Climate Change Risk

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Abstract

If rising temperature has a long-run impact on the aggregate economy (i.e., it increases future volatility or tail risk, or lowers growth), it should be reflected in current equity prices and the risk-return tradeoff. Our empirical analysis shows that this is indeed the case — the long-run temperature elasticity of equity valuations is significantly negative and long-run temperature fluctuations carry a positive risk premium in equity markets. We use our theoretical framework and capital-market based estimates to provide a semi-parametric estimate of the welfare cost of carbon emissions. We find that the welfare cost of carbon emissions implied by capital market expectations is economically large. Overall, our analysis shows that temperature is a source of long-run economic risks and underscores the importance of forward-looking capital markets for understanding the impact and cost of climate change.

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Introduction

Climate change and its impact on the macroeconomy is a matter of considerable importance to the policy debate on the optimal response to global warming (Stern (2007), Nordhaus (2008)). However, measuring the economic cost of rising temperature presents significant empirical challenges as the most dire consequences of global warming have not yet been realized and therefore are hard to identify from the past output or income data. In this paper, we argue that forward-looking equity prices that reflect expectations about future growth and risk provide important insights into the economic cost of global warming. Our identification strategy exploits the impact of climate change on the short-term risk-return tradeoff driven by investors' concerns about long-run implications of rising temperature for the aggregate economy. Using capital market data, we establish that low-frequency variations in temperature have a significant negative effect on asset valuations and carry a positive risk premium. We use our empirical evidence to provide a semi-parametric capital-market based estimate of the welfare cost of carbon (i.e., marginal value of reducing emissions).

To understand the economic impact of long-run temperature variations on current asset prices and expected returns, we present a climate change model that accounts for the interaction between global warming and economic growth and incorporates (endogenous) risks of damages caused by global warming.[1] In the model, a sustained rise in temperature is anthropogenic, driven by economic activity. A persistent shock to temperature induces a low-frequency component in the drift and left tail of future output — i.e., temperature is a source of long-run risk in economic growth and this risk is impounded in current asset valuations and risk premia.[2] To demonstrate explicitly the implications of temperature risks, we derive analytical solutions for the life-time utility, asset prices, risk premia, and the welfare cost of carbon.

Our model makes several predictions that guide our empirical work. First, consistent with the consensus view, in the model, significant effects of global warming are more likely to unfold in the future and, therefore, are difficult to assess from past growth outcomes that might not yet have

[1]While climate change has a broader meaning, we use it to refer to anthropogenic global warming due to the continuing buildup of carbon dioxide in the atmosphere caused by the combustion of fossil fuels, manufacturing of cement and land use change.

[2]A summary of the scientific literature exploring the relationship between climate change, extreme weather and climate-related damages is presented in IPCC (2012).

been subject to substantial climate risks. However, because rising temperature is expected to affect future long-term growth and risk, it is reflected in aggregate wealth, current asset valuations and current returns. Hence, its economic impact can be identified by the price response of long-duration assets traded in capital markets. Second, under preferences for early resolution of uncertainty, the model-implied price of low-frequency temperature risks is negative (that is, high temperature is a state of high marginal utility) and the temperature risk premium is positive. Third, due to the interaction between economic growth and temperature risks, the cross-sectional variation in temperature risk is determined endogenously by the cross-sectional differences in long-run growth risks in assets' cash flows (dividends). In particular, our model predicts that assets that have high exposure to persistent growth risks have high (i.e., large negative) exposure to long-run temperature risks. We test these implications in the data.

In our model, the cross-sectional variation in long-run growth risks in cash flows helps identify the economic impact of temperature risks. Therefore, our baseline empirical analysis of the U.S. capital markets is based on ten book-to-market sorted portfolios that are known to feature a significant dispersion in long-run growth risks (Bansal, Dittmar, and Lundblad (2005), Parker and Julliard (2005), Hansen, Heaton, and Li (2008), Bansal, Dittmar, and Kiku (2009)).[3] We first show that in the data, the average elasticity of equity valuations to temperature fluctuations is significantly negative. Importantly, we find that the negative impact of temperature on equity valuations is particularly strong for low-frequency (i.e., long-run) temperature shifts that correspond to global warming. On average, a one standard deviation increase in the temperature trend leads to about 3% decline in equity valuations. In contract, the impact of high-frequency temperature fluctuations that represent transient variations in weather is small and insignificant.

Further, consistent with the cross-sectional implications of our model, we find that in the data, temperature elasticities mirror equity exposure to long-run growth risks — assets that have relatively high long-run consumption exposure (such as high book-to-market stocks) also feature relatively large negative temperature elasticities. Similarly, we show that the temperature beta of equity returns (i.e., exposure of equity returns to temperature risks), on average, is negative and more so for portfolios that have high exposure to long-run consumption risks. The cross-sectional variation

[3] Book-to-market sorted portfolios are commonly used in the asset pricing literature, eg., Fama and French (1992, 1993), Jagannathan and Wang (1996), Zhang (2005), among many others.

in temperature betas allows us to measure the price of long-run temperature risks embedded in current equity prices.

Exploiting the pricing restriction for the cross-section of equity portfolios, we find that the price of low-frequency temperature risk is significantly negative as predicted by our climate change model. For example, the price of variations in the five-year moving-average temperature trend is estimated at -2.7 with a robust t-statistic of -2.76. Because the price of temperature risk and the average temperature beta are both negative, temperature risk carries a positive premium in equity markets. The average compensation for low-frequency temperature risks that correspond to global warming is about 0.8% per annum. This evidence confirms our hypothesis that rising temperature is a source long-run macroeconomic risks.

We show that our key empirical findings are robust. Using international data on temperature and equity prices for a cross-section of 48 countries, we show that the temperature elasticity of equity valuations in global markets is significantly negative, particularly when temperature fluctuations are measured at low frequencies. We also confirm that our evidence of a negative elasticity of equity valuations to temperature and a negative price of temperature risk is robust to the exclusion of firms that could be considered heavy emitters (i.e., those that contribute significantly to air pollution) and might be subject to environmental regulations.

Our empirical evidence suggests that climate-change risk is already impounded in asset prices, and therefore, capital markets contain valuable information about the cost of climate change. In the cost-benefit analysis of environmental regulations, the cost of carbon is measured by the social cost of carbon and is typically calculated as an output of calibrated integrated assessment models (IAMs) that are mostly deterministic and do not take into account equity market data (eg., Nordhaus (2008), Tol (2002a), Hope (2011), Golosov, Hassler, Krusell, and Tsyvinski (2014)).[4] Instead, we exploit information embedded in asset valuations to provide a semi-parametric estimate of the (private) welfare cost of carbon (WCC) emissions. In particular, we show that the cost of carbon can be measured using temperature elasticities of equity valuations that we estimate in the data. Note that in contrast to IAMs, our capital-market based approach takes into account the discount-rate (i.e., risk) effect of rising temperature and market expectations about future path of emissions,

[4] An assessment of IAMs for evaluating alternative abatement policies and estimating the social cost of carbon is provided in Pindyck (2013).

climate risks and future abatement efforts. Also note that if carbon emissions impose a negative externality on society, then our WCC estimate provides a lower bound on the social cost of carbon emissions.

Our capital-market based estimates imply a significant cost of carbon emissions — at the end of 2016, the WCC is measured at about \$45 per metric ton of carbon dioxide (CO_2), which implies that society would be willing to give up about 1.4% of world gross domestic product to eliminate all global industrial emissions produced in the following year. We also show that even after accounting for sampling variation in the estimated temperature elasticity and uncertainty about climate sensitivity, the lower bound of the welfare cost of carbon remains economically large. The high estimate of the WCC suggests that capital markets perceive the unfolding trajectory of global warming to be a serious concern.

Dell, Jones, and Olken (2012), Bansal and Ochoa (2012), and Colacito, Hoffmann, and Phan (2019) examine the effect of temperature variations on economic growth. In contrast, we focus on forward-looking equity valuations and asset returns that incorporate the impact of global warming on risk premia, which cannot be identified from past growth rate data. Our empirical evidence of a robustly negative temperature elasticity of equity valuations and a positive temperature risk premium implies a preference for early resolution of uncertainty, and hence, rejects time-separable power-utility preferences that are commonly assumed in the integrated assessment models. The implications of risk preferences for the optimal policy response to global warming are explored in Bansal, Kiku, and Ochoa (2019). Pindyck (2007), Gollier (2012), Lemoine and Traeger (2012), and Brock and Hansen (2019) discuss the implications of various types of uncertainty in the context of climate change. Barnett (2018) focuses on the impact of climate policy risks, and Pindyck and Wang (2013), and Martin and Pindyck (2015) analyze policy implications of catastrophic consequences of climate change. Recently, Jagannathan, Ravikumar, and Sammon (2018) show that incorporating environmental concerns in investment portfolio decisions helps reduce exposure to systematic risks, which corroborates our key argument that climate change is a source of macroeconomic risks.

The rest of the paper is organized as follows. In the next section, we present a model of climate change and the macroeconomy to establish the link between temperature and asset prices. In Section 2, we identify the economic impact of temperature risks using capital market data. The measurement and the estimates of the welfare cost of carbon are discussed in Section 3. Section 4 provides interpretation of our empirical evidence, and Section 5 concludes.

1 Climate Change and Asset Prices

Figure 1 shows historical and predicted paths of temperature anomaly reported in IPCC (2014). Note a dramatic rise in temperature post 1970 and a far more significant trend that is predicted in the coming decades even under most optimistic scenarios. If rising temperature is expected to affect future growth and/or risk, it ought to be impounded in forward-looking asset prices. In this section, we present a stylized model of the macroeconomy and climate to illustrate the implications of rising temperature on asset prices and risk premia. A unique dimension of our model is that it accounts for the interaction between economic growth and climate change and incorporates (endogenous) risks of damages caused by global warming.[5] The model framework outlined below is a simplified version of the extended quantitative model presented in the Online Appendix. We intentionally simplify the dynamics of our stylized economy in order to derive analytical solutions, and hence, provide a sharp characterization of the welfare and pricing implications of temperature risks.

1.1 Climate Change Economy

We assume that climate change due to rising global temperature has an adverse effect on the economy.[6] In particular, we assume that aggregate economic growth is exposed to risks of temperature-induced damages (eg., temperature-driven natural disasters):

$$\Delta c_{t+1} = \mu + \sigma_\eta \eta_{t+1} + D_{t+1}\,, \tag{1}$$

[5]Our model features elements of the long-run risks model of Bansal and Yaron (2004), and rare disaster models of Rietz (1988), Barro (2009), Bansal, Kiku, and Yaron (2010), Gourio (2012), Wachter (2013), and Barro, Nakamura, Steinsson, and Ursúa (2013).

[6]We focus on an exchange economy to maintain tractability.

where $\Delta c_{t+1} \equiv \log(C_{t+1}/C_t)$ is the log of aggregate consumption growth, $\eta_{t+1} \sim i.i.d.\ N(0,1)$ is consumption growth innovation, and D_{t+1} are climate-change driven damages:

$$D_{t+1} = N_{t+1} d\,, \tag{2}$$

where $d < 0$ is the temperature-induced decline in consumption growth, and N_{t+1} is a Poisson process with time-varying intensity that increases with temperature:

$$\pi_t = \ell_0 + \ell_1 T_t\,, \tag{3}$$

where T_t is global temperature relative to its pre-industrial level (i.e., the global temperature anomaly), and $\ell_0,\ \ell_1 > 0$. The global temperature anomaly is driven by anthropogenic carbon emissions:[7]

$$\begin{aligned} T_{t+1} &= \chi \mathcal{E}_{t+1}\,, & (4) \\ \mathcal{E}_{t+1} &= \nu \mathcal{E}_t + \Theta(\mu + \sigma_\eta \eta_{t+1}) + \sigma_\zeta \zeta_{t+1}\,, & (5) \end{aligned}$$

where $\mathcal{E}_t$ are carbon emissions, $\nu \in (0,1)$ determines the persistence of carbon emissions and temperature, Θ measures carbon intensity of consumption, and $\chi > 0$ is climate sensitivity to emissions.[8] Anthropogenic carbon emissions (and hence, temperature) are driven by two types of shocks — endogenous industrial emissions that are a by-product of aggregate output $(\mu + \sigma_\eta \eta_{t+1})$ and an exogenous innovation $\zeta_t \sim i.i.d.\ N(0,1)$. We assume that $\Theta > 0$; hence, an increase in economic growth leads to a higher level of emissions, which in turn increases temperature and the likelihood of climate-related economic damages. This feedback loop — from growth to temperature and back to growth — is a unique dimension of climate change that, as we show below, has important implications for asset prices. Figure 2 illustrates the circular link between economic

[7] This assumption is consistent with the conclusions of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) that establishes an unequivocal link between the increase in the atmospheric concentration of greenhouse gasses and the rise in global temperature (IPCC (2013)).

[8] In the online appendix, we consider a richer specification, where temperature dynamics are driven by the trend in carbon concentration, emissions are driven by the level of consumption, and the parameter of carbon intensity is time varying. We simplify these dynamics here without any loss of generality, solely to achieve analytical solutions. For tractability, we also simplify the mapping from emissions to carbon concentration by assuming that concentration is proportional to emissions. The implications of the model are unaffected if instead we model concentration by a slow accumulation of emissions as is typically done in the climate-change literature.

output, emissions and climate change that is formalized in Equations (1)–(5).

Note that in our model, temperature fluctuations are a source of economic risk — an increase in temperature raises the likelihood of damages, which if realized, lead to a decline in economic growth. Further, because emission shocks have a persistent effect on temperature, an increase in current emissions increases temperature-related risks in the long run. In essence, temperature is a source of long-run risks in consumption — temperature variations induce a time-varying low-frequency component in the drift and tail of consumption growth.

Figure 3 illustrates the implications of global warming for the distribution of future consumption growth. In particular, it presents a side-by-side comparison of the distribution of the normalized consumption growth in the future when temperature anomaly reaches 2°C and the corresponding distribution in the economy without climate change. Because temperature-driven damages represent tail risks, the distribution of future consumption growth is both negatively skewed and fat-tailed. As Figure 3 illustrates, a persistent increase in current temperature affects the distribution of future consumption by inducing long-run tail risks in consumption growth.

Note that the use of a disaster model specification is not critical in itself — as long as temperature fluctuations affect the distribution of future consumption growth (its level, volatility, skewness, or higher moments), they represent a long-run risk.

1.2 Preferences

We consider a representative agent with recursive preferences as in Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1990). The time-t utility of lifetime consumption is given by the following recursion,

$$U_t = \left\{(1-\delta)C_t^{1-\frac{1}{\psi}} + \delta\Big(\mathbb{E}_t\Big[U_{t+1}^{1-\gamma}\Big]\Big)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right\}^{\frac{1}{1-\frac{1}{\psi}}}, \tag{6}$$

where U_{t+1} is the continuation value of a consumption plan starting in $t+1$, δ is the rate of time preference, γ is the coefficient of relative risk aversion, and ψ is the intertemporal elasticity of substitution (IES).

In contrast to the power-utility formulation that is commonly employed in the integrated assessment models of climate change, recursive preferences allow for a separation between willingness to substitute consumption over time and across different states of nature (i.e., $\gamma \neq \psi$). Recursive preferences, specifically preferences for early resolution of uncertainty that arise when risk aversion exceeds the reciprocal of IES ($\gamma > \frac{1}{\psi}$) are commonly used in the macro-finance literature because, as shown, they are able to account for the joint dynamics of aggregate cash flows and equity prices and provide a resolution of the well-known risk-free rate, equity premium and volatility puzzles (Bansal and Yaron (2004)). Note that under a preference for early resolution of uncertainty, agents are concerned about variations in future growth and uncertainty, particularly those that persist in the long run, which climate-change risks represent. Bansal, Kiku, and Ochoa (2019), Daniel, Litterman, and Wagner (2019), and Cai and Lontzek (2018) explore the implications of risk preferences for the social cost of carbon and optimal abatement policies.

The log of the intertemporal marginal rate of substitution (IMRS), which determines asset prices through the Euler condition, is given by:

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{c,t+1}\,, \tag{7}$$

where $r_{c,t+1}$ is the endogenous return on wealth, and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$. Note that if $\gamma = \frac{1}{\psi}$, then $\theta = 1$ and the IMRS reduces to the one implied by the standard constant relative risk aversion (CRRA) specification.

The maximized life-time utility in this setting is proportional to the wealth-consumption ratio provided that $\psi \neq 1$. Specifically, the value function normalized by current consumption is given by:

$$\frac{U_t}{C_t} = \left[(1-\delta) Z_t\right]^{\frac{\psi}{\psi-1}}\,, \tag{8}$$

where $Z_t \equiv \frac{W_t}{C_t}$ is the aggregate wealth-consumption ratio.[9] Note that aggregate valuation, Z_t, is the (normalized) present value of current and future consumption, and hence, it reflects agents' expectations about future expected growth, uncertainty, and tail risks that are driven by climate change.

[9] If IES equals one, the wealth-consumption ratio is constant and the normalized value function is determined recursively.

