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Ravi Bansal
Dana Kiku
Marcelo Ochoa

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ABSTRACT

We use the forward-looking information from the US and global capital markets to estimate the economic impact of global warming, specifically, long-run temperature shifts. We find that global warming carries a positive risk premium that increases with the level of temperature and that has almost doubled over the last 80 years. Consistent with our model, virtually all US equity portfolios have negative exposure (beta) to long-run temperature fluctuations. The elasticity of equity prices to temperature risks across global markets is significantly negative and has been increasing in magnitude over time along with the rise in temperature. We use our empirical evidence to calibrate a long-run risks model with temperature-induced disasters in distant output growth to quantify the social cost of carbon emissions. The model simultaneously matches the projected temperature path, the observed consumption growth dynamics, discount rates provided by the risk-free rate and equity market returns, and the estimated temperature elasticity of equity prices. We find that the long-run impact of temperature on growth implies a significant social cost of carbon emissions.

Ravi Bansal
Fuqua School of Business
Duke University
1 Towerview Drive
Durham, NC 27708
and NBER
ravi.bansal@duke.edu

Dana Kiku
1206 South Sixth Street
Champaign IL 61820
dka@illinois.edu

Marcelo Ochoa
Federal Reserve Board
Division of Monetary Affairs
20th and C Streets, NW
Washington, DC 20551
marcelo.ochoa@frb.gov

Introduction

Global warming and its impact on the macro-economy is a matter of considerable importance (see Stern (2007) and Nordhaus (2008)). However, measuring the economic costs of global warming pose significant empirical challenges. This article shows that forward-looking equity prices that are determined by the discounted value of future growth rates provide important information about the cost of long-horizon temperature fluctuations. Using data from the US and global equity markets, we document that persistent temperature shifts have a significant negative effect on aggregate wealth and carry a positive risk premium in equity markets. We find that the risk premium for low-frequency (i.e, long-run) temperature fluctuations has been increasing over time along with temperature. To interpret our empirical evidence and to quantify the social cost of carbon, we provide a temperature-augmented long-run risk model. Our model, calibrated to match financial market data and our empirical evidence, implies that the social cost of carbon is quite large.

Our temperature-augmented long-run risks (LRR-T) model builds on the long-run risks framework of Bansal and Yaron (2004) and accounts for the interaction between climate change, economic growth and risk. To account for the potentially severe consequences of global warming, the model features temperature-induced natural disasters in future output and growth.[1] Disasters are triggered when temperature breaches a threshold level (tipping point) and capture the idea of tail risk related to global warming as discussed in Pindyck (2012). Different from the standard integrated assessment (IAM) models, in which climate change is assumed to cause a deterministic loss in output, in the LRR-T model, temperature is a source of economic risk — a persistent increase in temperature rises the likelihood of breaching the temperature tipping point and causing economic disasters. Temperature risks in our model affect aggregate wealth and asset valuations through the variation in expected growth rates and discount rates. In particular, a rise in temperature raises the marginal utility and lowers the current wealth to consumption ratio. Thus, temperature risks carry a positive premium, which is reflected in prices of forward-looking assets such as equities. The LRR-T model makes several predictions that guide our empirical work. First, consistent with the consensus view, in the model, the most significant effects of global warming unfold in the relatively

[1] Earlier work on economic disasters includes Rietz (1988), Barro (2009), Gourio (2012), and Bansal, Kiku, and Yaron (2010), among others.

distant future and, therefore, they are difficult to assess from the current and historical output data. However, temperature risks have a measurable impact on current equity valuations. We exploit this implication in our empirical work and use capital market data to estimate the price of temperature risks. Second, the model predicts that the price of low-frequency temperature risks and their risk premia increase with temperature. We test this implication using a conditional factor model specification that allows for variation in the market price of long-run temperature risk.

Using a cross-section of 25 book-to-market and size sorted portfolios from the US capital markets, we find that controlling for market and consumption growth risks, with only few exceptions, equities have negative exposure to temperature fluctuations. That is, higher temperature lowers equity valuations. Exploiting the cross-sectional relationship between average excess returns and temperature betas, we find that the market price of low-frequency temperature risks is significantly negative as predicted by our LRR-T model. In particular, the price of variations in five-year temperature trend is estimated at -0.19 with the Shanken (1992)-corrected t-statistics of -2.08. The negative price of temperature risks implies that a long-run increase in temperature is a bad economic state. Given that equity temperature betas are also negative, temperature risks carry a positive premium in equity markets. Our evidence is robust to the inclusion of industry portfolios. Further, consistent with the model's prediction, we document that the premium for long-run temperature risks associated with global warming has increased significantly along with the rise in temperature. The premium for a one-standard deviation exposure to long-run temperature risks has doubled over the past 80 years from about 0.2% to 0.4%.

We confirm our US-based evidence using a panel of 39 countries over the 1970-2012 time period. We find that after controlling for global and local risk factors, temperature has a significantly negative impact on equity valuations. We also find that temperature elasticity has become more negative over time; for example, the elasticity of equity prices to temperature fluctuations changes from about -1.6% in the early pre-2000 sample to -7.6% over the entire sample period. This evidence suggests that during the period over which temperature has risen, its impact on the economy has amplified. Importantly, we show that the negative impact of temperature on equity valuations is mostly driven by its low-frequency (i.e., trend) fluctuations that most closely correspond to global warming. Earlier empirical works by Dell, Jones, and Olken (2012), and Bansal and Ochoa

(2012) examine the effect of temperature variations on gross domestic product. In contrast, we focus on forward-looking equity valuations — this allows us to learn about both long-term growth and risk effects of temperature, which past income data do not provide.

We use our empirical estimates and the LRR-T model to quantify the social cost of carbon (SCC) that has become an important concept in the economic analysis of global warming and policy decision making. Intuitively, SCC measures the present value of damages due to a marginal increase in carbon emissions and as such, it allows us to assess the incentive to curb industrial emissions. To provide the estimate of SCC, we calibrate our model to match the projected trend in global temperature, consumption dynamics, our estimates of temperature elasticity of equity valuations and the observed discount rates from capital markets.[2] The latter is important as the social cost of carbon can be highly sensitive to discount rates as highlighted in Nordhaus (2008), Gollier (2012) and Golosov, Hassler, Krusell, and Tsyvinski (2014). We find that with a preference for early resolution of uncertainty, the social cost of carbon is quite significant. In our baseline LRR-T model, SCC is measured at about 100 dollars of world consumption per metric ton of carbon, which is equivalent to a tax of about 20 cent per gallon of gas. It declines to a still sizable $40 when temperature is assumed to affect only the level of output but not the long-term growth. Thus, when distant risks matter, carbon emissions and rising temperature carry a significant price. In sharp contrast, we show that in a power-utility setting, long-run temperature is not perceived as sufficiently risky because its impact is deferred to the future. Consequently, the social cost of carbon under power-utility preferences is very small, of merely 1 cent per metric ton of carbon. We also show that a power-utility specification, which is the standard assumption in the integrated assessment models, fails to explain the empirical finding of negative elasticity of wealth valuations to temperature risks — in contrast to the data, under power utility (with risk aversion above one), aggregate wealth increases in states of high temperature and high likelihood of disasters. In all, this evidence shows that the social cost of carbon emissions and, hence, the incentive to abate global warming depend critically on the attitude towards long-run risks. The implications of risk preferences for the optimal policy response to climate change are explored in a companion paper (see Bansal, Kiku, and Ochoa (2015)).

[2] We focus on the exchange economy to maintain tractability and ensure that the model is able to match the asset market data. This is quantitatively difficult to achieve in a production-based setting.

The rest of the paper is organized as follows. In the next section, we set up the LRR-T model. Section 2 provides specifics of our calibration. In Section 3, we present the quantitative solution to the model and discuss its implications. In Section 4 we provide empirical evidence of the impact of temperature risks using the US data. In Section 5, we document the impact of long-run temperature fluctuations on equity prices using data from global capital markets. Section 6 concludes.

1 LRR–T Model

In this section, we set up a unified general equilibrium model of the world economy and global climate. Our LRR-T model accounts for the interaction between current and future economic growth and climate change in a framework that features elements of Epstein and Zin (1989), Bansal and Yaron (2004), Hansen and Sargent (2006), Rietz (1988) and Barro (2009) models. A unique dimension of our model is that it incorporates temperature-induced natural disasters that are expected to have a long-run effect on future well-being. This feature is consistent with by now the consensus view that global warming will have a long-lasting negative effect on ecological systems and human society (IPCC (2007, 2013)).[3]

1.1 Climate-Change Dynamics

We assume that industrial carbon emissions are driven by technologies that are used to produce consumption or output. Let C_t denote the total amount of consumption goods, then the level of CO_2 emissions is given by:

$$E_t = C_t^{\lambda_t} , \tag{1}$$

where $\lambda_t \geq 0$ is carbon intensity of consumption. The (log) growth rate of emissions is, therefore,

$$\Delta e_{t+1} = \lambda_{t+1} \Delta c_{t+1} + \Delta \lambda_{t+1} c_t , \tag{2}$$

where $e_t \equiv \log E_t$, $c_t \equiv \log C_t$, and Δ is the first difference operator.

