.40	1.37	−4.03	0.71	SH	H	−0.17	1.09	−23.73	0.88
		(−2.14)	(26.76)	(−1.44)				(−2.04)	(47.87)	(−24.02)	
	L	0.07	1.41	6.97	0.73		L	−0.12	1.27	−24.42	0.85
		(0.35)	(21.28)	(2.11)				(−0.97)	(40.64)	(−16.98)	
	H-L	−0.47	−0.04	−11.00	0.08		H-L	−0.05	−0.18	0.69	0.10
		(−2.33)	(−0.81)	(−5.74)				(−0.33)	(−4.93)	(0.38)	
Hlth	H	0.52	0.81	5.21	0.45	BL	H	−0.07	0.94	0.50	0.82
		(3.00)	(9.56)	(2.02)				(−0.84)	(27.64)	(0.30)	
	L	0.27	1.19	−0.38	0.49		L	0.17	1.16	9.02	0.88
		(0.92)	(12.33)	(−0.10)				(1.78)	(40.35)	(8.04)	
	H-L	0.25	−0.39	5.59	0.07		H-L	−0.24	−0.22	−8.52	0.18
		(0.90)	(−5.66)	(1.38)				(−1.63)	(−4.10)	(−3.34)	
Other	H	−0.02	1.03	−5.83	0.74	BM	H	0.05	0.94	−5.36	0.80
		(−0.19)	(22.08)	(−3.06)				(0.53)	(28.07)	(−3.72)	
	L	−0.33	1.21	−11.82	0.82		L	0.02	0.92	−3.26	0.79
		(−3.50)	(31.88)	(−7.85)				(0.18)	(38.91)	(−2.37)	
	H-L	0.31	−0.19	5.98	0.14		H-L	0.03	0.01	−2.10	0.00
		(3.08)	(−5.37)	(4.04)				(0.32)	(0.34)	(−1.60)	
						BH	H	−0.12	0.95	−12.23	0.69
								(−1.02)	(23.93)	(−6.96)	
							L	−0.10	0.98	−16.07	0.71
								(−0.81)	(18.70)	(−7.51)	
							H-L	−0.02	−0.03	3.84	0.01
								(−0.14)	(−0.48)	(1.64)	

6.5. SMB, HML, and the temperature shock factor

As small-big and value-growth stocks are differently affected by temperature shocks, it is possible that SMB and HML capture some of the information in the temperature shock factor. We explore this perspective by separately regressing SMB and HML on the temperature shock factor. The results are reported in Panel B of Table 8 for both sets of basis assets. As expected, SMB and HML capture some information in the temperature shock factor, since there are significant correlations between the temperature shock factor and SMB/HML. Thus, a part of the well-known explanatory power of the size factor (SMB) and the value factor (HML) for cross-sections of returns may arise from differing sensitivities of assets to the temperature factor.

6.6. Temperature variability and exposure to temperature shocks

If temperature shocks really matter in terms of their local effects (on, for instance, labor supply and productivity), we should expect that firms in areas with more temperature variation are more negatively affected by temperature shocks. To capture local temperature variation, we retrieve state-level temperature data from the National Climatic Data Center, and rank the U.S. states according to the standard deviation of the state-level temperature from 1953 to 2015. We define the 10 states with the highest standard deviation of temperatures as high-temperature-variation states (H), and the 10 states with the lowest standard deviation of temperatures as low-temperature-variation states (L).[15] Since firms often have their production facilities close by their headquarters (Coval and Moskowitz, 1999), we identify the location of a firm by its headquarter location, and form size-value as well as industry portfolios within states. We then run time-series regressions to examine if firms in high-temperature-variation states are more negatively affected by the temperature shock factor relative to similar firms (in terms of size-value or industry) in low-temperature-variation states.