1.3 Long-Run Temperature Risks and Short-Run Risk-Return Tradeoff

We solve for the equilibrium dynamics of the wealth-consumption ratio, Z_t, by exploiting the Euler equation and the log-linear approximation of the wealth return following the approach of Bansal, Kiku, and Yaron (2016). As shown in Appendix A, the analytical solution for the log of the wealth-consumption ratio is given by:

$$z_t = A_0 + A_1 T_t \ , \tag{9}$$

where $z_t \equiv \log Z_t$, and the sensitivity of the wealth-consumption ratio to temperature is given by:

$$A_1 = \frac{\frac{1}{\psi} - 1}{\gamma - 1} \, \Phi \, , \tag{10}$$

where $\Phi = \dfrac{\ell_1 \Big(e^{(1-\gamma)d} - 1 \Big)}{\kappa_1 - \nu}$, and $\kappa_1 > 1$ is determined endogenously by the mean of the wealth-consumption ratio. Note that for values of risk aversion greater than one ($\gamma > 1$), the term Φ is always positive. Consequently, the (semi) elasticity of the wealth-consumption ratio to temperature is determined by the magnitude of the IES. In particular, when the representative agent has a preference for early resolution of uncertainty, namely $\gamma > \frac{1}{\psi}$, the wealth-consumption ratio declines with temperature. In contrast, in the standard power-utility specification, when $\frac{1}{\psi} = \gamma$, the wealth-consumption ratio responds positively to temperature fluctuations.

We use the solution for z_t to obtain the expression for the IMRS or the stochastic discount factor (SDF). The innovation into the SDF conditional on time-t information is given by,

$$m_{t+1} - \mathbb{E}_t \big[m_{t+1} \big] = -\lambda_\eta \sigma_\eta \eta_{t+1} - \lambda_\zeta \sigma_\zeta \zeta_{t+1} - \lambda_D (N_{t+1} - \pi_t) \, , \tag{11}$$

where

$$\lambda_\eta = \gamma + (1-\theta)\chi\Theta A_1 \tag{12}$$

$$\lambda_\zeta = (1-\theta)\chi A_1 \tag{13}$$

$$\lambda_D = \gamma d \tag{14}$$

Notice three effects of temperature risks. First, different from the standard consumption-based CAPM (C-CAPM), where $\lambda_\eta = \gamma$, the SDF exposure to consumption growth shocks is altered by $(1-\theta)\chi\Theta A_1$. This is due to endogenous temperature variations driven by economic growth. Recall that consumption growth raises temperature, which in turn, feeds back into the economy by propagating damages. Note that under a preference for early resolution of uncertainty, $(1-\theta)\chi\Theta A_1 < 0$; thus, the impact of growth shocks on marginal utility is partially offset by the feedback effect of temperature. Intuitively, a positive consumption growth shock carries mixed signals — it is good news in the short run (as in the standard C-CAPM) but simultaneously, it is bad news in the long run because an increase in economic growth raises industrial carbon emissions and temperature and, hence, the likelihood of future damages. Effectively, in Equation (12), $\gamma > 0$ represents the price of short-run risk of growth, and $(1-\theta)\chi\Theta A_1 < 0$ represents the price of long-run temperature variations endogenously driven by economic growth.

Second, exogenous temperature risks have a separate effect on the stochastic discount factor. Their impact is similar to that of endogenous variations — provided that $\gamma > 1$ and $\psi > 1$, a positive exogenous innovation in temperature raises marginal utility and, thus, temperature risks carry a negative price. Third, temperature variations expose the economy to the risk of damages and amplify volatility of marginal utility. Note that under CRRA preferences, $\theta = 1$ and the first two effects are absent — i.e., temperature variations (endogenous and exogenous) are not priced directly and they affect the SDF only indirectly through the damage channel.

It is important to re-iterate that under a preference for early resolution of uncertainty, an increase in temperature due to either endogenous or exogenous variations raises marginal utility. That is, high temperature is a bad state for the economy because, as discussed above, a persistent increase in current temperature amplifies consumption growth risks in the long run. Note that the response of marginal utility to temperature variations is non-zero only if climate change has a non-trivial impact on the distribution of future consumption. If temperature does not affect the likelihood of future economic damages (i.e., $\ell_1 = 0$ in Equation (3)) or, more generally, if climate change has no effect on long-run economic growth, then $A_1 = 0$ and temperature variations have no impact on marginal utility and, hence, they are not priced. In other words, temperature risks carry risk premia and affect asset valuations only if they affect on the distribution of future economic growth, i.e., if they manifest in long-run consumption risks.

The conditional risk premium of consumption claim is given by:

$$\ln \mathbb{E}_t\left[R_{c,t+1}\right] - r_{f,t} = \underbrace{\left(1+\chi\Theta A_1\right)\left(\gamma+(1-\theta)\chi\Theta A_1\right)\sigma_\eta^2}_{Growth\ Premium} + \underbrace{(1-\theta)(A_1\chi\sigma_\zeta)^2}_{Temp-Premium} + \underbrace{\gamma d^2(\ell_0+\ell_1 T_t)}_{Damage-Premium}. \quad (15)$$

The first term is the risk premium for consumption growth variations. Once again notice that in addition to the C-CAPM-implied premium of $\gamma\sigma_\eta^2$, it incorporates the impact of endogenous temperature risks. The second and third terms represent premia for exogenous temperature variations and temperature-induced damage risks. As Equation (15) shows, risk premia rise with temperature — higher temperature makes damages more likely and, hence, leads to an increase in risk premia. Also, while the damage risk premium is invariant to preferences for the timing of resolution of uncertainty, the temperature risk premium is not. When $\gamma > 1$ and $\psi > 1$, temperature risks carry positive risk premia, whereas under CRRA preferences, the temperature risk premium is zero. Because temperature fluctuations are persistent, an increase in carbon emissions increases risk of damages in the long run by rising volatility of future consumption and making its distribution more negatively skewed and leptokurtic. Under a preference for early resolution of uncertainty, agents have significant concerns about risks that persist and affect the economy long term and, therefore, they demand positive compensation for exposure to temperature risks. That is, investors' concerns about long-run consequences of climate change determine the short-run risk-return tradeoff. Such long-run concerns are absent under power utility and so is the temperature risk premium.[10]

The impact of temperature on discount rates is also very different under the two preference specifications. Under a preference for early resolution of uncertainty, future discount rates increase due to the increase in risk premia, and consequently, asset valuations decline with temperature. However, under power utility with $\gamma > 1$, rising temperature lowers future discount rates because the increase in risk premia is dominated by a simultaneous decline in the risk-free rate leading to a positive temperature elasticity of asset prices.[11]

[10]Under power utility, temperature risks still contribute to risk premia through their immediate impact on consumption damages but temperature variations do not receive a separate premium for their long-run effect on the economy.

[11]The solutions for the risk-free rate and the return on wealth are provided in Appendix A.

From the econometric perspective, Equations (11)–(15) emphasize the importance of controlling for economic growth in measuring the impact of temperature risks and their premia. Under a preference for early resolution of uncertainty, an increase in temperature, either endogenous or exogenous, rises marginal utility. However, the adverse effect of endogenous temperature variations is confounded by the positive effect of economic growth. Therefore, in order to correctly identify the distinct negative impact of temperature, it is critical to control for the countervailing impact of growth variations. Similarly, omitting growth controls may lead to biases in the estimate of the temperature risk premium.

In our feedback model of climate change, when consumption rises so does temperature, which raises the likelihood of climate-change induced damages. Hence, on the margin, a climate abatement policy that mitigates emissions will have a larger benefit in high consumption states.[12] Clearly, any abatement actions that lower the probability of damages will lower the climate-change risk premium. Indeed, along the future path of the economy, if abatement policies succeed in mitigating climate risks, then the climate-change risk premium could decline.[13] Our focus is on understanding the impact of rising temperature on asset prices that reflect capital market expectations about the future, including the anticipated effects of future abatement efforts.

1.4 Long-Run Temperature Risks and the Cross-Sectional Risk-Return Tradeoff

Our empirical identification of the economic impact of climate change exploits the cross-sectional variation in temperature exposure. What is the source of this cross-sectional variation? Assets differ in exposure of their dividends to macroeconomic growth risks (i.e., consumption risks). Because climate change affects consumption dynamics, assets that are highly exposed to consumption growth risks are consequently highly affected by climate-change risks. We formalize this intuition below. In particular, we show that cross-sectional differences in consumption risks in assets' dividends translate into cross-sectional differences in temperature risks in assets' returns.

Consider a cross-section of equity securities, indexed by i, that feature heterogenous exposure

[12] In the language of Dietz, Gollier, and Kessler (2018), the climate sensitivity of abatement benefits with respect to consumption is positive.

[13] Giglio, Maggiori, Rao, Stroebel, and Weber (2015) seem to argue that the climate risk reflected in really long horizon real-estate discount may be reflecting the abatements that may come about in the future.

to consumption risks:

$$\begin{aligned}
\Delta d_{i,t+1} &= \varphi_i \Delta c_{t+1} + \sigma_i u_{i,t+1} && (16)\\
&= \varphi_i\big(\mu + \sigma_\eta \eta_{t+1} + D_{t+1}\big) + \sigma_i u_{i,t+1}\,, && (17)
\end{aligned}$$

where φ_i is the measure of long-run risk in dividends, which we refer to as dividend beta, and $u_{i,t+1} \sim i.i.d.\ N(0,1)$ is the asset-specific dividend shock. From the Euler equation, it follows that the risk premium of asset i is given by:

$$\ln \mathbb{E}_t\big[R_{i,t+1}\big] - r_{f,t} \;=\; \beta_{i,\eta}\lambda_\eta\sigma_\eta^2 \;+\; \beta_{i,\zeta}\lambda_\zeta\sigma_\zeta^2 \;+\; \beta_{i,D}\lambda_D(\ell_0 + \ell_1 T_t)\,, \tag{18}$$

where asset exposure to the three sources of risks (i.e., beta) is given by:

$$\begin{aligned}
\beta_{i,\eta} &= \varphi_i + \kappa_{i,1}\chi\Theta B_{i,1}\,, && (19)\\
\beta_{i,\zeta} &= \kappa_{i,1}\chi B_{i,1}\,, && (20)\\
\beta_{i,D} &= \varphi_i d\,, && (21)
\end{aligned}$$

where $\kappa_{i,1} < 1$ is the constant of log-linearizaion, and $B_{i,1}$ is the (semi) elasticity of the price-dividend ratio of asset i to temperature fluctuations that is derived in Appendix A. Note that $B_{i,1}$ is the asset-specific counterpart to A_1, which measures temperature (semi) elasticity of aggregate wealth. As Equation (19) shows, return exposure to consumption growth risks is determined by dividend beta φ_i (as in a standard consumption-based framework) and, in addition, by $\kappa_{i,1}\chi\Theta B_{i,1}$ that accounts for exposure to endogenous temperature variations. Return exposure to exogenous temperature risks is measured by $\beta_{i,\zeta}$ and we refer to it as the temperature beta of asset i. The cross-sectional variation in temperature beta is determined by the cross-sectional dispersion in temperature elasticity that declines in dividend beta: $\frac{\partial B_{i,1}}{\partial \varphi_i} < 0$, as shown in the appendix.

The cross-sectional variation in temperature elasticity ($B_{i,1}$) is illustrated in Figure 4. The figure is constructed from a model calibration based on a preference for early resolution of uncertainty and is designed to roughly match the dynamics of annual consumption and temperature. As the figure shows, while the relationship between dividend betas and temperature elasticities is non-linear, it is strongly negative. Similarly, temperature betas are inversely related to dividend betas, i.e., $\mathrm{Corr}(\beta_{i,\zeta}, \varphi_i) \ll 0$. Assets that have a negative or relatively low dividend beta have positive temperature elasticity and temperature beta. Such assets provide insurance against temperature risks — they pay off in bad times of high temperature. In contrast, assets that feature high dividend exposure have negative temperature elasticity and temperature beta — these assets are highly sensitive to damage risks, consequently, when temperature rises and the likelihood of economic damages increases, their prices and returns fall. Recall that when $\gamma > 1$ and $\psi > 1$, the price of temperature risk is negative; thus, negative temperature beta assets carry a positive temperature risk premium.

To summarize, because temperature risks affect the economy through their impact on future growth, the cross-sectional variation in temperature risks is governed by the cross-sectional variation in consumption risks — the higher the dividend beta is, the higher (more negative) the temperature beta is. Our model's falsifiable prediction is that these two relatively independent measures of risks in the cross section, dividend beta and temperature beta, should be negatively correlated if temperature is a source of future macroeconomic risk.

2 Temperature and Asset Prices: Empirical Evidence

The analysis of the climate change economy in Section 1 shows that forward-looking equity prices reflect expectations about the impact of rising temperature on the macroeconomy. A risk-averse investor with preferences for early resolution of uncertainty experiences a decline in wealth when temperature rises and requires a positive premium for assets that covary negatively with temperature. Furthermore, even if the most significant effects of rising temperature have not yet been realized, the anticipated impact of global warming on the future economy is embedded in current asset prices and returns.

Motivated by these implications, we exploit capital market data to quantify the economic cost of persistent variations in temperature. In contrast to the empirical economic literature that measures the impact of global warming on the macroeconomy by looking at the historical (backward-looking) relationship between temperature and national income (eg., Nordhaus (2006), Dell, Jones, and Olken

(2012)), our approach relies on forward-looking information from capital markets — information that may not be captured by income measures.

2.1 Data

We obtain time series of temperature for the U.S. from 1970 through 2016.[14] Figure 5 displays the annual average temperature in the U.S. along with its five-year moving average trend. While there are large fluctuations in temperature year-over-year, the long-run trend is unambiguously increasing. Since 1970, there has been an increase in temperature of about 1.5°C.

Guided by the intuition of our model economy, in our empirical analysis of the U.S. capital markets, we exploit portfolios that are known to feature robustly different exposure to persistent macroeconomic growth risks, in particular, we use ten portfolios sorted on book equity to market equity ratio (BM). As documented in Bansal, Dittmar, and Lundblad (2005), and Hansen, Heaton, and Li (2008), high BM stocks have much higher sensitivity to long-run growth risks relative to low BM stocks. We exploit the well-established measurable differences in long-run growth risks across BM portfolios to test our hypothesis that climate change affects the economy through the long-run growth-risk channel. In addition to the benchmark book-to-market portfolios, in the robustness section, we also consider portfolios double sorted on book-to-market ratio and market capitalization.[15] For each equity portfolio, we collect data on its price to dividend ratio (valuation ratio) and returns. A more detailed description of the data is provided in Appendix B.

Our main focus is on the economic implications of long-run variations in temperature that are associated with global warming rather than short-run variations that represent fluctuations in weather. The low-frequency component in temperature can be extracted by taking a trailing average of temperature. However, as Figure 5 shows, long-horizon moving-averages of temperature reflect global warming and, hence, feature trending behavior. To avoid econometric issues that might arise due to trending dynamics, in our empirical work we focus on long-run shifts (shocks) in temperature

[14]We choose to start the sample in 1970 because beginning in the 1970s, there was a major increase in social concern about environmental problems. For example, in the early 1970s, the U.S. and other developed countries established national-level environmental agencies, and international environmental agreements led to the creation of the UN Environment Programme.

[15]We thank Kenneth R. French for making these and other portfolio data available online at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

that we measure by the difference in temperature at different frequencies. To explore and highlight any differences between short- and long-run temperature shocks, we consider different horizons, K's, ranging from one to five years. Let T_t denote annual temperature; when $K = 1$, $\Delta_1 T \equiv \Delta T$ corresponds to annual (short-run) fluctuations in weather; when $K \gg 1$, $\Delta_K T \equiv T_t - T_{t-K}$ represents long-run temperature risks that corresponds to global warming. The standard deviation of temperature shocks per unit of time at the one-, three-, and five-year horizon is 0.57, 0.20, and 0.12, respectively. In essence, by averaging temperature variations over time, we filter out short-run fluctuations and isolate the low-frequency component in temperature (i.e., temperature trend).[16] Because the post 1970 sample is relatively short, the number of independent observations shrinks rapidly with the horizon. For this reason, we do not consider horizons beyond five years.

2.2 Temperature and Long-Run Growth Risks

We measure temperature risk in equity returns (i.e., temperature beta) by their exposure to temperature variations. Specifically, for each BM portfolio we run the following regression,

$$R^e_{i,K,t} = a_i + \beta_{i,T}\,\Delta_K T_t + \beta_{i,m} R^e_{m,K,t} + \beta_{i,c}\Delta_K c_t + u_{i,K,t}\ , \tag{22}$$

where $R^e_{i,K,t}$ is the K-period cumulative excess return of portfolio i, $\Delta_K T_t$ is the K-year change in temperature, $R^e_{m,K,t}$ is the cumulative excess return of the aggregate market portfolio, and $\Delta_K c_t$ is the cumulative log growth of aggregate consumption.[17] To facilitate the comparison across various horizons, in this and other regressions, temperature series are normalized to have zero mean and unit standard deviation. Our controls for sources of risk other than temperature are motivated by our model economy and, more generally, by the consumption-based CAPM of Sharpe (1964), Lucas (1978), and Breeden (1979).

The five-year temperature betas are reported in Table I. Note first that on average, temperature beta is negative. Further, high BM portfolios (the top two portfolios) have significantly negative exposure to temperature risks, that is, they tend to perform poorly when temperature rises. In

[16] Our evidence remains virtually unchanged if we use innovations in the long-run change of temperature instead of first differences. The advantage of using first differences is that they are observable and, thus, are not subject to estimation errors.