[3]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.

Carbon intensity is assumed to be exogenous and we calibrate it to match the projected path of CO_2 emissions under the business-as-usual (BAU) scenario of Nordhaus (2010). We assume that in the long-run limit, both intensity and emissions decline to zero to capture the eventual replacement of current production technologies with carbon-free technologies as fossil fuel resources become depleted. We will discuss our calibration in more details below.

The accumulation of greenhouse gasses, of which carbon dioxide is the most significant anthropogenic source, leads to global warming due to an increase in radiative forcing. The geophysical equation linking CO_2 emissions and global temperature is a modified version of that in Nordhaus (2008)'s DICE model.[4] In particular, we assume that global temperature relative to its pre-industrial level follows:

$$T_t = \nu_t T_{t-1} + \chi e_t \,, \tag{3}$$

where T_t is temperature anomaly (i.e., temperature above the pre-industrial level), e_t is the log of CO_2 emissions, $\nu_t \in (0, 1)$ is the rate of carbon retention in the atmosphere and, hence, the degree of persistence of temperature variations, and $\chi > 0$ is temperature sensitivity to CO_2 emissions.[5] Note that, effectively, Equation (3) describes a stock of man-made emissions in the atmosphere (i.e., CO_2 concentration), and temperature anomaly is assumed to be proportional to the level of carbon concentration. These dynamics are 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)).

We assume that climate change due to global warming has a damaging effect on the economy. Once temperature crosses a tipping point, $T_t \geq T^*$, the economy becomes subject to natural disasters that result in a significant reduction of economic growth. The probability of natural disasters and the loss function are described next.

[4] Nordhaus (2008) models carbon-cycle dynamics using a three-reservoir system that accounts for interactions between the atmosphere, the upper and the lower levels of the ocean. The dynamics of temperature that we use is qualitatively consistent with the implications of his structural specification. Also, quantitatively, our calibration is designed to match temperature dynamics under the BAU policy as predicted by Nordhaus (2010).

[5] We assume that ν_t is increasing in carbon intensity. This feature implies a more persistent effect of emissions at high levels of CO_2 concentration and temperature and is designed to capture re-inforcing feedbacks of global warming due to melting ice and show that increases absorbtion of sunlight, an increase in water vapor that causes temperature to climb further, a more intensive release of carbon dioxide and other greenhouse gases from soils as temperature rises, a reduced absorbtion of carbon by warmer oceans, etc.

1.2 Consumption Growth Dynamics

Consumption growth follows the dynamics as in Bansal and Yaron (2004) augmented by the impact of natural disasters caused by global warming. The log growth rate of consumption is given by:

$$\Delta c_{t+1} = \mu + x_t + \sigma\eta_{t+1} - D_{t+1}\,, \tag{4}$$

$$x_{t+1} = \rho_x x_t + \varphi_x \sigma \epsilon_{t+1} - \phi_x D_{t+1}\,, \tag{5}$$

where μ is the unconditional mean of gross consumption growth; x_t is the expected growth component; η_{t+1} and ϵ_{t+1} are standard Gaussian innovations that capture short-run and long-run risks, respectively; and $-D_{t+1}$ is a decline in consumption growth due to temperature-induced disasters.

We assume that natural disasters are triggered when temperature reaches a tipping point T^* and model their impact using a compensated compound Poisson process,

$$D_{t+1} = \sum_{i=1}^{N_{t+1}} \zeta_{i,t+1} - d_t \pi_t\,, \tag{6}$$

where N_{t+1} is a Poisson random variable with time-varying intensity π_t, and $\zeta_{i,t+1} \sim \Gamma(1, d_t)$ are gamma distributed jumps with a time-varying mean of d_t. We assume that both occurrence of natural disasters and their damages are increasing in temperature. In particular, the expected size of disasters is given by:

$$d_t = \begin{cases} q_1 T_t + q_2 T_t^2\,, & \text{if } \; T_t \geq T^* \\ 0\,, & \text{otherwise} \end{cases} \tag{7}$$

and disaster intensity follows:

$$\pi_t \equiv E_t[N_{t+1}] = \begin{cases} l_0 + l_1 T_t\,, & \text{if } \; T_t \geq T^* \\ 0\,, & \text{otherwise,} \end{cases} \tag{8}$$

where parameters q_1, q_2, l_0 and l_1 are greater than zero. Quadratic loss functions are commonly used in the climate-change literature, e.g., Nordhaus (2008), Weitzman (2010), Lemoine and Traeger (2012), Golosov, Hassler, Krusell, and Tsyvinski (2014), and Heutel (2012).

Note that in our specification, climate-change disasters affect consumption growth rate and, therefore, have a permanent effect on the economy. We focus on potentially catastrophic consequences of climate change that might not be possible to reverse or easily adapt to, and as such they are expected to have a long-lasting impact on human well-being. These include but not limited to rising sea levels and drowning of currently populated coastlines and islands, intensified heat waves, severe droughts, storms and floods, destruction of ecosystems and wildlife, spreading of contagious tropical diseases, shortages of food and fresh water supply, significant destruction of property and human losses. To incorporate these types of large-scale and permanent effects we assume that disasters affect the growth rate of the economy instead of just the current level of output as is typically assumed in the integrated assessment models.[6] A permanent impact of climate change and its implications for policy decisions are also analyzed in Pindyck (2012). We consider a more general specification in which global warming may affect not only current but also future consumption growth. While uncertainty over adaptation to global warming is well recognized, the assumption that rising temperature will have a negative effect on human welfare and global economy is standard in the climate-change literature (eg., Nordhaus (2010), Weitzman (2010), Anthoff and Tol (2012), Pindyck (2012)).[7]

1.3 Preferences

Following the long-run risk literature, we define preferences recursively as in Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1990). We use U_t to denote the continuation utility at time t, which is given by:

$$U_t = \left\{ (1-\delta) C_t^{1-\frac{1}{\psi}} + \delta \Big(E_t \Big[U_{t+1}^{1-\gamma} \Big] \Big)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}}, \tag{9}$$

where δ is the time-discount rate, γ is the coefficient of risk aversion, and ψ is the intertemporal elasticity of substitution (IES). When $\gamma = \frac{1}{\psi}$, than preferences collapse to the power utility specification, in which the timing of the resolution of uncertainty is irrelevant. When risk aversion

[6]For example, the DICE/RICE models of Nordhaus (2008, 2010), the FUND model of Tol (2002a, 2002b) and Anthoff and Tol (2013), and the PAGE model of Hope (2011).

[7]The implications of tail risks in the presence of uncertainty about climate-change impact are analyzed in Weitzman (2009).

exceeds the reciprocal of IES, $\gamma \geq \frac{1}{\psi}$, early resolution of uncertainty about future consumption path is preferred. Power utility is the standard assumption in the integrated assessment models of climate change. Preferences for early resolution of uncertainty are the benchmark in the long-run risks literature and, as emphasized in Bansal and Yaron (2004), are critical for explaining the dynamics of financial markets. We consider both specifications and highlight the importance of preferences to risks and to temporal resolution of risks for the welfare analysis of global warming.

Note that the maximized life-time utility is proportional to the wealth to consumption ratio and as such it is determined by the present value of expected consumption growth from now to infinity. Specifically, the value function normalized by current consumption is given by:

$$\frac{U_t}{C_t} = \left[(1-\delta)Z_t\right]^{\frac{\psi}{\psi-1}}, \tag{10}$$

where $Z_t \equiv \frac{W_t}{C_t}$ is the aggregate wealth-consumption ratio. Aggregate wealth can be represented by a portfolio of consumption strips:

$$W_t = \sum_{j=0}^{\infty} P_t^{(j)}, \tag{11}$$

where $P_t^{(j)}$ is the price of the consumption strip that matures at time $t+j$ (i.e., the price of the asset that pays aggregate consumption at time $t+j$). Consequently, the wealth-consumption ratio can be expressed as:

$$Z_t = \sum_{j=0}^{\infty} \frac{E_t\left[C_{t+j}/C_t\right]}{E_t R_{j,t+j}}, \tag{12}$$

where $E_t R_{j,t+j} \equiv \frac{E_t C_{t+j}}{P_t^{(j)}}$ is the discount rate of the consumption strip with j-periods to maturity. The prices (hence, discount rates) of consumption strips are determined by the standard Euler equation:

$$P_t^{(j)} = E_t\left[M_{t+j} C_{t+j}\right], \tag{13}$$

where the j-period stochastic discount factor (SDF) is given by:

$$M_{t+j} = \prod_{i=1}^{j} \delta^{\theta} G_{t+i}^{-\theta/\psi} R_{t+i}^{\theta-1}, \tag{14}$$

where $G_{t+i} \equiv \frac{C_{t+i}}{C_{t+i-1}}$, R_{t+i} is the endogenous return on wealth, and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$.