The results are reported in Table 9. The "Industry portfolios" section presents the results for the five industry portfolios. In three of five industries, the loadings on the temperature shock factor are significantly more negative for firms in the high-temperature-variation states. For instance, for manufacturing

[15] Although coastal areas are typically vulnerable to climate change (Melillo, Richmond, and Yohe, 2014), many effects are not directly related to local temperatures. For instance, rising sea levels may be more due to global temperatures instead of local temperatures. The 10 high temperature-variation states in our sample are: Alaska, Illinois, Iowa, Minnesota, Michigan, Montana, Nebraska, North Dakota, South Dakota, and Wisconsin; The 10 low temperature-variation states are: Alabama, Arizona, California, Florida, Georgia, Louisiana, Mississippi, New Mexico, North Carolina, and South Carolina.

firms, while the loading on the temperature shock factor is −5.14 (t = −2.68) for firms in the high-temperature-variation states, it is −0.00 (t = −0.00) for firms in the low-temperature-variation states. The results for Other are inconsistent with our expectation, which may be partially due to our identification strategy. For instance, Other includes Trans (transportation). Although a transportation company's headquarter may be located in a low-temperature-variation state, it may provide its services in high-temperature variation states too, making our results difficult to interpret. The results for the size-value portfolios are shown in the "Size-value portfolios" section, and suggest that temperature shocks in general have more negative impact on firms in high-temperature-variation states.

6.7. Uncertainty about regulation

One potential explanation for the sensitivity of particular industries to the temperature shock factor is that the indicator has little intrinsic economic importance for temperature fluctuations 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, it is apparent from Table 4 that 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.

We also carry out a more formal test. If concerns about regulation drive temperature sensitivity, firms headquartered in states run by Democrats should be more exposed to temperature shocks than firms headquartered in states run by Republicans, given the different climate policies advocated by the two parties. We thus form size-value as well as industry portfolios within Republican

Table 10
Climate sensitivity in Republican and Democrat states.

If concerns about regulation drive temperature sensitivity, firms headquartered in states run by Democrats should be more exposed to temperature shocks than firms headquartered in states run by Republicans, given the different climate policies advocated by two parties. We form size-value as well as industry portfolios within Republican and Democrat states, and run time-series regressions to examine if firms in Republican states are less negatively affected by the temperature shock factor, relative to similar firms (in terms of size-value or industry) in Democrat states. Section "Industry portfolios" present the results for five industry portfolios, those for the size-value portfolios are shown in the section "Size-value portfolios". Standard t-statistics are presented in parentheses.

Industry portfolios						Size-value portfolios					
		Alpha	MKT	TSF	R^2			Alpha	MKT	TSF	R^2
Cnsmr	R	0.31	0.93	−4.24	0.49	SL	R	−0.20	1.20	−5.34	0.69
		(1.53)	(11.96)	(−1.44)				(−1.39)	(28.34)	(−2.90)	
	D	−0.04	0.98	−4.04	0.84		D	−0.26	1.40	−1.54	0.74
		(−0.47)	(34.07)	(−3.18)				(−1.53)	(33.92)	(−0.69)	
	R-D	0.35	−0.06	−0.20	0.00		R-D	0.07	−0.20	−3.80	0.09
		(1.90)	(−0.95)	(−0.09)				(0.54)	(−5.51)	(−1.69)	
Manuf	R	−0.05	0.94	−3.66	0.65	SM	R	−0.05	1.00	−14.42	0.82
		(−0.32)	(20.42)	(−1.75)				(−0.46)	(36.73)	(−11.60)	
	D	−0.06	0.95	−2.95	0.88		D	−0.05	1.19	−13.41	0.83
		(−0.85)	(48.76)	(−2.43)				(−0.38)	(36.58)	(−10.25)	
	R-D	0.02	−0.01	−0.71	−0.00		R-D	−0.00	−0.19	−1.01	0.13
		(0.17)	(−0.38)	(−0.51)				(−0.00)	(−7.45)	(−0.71)	
HiTec	R	−0.07	1.26	2.03	0.56	SH	R	−0.03	1.06	−22.99	0.83
		(−0.30)	(23.21)	(0.64)				(−0.29)	(53.01)	(−15.99)	
	D	0.15	1.06	7.53	0.76		D	−0.13	1.19	−23.56	0.90
		(1.14)	(19.68)	(3.08)				(−1.33)	(56.33)	(−25.12)	
	R-D	−0.22	0.20	−5.50	0.03		R-D	0.10	−0.13	0.57	0.05
		(−0.92)	(3.08)	(−1.73)				(0.70)	(−5.45)	(0.43)	
Hlth	R	0.19	0.80	2.44	0.34	BL	R	0.16	0.86	6.66	0.62
		(0.96)	(11.49)	(0.73)				(1.24)	(18.06)	(3.39)	
	D	0.49	0.77	7.66	0.57		D	0.12	1.01	5.89	0.93
		(3.79)	(16.01)	(3.54)				(2.04)	(59.03)	(8.67)	
	R-D	−0.30	0.04	−5.22	0.01		R-D	0.04	−0.15	0.78	0.03
		(−1.87)	(0.69)	(−2.76)				(0.28)	(−2.68)	(0.34)	
Other	R	0.05	0.93	−3.70	0.64	BM	R	0.03	0.89	−3.56	0.69
		(0.36)	(18.28)	(−1.70)				(0.24)	(23.33)	(−1.66)	
	D	−0.19	1.18	−6.77	0.86		D	−0.02	0.96	−2.84	0.87
		(−2.25)	(38.10)	(−5.06)				(−0.30)	(33.36)	(−2.99)	
	R-D	0.24	−0.25	3.06	0.10		R-D	0.05	−0.07	−0.71	0.01
		(1.60)	(−4.67)	(1.43)				(0.45)	(−1.54)	(−0.37)	
						BH	R	0.31	0.96	−10.56	0.53
								(1.49)	(17.87)	(−4.11)	
							D	−0.12	0.97	−13.41	0.81
								(−1.43)	(31.26)	(−9.28)	
							R-D	0.43	−0.01	2.86	0.00
								(2.35)	(−0.21)	(1.23)	