[17] To simplify the notation, we suppress the dependance of all regression coefficients on K.

contrast, low BM portfolios (the bottom two portfolios) feature positive temperature betas. A similar cross-sectional pattern holds when temperature fluctuations are measured at other frequencies — across all horizons ($K = 1, ..., 5$), temperature betas feature an almost monotonic decline across BM portfolios.

What drives the cross-sectional variation in temperature betas? Recall that high economic growth leads to climate change due to high carbon emissions and temperature, which in its turn magnifies economic risks in the future by raising the likelihood of future damages. Consequently, as discussed in Section 1.4, asset exposure to temperature risk is determined endogenously by asset's dividend exposure to macroeconomic risk (measured by dividend beta). High dividend beta reflects high low-frequency consumption risk and translates into high (negative) temperature elasticity and high (negative) temperature beta.

We explore the cross-sectional relationship between dividend and temperature betas in Table I. The dividend beta of each portfolio ($\beta_{i,LR}$) is measured by regressing log level of portfolio dividends ($d_{i,t}$) on the log-level of consumption (c_t), specifically,[18]

$$d_{i,t} = \bar{d}_i + \beta_{i,LR} c_t + w_{i,t} \,. \tag{23}$$

Consistent with the evidence in Hansen, Heaton, and Li (2008), and Bansal, Dittmar, and Kiku (2009), we find that dividend betas increase with book-to-market characteristic. The estimated dividend beta of the high BM portfolio is 2.27 (SE=0.21) and that of the low BM portfolio is 0.38 (SE=0.15) that reflect significant differences in their exposure to low-frequency variations in consumption.[19] Importantly, notice that temperature betas mirror the cross-sectional pattern in dividend betas.

Figure 6 presents a scatter plot of five-year temperature betas against dividend betas for ten book-to-market portfolios. In the cross-section, temperature risk is strongly inversely related to long-run growth risk — the cross-sectional correlation between dividend beta and the return-based temperature beta, that is, $corr(\beta_{i,LR}, \beta_{i,T})$, is -65%, -88%, and -79% at the one-, three- and

[18]Because establishing and estimating a cointegration relation requires a long span of data, we measure dividend betas using data from 1940 to 2016. The pre-1940 data are excluded due to zero dividend records.

[19]The growth-based measure of long-run consumption risks in dividends as in Bansal, Dittmar, and Lundblad (2005), and Hansen, Heaton, and Li (2008) yields similar evidence and, therefore, is not reported.

five-year horizon, respectively. The significant negative correlation between dividend beta and temperature beta is consistent with the prediction of our model. Note also that temperature betas mirror variation in risk premia across assets — the cross-sectional correlation between the risk premium and temperature beta at one-, three-, and five-year horizon is -75%, -91% and -0.88%, respectively. The strong correlation of temperature betas with dividend betas and risk premia that we document suggests that temperature is a priced source of long-run macroeconomic risk.

2.3 Temperature Elasticity of Equity Valuations

The (semi) elasticity of equity prices to temperature variations provide important information about the welfare cost of carbon as we show below. To quantify the response of equity prices to temperature fluctuations we estimate the following panel regression specification,

$$v_{i,t} = \bar{v}_i + \phi_K \, \Delta_K T_t + \varrho_i \, v_{i,t-1} + \alpha_i \, v_t + \varepsilon_{i,t} \, , \tag{24}$$

where $v_{i,t}$ is the log of the price-dividend ratio of portfolio $i = 1, \ldots, N$, $\bar{v}_i$ is a portfolio-specific fixed effect, $\Delta_K T_t$ is the K-year change in U.S. temperature, v_t is the price-dividend ratio of the market portfolio, and $\varepsilon_{i,t}$ is an error term. To capture heterogeneity across portfolios, we allow the estimated parameters on the lagged price-dividend ratio and on the market price-dividend ratio to vary with the portfolio's average book-to-market ratio ($\overline{bm}_i$), namely, $\varrho_i = \varrho + \varrho_b \overline{bm}_i$ and $\alpha_i = \alpha + \alpha_b \overline{bm}_i$.

Table II shows the estimates of the (semi) elasticity of the price-dividend ratio to temperature variations, ϕ_K, over one-, three- and five-year horizons.[20] T-statistics reported in parenthesis are based on standard errors clustered by portfolio and time using the Newey and West (1987) estimator with three lags.[21] Our results show that, on average, the price-dividend ratio falls when temperature rises and that the negative effect of persistent temperature fluctuations is statistically and economically significant. In particular, a standard deviation increase in temperature over three and five years leads to a decline in equity valuations by 2.7% (SE=1.29%) and 3.7% (SE=1.25%), respectively. Note that t-statistics tend to increase with the horizon suggesting that the impact of

[20] The panel regression is estimated by ordinary least squares; the weighted least squares estimates are similar in magnitude and their significance.

[21] The robust standard errors that account for correlations across portfolios and time are constructed using the approach developed in Thompson (2011).

temperature on equity valuations is more significant when temperature risks are measured at low frequencies that correspond to climate change.

To examine the cross-sectional variation in temperature exposure, we estimate temperature elasticities by running a similar regression separately for each portfolio, i.e.,

$$v_{i,t} = \bar{v}_i + \phi_{i,K}\,\Delta_K T_t + \varrho_i\, v_{i,t-1} + \alpha_i\, v_t + \varepsilon_{i,t}\,. \tag{25}$$

where the regression coefficients are all asset specific. Table I that shows the estimated response of equity valuations to the five-year change in temperature reveals a strong cross-sectional variation in temperature elasticities. We find that temperature elasticities decline almost monotonically across portfolios: low book-to-market assets have a slightly positive (insignificant) exposure to temperature fluctuations whereas high book-to-market assets feature a significantly negative exposure. Also, consistent with the prediction of our model (see Equation (A.11) in the appendix), assets with high dividend betas have large negative elasticities to temperature risks. The cross-sectional correlation between dividend beta and five-year temperature elasticity is -0.58.

To further corroborate the cross-sectional implications of our theoretical framework, in Table III, we explicitly impose the model's restrictions on the cross-sectional variation in temperature elasticities. Specifically, we consider the following scaled panel regression specification:

$$v_{i,t} = \bar{v}_i + (\phi_K \cdot \beta_{i,LR})\,\Delta_K T_t + \varrho_i\, v_{i,t-1} + \alpha_i\, v_t + \varepsilon_{i,t}\,, \tag{26}$$

$$\overline{\Delta d}_{i,t} = \mu_i + \beta_{i,LR}\overline{\Delta c}_t + w_{i,t}\,, \tag{27}$$

where temperature elasticities, $(\phi_K \cdot \beta_{i,LR})$, are forced to vary with consumption risks, $\beta_{i,LR}$. Table III shows the estimated scaled elasticities of equity valuations with respect to one-, three- and five-year variation in temperature.[22] If the cross-sectional variation in temperature elasticities were not related to the cross-sectional dispersion in dividend betas, the slope coefficient ϕ_K in Equation (26) would be zero. Instead, we find that for low-frequency temperature fluctuations, the estimated coefficients are negative and statistically significant — that is, in the data, assets that are highly

[22] Although the model-implied cross-sectional relationship between temperature risks and consumption risks is nonlinear, a linear approximation should provide a reasonably good approximation as Figure 4 shows.

exposed to long-run consumption risks are also highly (negatively) exposed to long-run temperature risks. This evidence provides a strong support to our view that rising temperature is expected to affect the distribution of future economic growth, and therefore, asset exposure to temperature risks is governed by its exposure to long-run growth risks.

2.4 Temperature Risk and Risk Premia

Figure 7 presents a scatter plot of average excess returns and five-year temperature betas. In the data, risk premia increase with book-to-market and temperature betas decline with book-to-market characteristic. The inverse relationship between temperature betas and average returns suggests that the market price of temperature risk is negative as predicted by our model. We exploit the Euler condition to obtain an estimate of the market price of temperature risks. In particular, we consider the following linear factor model,

$$\begin{aligned} & E\Big[R^e_{i,K,t}(1+M_{K,t})\Big] = 0\,, \quad \text{for } i = 1, \ldots, N\,, \\ & M_{K,t} = -\lambda_{\Delta T}\Big[\Delta_K T_t - \mu_T\Big] - \lambda_m\Big[R^e_{m,K,t} - \mu_m\Big] - \lambda_c\Big[\Delta_K c_t - \mu_c\Big]\,, \end{aligned} \tag{28}$$

where $R^e_{i,K,t}$ is the K-period cumulative return of portfolio i in excess of the risk-free rate; $M_{K,t}$ is the stochastic discount factor that is driven by the K-year change in temperature ($\Delta_K T_t$), the cumulative excess return of the market portfolio ($R^e_{m,K,t}$), and the cumulative consumption growth ($\Delta_K c_t$); μ's denote the means of the corresponding factors.[23] The estimation of the market prices of risks (λ's) is carried out in one step using the efficient GMM estimator of Hansen (1982) and the standard errors are constructed using the heteroscedasticity and autocovariance consistent (HAC) estimator based on the Newey and West (1987) kernel with K lags.

Table IV reports the GMM estimates of the price of temperature, market and consumption risks — $\lambda_{\Delta T}$, λ_m, λ_c, respectively, and the corresponding t-statistics that account for the estimation error in the factor means. Consistent with the prediction of our model, we find that the price of temperature risks is negative and statistically significant when temperature variations are measured

[23] We remove the mean of the SDF that determines the price of the risk-free asset because it is not identified in the cross section of excess returns. Once again, we suppress the dependance of all parameters on horizon K to simplify the notation.

at low frequencies. For example, variations in temperature over the five-year horizon have a market price of risk of -2.68 with a robust t-statistic of -2.76. Because, on average, equity portfolios have negative temperature betas, temperature risks carry a positive premium in equity markets. In particular, on average across book-market sorted portfolios, the premium for five-year variations in temperature is about 0.8% per annum.[24] The temperature premium varies substantially in the cross section — assets with high exposure to temperature risks, such as high book-to-market firms, carry large temperature risk premium. As the bottom panel of Table IV shows, our linear model specification is not rejected by the χ^2-test of overidentifying restrictions.

It is important to note that temperature fluctuations are exogenous relative to a long list of reduced-form return-based factors that are popular in empirical asset pricing. Therefore, while we control for market and economic growth risks (as motivated by the theory), we do not include any ad-hoc empirical factors. Further, to ensure that our evidence is not simply due to a lucky draw, we run the following simulation experiment. We generate temperature shocks of the sample size that matches the data by randomly sampling from the observed temperature series and then re-estimate the price of temperature risks using simulated temperature as we do in the actual data. We run this simulation exercise 10,000 times and construct Monte Carlo distributions of t-statistics under the null that temperature variations carry a zero price.[25] We find that at long horizons, sample t-statistics for the estimate of the price of temperature risks are in the bottom fifth percentile of the null distribution. In particular, under the null that temperature risk has no effect on prices, the probability of observing sample-based t-statistics is 0.003 and 0.039 at the three- and five-year horizon, respectively. That is, if temperature were an ad-hoc spurious factor, it would be highly unlikely to find that it carries a significant price.

2.5 Long-Run vs. Short-Run Temperature Risks

The evidence presented above shows that only low-frequency temperature variations have a significant impact on asset prices and returns. To explore more formally if short-run variations

[24]The temperature risk premium for a given portfolio is computed as a product of its temperature beta and the cross-sectional price of temperature risk implied by the GMM estimates (in particular, the implied cross-sectional price of five-year variations in temperature is -2.5.)

[25]We focus on the distribution of test statistics because t-statistics are pivotal quantities.

in temperature have any incremental impact, we consider the following panel regression:

$$v_{i,t} = \bar{v}_i + \phi_K^{LR}\, LR_t^K + \phi_K^{SR}\, SR_t^K + \varrho_i\, v_{i,t-1} + \alpha_i\, v_t + \varepsilon_{i,t}\,, \tag{29}$$

where $v_{i,t}$ is the log of the price-dividend ratio of portfolio i, $LR_t^K \equiv \Delta_K T_t$ represents low-frequency fluctuations in temperature measured by the three- or five-year change in temperature, $SR_t^K \equiv \Delta T_t \perp \Delta_K T_t$ represents short-run temperature fluctuations measured by changes in annual temperature that are orthogonal to long-run fluctuations, and v_t is the price-dividend ratio of the market portfolio.[26] As in Equation (24), the coefficients on the lagged price-dividend ratio and on the market price-dividend ratio are a function of the portfolio's average book-to-market ratio.

Table V presents the estimated slope coefficients, ϕ_{LR} and ϕ_{SR}, along with the corresponding t-statistics. We find a negative and statistically significant response of equity valuations to low-frequency fluctuations in temperature and a statistically insignificant response to short-run fluctuations. Further, comparing the estimates in Tables II and V, we find that the magnitude of the long-run temperature elasticities is unaffected by the inclusion of short-run temperature risks. In unreported results, we also estimate exposure of equity returns to long- and short-run temperature fluctuations and find similar results. Thus, our evidence suggests that the negative impact of temperature on the economy is mostly driven by its low-frequency component that is associated with global warming.

2.6 Robustness of the Empirical Evidence

This section summarizes additional tests that we carry out to confirm the robustness of our empirical evidence.

Data Sample: Table VI presents temperature elasticities of equity valuations estimated using the pre-1970 sample. We find that in the early sample, when carbon emissions had not yet reached a critical mass to trigger climate change, temperature variations had no effect on asset prices — all estimates of temperature elasticities are insignificantly different from zero.

[26] We orthogonalize short-run temperature risks to identify their separate impact; our evidence remains virtually unchanged if instead we simply include ΔT_t alongside $\Delta_K T_t$.

Data Frequency: We re-estimate temperature elasticities, betas and the compensation for temperature risk using quarterly U.S. data and confirm that the frequency of the data does not affect our empirical evidence. Consistent with the evidence based on the annual data, we find that temperature betas feature a strong cross-sectional variation across book-to-market sorted portfolios, which mirrors variation in long-run growth risks and risk premia. As Table A.I shows, in the quarterly data, temperature carries a negative and statistically significant price of risk. Overall, the magnitude and significance of the quarterly estimates are consistent with the evidence based on the annual data.

Asset Menu: As discussed earlier, we choose ten BM portfolios because they feature significant differences in long-run dividend betas. We exploit this heterogeneity to identify the climate risk channel. Portfolios sorted on other firm characteristics do not feature such a pronounced cross-sectional variation in macroeconomic growth risks, and therefore, may not be informative about the growth-risk channel of rising temperature. Hence, to verify the robustness of our evidence, we confine our attention to BM sorted portfolios but expand their number by slicing them by size. In particular, we consider a set of 25 portfolios double sorted on book-to-market ratio and market capitalization. Consistent with the evidence that we report above, we find that in a larger cross section, temperature elasticities are significantly negative and more so when temperature risks are measured at low frequencies. In particular, in the cross section of 25 portfolios, (semi) elasticities of equity valuations to variations in temperature at one-, three-, five-year horizons are estimated at -0.032, -0.037, -0.053 and with robust t-statistics of -1.85, -2.05, and -3.89, respectively (see Panel A of Table A.II). Further, we also find that the variation in temperature risks across 25 portfolios mirrors the cross-sectional variation in long-run consumption risks. Panel B of Table A.II presents the estimates of temperature elasticities scaled by dividend betas and confirms that low-frequency temperature risks affect equity valuation through their impact on long-run growth. Similar to our baseline evidence, we also find that the market price of temperature risk estimated using size and book-to-market sorted portfolios is significantly negative when temperature risks are measured at low frequencies (this evidence is available upon request).

Environmental Regulation Risk: We verify that our empirical evidence is robust to excluding firms that could be the target of environmental regulations. Following Greenstone (2002), we identify firms that account for an important share of industrial emissions and, therefore, are very likely subject to significant regulatory oversight, and we exclude these firms from our sample. In essence, by removing firms considered heavy-emitters from our test portfolios we remove the effect of regulatory risk that might be driven by climate change. Using 25 size and book-to-market sorted portfolios composed of non-emitters only, we re-estimate the sensitivity of the price-dividend ratio to temperature as in Section 2.3. As Table A.III shows, we find that the price-dividend ratio of non-emitters falls when temperature rises, and the magnitude and significance of the estimated temperature elasticities are virtually unaffected by the exclusion of regulated firms. As further discussed in Appendix C, these results are robust to different thresholds that are used to determine the emitter status. In sum, our empirical evidence suggests that the economic impact of climate-change risks is different from and is not driven by environmental regulations.

Macro Factors: We evaluate if macro factors that are known to be priced in equity markets are collinear with temperature. As Table A.IV shows, we find that the correlation between temperature and a set of factors that are commonly used in the macro asset pricing literature is low, generally close to zero. We also find that adding any of these factors in our panel regressions or GMM estimation does not alter the magnitude of temperature elasticities or the significance of temperature risk in pricing the cross-section of asset returns. This evidence shows that temperature is a distinct source of risk in capital markets.

Evidence from Global Financial Markets: In Appendix D, we evaluate the impact of temperature fluctuations on equity valuations using information from global financial markets. Our analysis exploits data on the country-level temperature and price-dividend ratio for a panel of 48 countries. A detailed description of the data is provided in Appendix B. As Tables A.VII and A.VIII show, we find that the temperature elasticity of equity valuations in global capital markets is significantly negative, particularly when temperature fluctuations are measured at low frequencies.