Equation (12) highlights the forward-looking nature of aggregate wealth and asset prices — the current price of the consumption claim carries information about agents' expectations about future economic growth (C_{t+j}/C_t) and risk ($E_t R_{j,t+j}$). If climate change is expected to have a significant impact of either future growth or risk, it will be reflected in current wealth and asset prices. Also, as Equation (10) shows, the agent's utility is affected by climate change through the impact of temperature risk on the wealth-consumption ratio. Hence, the elasticity of aggregate wealth and asset prices to temperature risk determines the economic impact of climate change on the life-time utility.

1.4 Social Cost of Carbon

The social cost of carbon (SCC) has become an important concept in the cost-benefit analysis of global warming. SCC measures the present value of damages due to a marginal increase in carbon emissions. Formally, it is defined as marginal utility of carbon emissions:

$$SCC_t = -\frac{\partial U_t}{\partial E_t} \Big/ \frac{\partial U_t}{\partial C_t} \tag{15}$$

The scaling by marginal utility of consumption allows us to express the cost in units of consumption goods (time-t dollars), which makes SCC easy to interpret. Using Equation (10), we can express the social cost of carbon at time 0 as:

$$SCC_0 = \frac{\psi}{\psi - 1} \frac{-\partial Z_0 / \partial E_0}{Z_0} C_0 \,. \tag{16}$$

That is, SCC is equal to the (appropriately scaled) monetized value of a percentage change in wealth due to an additional unit of emissions. Intuitively, the social cost of carbon measures an increase in current consumption that is required to compensate for damages caused by a marginal increase in date-0 emissions.

As Equation (16) shows, the social cost of carbon emissions is determined by the elasticity of the valuation ratio to carbon emissions. An increase in current emissions leads to higher temperature and affects asset prices through two channels — the cash-flow channel that carries the impact of temperature variations on future consumption, and the discount-rate channel that carries the impact of temperature on future risk. Note that while the cash-flow effect depends on the temperature-induced damages and is invariant to agents' preferences, the discount rate effect is determined importantly by risk preferences. For example, in an economy, where agents do not care about distant risks including climate risks that are expected to unfold in the future, the discount rate effect and, therefore, the social cost of carbon might be quite small. In contrast, in an economy, where agents are concerned about future risks, the discount-rate effect of rising temperature on asset prices might be quite significant and carbon emissions might carry sizable risk premia.[8] Equation (16) implies that discount rates from capital markets provide very useful information about the magnitude of the social cost of carbon and the economic importance of temperature risks.

2 Calibration and Model Implications for Temperature Risk

We calibrate the path of carbon intensity (λ_t) and temperature (T_t) to match the business-as-usual forecasts of CO_2 emissions and global warming in Nordhaus (2010) and IPCC (2007, 2013). Time in the model is measured in decades and we assume that the steady state in the BAU case will be reached in 60 periods or 600 years from now. The steady state corresponds to the state in which anthropogenic emissions decline to zero and the temperature anomaly disappears due to the ultimate de-carbonization of the economy. The first two panels of Figure 1 show the calibrated path of carbon intensity and the amount of emissions along the transitional path. Under the BAU policy, carbon intensity is expected to remain relatively high over the next two centuries and carbon emissions are expected to accelerate.

As more and more CO_2 emissions are released, the concentration of carbon in the atmosphere increases and temperature anomaly escalates. The projected BAU path of temperature is shown in Panel (c) of Figure 1. Calibration of global warming dynamics and the impact of climate change on consumption growth are presented in Table I.[9] To capture re-enforcing feedback effects of emissions, we allow the retention of carbon in the atmosphere, ν_t, to increase in carbon intensity. We assume that about 80% of current CO_2 emissions will remain in the atmosphere for another century, their

[8] Hansen and Scheinkman (2012), and Borovička and Hansen (2014) develop a rigorous analysis of how price elasticities relate to growth and discount-rate elasticities to exogenous shocks.

[9] To facilitate interpretation of the calibrated parameters, we report and discuss them in annualized terms.

decay will increase as the rate of emissions slows down. The average value of the retention rate under the BAU scenario is equal to 0.962, which implies that about 70% of CO_2 molecules emitted along the transitional path are removed from the atmosphere within a century. The precise atmospheric life of carbon dioxide is yet unknown but our calibration is designed to roughly match the available estimates in the geophysical literature (Jacobson (2005), and Archer (eg., 2005, 2009)).

We set the tipping point of global warming disasters to 2°C that according to the Copenhagen accord is internationally recognized as a likely trigger of dangerous changes in the climate system. If the current trend in emissions continues, temperature is expected to cross the disaster threshold in about 30-35 years from now (see Figure 1c). This assumption is fairly consistent with the most recent forecast of the IPCC. As reported in the Fifth Assessment Report, the global mean surface temperature anomaly is expected to exceed 2°C in three to four decades from now (IPCC (2013)).

Once the 2°C tipping point is crossed, the global economy faces the risk of natural cataclysms. Both intensity and size of climate-induced disasters are increasing with temperature and their expected paths are presented in Figure 2. Time-varying intensity dynamics are motivated by the evidence in Raddatz (2009) that, worldwide, the number of climatic disasters (such as droughts, floods, and extreme temperature) has increased over the last four decades — the period that has experienced a steep increase in temperature. The initial impact of global warming is assumed to be relatively moderate but it is intensified as temperature keeps rising. In particular, we assume that upon the crossing of the 2°C threshold, the annual probability of disasters is about 1.2% and their average size is −0.7%. As temperature reaches its peak, the disaster probability rises to 2.8% per annum and average losses increase to −6.0%. Note that our calibration of disaster distribution is very conservative relative to the rare disaster asset pricing literature (Barro (2009), Barro and Ursua (2012), and Wachter (2013)).

Table II summarizes our calibration of preferences and consumption dynamics. Our LRR-T model features preferences for early resolution of uncertainty and incorporates a negative effect of global warming on current and future consumption growth. We choose preference parameters so that the model is able to match key moments of financial data. In particular, we set risk aversion at 5, the intertemporal elasticity of substitution at 1.5, and the subjective time-discount factor at 0.99. We set the unconditional mean of consumption growth at 1.8% and assume that the standard deviation of i.i.d. gaussian shocks is 1.6% per annum. We calibrate the dynamics of the long-run risk component to match persistence of consumption growth in normal times. Consistent with the US consumption data, in our specification the first-order autocorrelation of consumption growth absent climate disasters is equal to 0.44. Exposure of the expected consumption growth to disaster risks is set at 0.05. Note that while the average size of climate disasters in the expected growth component is assumed to be quite modest, their effect on consumption is propagated due to persistence of long-run risks. That is, upon a disaster, consumption growth does not immediately bounce back to its normal level but is expected to remain low for a relatively long while.

The dynamics of future climate changes and their economic consequences are highly uncertain and not yet well-understood. Pindyck (2007), and Heal and Millner (2014) provide a comprehensive discussion of various sources of uncertainty in environmental economics. While some empirical evidence on the impact of rising temperature and climatic disasters does exist (for example, Tol (2002a, 2002b)), it is based on human experiences that have not yet been subjected to catastrophic climate changes that we consider. Therefore, we can use it only as a guidance rather than a target. Whenever possible, we calibrate the model parameters to be broadly consistent with assumptions of the standard integrated assessment models and consensus forecasts outlined by the IPCC. With this in mind, we do not intend to claim that our calibrated dynamics represent the future better than others. We consider plausible dynamics and focus on highlighting the channels through which beliefs about climate-change risks and risk preferences affect aggregate wealth. To discriminate across the LRR-T model and alternative specifications, we confront each with financial market data and empirical evidence on the impact of rising temperature on equity prices.

We solve the model numerically using value function iterations. We start at the "terminal" date at which temperature anomaly disappears and the solution becomes stationary, and work backwards in time. We discretize the state space and use Chebyshev polynomial approximation of the value policy function.