and Democrat states, and run time-series regressions to examine if firms in Republican states are less negatively affected by the temperature shock factor, relative to similar firms (in terms of size-value or industry) in Democrat states.

The results are in Table 10. The "Industry portfolios" section shows that in all five industries, the loadings on the temperature shock factor are not significantly less negative for firms in the Republican states. E.g., for manufacturing firms the loading on the factor is −3.66 (t = −1.75) for firms in Republican states but −2.95 (t = −2.43) for firms in Democrat states. The results for the size-value portfolios are in the "Size-value portfolios" section and suggest that temperature shocks in general do not have less negative impact on stock returns of firms in Republican states.

7. Summary and implications

How do US equity markets react to news contained in US temperature changes? Tracking portfolios formed from basis assets distinguished by value, size, and/or industry have significant value in filtering the economic importance of persistent temperature changes inferred from temperature shocks. We hypothesize that *(i)* a significant risk premium exists on a temperature tracking portfolio, *(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 tracking portfolio are generally negative and more so for industries 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 as a result of uncertainty related to future temperatures.

The severity of impact and even the existence of climate change are heavily debated, and it is difficult to obtain an objective perspective. For this purpose, financial markets may be helpful in uncovering true perceptions as they aggregate the beliefs of market participants who do not merely offer opinions but have "skin in the game." So, what does the result we find from the U.S. equity market data, that the uncertainty about temperature changes contributes an annual average of 0.22 percentage points to costs of capital, say about costs of climate change?

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) 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. Our explanation for the reduction in the GDP growth rate answers Dell, Jones and Olken's (2014) call for mechanisms explaining the empirical temperature-growth linkage. It also provides a perspective, showing that the impact of temperature fluctuations on the cost of equity capital alone is of higher magnitude than the total policy cost of mitigation, an annualized reduction of consumption growth by 0.04 to 0.14 percentage (IPCC, 2014), which allows room to contemplate more aggressive climate-change mitigation policies.

(2) 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 is $36 \times 0.22\% = 7.92\%$. To put our estimate of a 7.92 percent loss due to climate change in the perspective of previous estimates, consider that: 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 climate changes. The estimated cost of climate change based on these mechanisms varies from around 0.2% to 1.0% (Stern, 2007) to 2.0% to 3.5% per 1 °Celsius increase in temperature (Choinière and Horowitz, 2006) and a maximum of 3.75% (Heal and Kriström, 2002). However, the uncertainty about temperature fluctuations adds substantially to the overall costs and shows up in the higher cost of equity capital which previous studies have ignored in this context. Our result amounts to adding an additional present value cost of climate change of larger magnitude to previously identified costs.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2016.12.013.

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