In sum, in the U.S. and consistently in global capital markets, a persistent rise in temperature leads to an economically and statistically significant decline in equity valuations. This evidence suggests that rising temperature is expected to affect economic growth in the long run. As discussed in Section 1, temperature risk manifests in current asset prices and short-run risk-return tradeoff only if it affects future consumption, i.e., only if it contributes to long-run risks in aggregate growth.

3 The Welfare Cost of Carbon Based on Asset Prices

Our empirical evidence suggests that climate risk is embedded in asset prices, and hence, asset prices provide valuable information about the cost of climate change. We measure economic implications of rising temperature by the welfare cost of carbon emissions (WCC) that is defined by the marginal utility of emissions:

$$WCC_t = -\frac{\partial U_t}{\partial \mathcal{E}_t} \Big/ \frac{\partial U_t}{\partial C_t}\,, \tag{30}$$

where U_t is the life-time utility of the agent; the scaling by the marginal utility of consumption allows us to express the cost in units of current consumption goods (time-t dollars). A marginal increase in current emissions affects temperature into the future and rises future damages and risks in the economy. The WCC measures by how much the current level of consumption should rise to compensate for the ensuing future losses.

In economic literature and policy analysis, the cost of carbon (defined as the social cost of carbon emissions) is typically measured using integrated assessment models (IAMs). For example, the federal Interagency Working Group on the Social Cost of Greenhouse Gases that operated over the 2009–2017 period calculated the social cost of carbon based on the output of three IAMs: the DICE model of Nordhaus (2008, 2010), the FUND model of Tol (2002a, 2002b) and Anthoff and Tol (2013), and the PAGE model of Hope (2011). The output of the models is based on a number of assumptions about socioeconomic trends and future emissions, climate sensitivity, benefits and damages of climate change, and discount rates, all of which are highly uncertain and, thus, are hard to calibrate.

Instead, we compute the cost of carbon directly from the observed capital market data. As we show below, the WCC is determined by the temperature (semi) elasticity of asset valuations that we estimate in the data. Because our measurement is based on forward-looking asset prices, our estimate reflects the discount rates prevailing in capital markets and market expectations of the future path of emissions and economic losses as well as future abetment efforts and future technological progress in combating climate change. We refer to our approach as semi-parametric because relative to the IAM-based measurement it is much less reliant on parametric modeling assumptions about the macroeconomy and climate dynamics. Note that if carbon emissions impose a negative externality, then the social cost of carbon exceeds the private cost; in this case, our WCC estimate sets a lower bound on the social cost of carbon.

As shown in Equation (8), the life-time utility is a function of the wealth-consumption ratio; hence, the welfare cost of carbon emissions is determined by the elasticity of aggregate wealth to emissions. Specifically, taking the derivative of Equation (8), obtain:[27]

$$WCC_t \;=\; \frac{\psi}{\psi-1}\,\frac{-\partial Z_t}{\partial \mathcal{E}_t}\,\frac{C_t}{Z_t}\,. \tag{31}$$

As we show in Appendix A.5, the marginal impact of emissions of the wealth-consumption ratio $\left(\frac{-\partial Z_t}{\partial \mathcal{E}_t}\right)$ is determined by the present value of marginal damages in future consumption and their impact on continuation utility. Consequently,

$$WCC_t \;=\; \frac{\sum_{j=0}^{\infty} E_t\Big[-\frac{\partial C_{t+j}}{\partial \mathcal{E}_t} M_{t\to t+j}\Big]}{W_t}\, C_t \;+\; Q_t\,, \tag{32}$$

where $\frac{\partial C_{t+j}}{\partial \mathcal{E}_t}$ is the loss in time $t+j$ consumption induced by a marginal increase in current emissions and $M_{t\to t+j}$ is the stochastic discount factor. The first term in Equation (32) is the present value of damages in future consumption stream due to an increase in current emissions (as a fraction of current wealth, W_t), and the second term measures the marginal impact of emissions on future utility (which is shown in the appendix). Note that under time-separable expected utility, the term Q_t is absent and the WCC equals the present value of damages. In our analysis below, we compute the WCC by estimating directly the elasticity of the wealth-consumption ratio, $\frac{-\partial Z_t}{\partial \mathcal{E}_t}$, using capital market data.

In particular, as Equation (31) shows, the welfare cost of carbon emissions can be measured in the data by the (semi) elasticity of asset prices to temperature. Factoring out the impact of a marginal change in current emissions on time-t temperature, obtain:

$$WCC_t \;=\; \frac{\psi}{\psi-1}\,\frac{-\partial \log Z_t}{\partial T_t}\,\frac{\partial T_t}{\partial \mathcal{E}_t}\, C_t\,. \tag{33}$$

[27]When IES is equal to one, then the wealth-consumption ratio is constant, and the welfare cost of carbon is computed directly using Equation (30).

Although aggregate wealth is not observable, its dynamics can be measured using equity securities that are traded in capital markets. Similar to wealth, equities are long-duration assets and hence, their prices reflect expectations and concerns about the impact of climate change on the future economic growth and risk. Thus, we can learn about the welfare implications of temperature fluctuations from their impact on equity valuations. Note that by using forward-looking information in equity prices, we effectively let capital markets reveal the cost of carbon emissions.

To compute the welfare cost of carbon, we set $\frac{\partial T_t}{\partial \mathcal{E}_t} = 1.72°\text{C}$ per trillion tonnes of carbon to match the mean value of temperature sensitivity to carbon emissions estimated in MacDougall, Swart, and Knutti (2017) based on the carbon-climate response established in Matthews, Gillett, Stott, and Zickfeld (2009).[28] Because aggregate wealth is a value of current and future consumption, we measure its exposure to temperature risks by the response of an equity portfolio that has unit exposure to long-run consumption risks, i.e., unit cointegration with consumption. In particular, we set $\frac{-\partial \log Z_t}{\partial T_t} = -0.266$ — the point estimate of the semi-elasticity to five-year temperature variations (per unit temperature) from Table III. Recall that the estimates reported in Table III measure the response of equity valuations to standardized temperature variations. Hence, the semi-elasticity of aggregate valuations to a unit change in temperature is obtained by dividing the reported point estimate, -0.032, by the standard deviation of variations in the five-year temperature trend, which is equal to 0.121. Finally, we set $\psi = 1.5$. Note that our empirical evidence rules out values of the IES parameter less than one — if $\psi < 1$, the temperature elasticity of equity valuations would be positive for any $\gamma > 1$, which is inconsistent with the data (see Equation (10)).[29] Importantly, because we use equity valuations to measure the WCC, we choose the value of IES that is consistent with key features of capital market data such as the observed level and dynamics of the risk-free rate, equity prices and equity risk premia.

Table VII presents our semi-parametric capital-market based estimate of the welfare cost of carbon. The WCC is measured in 2016 international dollars of world gross domestic product per

[28] In the scientific climate literature, the climate sensitivity parameter is known as transient climate response to cumulative CO_2 emissions (TCRE); see also MacDougall (2016), Millar and Friedlingstein (2018), and Rogelj, Forster, Kriegler, Smith, and Séférian (2019).

[29] Equivalently, if we assume that IES is less than one, then the welfare cost of carbon implied by Equation (33) would be negative.

metric ton of CO_2 (Panel A) and in equivalent dollars per gallon of gasoline (Panel B).[30] The WCC implied by capital market data (highlighted in bold) is economically large of about $45 per metric ton of carbon dioxide, which is equivalent to about 40 cents per gallon of gasoline. To better understand the magnitude of the WCC, in Table VIII we show how much society would be willing to give up to eliminate the 2017 volume of global industrial emissions. In particular, we compute:

$$\frac{(-\partial U_t/\partial \mathcal{E}_t)\,\mathcal{E}_t^*}{(\partial U_t/\partial C_t)\,C_t}, \tag{34}$$

which measures the fraction of time-t consumption that society is willing to forgo (permanently) to eliminate $\mathcal{E}_t^*$ units of carbon emissions. We set $\mathcal{E}_t^* = 36.2$ gigatonnes of carbon dioxide that correspond to total industrial emissions in 2017. Our WCC estimate implies that the cost of 2017 emissions amounts to a sizable 1.4% of world GDP.

To account for uncertainty about the climate sensitivity parameter and sampling variation in the estimate of temperature elasticity of equity prices, we also compute the 5th to 95th percentile range of the welfare cost of carbon.[31] As Tables VII and VIII show, while the potential range of the WCC is quite wide, even at its lowest end, the welfare cost of carbon remains quantitatively large of about $13 per metric ton of CO_2 or 12 cents per gallon of gasoline, which translates into a total cost of 2017 carbon emissions of about 0.4% of world GDP.

4 The Climate Risk Channel

Our empirical analysis of capital markets shows that (i) a persistent increase in temperature leads in a decline in asset valuations and returns; (ii) assets with high exposure to long-run growth risks are highly affected by low-frequency variations in temperature; and (iii) the price of temperature risk is negative (hence, temperature risk carries a positive premium). Taken together, our empirical evidence suggests that climate change is a source of long-run economic growth risk.

[30] We use the World Bank value of the gross domestic product (GDP) that is converted into international dollars using purchasing power parity rates, which at the end of 2016 is estimated at about 121.4 trillion. The WCC per metric ton of carbon can be computed by multiplying the CO_2-based cost by 3.67.

[31] The 5th and 95th quantiles of the climate sensitivity reported in MacDougall, Swart, and Knutti (2017) are 0.88 and 2.52, respectively. The 5%–95% confidence interval of the estimated elasticity of equity prices to variations in the five-year temperature trend is $[-0.38; -0.15]$.

The impact of rising temperature can be understood through the lens of our stylized economy. In the model, high current growth leads to high industrial emissions and high temperature. Rising temperature increases the likelihood of damages in future output and consumption, i.e., it amplifies economic risks in the long run. The asset pricing and welfare implications of climate change, thus, depend on how much markets care about future risks. In particular, if they are concerned about long-run growth, then high temperature raises marginal utility and lowers assets' valuations and more so of cash flows that are highly exposed to long-run growth risks. These predictions all bear out in the data.

Table IX illustrates the qualitative implications of climate change under alternative specifications of preferences. Two salient results stand out. First, only the configurations where IES and risk aversion are larger than one are consistent with the negative temperature elasticity of equity valuations and the negative market price of temperature risk documented in the data. Recall that $\gamma > 1$ and $\psi > 1$ imply that investors are concerned about long-run growth, and hence, they require compensation for long-run risks driven by temperature. In contrast, under CRRA preferences, asset valuations feature a positive response to temperature and climate-change risks carry a zero premium.

Second, the welfare cost of carbon increases with both risk aversion and IES. The model solution for the WCC, derived in the appendix, is given by:

$$WCC_t \;=\; \frac{\psi}{\psi-1}\big(-A_1\big)\,\chi\,C_t \;=\; \frac{\Phi}{\gamma-1}\,\chi\,C_t\,, \tag{35}$$

where A_1 is the temperature (semi) elasticity of the wealth-consumption ratio given in Equation (10). To understand the distinct impact of preference parameters, in Appendix A.5, we show that the WCC can be expressed as a weighted sum of horizon-specific marginal costs. In particular,

$$WCC_t \;=\; \left[\sum_{n=1}^{\infty} w_n \cdot wcc_t^{(n)}\right] C_t\,, \tag{36}$$

where $wcc_t^{(n)}$ is the horizon-specific cost (i.e., the n-period WCC strip) expressed as a fraction of current consumption, and w_n is the value-weight of the n-period strip. The term structure of WCC strips and weights is illustrated in Figure 8. The magnitude of cost strips (across all maturities) increases with risk aversion but is invariant to IES. Further, because temperature is long-run risk and has a larger impact on more distant consumption, the term structure of marginal costs is upward sloping. How much each horizon contributes to the overall WCC is largely determined by IES. When IES is low, the risk-free rate and therefore discount rates are high; hence, relatively distant welfare losses are heavily discounted and the welfare cost of carbon is low. As IES increases, the risk-free rate and discount rates decline, and thus, the contribution of long-horizon climate costs increases and so is the WCC.

Our empirical evidence of the robustly negative response of equity valuations to rising temperature and the negative price of temperature risk suggests that capital markets are indeed concerned about long-run economic prospects and the potential impact of climate change on long-term growth and risk. These concerns are reflected in a significant cost of carbon emissions implied by capital market data.

5 Conclusion

We show analytically that investors concerns about the impact of rising temperature on long-run economic growth and risk should be reflected in current equity prices and short-run risk-return tradeoff. Guided by the model's predictions, we exploit the forward-looking information in capital markets to measure the economic cost of rising temperature. Our empirical work shows that in both U.S. and global capital markets, the temperature elasticity of equity valuations is significantly negative, particularly when temperature fluctuations are measured at low frequencies that correspond to global warming. We also find that long-run temperature fluctuations carry a significantly positive risk premium in equity markets. This evidence suggests that climate risk is impounded in asset prices, which therefore contain valuable information about the costs of climate change. We use our empirical evidence to provide a semi-parametric capital-market based estimate of the welfare cost of carbon emissions. We find that concerns about the potential impact of climate change on long-term economic growth and risk imply a significant welfare cost. Our analysis underscores the importance of forward-looking information embedded in asset prices for identifying the impact and cost of rising temperature.

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Table I

Long-run Growth Risk and Temperature Risk

Portfolio	Premia	Long-Run Growth Risk		Temperature Risk			
		Dividend Beta		PD-elasticity		Return Beta	
BM1	0.052	0.38	(2.61)	0.003	(0.17)	0.0092	(2.11)
BM2	0.071	0.83	(5.22)	0.032	(1.31)	0.0054	(1.84)
BM3	0.080	0.60	(3.33)	−0.058	(−3.22)	−0.0021	(−0.96)
BM4	0.075	0.63	(5.84)	−0.031	(−1.71)	−0.0039	(−0.97)
BM5	0.074	0.85	(6.05)	−0.051	(−2.30)	−0.0037	(−1.02)
BM6	0.086	1.26	(11.51)	−0.025	(−1.57)	−0.0028	(−1.12)
BM7	0.083	0.88	(13.51)	−0.052	(−2.55)	−0.0044	(−0.95)
BM8	0.088	1.56	(9.33)	−0.034	(−1.53)	−0.0080	(−1.73)
BM9	0.111	2.03	(13.88)	−0.058	(−3.33)	−0.0101	(−4.23)
BM10	0.117	2.27	(10.81)	−0.093	(−2.37)	−0.0105	(−1.91)

Table I shows the average excess return, long-run cash-flow risk, and temperature risk for ten portfolios sorted by book-to-market. Long-run risk is measured by cointegration between log portfolio dividends and log aggregate consumption. The elasticity of the price-dividend ratios to temperature is measured by regressing valuation ratios on the standardized five-year change in temperature controlling for the market price-dividend ratio and lagged valuation ratio of the corresponding portfolio. Temperature return beta of a portfolio is estimated by regressing five-year cumulative excess return on the standardized five-year change in temperature controlling for cumulative market and consumption growth risks. T-statistics (in parenthesis) are based on the Newey and West (1987) estimator of the variance-covariance matrix with five lags. The data are annual; the cointegrating parameters are estimated using the 1940-2018 sample, all other statistics are estimated using the 1970-2016 sample.

Table II

Elasticity of Equity Prices to Temperature Variations

	Horizon (K)		
	1-year	3-year	5-year
ϕ_K	-0.013	-0.027	-0.037
	(-1.15)	(-2.12)	(-2.99)

Table II reports the response of equity valuations to temperature fluctuations based on the following panel regression specification,

$$v_{i,t} = \bar{v}_i + \phi_K \, \Delta_K T_t + \varrho_i \, v_{i,t-1} + \alpha_i \, v_t + \varepsilon_{i,t} \, ,$$

where $v_{i,t}$ is the log of the price-dividend ratio of portfolio i, $\bar{v}_i$ is a portfolio-specific fixed effect, $\Delta_K T_t$ is the standardized K-year change in U.S. temperature, v_t is the price-dividend ratio of the market portfolio. The coefficients on the lagged price-dividend ratio and on the market price-dividend ratio are a function of the portfolio's average book-to-market characteristic ($\overline{bm}_i$), namely, $\varrho_i = \varrho + \varrho_b \overline{bm}_i$, and $\alpha_i = \alpha + \alpha_b \overline{bm}_i$. The table shows (semi) elasticities of price-dividend ratios to temperature variations, ϕ_K, and the corresponding t-statistics (in parenthesis) that are based on standard errors clustered by portfolio and time using the Newey and West (1987) estimator with three lags. The regression is estimated using ten book-to-market sorted portfolios. The data are annual and cover the 1970-2016 period.