3 Asset Pricing Implications of Temperature Risks

Different from the standard integrated assessment models, in which climate change is assumed to cause a deterministic loss in future output or consumption, in our model, global warming affects the economy through a risk channel. That is, climate change is a source of economic risk. Figure 3 displays the implications of global warming for the distribution of consumption growth. Notice that because temperature-induced disasters are compensated, they have no effect on the ex-ante mean of log consumption growth. This is similar to gaussian i.i.d. and long-run risks — ex-ante, global warming does not affect the log level of future consumption path but does affect its variation, i.e., risk. As Panel (a) shows, climate-change driven disasters increase the ex-ante variation of future growth. In our calibration, at the peak of temperature anomaly, the ex-ante annualized volatility of cumulative consumption growth is about 0.18% higher compared with a no-disaster economy (in relative terms this corresponds to more than ten percent increase in volatility). Also, because global-warming disasters represent tail risks, the distribution of future consumption growth is both negatively skewed and fat-tailed. Panel (b) of Figure 3 presents a side-by-side comparison of the distribution of the normalized consumption growth at the peak of climate-driven disasters and the corresponding distribution in the economy with no disasters.

Given the preference parameters and the dynamics of consumption in Section 2, we solve the model numerically to account for the intrinsic non-linearities. To understand intuitively the pricing implications of carbon emissions and temperature risks, it is useful to consider a log-linear approximation of the stochastic discount factor stated in Equation (14). Similar to the LRR model, the innovation in the log of the SDF that determines risk prices can be approximately written as:

$$m_{t+1} - E_t[m_{t+1}] \approx - \lambda_\eta \eta_{t+1} - \lambda_\epsilon \epsilon_{t+1} - \lambda_D(T_t)\big(- D_{t+1}\big)\,, \tag{17}$$

where η_{t+1} and ϵ_{t+1} are short- and long-run consumption risks, respectively, and $-D_{t+1}$ is a temperature-induced disaster. Consider the impact of a marginal increase in current emissions. An increase in emissions leads to higher temperature. A positive shock to temperature rises the likelihood of future disasters and, therefore, the marginal utility. Thus, temperature risks carry a negative price: $\lambda_D(T_t) < 0$. Further, because both the frequency and the size of potential damages depend on the level of temperature, so does the magnitude of the price of temperature risks. That is, the price of temperature risk rises as temperature climbs up: $\frac{\partial \lambda_D(T_t)}{\partial T_t} < 0$. Panel (a) of Figure 4 shows the elasticity of the stochastic discount factor to a one-percent increase in time-0 emissions. As the figure shows, the marginal utility increases in response to higher emissions, and the increase in marginal utility is amplified with temperature — the higher the temperature, the larger the response of the marginal utility, i.e., the larger the price of temperature risks.

The premium for temperature risks is determined by their price and an asset exposure to temperature fluctuations. Consider the return on aggregate wealth. Using log-linearization, we can write the innovation in the log return, r_{t+1}, as a sum of innovations in consumption growth and the wealth to consumption ratio, i.e.,

$$r_{t+1} - E_t[r_{t+1}] \;\approx\; \Big(\Delta c_{t+1} - E_t[\Delta c_{t+1}]\Big) \;+\; \Big(z_{t+1} - E_t[z_{t+1}]\Big)\,, \tag{18}$$

where $z_{t+1} \equiv \log(Z_t)$ is the log of the aggregate wealth-consumption ratio.[10] As Equation (18) shows, exposure of wealth return to temperature risks depends on the impact of temperature fluctuations on consumption growth and aggregate wealth. In our model, climate change is assumed to cause disasters in consumption that become more severe as temperature keeps rising (see Equation (4)). Under a preference for early resolution of uncertainty, that is, when risk aversion is larger than the reciprocal of intertemporal elasticity of substitution, the impact of temperature fluctuations on aggregate wealth is also negative. The elasticity of the wealth-consumption ratio to a marginal increase in current emissions and and temperature is presented in Panel (b) of Figure 4. As the figure shows, the wealth-consumption ratio falls in response to an increase in temperature. Thus, the temperature beta of the aggregate wealth return (i.e., the projection coefficient of the asset return on temperature shock) is negative and is increasing in magnitude with temperature. Recall that temperature risk has a negative market price; hence, the product of the temperature beta and its price that determines the temperature risk premium is positive. Higher emissions and temperature raise temperature risk premia and future discount rates and lead to a decline in the wealth to consumption ratio and asset valuations.

[10] This is similar to the innovation in an equity return, which is approximately equal to a sum of innovations in dividend growth and the price to dividend ratio.

To explore the implications of risk preferences for the joint dynamics of asset prices and temperature, we consider two alternative specifications: (1) preferences for early resolution of uncertainty, which we refer to as "Pref for ERU", and (2) constant relative risk aversion preferences that we refer to as "Power Utility". To facilitate the comparison, we simplify consumption dynamics by shutting off the long-run risk component and assuming that global warming affects only realized consumption growth. Under these dynamics, climate risks continue to have a permanent negative impact on consumption level but are assumed to have no effect on future economic growth. The calibration of the two alternative specifications is summarized in Table II.

Figure 5 shows the response of aggregate wealth-consumption ratio to a one-percent increase in current emissions under the two preference specifications. Similar to our baseline LRR-T model, under preferences for early resolution of uncertainty, higher emissions lead to an increase in discount rates and a fall in asset valuations. In contrast, in the power-utility economy with risk aversion larger than one, discount rates decline in response to higher emissions and higher temperature (due to a significant decline in risk-free rates) and asset prices feature a positive elasticity to temperature risks. That is, under power utility, the wealth-consumption ratio rises when disasters are expected to be more frequent and economic losses are expected to be larger.[11] The implications of temperature for the wealth to consumption ratio and equity valuations (price-dividend ratios) are important in identifying the role of temperature risks.

The response of asset prices to temperature fluctuations in our baseline LRR-T model and under the two alternative specifications is summarized in Table III. For each specification, we simulate 50,000 paths of emissions, temperature and consumption and solve for the price of the consumption claim. Temperature elasticities of asset prices are estimated by regressing the log of the price-consumption ratio on temperature controlling for the relevant state variables. As the table shows, under recursive preferences, asset valuations fall in response to an increase in temperature. In particular, in the LRR-T model, a 0.5°C increase in temperature (which corresponds to one standard deviation of the empirical distribution) lowers the price of the consumption claim by about 0.87%. If we account for market leverage of around three, the response of equity prices to temperature shocks

[11] The power-utility agents are still worse off since their utility is inversely related to wealth, but because the elasticity of utility to wealth is quite low, the decline in utility is very tiny, more than three orders of magnitude smaller than the corresponding decline under recursive preferences.

implied by our LRR-T model is about -2.6%, which as we show below is quantitatively similar to our empirical estimates. Also, as shown in Figure 4, the sensitivity of asset prices to temperature risks increases with temperature (as the economy gets closer to the disaster threshold). For example, ten and twenty years from now, the price response rises in magnitude from the current -0.0174 to -0.019 and -0.021, respectively.

As Table III further shows, the power-utility implied response of prices to temperature risks is very different compared with recursive preferences. In the power-utility case, asset prices rise with temperature. Quantitatively, the price-consumption ratio increases by about 0.024% in response to a 0.53°C increase in temperature. This is the discount-rate or, more precisely, the risk-free rate effect that we discussed above. In the power-utility setting, an increase in temperature leads to a significant decline in discount rates and, consequently, an increase in asset prices.

Risk preferences have also important implications for the marginal cost of carbon emissions, which we present in Table IV. In our LRR-T model, SCC is estimated at about \$104 per ton of carbon.[12] In the presence of risks that affect long-term growth, agents' utility is highly sensitive to emissions due to both high potential damages and late resolution of temperature risks. The two channels combined lead to the high price of carbon emissions. Further, even when the long-run risk channel is shut off, under preferences for early resolution of uncertainty, distant climate risks continue to carry a significant weight and the social cost of carbon remains significant, of about \$40. In contrast, in the power-utility setting, SCC is quite small as temperature risks under power utility are effectively discounted out as they are expected to realize in a relatively distant future. Note that Nordhaus (2014), and Golosov, Hassler, Krusell, and Tsyvinski (2014) report significant estimates of the social cost of carbon under power utility preferences because they assume that climate change causes a sizable reduction in the current and near-future output. Differently, we assume that significant consequences of temperature risks will be realized in the future rather than today and, therefore, find that the power-utility agent assigns a small price to carbon emissions. It is important to note that weather the impact of climate change is realized now or in the future, under power utility with risk aversion above one, asset prices always feature a positive elasticity to temperature risks, which is inconsistent with the robustly negative response of asset prices to

[12]The social cost of carbon is measured in 2012 dollars of world household final consumption expenditure per metric ton of carbon.

temperature fluctuations in the data that we document and discuss below.

Temperature risks aside, our LRR-T model corresponds to the long-run risks model of Bansal and Yaron (2004). As they show, with preferences for early resolution of uncertainty, risks that matter for the long run carry high risk premia and are able to account for the dynamics of equity prices and asset returns. Our calibration of the gaussian part of consumption dynamics is similar to theirs and, therefore, is consistent with financial market data. As Table IV shows, the average risk-free rate in the LRR-T specification is 0.9%, and the risk premium on consumption claim is about 1.7%. Hence, the implied equity premium, assuming leverage of 3, is about 5% per annum. It is important to emphasize that most of the risk premium is the compensation for long-run gaussian risks, and only a relatively modest fraction of the overall premium is due to temperature risks.

4 Temperature and Asset Prices: Evidence from the US Markets

In our model, rising temperature increases economic risk and thus has a negative effect on the macro-economy. Further, with a preference for early resolution of uncertainty, higher temperature leads to a decline in aggregate wealth and asset prices. The empirical research on the impact of global warming on the macro-economy has primarily focused on the effect of temperature on growth. For example, Dell, Jones, and Olken (2012) analyze the impact of rising temperature on output and find evidence that current output and short-term future growth tend to decrease with temperature, although the negative effect seems to be entirely concentrated in low-income countries. Motivated by our model, we take a different approach and measure the impact of temperature on the macro-economy using forward-looking equity prices rather than past growth rates. Long-horizon equity prices reflect information about future expected growth rates and future risks. If temperature is expected to affect future growth and/or risk, these expectations ought to be reflected in capital markets provided that agents care about the future. Note that if past and current growths have not yet been exposed to catastrophic temperature risks, it would not be possible to detect the impact of temperature from the available output data. In contrast to backward-looking output growth rates, equity prices reveal agents' expectations about the future and, thus, contain information about a potential impact of temperature on the economy. This is the idea that we pursue in our empirical analysis of equity prices and temperature fluctuations.

Although, for simplicity, in the theory section we consider the economy in aggregate without explicitly modeling its sectors or markets, the cross-sectional implications of our model are straightforward. Assets that are highly exposed to temperature risks should carry higher risk premia relative to assets with lower sensitivity. We exploit this prediction to measure the impact of temperature fluctuations on equity prices and to estimate the price of temperature risks.

4.1 US Data

We use two data sets from the US equity markets: the standard set of 25 portfolios sorted by market capitalization and book-to-market ratio and a set of industry portfolios.[13] Following the classification of the National Institute for Occupational Safety and Health (NIOSH) and Graff Zivin and Neidell (2014), we construct ten industry portfolios that represent high and low heat-exposed sectors of the US economy. The first group comprises mining, oil and gas extraction, construction, transportation, and utilities — industries that operate in hot and humid environments. The remaining sectors: manufacturing, wholesale, retail trade, services, and communications, are classified as sectors with low exposure to heat.[14] To control for market and consumption risks, we use the CRSP value-weighted portfolio of all stocks traded on the NYSE, AMEX, and NASDAQ and per-capita series of real consumption expenditure on non-durables and services from the NIPA tables available from the Bureau of Economic Analysis. Excess returns are constructed by subtracting the CRSP risk-free rate series from portfolio returns. Temperature data for the contiguous US are measured in degrees Fahrenheit and come from the National Oceanic and Atmospheric Administration of the US Department of Commerce. The data are sampled at the annual frequency and span the period from 1934 to 2014.

[13] Book-to-market and size sorted portfolio data are obtained from Kenneth French's online data library.

[14] We are unable to consider the agricultural sector because a portfolio of public agricultural firms is extremely thin — on average, it contains about 9 firms and in the first part of the sample it comprises only 1-2 firms. Firms in the financial section are excluded.

4.2 Temperature Betas

We measure equity exposure to temperature risks by regressing portfolio excess returns on temperature variations controlling for market and economic growth risks, specifically:

$$r_{i,t}^{e} = \bar{r}_i + \beta_{\Delta T,i}\, \Delta\overline{T}_t^K + \beta_{M,i} r_{M,t}^{e} + \beta_{C,i}\xi_{C,t} + u_{i,t} \ , \tag{19}$$

where $r_{i,t}^e$ is the excess return of portfolio i, $\Delta\overline{T}_t^K$ is the (de-meaned) change in K-year moving-average trend in temperature, $r_{M,t}^e$ is the excess return of the market portfolio, and $\xi_{C,t}$ is the innovation in a smoothed aggregate consumption growth that proxies for variations in macroeconomic growth (as in Parker and Julliard (2005), Bansal, Dittmar, and Lundblad (2005)). Our controls for market and consumption risks are motivated by our theoretical model, and the equilibrium CAPM and consumption-based CAPM frameworks of Sharpe (1964), Lucas (1978), and Breeden (1979).

To differentiate between low-frequency temperature shocks that contribute to global warming and short-term fluctuations in temperature that correspond to variations in weather and to understand the impact of both, we consider different horizons K's ranging from one to ten years. Note that when $K = 1$, $\Delta\overline{T}_t^K \equiv \Delta T$, which corresponds to annual (short-run) fluctuations in weather. When $K \gg 1$, $\Delta\overline{T}_t^K$ represents long-run temperature risks that are associated with global warming. In essence, by averaging temperature variations over time, we filter out short-run weather fluctuations and isolate shocks to the low-frequency component (i.e., temperature trend). Our empirical evidence is similar if, instead, we construct temperature trend using the Hodrick and Prescott (1997) filter.[15] Also, our evidence remains virtually the same if we use innovations in the trailing moving-average 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.

Figure 6 presents a scatter plot of average excess returns and equity exposure to annual change in temperature (Panel (a)) and variation in the five-year moving average trend (Panel (b)). Note that with only few exceptions, equity portfolios have negative elasticity to temperature fluctuations.

[15] Note that the Hodrick and Prescott (1997) filter is a two-sided filter and, hence, it is constructed using future temperature data. The one-sided trailing moving-average that we use is not subject to look-ahead biases because it uses only the already available, current and past, temperature data.

That is, equity prices tend to decline in response to an increase in temperature. Notice also that portfolios that carry high premia feature high sensitivity to low-frequency temperature risks, which suggests that temperature risks carry a negative price.

The magnitudes of long-run temperature betas corresponding to the five-year horizon are reported Table V. As Panel A shows, while almost all book-to-market and size sorted portfolios feature a negative response to long-run temperature risks, their exposure is not homogenous. In particular, high book-to-market firms tend to have much higher (i.e., more negative) exposure to temperature fluctuations relative to low book-to-market firms. Empirical evidence in Bansal, Dittmar, and Lundblad (2005), Hansen, Heaton, and Li (2008), and Bansal, Kiku, Shaliastovich, and Yaron (2014) shows that high book-to-market firms are much more sensitive to persistent growth risks compared with low book-to-market firms, which accounts for the cross-sectional differences in temperature exposure that we document. According to our LRR-T model, an increase in temperature trend raises the likelihood of growth diasters in the long run; therefore, assets that are highly exposed to persistent growth risks also feature high sensitivity to long-run temperature risks.

The variation in temperature betas across industry portfolios, presented in Panel B of Table V, is fairly consistent with NIOSH classification. Only with the exception of wholesale, industries that are classified as low heat-exposure sectors have small positive sensitivity to temperature variation, whereas firms in high heat-exposure sectors have negative elasticity to temperature risks. In unreported results, we confirm that the differences between the two groups are strongly significant particularly when temperature risks are measured at low frequencies (i.e., beyond one-year horizon). In the next section, we test if temperature exposure carries a risk premium as predicted by our model.

4.3 Price of Temperature Risk

To estimate the price of temperature risks, we run a cross-sectional regression of average excess returns on temperature beta, controlling for market and consumption risk exposure. We present estimates based on two sets of portfolios: 25 book-to-market and size sorted portfolios, and an extended set augmented by the industry portfolios. Tables VI and VII report the cross-sectional estimates and their significance based on standard errors computed using the Fama and

MacBeth (1973) regression procedure, and Shanken (1992)-corrected standard errors that account for estimation errors in betas. Consistent with our model, we find that the estimate of the price of temperature risks, $\hat{\lambda}_{\Delta T}$, is significantly negative, especially when temperature risks are measured by low-frequency variations. For example, in the cross-section of 25 portfolios, risk prices of variations in five- and ten-year temperature trends are estimated at -0.193 and -0.126 with the corrected t-statistics of -2.08 and -2.01, respectively.