Table III

Scaled Elasticity of Equity Prices to Temperature Variations

	Horizon (K)		
	1-year	3-year	5-year
ϕ_K	-0.013	-0.024	-0.032
	(-1.48)	(-2.33)	(-3.81)

Table III reports the response of equity valuations to temperature fluctuations based on the following specification,

$$\begin{aligned} v_{i,t} &= \bar{v}_i + (\phi_K \cdot \beta_{i,LR})\, \Delta_K T_t + \varrho_i\, v_{i,t-1} + \alpha_i\, v_t + \varepsilon_{i,t}\,, \\ d_{i,t} &= \bar{d}_i + \beta_{i,LR} c_t + w_{i,t}\,, \end{aligned}$$

where $v_{i,t}$ is the log of the price-dividend ratio of portfolio i, $\bar{v}_i$ is a portfolio-specific fixed effect, $\Delta_K T_t$ is the standardized K-year change in U.S. temperature, v_t is the price-dividend ratio of the market portfolio. The coefficients on the lagged price-dividend ratio and on the market price-dividend ratio are a function of the portfolio's average book-to-market characteristic ($\overline{bm}_i$), namely, $\varrho_i = \varrho + \varrho_b \overline{bm}_i$, and $\alpha_i = \alpha + \alpha_b \overline{bm}_i$. The cross-sectional variation in temperature elasticity is governed by the long-run dividend betas, $\beta_{i,LR}$, measured by cointegration between log portfolio dividends ($d_{i,t}$) and log aggregate consumption (c_t) in the 1940-2016 sample. The table shows (semi) elasticities of price-dividend ratios to temperature variations, ϕ_K, and the corresponding t-statistics (in parenthesis) that are based on standard errors clustered by portfolio and time using the Newey and West (1987) estimator with three lags. The panel regression is estimated using ten book-to-market sorted portfolios; the data are annual and cover the 1970-2016 period.

Table IV

Price of Temperature Risk

	Horizon (K)		
	1-year	3-year	5-year
$\lambda_{\Delta T}$	-0.64	-1.59	-2.68
	(-1.39)	(-3.67)	(-2.76)
λ_m	1.75	8.35	14.18
	(1.16)	(2.88)	(2.82)
λ_c	0.62	0.28	0.79
	(1.45)	(0.74)	(1.74)
χ^2	4.26	9.43	5.12
p-value	0.75	0.22	0.64

Table IV reports the estimates of the price of temperature risks measured at different frequencies. The risk prices are estimated by exploiting the Euler equation for a cross-section of N portfolios using a linear stochastic discount factor (SDF),

$$E\Big[R^e_{i,K,t}(1+M_{K,t})\Big] = 0\,, \quad \text{for } i = 1,\ldots,N\,,$$

$$M_{K,t} = -\lambda_{\Delta T}\Big[\Delta_K T_t - \mu_T\Big] - \lambda_m\Big[R^e_{m,K,t} - \mu_m\Big] - \lambda_c\Big[\Delta_K c_t - \mu_c\Big]\,,$$

where $R^e_{i,K,t}$ is the K-period cumulative return of portfolio i in excess of the risk-free rate; $M_{K,t}$ is the SDF that is driven by the standardized K-year change in temperature, $\Delta_K T_t$, the cumulative excess return of the market portfolio, $R^e_{m,K,t}$, and the cumulative consumption growth, $\Delta_K c_t$ (multiplied by 100); μ's denote the corresponding factor means. The estimates are obtained through an efficient GMM using ten book-to-market sorted portfolios. T-statistics (in parenthesis) account for the estimation error in the factor means and are based on the Newey-West estimator of the variance-covariance matrix with K lags. The last two rows report the Sargan-Hansen test of over-identifying restrictions (χ^2) and its corresponding p-value. The data are annual and cover the 1970-2016 period.

Table V

Elasticity of Equity Valuations to Long- and Short-Run Temperature Variations

	Horizon (K)	
	3-year	5-year
ϕ_K^{LR}	-0.027	-0.037
	(-2.14)	(-3.08)
ϕ_K^{SR}	0.005	-0.011
	$(\ 0.34)$	(-0.59)

Table V reports the response of equity valuations to temperature fluctuations based on the following panel regression specification,

$$v_{i,t} = \bar{v}_i + \phi_K^{LR}\, LR_t^K + \phi_K^{SR}\, SR_t^K + \varrho_i\, v_{i,t-1} + \alpha_i\, v_t + \varepsilon_{i,t}\,,$$

where $v_{i,t}$ is the log of the price-dividend ratio of portfolio i, $\bar{v}_i$ is a portfolio-specific fixed effect, $LR_t^K \equiv \Delta_K T_t$ represents low-frequency fluctuations in temperature measured by the three- or five-year change in U.S. temperature, $SR_t^K \equiv \Delta T_t \perp \Delta_K T_t$ represents short-run temperature fluctuations measured by changes in annual temperature that are orthogonal to long-run fluctuations, v_t is the price-dividend ratio of the market portfolio. The coefficients on the lagged price-dividend ratio and on the market price-dividend ratio are a function of the portfolio's average book-to-market characteristic ($\overline{bm}_i$), namely, $\varrho_i = \varrho + \varrho_b \overline{bm}_i$, and $\alpha_i = \alpha + \alpha_b \overline{bm}_i$. Short- and long-run temperature variations are standardized. The table shows (semi) elasticities of price-dividend ratios to long- and short-run temperature variations, ϕ_K^{LR} and ϕ_K^{SR}, and the corresponding t-statistics (in parenthesis) that are based on standard errors clustered by portfolio and time using the Newey and West (1987) estimator with three lags. The regression is estimated using ten book-to-market sorted portfolios. The data are annual and cover the 1970-2016 period.

Table VI

Elasticity of Equity Prices to Temperature Variations pre-1970

	Horizon (K)		
	1-year	3-year	5-year
ϕ_K	-0.006	0.014	-0.011
	(-1.49)	(1.10)	(-1.37)

Table VI reports the response of equity valuations to temperature fluctuations based on the following panel regression specification,

$$v_{i,t} = \bar{v}_i + \phi_K \, \Delta_K T_t + \varrho_i \, v_{i,t-1} + \alpha_i \, v_t + \varepsilon_{i,t} \, ,$$

where $v_{i,t}$ is the log of the price-dividend ratio of portfolio i, $\bar{v}_i$ is a portfolio-specific fixed effect, $\Delta_K T_t$ is the standardized K-year change in U.S. temperature, v_t is the price-dividend ratio of the market portfolio. The coefficients on the lagged price-dividend ratio and on the market price-dividend ratio are a function of the portfolio's average book-to-market characteristic ($\overline{bm}_i$), namely, $\varrho_i = \varrho + \varrho_b \overline{bm}_i$, and $\alpha_i = \alpha + \alpha_b \overline{bm}_i$. The table shows (semi) elasticities of price-dividend ratios to temperature variations, ϕ_K, and the corresponding t-statistics (in parenthesis) that are based on standard errors clustered by portfolio and time using the Newey and West (1987) estimator with three lags. The regression is estimated using ten book-to-market sorted portfolios. The data are annual and cover the 1940-1969 period.

Table VII
Capital-Market Based Measure of the Welfare Cost of Carbon

Panel A: In $ Per Metric Ton of CO_2

		Temperature Elasticity of Valuations		
		5%–bound	Estimate	95%–bound
Climate Sensitivity	5%–bound	33.3	23.3	13.2
	Mean	65.1	**45.4**	25.8
	95%–bound	95.3	66.6	37.8

Panel B: In $ Per Gallon of Gasoline

		Temperature Elasticity of Valuations		
		5%–bound	Estimate	95%–bound
Climate Sensitivity	5%–bound	0.30	0.21	0.12
	Mean	0.58	**0.40**	0.23
	95%–bound	0.85	0.59	0.34

Table VII presents the welfare cost of carbon (WCC) implied by the estimated (semi) elasticity of equity valuations to temperature variations. The table shows the WCC implied by the point estimate of the five-year temperature elasticity of equity valuations in Table III and the mean value of the climate sensitivity parameter reported in MacDougall, Swart, and Knutti (2017) (in bold), and its 5th to 95th percentile range. The 5th percentile, mean, and 95th percentile of the climate sensitivity parameter are 0.88, 1.72, and 2.52 degree Celsius per trillion tonnes of carbon, respectively. The estimated temperature elasticity of equity prices is -0.266, and its 5%–95% confidence interval is $[-0.38; -0.15]$. The WCC is measured in 2016 international dollars of world gross domestic product per metric ton of CO_2 (Panel A) and in equivalent dollars per gallon of gasoline (Panel B).

Table VIII

Cost of the 2017 Global Industrial Carbon Emissions

		Temperature Elasticity of Valuations		
		5%–bound	Estimate	95%–bound
Climate Sensitivity	5%–bound	0.99%	0.69%	0.39%
	Mean	1.94%	$\boxed{\textbf{1.36\%}}$	0.77%
	95%–bound	2.84%	1.99%	1.13%

Table VIII shows the cost of global industrial CO_2 emitted in 2017 as a percentage of gross domestic product. The table shows the cost implied by the point estimate of the five-year temperature elasticity of equity valuations in Table III and the mean value of the climate sensitivity parameter reported in MacDougall, Swart, and Knutti (2017) (in bold), and its 5th to 95th percentile range. The 5th percentile, mean, and 95th percentile of the climate sensitivity parameter are 0.88, 1.72, and 2.52 degree Celsius per trillion tonnes of carbon, respectively. The estimated temperature elasticity of equity prices is -0.266, and its 5%–95% confidence interval is $[-0.38; -0.15]$. Global industrial carbon dioxide emissions in 2017 amount to about 36.2 gigatonnes.

Table IX

Model Implications

Panel A: Risk-Free Rate (%)

		IES		
		0.2	1	1.5
	1/1.5	8.25	2.44	1.96
RA	1	8.21	2.43	1.95
	5	7.79	2.29	1.83

Panel B: Price of Temperature Risk (%)

		IES		
		0.2	1	1.5
	1/1.5	0.411	0.075	0.000
RA	1	0.384	0.000	−0.085
	5	0.000	−1.004	−1.215

Panel C: Temperature Elasticity of WC-ratio

		IES		
		0.2	1	1.5
	1/1.5	0.0190	0.0000	−0.0042
RA	1	0.0192	0.0000	−0.0042
	5	0.0219	0.0000	−0.0047

Panel D: Welfare Cost of Carbon (%)

		IES		
		0.2	1	1.5
	1/1.5	0.095	0.225	0.253
RA	1	0.096	0.227	0.255
	5	0.109	0.251	0.280

Table IX shows the model-implied risk-free rate, the price of temperature risk, the temperature elasticity of the wealth-consumption ratio and the welfare cost of carbon under various configurations of risk aversion (RA) and the intertemporal elasticity of substitution (IES). The risk-free rate and the price of temperature risk are expressed in percent per annum, the WCC is expressed as a percentage of the representative-agent consumption. The table is constructed using the following calibration of the stylized model economy: $\delta = 0.99,\ \mu = 0.015,\ \sigma_\eta = 0.018,\ d = -0.05,\ \ell_0 = 0.01,\ \ell_1 = 0.01,\ \nu = 0.966,\ \Theta = 1,\ \chi = 0.2,\ \sigma_\zeta = 1.$

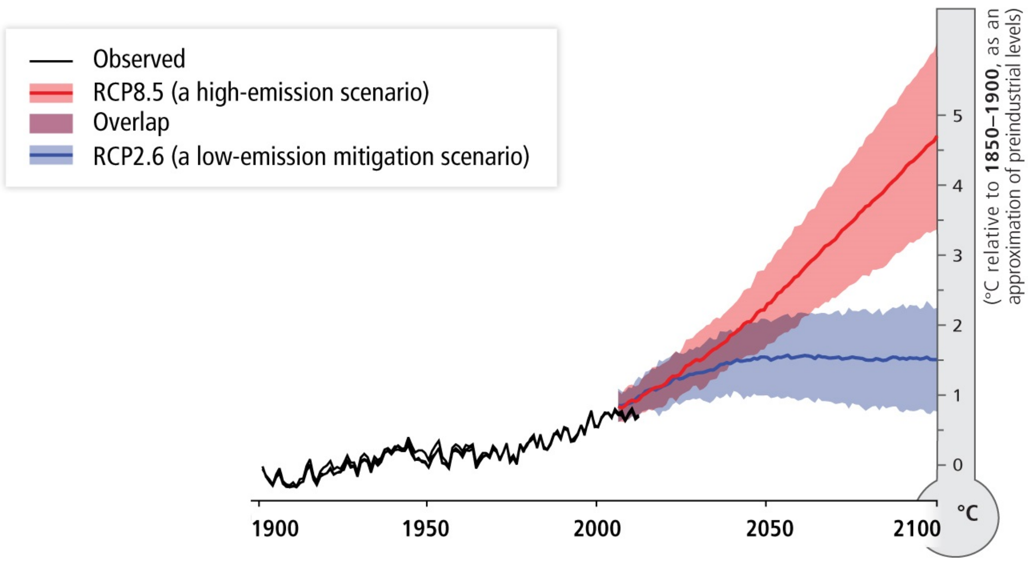


Figure 1. Global Temperature Projections (IPCC (2014))

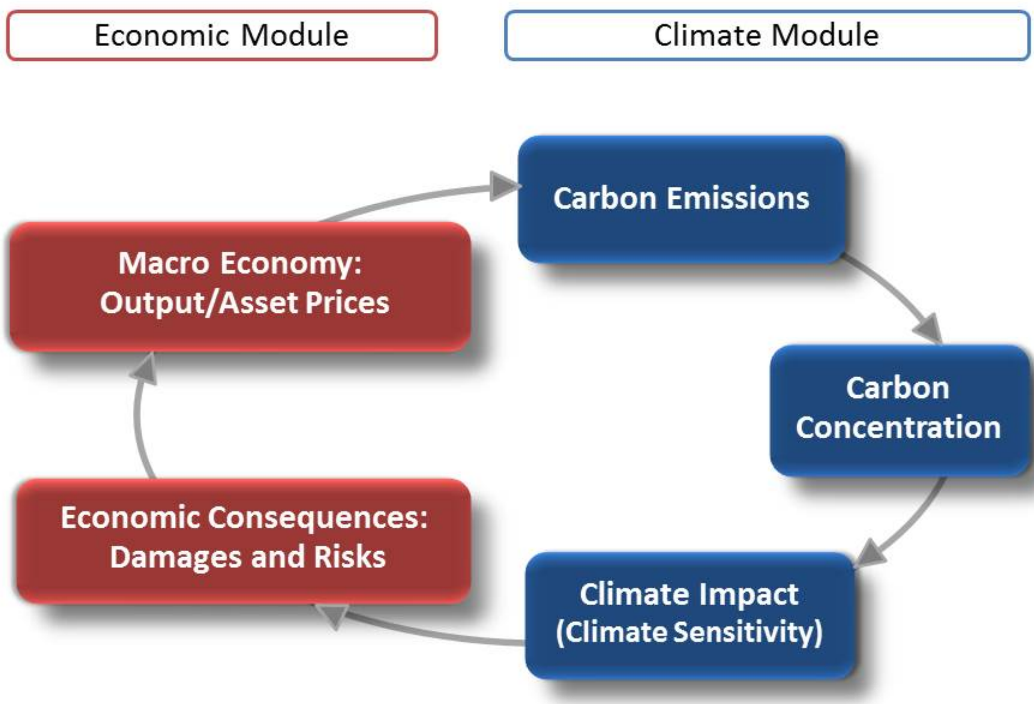


Figure 2. Climate and Economic Module

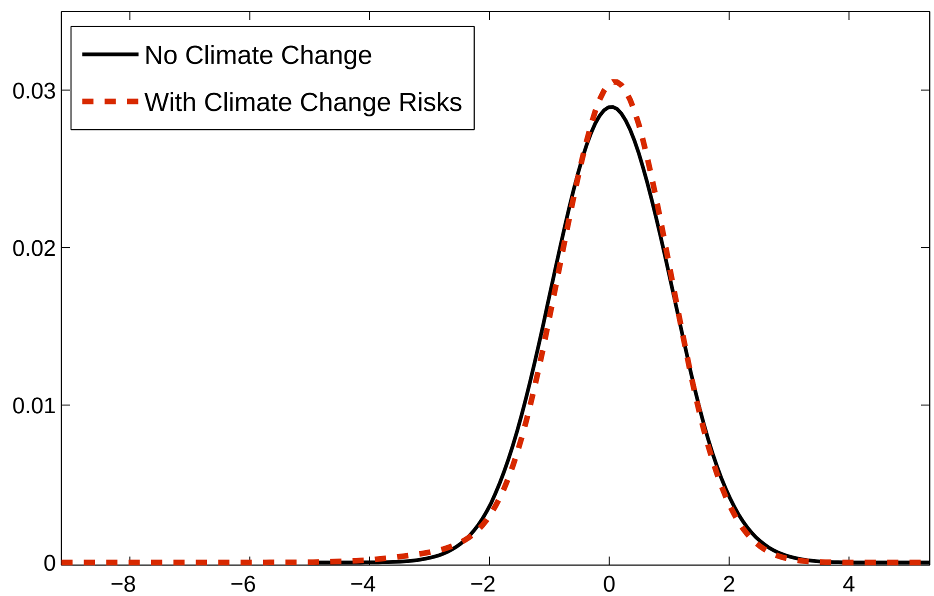


Figure 3. Implications of Global Warming for Consumption Growth

Figure 3 shows the distribution of normalized consumption growth when climate change is absent (solid line) and the corresponding distribution with climate-driven damages when temperature anomaly is set at 2°C (dashed line). The figure is constructed using the following calibration of consumption growth: $\mu = 0.015,\ \sigma_\eta = 0.018,\ d = -0.05,\ \ell_0 = 0.01,\ \ell_1 = 0.01$.