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 model), we do not include any ad-hoc empirical factors in our regression specifications. Further, to ensure that our evidence is not simply due to a lucky draw, we run the following simulation experiment. We generate temperature series of the sample size that matches the data and replace the observed temperature with the simulated draw. We then estimate equity exposure to simulated temperature and run a cross-sectional regression of average excess returns on the estimated betas as we do in the actual data. We repeat this simulation exercise 10,000 times and construct a Monte Carlo distribution of t-statistics under the null that temperature variations have no effect on equity prices. The "p-value*" row for $\hat{\lambda}_{\Delta T}$ in Tables VI and VII reports the fraction of Monte Carlo samples with Shanken (1992)-corrected t-statistics lower than the corresponding statistics in the data.[16] As the tables show, for both sets of portfolios, sample t-statistics for the estimate of the price of low-frequency temperature risks are in the bottom fifth percentile of the null distribution. That is, if temperature risks had no effect on equity prices, it would be highly unlikely to observe the evidence that we document.

4.4 Time-Varying Price of Temperature Risk

In this section we test if the price of temperature risks has risen over time along with the rise in temperature. As discussed in Section 3, our model predicts that the risk premium for temperature fluctuations increases with temperature as the impact of climate change on the economy intensifies. Motivated by the model's implications, we take into account potential variation in the conditional

[16] Because market and consumption risks should carry positive prices, p-value* for $\hat{\lambda}_M$ and $\hat{\lambda}_C$ corresponds to the fraction of Monte Carlo samples with a corrected t-statistic greater than the corresponding sample counterpart.

risk premium and parameterize the dynamics of the risk price to be a function of the temperature level. We consider a simple linear specification:

$$\lambda_t = \lambda_{\Delta T} + \lambda_{T \cdot \Delta T} T_t \,, \tag{20}$$

and evaluate the unconditional implications of the conditional factor model as in Jagannathan and Wang (1996), Lettau and Ludvigson (2001), and Lustig and Verdelhan (2007). In particular, we first estimate risk exposure of each portfolio i by running a time-series regression:

$$r^e_{i,t} = \bar{r}_i + \beta_{\Delta T,i} \, \Delta \overline{T}^K_t + \beta_{T \cdot \Delta T,i} \left(\overline{T}^K_{t-1} \cdot \Delta \overline{T}^K_t \right) + \beta_{M,i} r^e_{M,t} + \beta_{C,i} \xi_{C,t} + u_{i,t} \ , \tag{21}$$

where the scaled temperature factor, $\overline{T}^K_{t-1} \cdot \Delta \overline{T}^K_t$, captures time-variation in the conditional moments. Then, we run a cross-sectional regression of average excess returns on $\left\{ \beta_{\Delta T,i}, \ \beta_{T \cdot \Delta T,i}, \ \beta_{M,i}, \ \beta_{C,i} \right\}_{i=1}^N$ to estimate risk prices.

The cross-sectional estimates based on 25 book-to-market and size sorted portfolios are presented Table VIII. Our evidence reveals that long-horizon temperature fluctuations that contribute to global warming are significantly priced in equity markets. As the table shows, the estimates of the constant and the time-varying components of the price of temperature risks, $\hat{\lambda}_{\Delta T}$ and $\hat{\lambda}_{T \cdot \Delta T}$, are both negative and strongly significant at long horizons. For example, at the 10-year horizon, $\hat{\lambda}_{\Delta T}$ and $\hat{\lambda}_{T \cdot \Delta T}$ are -0.151 and -0.178 with the corrected t-statistics of -1.94 and -2.08, respectively. Our Monte Carlo simulations show that if the temperature factor were constructed randomly it would be very unlikely to find that it carried a significant price as all p-values for horizons beyond one year are less than five percent. The estimates and inference based on the extended asset menu, presented in Table IX, are very similar.

The negative coefficient on the scaled temperature factor indicates that the price of temperature risks has risen with temperature as predicted by our model. The overall magnitude and the dynamics of the risk premium for low-frequency temperature fluctuations are presented in Figure 7. The figure shows the premium for a (negative) one-standard deviation shock to temperature trend based on the cross-sectional estimates reported in Table IX that correspond to the 10-year horizon. A one-standard deviation exposure to low-frequency temperature risks carries a premium of around 0.24%, on average. As the figure shows, by the end of sample, the premium has increased by a factor of four relative to its level in mid-80's — from about 0.13% to almost 0.40%.

5 Temperature and Asset Prices: Evidence from Global Markets

In this section, we evaluate the impact of temperature risks on equity valuations using panel data from global financial markets. Because the span of the available international data is relatively short, we measure the impact of temperature fluctuations by pooling the data and simultaneously exploiting time-series and cross-sectional variation in country-level temperature and equity prices. Also, because historically international markets are not fully integrated and different countries feature different degrees of segmentation and frictions, we limit our attention on understanding the overall impact of temperature fluctuations on asset valuations.

5.1 Data

We use country-level panel data that cover 39 countries and span the time period from 1970 and 2012. Country-level and global temperature that correspond to land-surface temperature anomaly are taken from the Berkeley Earth open database. Temperature anomaly is measured in degrees Celsius and is defined relative to the 1951-1980 average. The price-dividend data come from the Global Financial Data and provide a market proxy for the wealth-to-consumption ratio. We also collect market equity returns for each country in our sample. Country-specific macro data (such as gross domestic product, inflation, unemployment, real interest rates) are taken from the World Bank database and are available for the 1980-2009 period. The list of 39 countries is provided in Table X. This is the most exhaustive set with reliable capital market data that we could find, as such, it is tilted towards developed economies as they are more likely to have a history of equity markets.

In our sample, 38 out of 39 countries have experienced a significant increase in temperature over the sample period. The median temperature anomaly across countries is about 0.38°C and over the last decade, between 2003 and 2012, the anomaly averages 0.73°C . Figure 8 shows the histogram of the temperature anomaly in the most recent decade in our sample. We find that local temperature series have a strong common component that is highly correlated with variation in global temperature. Using the cross-section of countries we carry out a principal component analysis on the country-level temperature data. We find that the first principal component of annual temperature series accounts for about 53% of the total variation in temperature across countries and has a 71% correlation with global temperature anomaly. At low 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 81% of the overall variation in local temperature trends. This evidence suggests that systematic climate risk is most likely driven by low-frequency temperature risks (i.e., risks associated with global warming) rather than by weather or short-run temperature fluctuations.

Our analysis of equity prices reveals a strong low dimensional factor structure also in price-dividend ratios. 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. Our empirical approach is conservative as we ask if, after controlling for global and local macro-risk factors, long-run fluctuations in temperature have any effect on equity valuations.

5.2 Impact of Temperature on Equity Valuations

To estimate the impact of temperature on asset prices, we run the following dynamic panel regression:

$$v_{i,t} = \bar{v}_i + \phi_K \, \overline{T}^K_{i,t} + \alpha'_x X_{i,t} + \alpha_v v_{i,t-1} + \varepsilon_{i,t} \tag{22}$$

where $v_{i,t}$ is the log of the equity price-dividend ratio of country i at date t, $\bar{v}_i$ is the country-specific fixed effect, $\overline{T}^K_{i,t}$ is a K-year moving-average of local temperature, and $X_{i,t}$ is a set of controls that captures the effect of global and local risks on asset prices, i.e., macro-economic risks that are distinct from temperature. We vary K between one and five years and do not consider longer horizons because of a relatively short span of panel data.[17] We control for common global macroeconomic variations using two price-dividend ratio factors.[18] The set of local controls comprises country-specific inflation, unemployment, real interest rate, and growth in gross domestic product (gdp). The remaining persistence in asset prices is absorbed by the lagged country-specific price-dividend ratio. We estimate the parameters using the Arellano and Bond (1991)'s GMM estimator applied to the first-differenced data and use the White (1980)'s robust estimator of the variance-covariance matrix.

Our focus is on parameter ϕ_K that measures sensitivity of equity prices to local temperature variations. The estimates of temperature elasticities for the full sample are reported in "1980-2009" rows of Table XI. We find that at both short and long horizons, temperature risks have a significant negative effect on equity valuations. The estimated elasticities vary between -0.076 (t-stat $= -4.41$) at the short horizon and -0.105 (t-stat $= -3.33$) at the long horizon. To interpret the magnitude of the estimates, note that ϕ_K measures semi-elasticity of asset prices to temperature fluctuations. Hence, a one standard-deviation increase in annual temperature anomaly of around 0.5°C leads to about 3.8% decline in equity valuations. The impact of low-frequency temperature risks is similar; for example, a one standard-deviation increase in the five-year temperature trend lowers equity valuations by about 3.4%.