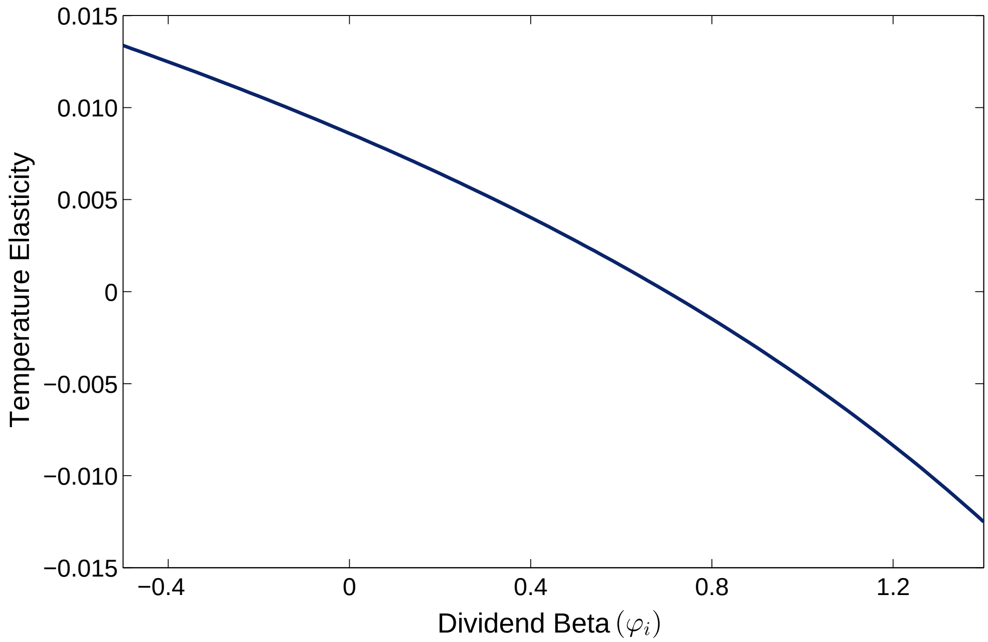


Figure 4. Cross-Sectional Variation in Temperature Elasticity

Figure 4 shows temperature elasticity $(B_{i,1})$ as a function of cash-flow exposure to consumption risks (φ_i). The plot is constructed using the following calibration of the stylized model economy: $\delta = 0.99,\ \gamma = 5,\ \psi = 1.5,\ \mu = 0.015,\ \sigma_\eta = 0.018,\ d = -0.05,\ \ell_0 = 0.01,\ \ell_1 = 0.01,\ \nu = 0.966,\ \Theta = 1,\ \chi = 0.2,\ \sigma_\zeta = 1,\ \sigma_i = 0.018.$

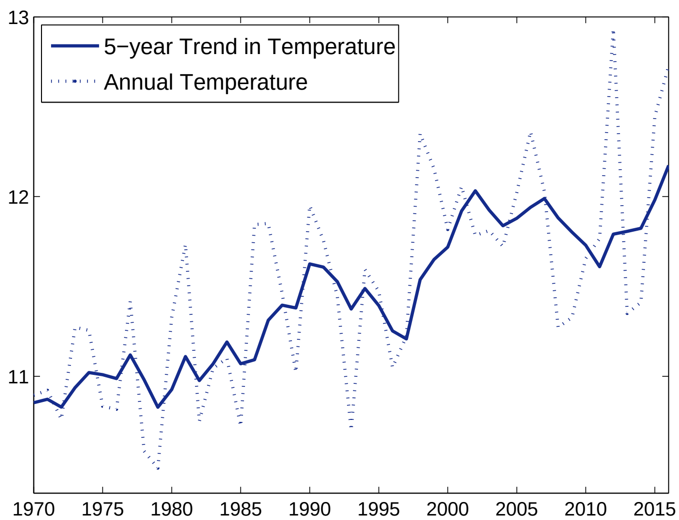


Figure 5. Long- and Short-Run Fluctuations in U.S. Temperature

Figure 5 shows the five-year moving-average of U.S. temperature (solid line) and annual temperature variations (dashed line). Temperature is measured in degrees Celsius.

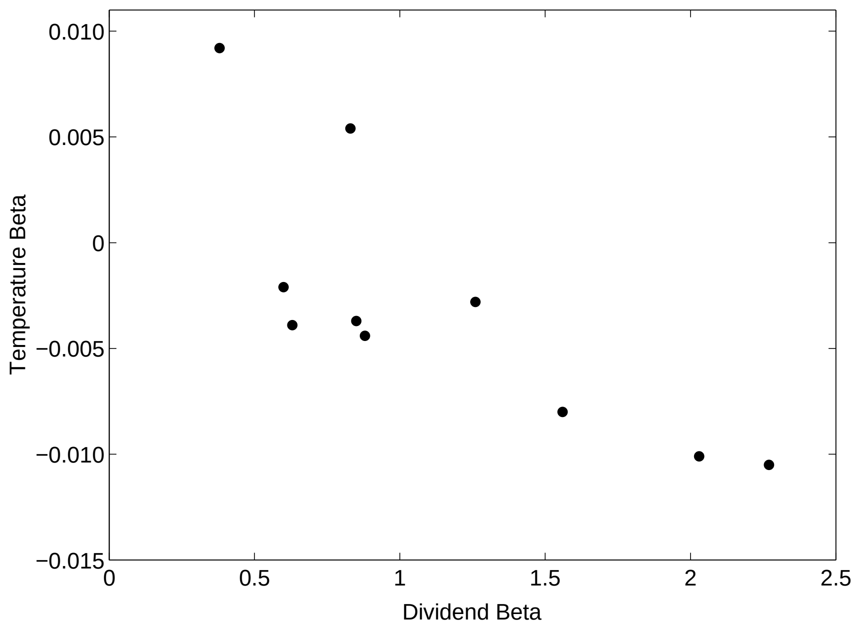


Figure 6. Dividend Betas and Temperature Betas

Figure 6 presents the scatter plot of long-run dividend betas and temperature betas of ten book-to-market sorted portfolios. Dividend betas are measured by cointegration between log portfolio dividends and log aggregate consumption in the 1940-2016 sample. Temperature return beta of a portfolio is estimated by regressing five-year cumulative excess return on the standardized five-year change in temperature controlling for cumulative market and consumption growth risks. The data are annual and cover the 1970-2016 period.

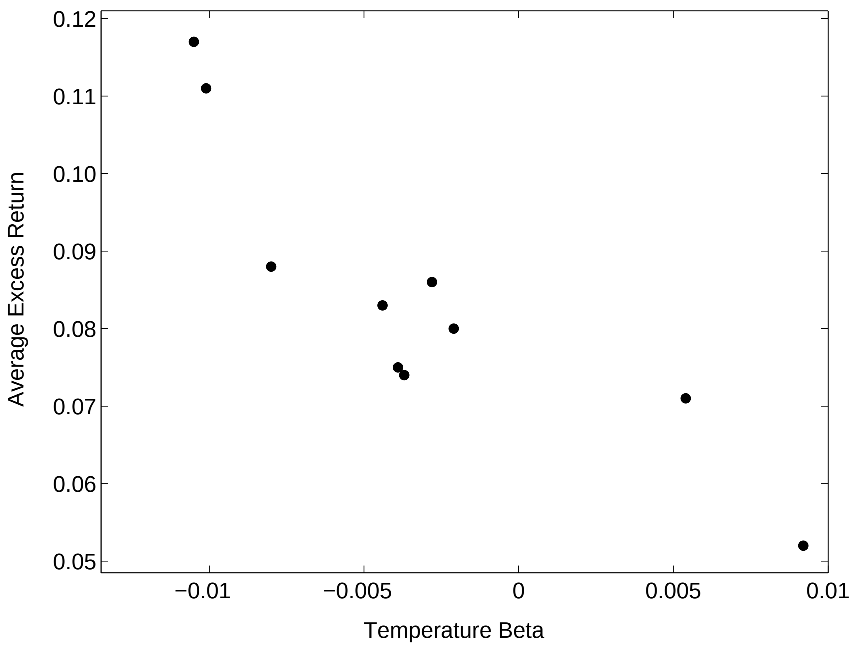
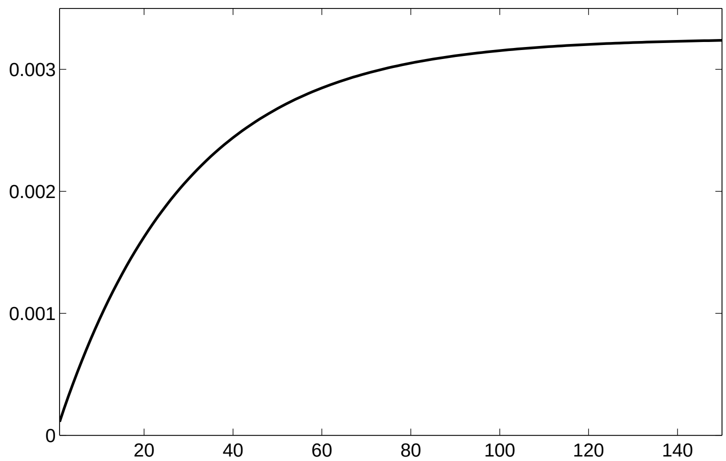
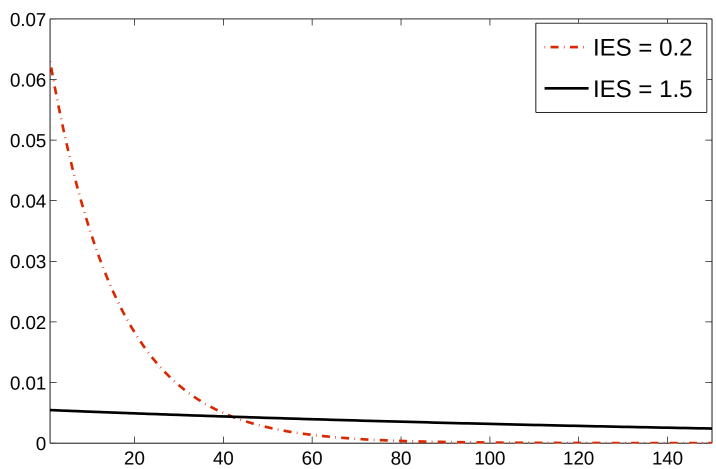


Figure 7. Temperature Betas and Risk Premia

Figure 7 presents the scatter plot of average excess returns and temperature betas of ten book-to-market sorted portfolios. Temperature beta of a portfolio is estimated by regressing five-year cumulative excess return on the standardized five-year change in temperature controlling for cumulative market and consumption growth risks. The data are annual and cover the 1970-2016 period.



(a) WCC Strips $\left(wcc_t^{(n)}\right)$



(b) Weights $\left(w_n\right)$

Figure 8. Decomposition of the Welfare Cost of Carbon

Figure 8 shows the following decomposition of the welfare cost of carbon:

$$WCC_t \;=\; \left[\sum_{n=1}^{\infty} w_n \cdot wcc_t^{(n)}\right] C_t\,,$$

where $wcc_t^{(n)}$ is the horizon-specific cost (i.e., the n-period WCC strip) expressed as a fraction of current consumption, and w_n is the value-weight of the n-period strip. The figure is constructed using the following calibration of the stylized model economy: $\delta = 0.99$, $\mu = 0.015$, $\sigma_\eta = 0.018$, $d = -0.05$, $\ell_0 = 0.01$, $\ell_1 = 0.01$, $\nu = 0.966$, $\Theta = 1$, $\chi = 0.2$, $\sigma_\zeta = 1$; and risk aversion is set at 5. The term-structure of WCC strips in Panel (a) is invariant to the intertemporal elasticity of substitution (IES); the term-structure of weights in Panel (b) depends on IES and is plotted for IES of 0.2 and 1.5.

Appendix

A Solution to the Climate Change Economy

A.1 Solving for the Wealth-Consumption Ratio

We conjecture that the wealth-consumption ratio follows $z_t = A_0 + A_1 T_t$. To determine A_0 and A_1, we exploit the representative agent's Euler equation to solve for the return on wealth, in particular, $\mathbb{E}_t\left[\exp(m_{t+1} + r_{c,t+1})\right] = 1$. Substituting the log-linear approximation of the wealth return:

$$r_{c,t+1} = \kappa_0 + \Delta c_{t+1} + z_{t+1} - \kappa_1 z_t \,, \tag{A.1}$$

and the IMRS (see Equation (7)) into the Euler equation, obtain:

$$\mathbb{E}_t\left[\exp\Big(\theta \ln \delta + (1-\gamma)\Delta c_{t+1} + \theta\kappa_0 + \theta(z_{t+1} - \kappa_1 z_t)\Big)\right] = 1 \,, \tag{A.2}$$

where $\kappa_1 = \frac{e^{\bar{z}}}{e^{\bar{z}}-1}$, $\kappa_0 = \kappa_1 \bar{z} - \ln(e^{\bar{z}} - 1)$, and $\bar{z}_t$ is the unconditional mean of the log wealth-consumption ratio. Plugging in the dynamics of consumption growth and the conjecture for z_t yields:

$$\begin{aligned}\mathbb{E}_t\Big[&\theta \ln \delta + (1-\gamma+\chi\Theta\theta A_1)\mu + \theta\kappa_0 + (1-\kappa_1)\theta A_0 + \theta(\nu-\kappa_1)A_1 T_t \\ &+ (1-\gamma+\chi\Theta\theta A_1)\sigma_\eta \eta_{t+1} + \chi\theta A_1 \sigma_\zeta \zeta_{t+1} + (1-\gamma)D_{t+1}\Big] = 1 \,.\end{aligned} \tag{A.3}$$

Evaluating the expectation and taking logs we obtain the equilibrium condition that A_0 and A_1 must satisfy:

$$\begin{aligned}0 = \;& \theta \ln \delta + (1-\gamma+\chi\Theta\theta A_1)\mu + \theta\kappa_0 + (1-\kappa_1)\theta A_0 + 0.5\,(1-\gamma+\chi\Theta\theta A_1)^2\sigma_\eta^2 \\ &+ 0.5\,(\chi\theta A_1\sigma_\zeta)^2 + \ell_0\phi\big\{(1-\gamma)\,d\big\} + \Big(\theta(\nu-\kappa_1)A_1 + \ell_1\phi\big\{(1-\gamma)\,d\big\}\Big)T_t \,,\end{aligned} \tag{A.4}$$

where we use the moment generating function of the Poisson distribution to obtain:

$$E_t\Big[\exp\big((1-\gamma)dN_{t+1}\big)\Big] = \exp\Big(\pi_t\phi\big\{(1-\gamma)\,d\big\}\Big)\,,$$

with $\phi\big\{(1-\gamma)\,d\big\} \equiv e^{(1-\gamma)\,d} - 1$.

It follows from Equation (A.4) that:

$$A_1 = \frac{\ell_1}{\theta}\frac{\phi\big\{(1-\gamma)d\big\}}{\kappa_1-\nu}\,, \tag{A.5}$$

and,

$$\begin{aligned} A_0(\kappa_1-1) = \;& \ln\delta + \kappa_0 + \Big(1-\frac{1}{\psi}+\chi\Theta A_1\Big)\mu + \frac{\ell_0}{\theta}\phi\big\{(1-\gamma)\,d\big\} \\ & + 0.5\,\theta\bigg[\Big(1-\frac{1}{\psi}+\chi\Theta A_1\Big)^2\sigma_\eta^2 + \Big(\chi A_1\sigma_\zeta\Big)^2\bigg]\,. \end{aligned} \tag{A.6}$$

A.2 Solving for the IMRS and the Risk-Free Rate

We use the solution for z_t to derive the dynamics of the IMRS:

$$m_{t+1} = m_0 - (\theta-1)(\kappa_1-\nu)A_1T_t - (\gamma-(\theta-1)\chi\Theta A_1)\sigma_\eta\eta_{t+1} - (1-\theta)\chi A_1\sigma_\zeta\zeta_{t+1} - \gamma D_{t+1}\,, \tag{A.7}$$

where,

$$m_0 = \theta\ln\delta + (\theta-1)\kappa_0 - \Big(\gamma-(\theta-1)\chi\Theta A_1\Big)\mu + (\theta-1)(\kappa_1-1)A_0\,.$$

We can now solve for the risk-free rate by exploiting the Euler condition $\mathbb{E}_t[\exp(m_{t+1}+r_{f,t})] = 1$. In particular,

$$r_{f,t} = r_f + \ell_1\left(\frac{\theta-1}{\theta}\phi\big\{(1-\gamma)d\big\} - \phi\big\{-\gamma d\big\}\right)T_t\,, \tag{A.8}$$

where

$$\begin{aligned} r_f = & -\theta\ln\delta + \gamma\mu - (\theta-1)\left(\kappa_0 + (1-\kappa_1)A_0 + \chi\Theta A_1\mu\right) \\ & - \Big[\big(\gamma-(\theta-1)\chi\Theta A_1\big)^2\sigma_\eta^2 + \big((1-\theta)A_1\chi\sigma_\zeta\big)^2\Big] - \ell_0\phi\big\{-\gamma d\big\}\,. \end{aligned}$$

A.3 Risk Premium

To solve for the risk premium we first obtain the expression for the return on wealth. Substituting the solution for the wealth-consumption ratio and the dynamics of consumption growth into the log-linear return approximation, obtain:

$$r_{c,t+1} = r_c - (\kappa_1 - \nu)A_1 T_t + (1 + \chi\Theta A_1)\sigma_\eta \eta_{t+1} + A_1 \chi \sigma_\zeta \zeta_{t+1} + D_{t+1} \,, \tag{A.9}$$

where:

$$r_c = A_0(1 - \kappa_1) + \kappa_0 + (1 + \chi\Theta A_1)\mu \,.$$

Using the return dynamics and the solution for the IMRS, we derive the conditional risk premium:

$$\ln \mathbb{E}_t[R_{c,t+1}] - r_{f,t} = (\gamma + (1-\theta)\chi\Theta A_1)(1 + \chi\Theta A_1)\sigma_\eta^2 + (1-\theta)(A_1\chi\sigma_\zeta)^2 + \gamma d^2(\ell_0 + \ell_1 T_t) \,. \tag{A.10}$$

A.4 The Cross Section of Equities

We similarly conjecture that the log of the price-dividend ratio of equity security i follows $z_{i,t} = B_{i,0} + B_{i,1}T_t$ and solve for the solution coefficients by exploiting the Euler equation. In particular, we obtain:

$$B_{i,1} = \ell_1 \frac{\frac{1-\theta}{\theta}\phi\big\{(1-\gamma)\, d\big\} + \phi\big\{(\varphi_i - \gamma)\, d\big\}}{1 - \kappa_{i,1}\nu} \,, \tag{A.11}$$

where $\kappa_{i,1} = \frac{e^{\bar{z}_i}}{e^{\bar{z}_i}+1}$ is the constant of log-linearizaion, and $\bar{z}_i$ is the mean of the log price-dividend ratio. Note that $\frac{\partial B_{i,1}}{\partial \varphi_i} = \frac{\ell_1 e^{(\varphi_i - \gamma)d} d}{1-\kappa_{i,1}\nu} < 0$, that it, in the cross section, equity elasticity to temperature is inversely related to dividend beta. The equity risk premium is provided in Equations (18–21) in the main text.