In Table XI we also explore if the effect of temperature on the economy has changed across time. Ideally, to uncover such changes, we would want to compare temperature elasticities measured over earlier and more recent sample periods. This, however, is not entirely feasible given the fairly short span of the available data. Therefore, to explore time-variation in elasticities we estimate them using overlapping samples. We start with the early 1980-2000 sample and then progressively increase the sample end to 2005 and 2009 by adding more recent data. Our estimates show that the effect of temperature on equity valuations has risen considerably over time. At the one-year horizon, the point estimates change from -0.016 in the early sample to -0.076 in the full sample. Similarly, the

[17] Given the limited availability of the country-specific controls, the panel regression is estimated on a subsample of 34 countries over the 1980-2009 period.

[18] To allow global macro risks have differential effect across countries, we also include the interaction of the two principal components with country-income dummies. While the estimates on the interaction terms are mostly significant, their inclusion has virtually no effect on the estimated elasticity of equity prices to temperature risks and its significance. Therefore, for parsimony, we report evidence based on the specification with no interaction terms.

price impact of temperature risks measured at lower frequencies (i.e., for $K > 1$) more than doubles when more recent data are incorporated in estimation. This evidence suggests that as temperature rises, global warming imposes higher risks on the economy and, therefore, leads to a larger decline in wealth. As discussed above, our model is consistent with this evidence — in the model, rising temperature increases the size and the probability of disasters over time, leading to a steeper decline in aggregate wealth.

In our panel regression setting we measure the economic impact of temperature risks by exploiting both time-series and cross-sectional variation in temperature. Local temperature series, especially their low-frequency fluctuations, feature a strong common (global) component. Replacing local temperature series in regression specification in Equation (22) with global temperature, we find that global temperature risks have also a strongly significant negative effect of equity prices. This evidence (which is available upon request) suggests that the negative elasticity of equity valuations to local temperature risks is largely due to common time-series variation in temperature across countries.

5.3 Long-Run vs. Short-Run Temperature Risks

To better understand which risks, short-run (i.e., weather-type) risks or long-run temperature variations associated with global warming, matter more we consider the following panel regression:

$$v_{i,t} = \bar{v}_i + \phi_{LR}\, LR^K_{i,t} + \phi_{SR}\, SR_{i,t} + \alpha'_x X_{i,t} + \alpha_v v_{i,t-1} + \varepsilon_{i,t} \ , \tag{23}$$

where $LR^K_{i,t}$ proxies for low-frequency temperature risks and is measured by the K-year moving-average of local temperature, for $K = \{3,\ 5\}$, and $SR_{i,t}$ is annual temperature orthogonalized with respect to long-run fluctuations. We orthogonalize short- and long-run temperature variations in order to identify their separate effects. The estimates of long- and short-run elasticities, $\hat{\phi}_{LR}$ and $\hat{\phi}_{SR}$, are presented in Table XII.

Consistent with the evidence discussed above, we find a negative and statistically significant response of equity valuations to low-frequency variations in temperature. We also find that once we control for long-run fluctuations in temperature, short-run temperature risks tend to also have a negative effect on equity prices, however, its magnitude is generally small and not as significant. In unreported results, we also estimate exposure of equity returns to long- and short-run temperature risks and similarly find statistically negative betas with respect to low-frequency risks and generally insignificant exposure to short-run variations in temperature. Our evidence thus suggests that the negative impact of temperature on the economy is mostly driven by its low-frequency (i.e., trend) risks that correspond to global warming.

To further examine the impact of long- and short-run temperature risks on equity prices, we estimate their joint dynamics using a first-order vector-autoregression (VAR). Specifically, we exploit the following panel VAR specification:

$$Y_{i,t} = \bar{a}_i + A\,Y_{i,t-1} + b\,X_t + u_{i,t} \tag{24}$$

where $Y_{i,t} = (\overline{T}^{8}_{i,t},\ T_{i,t},\ v_{i,t})'$ is a vector of the eight-year moving-average of local temperature, the annual temperature series and the price-dividend ratio of country i. We include country fixed effects ($\bar{a}_i$) and use the two price-dividend ratio factors to control for global risks (X_t denotes the vector of global controls). We estimate the VAR using the full sample of panel data from 1970 until 2012 and, therefore, we able to consider a relatively long horizon of eight years to measure low-frequency temperature risks. The VAR-regression output is reported in Table XIII, and in Figure 9 we plot the implied impulse responses of equity prices to a one-standard deviation shock in temperature trend ($\overline{T}^{8}_{i,t}$) and a one-standard deviation innovation in annual temperature ($T_{i,t}$). The shaded area around the estimated responses represents the two standard-error band. As Panel (a) shows, the VAR-based response of equity prices to low-frequency temperature risks is significantly negative. Notice also that the effect of trend shocks is quite persistent — an increase in temperature trend leads to a decline in equity prices on impact and in the long run. Similar to the evidence presented above, short-run temperature fluctuations do not seem to have a sizable effect. In all, our empirical evidence suggests that climate change measured by a long-term increase in temperature has a significant negative impact on the world economies.

6 Conclusion

Using capital market data, we show that temperature risks have a significant negative effect on wealth. An increase in temperature, especially at low frequencies, lowers equity valuations around the globe and in the US markets. To understand the implications of persistent temperature risks and to guide our empirical analysis, we model the dynamic interaction between economic growth and climate change. We show that even if the real effect of rising temperature is deferred into the future, its wealth effect is realized today. That is, even if global warming increases uncertainty or lowers expectations about growth in a relatively distant future, under preferences for early resolution of uncertainty, it leads to an immediate decline in wealth and equity valuations. Hence, forward-looking capital markets might provide valuable information about the economic impact of temperature risks — information that might not be possible to learn from the past (backward-looking) income growth data. We explore this idea in our empirical work. Consistent with our model's predications, we find that low-frequency temperature risks have a significant negative effect on equity valuations and carry a positive premium in equity markets. We also show that the premium for low-frequency temperature risks that contribute to global warming has been increasing over time along with the rise in temperature.

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Table I

Calibration of Global Warming

Parameter	Description	Value
Climate Dynamics		
$\bar{\nu}$	Atmospheric retention of carbon	0.962
χ	Temperature sensitivity to emissions	0.0045
Natural Disasters		
T^*	Tipping point	2.0°C
ℓ_0	Disaster intensity parameters	0.0050
ℓ_1	Disaster intensity parameters	0.0033
q_1	Damage function parameter	0.0011
q_2	Damage function parameter	0.0011

Table I presents calibration of global warming under the business-as-usual scenario. The parameter values are annualized.

Table II

Calibration of Preferences and Consumption Dynamics

	LRR-T Model	**Alternative Specifications**	
		Pref for ERU	Power Utility
Preferences			
β	0.99	0.99	0.99
γ	5	5	5
ψ	1.5	1.5	0.2
Consumption			
μ	0.018	0.018	0.018
σ	0.016	0.016	0.016
ρ_x	0.96		
φ_x	0.25		
ϕ_x	0.05		

Table II presents calibration of preferences and consumption dynamics under the business-as-usual scenario. Our LRR-T model features preference for early resolution of uncertainty and incorporates a negative impact of global warming on consumption level and expected consumption growth. Under Alternative Specifications, the conditional mean of consumption growth is constant and climate change is assumed to only affect the level of consumption. We consider two specifications of preferences under the alternative dynamics: preferences for early resolution of uncertainty (Pref for ERU) and CRRA preferences (Power Utility). Empty entries in the table correspond to zeros. The parameter values are annualized.

Table III

Model-Implied Response of Equity Prices to Temperature Risks

	Response
LRR-T Model	−0.0174
Alternatives:	
Pref for ERU	−0.0063
Power Utility	0.0002

Table III reports the response of the price-consumption ratio to temperature risks for the LRR-T model that features the long-run risk component and preferences for early resolution of uncertainty, and alternative specifications with constant expected growth and two types of risk preferences: preferences for early resolution of uncertainty (Pref for ERU) and CRRA preferences (Power Utility). For each specification, we simulate the data and compute the model-implied response by regressing the price-consumption ratio on temperature controlling for the relevant state variables. The simulated data consist of 50,000 draws.

Table IV

Capital Market Implications

	LRR-T Model	**Alternative Specifications**	
		Pref for ERU	Power Utility
SCC	103.6	39.01	0.01
Risk-Free Rate	0.91	2.11	10.08
Risk Premia	1.70	0.16	0.17
Discount Rates:			
10yr Strip	1.51	2.28	10.33
100yr Strip	2.41	2.29	10.31

Table IV presents the social cost of carbon (SCC) and asset pricing implications of the LRR-T Model that features the long-run risk component and preferences for early resolution of uncertainty, and alternative specifications with constant expected growth and two types of risk preferences: preferences for early resolution of uncertainty (Pref for ERU) and CRRA preferences (Power Utility). SCC is measured in 2012 dollars of world consumption per metric ton of carbon. The risk-free rate and risk premia on consumption claim are averaged over the transitional path, discount rates represent expected rates of returns on consumption strips with 10- and 100-year maturities. Returns and premia are expressed in annualized percentage terms.