A.5 Welfare Cost of Carbon

Recursive preferences imply the following relationship between the wealth-consumption ratio and the maximized lifetime utility,

$$\frac{U_t}{C_t} = \omega Z_t^{\frac{\psi}{\psi-1}} \,, \tag{A.12}$$

where $Z_t = \frac{W_t}{C_t}$ and $\omega = (1-\delta)^{\frac{1}{1-1/\psi}}$. Consider the marginal cost of an additional unit of emissions in terms of current consumption:

$$WCC_t = -\frac{\partial U_t}{\partial \mathcal{E}_t} \Big/ \frac{\partial U_t}{\partial C_t}\,. \tag{A.13}$$

From Equation (A.12) it follows that the derivatives of lifetime utility with respect to consumption and emissions are:[32]

$$\frac{\partial U_t}{\partial C_t} = \omega Z_t^{\frac{1}{1-1/\psi}}\,, \tag{A.14}$$

$$\frac{\partial U_t}{\partial \mathcal{E}_t} = \frac{\partial U_t}{\partial Z_t}\frac{\partial Z_t}{\partial \mathcal{E}_t} = \frac{\omega}{1-1/\psi} Z_t^{\frac{1/\psi}{1-1/\psi}} \frac{\partial Z_t}{\partial \mathcal{E}_t}\,. \tag{A.15}$$

Hence, the WCC can be measured by the elasticity of Z_t to emissions, i.e.,

$$WCC_t = \frac{1}{1-1/\psi}\,\frac{-\partial Z_t}{\partial \mathcal{E}_t}\,\frac{C_t}{Z_t} \tag{A.16}$$

The wealth-consumption ratio is the present value of future consumption growth:

$$Z_t \;=\; \sum_{j=0}^{\infty} E_t\Big[M_{t\to t+j}\frac{C_{t+j}}{C_t}\Big]\,, \tag{A.17}$$

where the stochastic discount factor is given by:

$$M_{t\to t+j} = \delta^j \left(\frac{C_{t+j}}{C_t}\right)^{-1/\psi} S_{t\to t+j}\,, \tag{A.18}$$

for $j > 0$, $S_{t\to t+j}$ is a function of continuation utility, specifically, $S_{t\to t+j} = \prod_{k=1}^{j} S_{t+k}$, and $S_{t+k} = \Big[E_{t+k-1}U_{t+k}^{1-\gamma}\Big]^{\frac{\gamma-1/\psi}{1-\gamma}} \Big/ U_{t+k}^{\gamma-1/\psi}$, and $M_{t\to t} = 1$.

[32] Consistent with our model framework, we assume that an increase in current (time-t) emissions does not affect the level of time-t consumption.

Taking the derivative of Z_t with respect to current emissions, $\mathcal{E}_t$, can show that:

$$\frac{\partial Z_t}{\partial \mathcal{E}_t} = \sum_{j=0}^{\infty} E_t\Big[\frac{\partial C_{t+j}}{\partial \mathcal{E}_t}\frac{1}{C_t}M_{t\to t+j} + \frac{\partial M_{t\to t+j}}{\partial \mathcal{E}_t}\frac{C_{t+j}}{C_t}\Big] \tag{A.19}$$

$$= \big(1-1/\psi\big)\sum_{j=0}^{\infty} E_t\Big[\frac{\partial C_{t+j}}{\partial \mathcal{E}_t}\frac{1}{C_t}M_{t\to t+j}\Big] + \sum_{j=0}^{\infty} E_t\Big[\delta^j\Big(\frac{C_{t+j}}{C_t}\Big)^{1-1/\psi}\frac{\partial S_{t\to t+j}}{\partial \mathcal{E}_t}\Big] \tag{A.20}$$

Hence, we can represent the WCC as:

$$WCC_t = \frac{\sum_{j=0}^{\infty} E_t\Big[-\frac{\partial C_{t+j}}{\partial \mathcal{E}_t}M_{t\to t+j}\Big]}{W_t}C_t + Q_t\,, \tag{A.21}$$

where $Q_t = -\frac{1}{1-1/\psi}\sum_{j=0}^{\infty} E_t\Big[\delta^j\Big(\frac{C_{t+j}}{C_t}\Big)^{1-1/\psi}\frac{\partial S_{t\to t+j}}{\partial \mathcal{E}_t}\Big]\frac{C_t}{Z_t}$ measures the impact of a marginal increase in current emissions on future utility. Note that under power utility preferences, $S_{t\to t+j} = 1$, and the welfare cost of carbon is simply the present value of emission-induced damages in future consumption stream. Under recursive preferences, the WCC in addition accounts for the impact of emissions on higher moments of the distribution of future consumption, and hence, on future state-price density.

Using the model solution for the wealth-consumption ratio in Equation (A.5), we obtain the following model-implied cost of carbon emissions:

$$WCC_t = \frac{\psi}{\psi-1}\big(-A_1\big)\,\chi\, C_t = \frac{\Phi}{\gamma-1}\,\chi\, C_t\,. \tag{A.22}$$

Note that $\frac{\Phi}{\gamma-1} > 0$ and is increasing with risk aversion (γ), sensitivity of damage intensity to temperature (ℓ_1), and persistence of temperature fluctuations (ν). The welfare cost of carbon emissions is also affected by climate sensitivity, i.e., the elasticity of temperature to emissions (χ). Also, because rising temperature has a long-run impact on the economy, for any given size of damages, under a preference for early resolution of uncertainty agents would be willing to pay a higher price to resolve climate-change uncertainty compared with the power-utility specification (Bansal, Kiku, and Ochoa (2019)).

Further, it follow that,

$$WCC_t \;=\; \sum_{n=1}^{\infty} w_n \left[\frac{\psi}{\psi - 1} \left(-A_1^{(n)} \chi \right) \right] C_t \;=\; \left[\sum_{n=1}^{\infty} w_n \cdot wcc_t^{(n)} \right] C_t \,, \tag{A.23}$$

where $A_1^{(n)}$ is temperature (semi) elasticity of the consumption strip with n-period to maturity, i.e., $z_t^{(n)} = \log Z_t^{(n)} = A_0^{(n)} + A_1^{(n)} T_t$, $w_n = Z_t^{(n)}/Z_t$ is the value-weight of the n-period strip, and $wcc_t^{(n)}$ is the horizon-specific cost (i.e., the n-period WCC strip) expressed as a fraction of current consumption. The (semi) elasticity of the n-period consumption strip to temperature is given by:

$$A_1^{(n)} \;=\; \frac{1 - \frac{1}{\psi}}{1 - \gamma} l_1 \left(e^{(1-\gamma)d} - 1 \right) \frac{1 - \nu^n}{1 - \nu} \tag{A.24}$$

For a given level of risk aversion, the magnitude of WCC strips $\left(wcc_t^{(n)} \equiv -\frac{\psi}{\psi - 1} A_1^{(n)} \chi \right)$ is invariant to IES and is increasing with maturity. Hence, $WCC_t^{(n)}$ varies with risk aversion but not with IES. The effect of IES is embedded in the relative weights of near-future and distant consumption, w_n. At low IES, yields are high; hence, relatively distant consumption is heavily discounted and so is the impact of temperature risk on the future economy. As IES increases, the yield curve shifts down, and distant consumption carries greater weight. Consequently, future economic losses associated with temperature risks contribute non-trivially to the welfare cost of carbon driving it up.

B Data

Our analysis of the U.S. markets is based on the standard set of ten portfolios sorted by book-to-market ratio. In addition, in the robustness section, we also use a cross section of 25 equity portfolios sorted on market capitalization and book-to-market as in Fama and French (1993). The portfolios are constructed using the monthly stock file from the Center for Research in Security Prices (CRSP), which contains monthly stock returns and prices per share, and the COMPUSTAT annual research file, which contains accounting information for publicly traded U.S. firms. To compute excess returns on each portfolio we use the yield on the 1-month Treasury bill from CRSP. The data are obtained from Kenneth French's online data library. We also collect data on the return on the value-weighted market portfolio from CRSP and on aggregate real per capita consumption of nondurables plus services obtained from the Bureau of Economic Analysis' NIPA tables.

Our analysis of global financial markets exploits data on the country-level price-dividend ratio for a panel of 48 countries from Global Financial Data. We find that the first principal component extracted from the cross section of price-dividend ratios accounts for about 69% of the total variation in prices across countries and the second component explains an additional 10%. This suggests that the cross-country variation in equity valuations is influenced by common global macro-economic factors. Jagannathan and Marakani (2015) show that the first two price-dividend ratio factors provide robust proxies for future economic growth and variation in macro-economic uncertainty. Guided by their evidence, we use the first two principal components to control for global macro-economic risks in our regression analysis. We also control for country-level macroeconomic conditions by including their real GDP growth, inflation, unemployment, and real interest rate collected from the World Bank Open Data. Table A.V presents a list of countries in our sample; note that the sample is somewhat tilted towards developed economies as those are more likely to have a long enough history of capital markets.

We obtain time series of temperature for the U.S. from the National Oceanic and Atmospheric Administration. Historical temperature data for the other countries in our sample are obtained from the World Bank's Climate Change Knowledge Portal. In particular, we use land surface temperature anomalies measured by deviations from the average temperature over the 1951-1980 period. Temperature is expressed in degrees Celsius. Similar to the rise in the U.S. temperature, we find that on average across countries, temperature has increased by about by 1°C over the last four decades. Panel (a) of Figure A.1 shows the time-series dynamics of the common trend in country-level temperature. We also find that country temperature series have a strong common component that is highly correlated with variations in global temperature. As shown in Table A.VI, the first principal component of annual temperature series accounts for about 60% of the total variation in temperature across countries and has an 83% correlation with global temperature anomaly. At lower frequencies, the co-movement in local temperature becomes much stronger. For example, using five-year moving-averages of local temperature, we find that the first principal component explains about 83% of the overall variation in local temperature trends. This evidence suggests that systematic changes in climate are driven mostly by low-frequency movements in temperature (i.e., global warming) rather than by short-run temperature fluctuations (i.e., weather fluctuations). Note that while local temperature series share a common long-run component, there is also substantial heterogeneity in the amount of warming across countries. Panel (b) of Figure A.1 displays the distribution of the increase in average temperature between 2006-2015 and 1970-1979 time periods across countries in our sample. The histogram shows that countries have shown an increase in temperature ranging from about half a degree Celsius to two degrees Celsius, which suggests that there is significant cross-sectional variation in long-run temperature shifts in the data.

Our empirical analysis of the U.S. capital market is carried out using annual data from 1970 through 2016, and our global market evidence is based on annual data from 1970 to 2015. We choose to start the sample in 1970 because beginning in the 1970s, there was a major increase in social concerns about environmental problems, which in the U.S. resulted in the creation of the Environmental Protection Agency in 1970, the celebration of the first Earth Day on April 22, 1970, and the establishment of the National Climate Program during the Carter administration intended to improve our understanding of climatic changes, both natural and man-induced.[33] Awareness about environmental challenges was not confined to the U.S. Beginning in the 1970s, several developed countries such us France, Japan and Germany established environmental agencies, and the United Nations member countries started the United Nations Environment Programme in response to increasing concerns about environmental issues at the global and regional level.

C Environmental Regulations

In this section we check how robust our U.S. evidence is to excluding firms that might have been the target of significant environmental regulations by the Environmental Protection Agency (EPA). Since there is no explicit list of firms subject to regulatory oversight, we follow Greenstone (2002) to divide the industries covered by CRSP into heavy-emitters and non-emitters. In particular, we collect data on the EPA's estimates of industry-specific emissions to determine the contribution of each industry to industrial sector emissions.[34] We designate an industry a heavy-emitter if it accounts for an important share of the industrial sector emissions of at least one of the pollutants

[33] For a discussion of the outset of environmental policy in the U.S. see, for example, Freeman (2002).

[34] We collect data on industry-specific emissions for 2001 from the EPA's *Sector Notebook Project Series.*

regulated by the EPA under the Clean Air Act.[35] We consider three alternative thresholds for the contribution of an industry to industrial emissions to assign an emitter status to industries: 3%, 5% and 7%. Consequently, an industry is designated a heavy-emitter if its contribution to industrial emissions exceeds this threshold.[36]

Following this procedure and using 3%–threshold we identify 20 industries that have been main contributors to industrial emissions and very likely the target of EPA oversight. The top heavy-emitters include: fossil fuel electric generation (SIC 4911, 493), petroleum refining (SIC 2911), primary metal manufacturing (SIC 331), and the cement industry (SIC 3211–3299). There are 16 and 10 industries that are considered heavy-emitters under the 5%– and 7%–threshold, respectively.

With a list of industries classified as heavy-emitters for the three alternative thresholds, we proceed to construct 25 size and book-to-market sorted portfolios excluding from the CRSP dataset firms that belong to an industry identified as a heavy-emitter. The remaining firms belong to industries that are considered non-emitters. On average, the non-emitters represent about 75% and 85% of the market capitalization for classifications of emitters using 3%– and 7%–threshold, respectively. Using portfolios comprised of non-emitters, we re-estimate the response of equity prices to temperature fluctuations.

Table A.III presents the (semi) elasticity of the price-dividend ratio of non-emitters to the five-year change in temperature. The three columns report the estimates for three alternative thresholds of emitter status. Consistent with our baseline results, the price-dividend ratio falls with temperature and the price response is economically and statistically significant. Note that exposure of asset valuations to temperature is consistent across different thresholds, and it is also similar in magnitude to the estimate based on the entire cross section of firms suggesting that our results are robust to excluding heavy-emitters. Similarly, as Panel B of Table A.III shows, the cross-sectional variation in temperature elasticities of non-emitters is driven in large by long-run cash-flow risk. Further, we find that the estimates of the market price of low-frequency temperature risks estimated using non-emitters are negative and statistically significant regardless

[35] The Clean Air Act and its amendments set minimum level of air quality that counties in the U.S. are required to meet for four pollutants: carbon monoxide (CO), tropospheric ozone (O_3), sulfur dioxide (SO_2), and total suspended particles (TSPs).

[36] Greenstone (2002) uses a threshold of 7% and focuses only on the manufacturing industry. We focus on a broader set of industries and use alternative thresholds to explore if our results are sensitive to the assignment rule.

of the threshold that determines emitter status. That is, even after excluding firms that might have been affected by environmental regulations, we find that equity markets carry a significant positive temperature premium. In all, our empirical evidence suggests that the economic impact of climate-change risks is distinct from and is not driven by environmental regulations.

D Evidence from Global Financial Markets

In this section, we evaluate the impact of temperature fluctuations on equity valuations using information from global financial markets. Because international markets are not fully integrated and countries vary in the degree of segmentation and frictions, we focus our empirical analysis on the effects of temperature on equity valuations.[37]

Using annual data from 1970 to 2015 for 48 countries, we estimate the impact of temperature on asset valuations running the following panel regression,

$$v_{i,t} = \bar{v}_i + \phi_K \, \Delta_K T_{i,t} + \varrho_r \, v_{i,t-1} + \alpha_r' \, \mathbf{v}_t + \zeta' \mathbf{x}_{i,t} + \varepsilon_{i,t} \,, \tag{D.1}$$

where $v_{i,t}$ is the log of the price-dividend ratio of country i, $\bar{v}_i$ is a country-specific fixed effect, $\Delta_K T_{i,t}$ is the K-year change in country-level temperature, $\mathbf{v}_t$ is a vector that includes the first two principal components of the price-dividend ratios, and $\mathbf{x}_{i,t}$ is a vector of country-level control variables that includes inflation, unemployment, the real interest rate, and GDP growth. The principal components of the country-level price-dividend ratios control for common global macroeconomic fluctuations, and we allow exposure to global macroeconomic risks, α_r, to differ across five geographical regions. Similarly, the coefficient on $v_{i,t-1}$ is allowed to vary across regions. Note that in estimating the impact of temperature risks on equity valuations we exploit both time-series and cross-sectional variation in local temperature.

Table A.VII reports our estimates of the (semi) elasticity of global equity prices to one-, three- and five-year fluctuations in temperature and the corresponding t-statistics based on standard

[37] The expected returns of assets traded in segmented markets are not determined by a common stochastic discount factor, which prevents the identification of the price of temperature risks from a cross-section of international stocks. For evidence on international risk sharing and market segmentation see, for example, Backus, Kehoe, and Kydland (1992), Sørensen, Wu, Yosha, and Zhu (2007), Bekaert, Harvey, Lundblad, and Siegel (2011).

errors clustered by country and time-region. While short-run temperature fluctuations do not have a statistically significant effect on equity valuations, long-run fluctuations have a negative and statistically significant effect on global asset prices. Our evidence implies that equity valuations decline by about 1.5 percent in response to a one standard deviation increase in the five-year temperature trend. To verify the significance of the temperature impact, we run a Monte Carlo simulation. We simulate a panel of temperature that preserves the cross-sectional correlations in temperature series by (repeatedly) randomly drawing a column of observations from the observed panel of temperature data, $\left\{\Delta_K T_{i,t}\right\}$. We then re-estimate the specification in Equation (D.1) using the simulated temperature series and repeat this exercise to construct the distribution of t-statistics under the null that temperature risks have no effect on equity prices. The Monte Carlo based p-values reported in Table A.VII confirm that persistent temperature fluctuations have a significant impact in global capital markets. To further evaluate the separate impact of short- and long-run temperature fluctuations, in Table A.VIII we run a modified version of the panel regression in Equation (D.1). We find that global equity valuations decline in response to an increase in the long-run component of temperature and that short-run temperature fluctuations have no significant effect.

Table A.I

Quarterly Estimates of the Price of Temperature Risk

	Horizon (K)		
	1-year	3-year	5-year
$\lambda_{\Delta T}$	-0.79	-1.38	-1.78
	(-3.21)	(-2.74)	(-2.75)
λ_m	2.05	8.84	12.87
	(2.06)	(2.60)	(3.21)
λ_c	0.17	0.12	0.60
	(0.48)	(0.43)	(0.91)
χ^2	3.34	10.93	8.56
p-value	0.85	0.14	0.29

Table A.I reports the estimates of the price of temperature risks measured at different frequencies. The risk prices are estimated by exploiting the Euler equation for a cross-section of N portfolios using a linear stochastic discount factor (SDF),

$$E\Big[R^e_{i,K,t}(1+M_{K,t})\Big] = 0\,, \quad \text{for } i = 1,\ldots,N\,,$$

$$M_{K,t} = -\lambda_{\Delta T}\Big[\Delta_K T_t - \mu_T\Big] - \lambda_m\Big[R^e_{m,K,t} - \mu_m\Big] - \lambda_c\Big[\Delta_K c_t - \mu_c\Big]\,,$$

where $R^e_{i,K,t}$ is the K-period cumulative return of portfolio i in excess of the risk-free rate; $M_{K,t}$ is the SDF that is driven by the standardized K-year change in temperature, $\Delta_K T_t$, the cumulative excess return of the market portfolio, $R^e_{m,K,t}$, and the cumulative consumption growth, $\Delta_K c_t$ (multiplied by 100); μ's denote the corresponding factor means. The estimates are obtained through an efficient GMM using ten book-to-market sorted portfolios. T-statistics (in parenthesis) account for the estimation error in the factor means and are based on the Newey-West estimator of the variance-covariance matrix with $4 \cdot K$ lags. The last two rows report the Sargan-Hansen test of over-identifying restrictions (χ^2) and its corresponding p-value. Estimated are based on quarterly data over the 1970Q1-2016Q4 period.

Table A.II

Temperature Elasticity of Equity Valuations (Size/BM Portfolios)

Panel A: Temperature Elasticity

	Horizon (K)		
	1-year	3-year	5-year
ϕ_K	-0.032	-0.037	-0.053
	(-1.85)	(-2.05)	(-3.89)

Panel B: Scaled Temperature Elasticity

	Horizon (K)		
	1-year	3-year	5-year
ϕ_K	-0.020	-0.023	-0.031
	(-2.46)	(-1.96)	(-3.86)

Table A.II reports the response of equity valuations to temperature fluctuations based on the following panel regression specification,

$$v_{i,t} = \bar{v}_i + (\phi_K \cdot \beta_{i,LR})\, \Delta_K T_t + \varrho_i\, v_{i,t-1} + \alpha_i\, v_t + \varepsilon_{i,t}\,,$$

where $v_{i,t}$ is the log of the price-dividend ratio of portfolio i, $\bar{v}_i$ is a portfolio-specific fixed effect, $\Delta_K T_t$ is the standardized K-year change in U.S. temperature, v_t is the price-dividend ratio of the market portfolio. In Panel A, $\beta_{i,LR} = 1$; in Panel B, the cross-sectional variation in temperature elasticity is governed by the long-run dividend betas, $\beta_{i,LR}$, measured by cointegration between log portfolio dividends and log aggregate consumption in the 1940-2016 sample. The coefficients on the lagged price-dividend ratio and on the market price-dividend ratio are a function of the portfolio's average log market-capitalization share ($\bar{s}_i$) and average book-to-market ratio ($\overline{bm}_i$), namely, $\varrho_i = \varrho + \varrho_s \bar{s}_i + \varrho_b \overline{bm}_i$, and $\alpha_i = \alpha + \alpha_s \bar{s}_i + \alpha_b \overline{bm}_i$. The table shows (semi) elasticities of price-dividend ratios to temperature variations, ϕ_K, and the corresponding t-statistics (in parenthesis) that are based on standard errors clustered by portfolio and time using the Newey and West (1987) estimator with three lags. The regression is estimated by weighted least squared using 25 portfolios double sorted on market capitalization and book-to-market ratio. The data are annual and cover the 1970-2016 period.

Table A.III

Temperature Elasticity of Equity Valuations of Non-Emitters (Size/BM Portfolios)

Panel A: Temperature Elasticity

	Threshold for Emitter Status		
	3%	5%	7%
ϕ_5	−0.051	−0.051	−0.050
	(−3.84)	(−3.83)	(−3.85)

Panel B: Scaled Temperature Elasticity

	Threshold for Emitter Status		
	3%	5%	7%
ϕ_5	−0.031	−0.031	−0.031
	(−4.33)	(−4.32)	(−4.11)

Table A.III reports the response of equity valuations to temperature fluctuations based on the following panel regression specification,

$$v_{i,t} = \bar{v}_i + (\phi_5 \cdot \beta_{i,LR})\,\Delta_5 T_t + \varrho_i\, v_{i,t-1} + \alpha_i\, v_t + \varepsilon_{i,t}\,,$$

where $v_{i,t}$ is the log of the price-dividend ratio of portfolio i, $\bar{v}_i$ is a portfolio-specific fixed effect, $\Delta_5 T_t$ is the standardized five-year change in U.S. temperature, v_t is the price-dividend ratio of the market portfolio. In Panel A, $\beta_{i,LR} = 1$; in Panel B, the cross-sectional variation in temperature elasticity is governed by the long-run dividend betas, $\beta_{i,LR}$, measured by cointegration between log portfolio dividends and log aggregate consumption in the 1940-2016 sample. The coefficients on the lagged price-dividend ratio and on the market price-dividend ratio are a function of the portfolio's average log market-capitalization share ($\bar{s}_i$) and average book-to-market ratio ($\overline{bm}_i$), namely, $\varrho_i = \varrho + \varrho_s \bar{s}_i + \varrho_b \overline{bm}_i$, and $\alpha_i = \alpha + \alpha_s \bar{s}_i + \alpha_b \overline{bm}_i$. The table shows (semi) elasticities of price-dividend ratios to temperature variations, ϕ_5, and the corresponding t-statistics (in parenthesis) that are based on standard errors clustered by portfolio and time using the Newey and West (1987) estimator with three lags. The regression is estimated by weighted least squared using 25 portfolios double sorted on market capitalization and book-to-market ratio. When forming portfolios we exclude industries that account for more than 3%, 5% and 7% of the industrial emissions of at least one pollutant monitored by the Environmental Protection Agency (EPA) and regulated through the Clean Air Act Amendments. The data are annual and cover the 1970-2016 period.

Table A.IV

Temperature and Macro and Financial Factors

	Horizon (K)		
	1-year	3-year	5-year
Market	−0.11	−0.02	−0.30
Consummption	0.06	0.13	0.11
TFP shocks	0.18	0.10	0.08
Basu, Fernald, and Kimball (2006)			
Leverage factor	−0.03	−0.07	−0.07
Adrian, Etula, and Muir (2014)			
Leverage factor	−0.04	0.03	−0.14
He, Kelly, and Manela (2017)			
Collateral constraint shocks	−0.02	0.00	−0.06
Jermann and Quadrini (2012)			
Equity issuance cost shocks	−0.05	−0.06	−0.19
Belo, Lin, and Yang (2018)			
Investment shocks	0.01	0.15	−0.05
Kogan and Papanikolaou (2014)			
Sentiment change	0.07	0.04	0.05
Baker and Wurgler (2006)			
Volatility shocks	−0.20	0.00	0.08
Bansal, Kiku, Shaliastovich, and Yaron (2014)			

Table A.IV reports correlations between temperature and various macro and financial factors. Temperature variations are measured by the K-year change in U.S. temperature. The data are annual and cover the 1970-2016 period.

Table A.V

List of Countries

Argentina	Greece	Philippines
Australia	Hungary	Poland
Belgium	India	Portugal
Brazil	Indonesia	Russia
Bulgaria	Ireland	Singapore
Canada	Israel	Slovenia
Chile	Italy	South Africa
China	Jamaica	South Korea
Colombia	Japan	Spain
Croatia	Malaysia	Sri lanka
Czech Republic	Mexico	Sweden
Denmark	Morocco	Switzerland
Egypt	Netherlands	Thailand
Finland	New Zealand	U.K.
France	Norway	U.S.A.
Germany	Peru	Venezuela

Table A.V provides a list of the countries in our data set.

Table A.VI

Principal Components of Country-Level Temperature

	Horizon (K)		
	1-year	3-year	5-year
1	60.85	75.38	83.07
2	15.30	11.03	7.53
3	4.48	3.83	3.62
4	3.65	1.96	1.53
5	3.30	1.60	1.05

Table A.VI reports the percentage of variance of country-level temperature explained by each of the first five principal components of temperature. The principal components are computed using a panel of 48 countries over the 1970-2015 period.

Table A.VII

Elasticity of Global Equity Prices to Temperature Variations

	Horizon (K)		
Sample	1-year	3-year	5-year
ϕ_K	-0.002	-0.016	-0.015
(t-stat)	(-0.21)	(-2.29)	(-1.96)
[p-value*]	[0.426]	[0.029]	[0.051]

Table A.VII reports the response of global equity valuations to temperature fluctuations based on the following panel regression specification,

$$v_{i,t} = \bar{v}_i + \phi_K \, \Delta_K T_{i,t} + \varrho_r \, v_{i,t-1} + \alpha_r' \, \mathbf{v}_t + \zeta' \mathbf{x}_{i,t} + \varepsilon_{i,t} \, ,$$

where $v_{i,t}$ is the log of the price-dividend ratio of country i, $\bar{v}_i$ is a country-specific fixed effect, $\Delta_K T_{i,t}$ is the standardized K-year change in country-level temperature, $\mathbf{v}_t$ is a vector of global controls that include the first two principal components of the price-dividend ratios, and $\mathbf{x}_{i,t}$ is a vector of country-level control variables that include inflation, unemployment, the real interest rate, and GDP growth. The coefficients on $\mathbf{v}_t$ and $v_{i,t-1}$ vary across five geographical regions, r. The table presents the estimates of the (semi) elasticity of equity valuations to temperature, ϕ_K, and the corresponding t-statistics (in parenthesis) that are based on standard errors clustered by country and time-region. P-value* (in brackets) is the fraction of Monte Carlo samples generated under the null that temperature risks have no effect on equity prices in which t-statistics are lower than the sample statistics. The regression is estimated using 48 countries over 1970-2015.

Table A.VIII

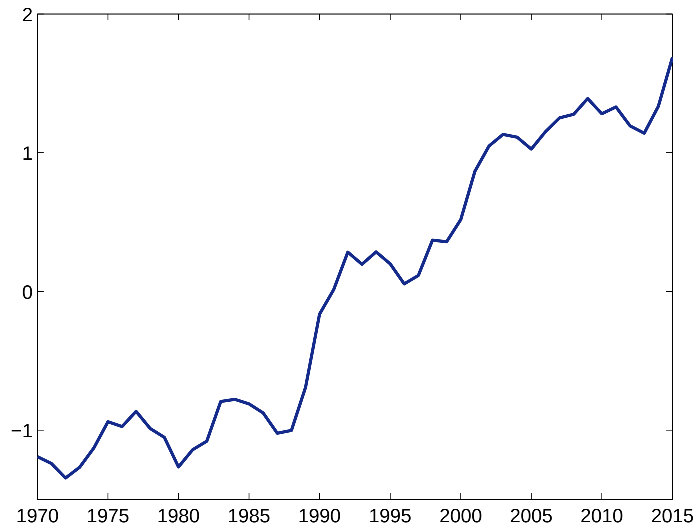
Elasticity of Global Equity Prices to Long- and Short-Run Temperature Variations

	Horizon (K)	
	3-year	5-year
ϕ_K^{LR}	-0.016	-0.015
(t-stat)	(-2.33)	(-1.99)
[p-value*]	[0.030]	[0.050]
ϕ_K^{SR}	0.007	0.004
(t-stat)	(0.74)	(0.45)
[p-value*]	[0.976]	[0.958]

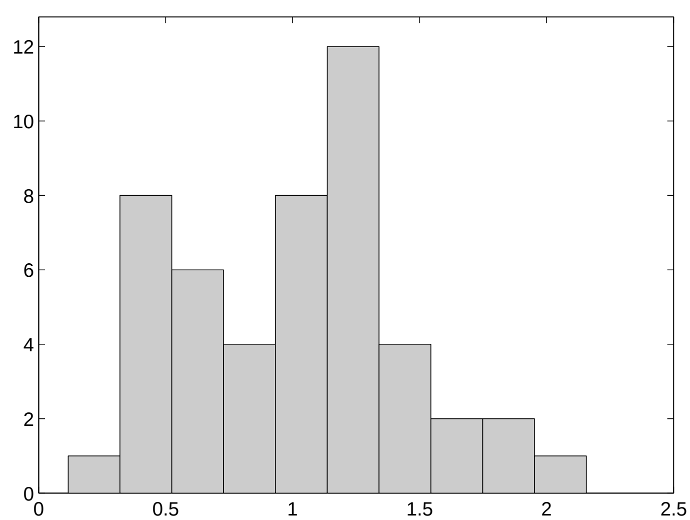
Table A.VIII reports the response of global equity valuations to temperature fluctuations based on the following regression specification,

$$v_{i,t} = \bar{v}_i + \phi_K^{LR}\, LR_{i,t}^K + \phi_K^{SR}\, SR_{i,t}^K + \varrho_r\, v_{i,t-1} + \alpha_r'\, \mathbf{v}_t + \zeta' \mathbf{x}_{i,t} + \varepsilon_{i,t}\ ,$$

where $v_{i,t}$ is the log of the price-dividend ratio of country i, $\bar{v}_i$ is a country-specific fixed effect, $LR_{i,t}^K$ represents low-frequency fluctuations in temperature measured by the three- or five-year change in local temperature, $SR_{i,t}^K$ represents short-run temperature fluctuations measured by changes in annual temperature that are orthogonal to long-run fluctuations, $\mathbf{v}_t$ is a vector of global controls that include the first two principal components of the price-dividend ratios, and $\mathbf{x}_{i,t}$ is a vector of country-level control variables that include inflation, unemployment, the real interest rate, and GDP growth. The coefficients on $\mathbf{v}_t$ and $v_{i,t-1}$ vary across five geographical regions, r. Short- and long-run temperature variations are standardized. The table presents the estimated slope coefficients, ϕ_{LR} and ϕ_{SR}, and the corresponding t-statistics (in parenthesis) that are based on standard errors clustered by country and time-region. P-value* (in brackets) is the fraction of Monte Carlo samples generated under the null that temperature risks have no effect on equity prices in which t-statistics are lower than the sample statistics. The regression is estimated using 48 countries over the 1970-2015 period.



(a) Trend in Temperature



(b) Histogram of the Trend in Local Temperature

Figure A.1. Trend in Country-Panel Temperature Data

Panel A of Figure A.1 shows the (normalized) first principal component of the five-year moving-average of local temperature series. Panel B shows the histogram of the trend in local temperature measured by the change in average temperature over the 2006-2015 period relative to the 1970-1979 average. The cross-sectional data comprise 48 countries; temperature is measured in degrees Celsius.