Table V

Temperature Exposure

Panel A: 25 BM/Size Sorted Portfolios

	Small	2	3	4	Large
Growth	−0.129	−0.074	0.074	0.035	0.112
2	−0.087	−0.048	−0.061	−0.011	−0.011
3	−0.053	−0.064	−0.060	−0.024	−0.071
4	−0.065	−0.106	−0.095	−0.127	−0.025
Value	−0.172	−0.199	−0.277	−0.092	−0.047

Panel B: Industry Portfolios

High Heat-Exposed		Low Heat-Exposed	
MINE	−0.051	MANU	0.031
OILG	−0.101	WHOS	−0.055
CNST	−0.173	RETS	0.008
TRAN	−0.124	SERV	0.067
UTIL	−0.130	COMM	0.039

Table V shows exposure of returns of 25 book-to-market and size sorted portfolios (Panel A) and 10 industry portfolios (Panel B) to long-run temperature risks estimated by regressing portfolio excess returns on the change in five-year moving average of temperature controlling for market and consumption growth risks. Industry classification of high and low heat-exposed sectors is according to the National Institute for Occupational Safety and Health. The data are annual and cover the 1934-2014 period.

Table VI

Price of Temperature Risk:
25 BM/Size Sorted Portfolios

	Horizon		
	1-year	5-year	10-year
$\hat{\lambda}_{\Delta T}$	-1.528	-0.193	-0.126
(t-stat)	(-4.00)	(-3.14)	(-3.84)
[t-stat*]	$[-1.87]$	$[-2.08]$	$[-2.01]$
p-value*	0.03	0.02	0.02
$\hat{\lambda}_M$	0.003	-0.011	0.027
(t-stat)	(0.05)	(-0.24)	(0.51)
[t-stat*]	[0.11]	$[-0.54]$	[1.20]
p-value*	0.47	0.67	0.14
$\hat{\lambda}_C$	0.002	0.003	0.005
(t-stat)	(0.82)	(1.53)	(2.30)
[t-stat*]	[0.60]	[1.38]	[1.80]
p-value*	0.32	0.11	0.04
$\bar{R}^2$	0.56	0.52	0.63

Table VI presents the estimates of the cross-sectional regression of average excess returns of 25 book-to-market and size sorted portfolios on their exposure to temperature risks. Temperature exposure is estimated by regressing portfolio excess returns on the change in one-, five- or ten-year moving average of temperature controlling for market and consumption growth risks. The upper panel shows the estimates of the price of temperature risk ($\hat{\lambda}_{\Delta T}$), the Fama and MacBeth (1973)-based t-statistics (t-stat in parentheses), and the Shanken (1992)-corrected t-statistics (t-stat* in brackets). P-value* is the fraction of Monte Carlo samples generated under the null that temperature risks have no effect on equity prices with a corrected t-statistic lower than the sample statistics. Similar statistics are reported for the cross-sectional estimates of the market and consumption risk prices ($\hat{\lambda}_M$ and $\hat{\lambda}_C$, respectively). For market and consumption risks, p-value* is the fraction of Monte Carlo samples with a corrected t-statistic greater than the sample counterpart. The bottom line reports the adjusted R-squared. The data are annual and cover the 1934-2014 period.

Table VII

Price of Temperature Risk:
25 BM/Size Sorted Portfolios and 10 Industry Portfolios

	Horizon		
	1-year	5-year	10-year
$\hat{\lambda}_{\Delta T}$	-0.990	-0.138	-0.096
(t-stat)	(-3.06)	(-2.10)	(-3.26)
[t-stat*]	[-1.89]	[-1.69]	[-1.90]
p-value*	0.03	0.05	0.03
$\hat{\lambda}_M$	0.046	0.035	0.035
(t-stat)	(1.07)	(0.87)	(0.84)
[t-stat*]	[2.11]	[1.66]	[1.60]
p-value*	0.01	0.06	0.07
$\hat{\lambda}_C$	0.002	0.004	0.006
(t-stat)	(1.19)	(2.00)	(3.14)
[t-stat*]	[1.00]	[1.75]	[2.23]
p-value*	0.20	0.04	0.01
$\bar{R}^2$	0.49	0.47	0.58

Table VII presents the estimates of the cross-sectional regression of average excess returns of 25 book-to-market and size sorted portfolios and 10 industry portfolios on their exposure to temperature risks. Temperature exposure is estimated by regressing portfolio excess returns on the change in one-, five- or ten-year moving average of temperature controlling for market and consumption growth risks. The upper panel shows the estimates of the price of temperature risk ($\hat{\lambda}_{\Delta T}$), the Fama and MacBeth (1973)-based t-statistics (t-stat in parentheses), and the Shanken (1992)-corrected t-statistics (t-stat* in brackets). P-value* is the fraction of Monte Carlo samples generated under the null that temperature risks have no effect on equity prices with a corrected t-statistic lower than the sample statistics. Similar statistics are reported for the cross-sectional estimates of the market and consumption risk prices ($\hat{\lambda}_M$ and $\hat{\lambda}_C$, respectively). For market and consumption risks, p-value* is the fraction of Monte Carlo samples with a corrected t-statistic greater than the sample counterpart. The bottom line reports the adjusted R-squared. The data are annual and cover the 1934-2014 period.

Table VIII

Time-Varying Price of Temperature Risk: 25 BM/Size Sorted Portfolios

	Horizon		
	1-year	5-year	10-year
$\hat{\lambda}_{\Delta T}$	-0.887	-0.183	-0.151
(t-stat)	(-3.22)	(-2.90)	(-4.90)
[t-stat*]	[-1.15]	[-1.82]	[-1.94]
p-value*	0.15	0.03	0.02
$\hat{\lambda}_{T\cdot\Delta T}$	-0.174	-0.241	-0.178
(t-stat)	(-0.32)	(-5.09)	(-5.79)
[t-stat*]	[-0.11]	[-2.26]	[-2.08]
p-value*	0.47	0.01	0.01
$\hat{\lambda}_M$	-0.053	0.004	0.026
(t-stat)	(-1.04)	(0.09)	(0.49)
[t-stat*]	[-2.34]	[0.20]	[1.10]
p-value*	1.00	0.44	0.16
$\hat{\lambda}_C$	0.006	0.003	0.004
(t-stat)	(2.93)	(1.43)	(2.04)
[t-stat*]	[1.46]	[1.17]	[1.32]
p-value*	0.08	0.14	0.11
$\bar{R}^2$	0.70	0.54	0.67

Table VIII presents the estimates of the cross-sectional regression of average excess returns of 25 book-to-market and size sorted portfolios on their exposure to temperature risks and temperature risks scaled by the level of temperature. Temperature exposure is estimated by regressing portfolio excess returns on the change in one-, five- or ten-year moving average of temperature (ΔT_{t+1}) and the (de-meaned) change scaled by the level of temperature ($T_t \cdot \Delta T_{t+1}$) controlling for market and consumption growth risks. The upper panels show the estimates of the prices of temperature risks ($\hat{\lambda}_{\Delta T}$ and $\hat{\lambda}_{T\cdot\Delta T}$), the Fama and MacBeth (1973)-based t-statistics (t-stat in parentheses), and the Shanken (1992)-corrected t-statistics (t-stat* in brackets). P-value* is the fraction of Monte Carlo samples generated under the null that temperature risks have no effect on equity prices with a corrected t-statistic lower than the sample statistics. Similar statistics are reported for the cross-sectional estimates of the market and consumption risk prices ($\hat{\lambda}_M$ and $\hat{\lambda}_C$, respectively). For market and consumption risks, p-value* is the fraction of Monte Carlo samples with a corrected t-statistic greater than the sample counterpart. The bottom line reports the adjusted R-squared. The data are annual and cover the 1934-2014 period.

Table IX

Time-Varying Price of Temperature Risk:
25 BM/Size Sorted Portfolios and 10 Industry Portfolios

	Horizon		
	1-year	5-year	10-year
$\hat{\lambda}_{\Delta T}$	-0.871	-0.138	-0.099
(t-stat)	(-3.02)	(-2.12)	(-3.67)
[t-stat*]	[-1.73]	[-1.70]	[-1.98]
p-value*	0.04	0.05	0.02
$\hat{\lambda}_{T\cdot\Delta T}$	-0.175	-0.119	-0.096
(t-stat)	(-2.25)	(-2.95)	(-3.59)
[t-stat*]	[-1.16]	[-1.55]	[-1.78]
p-value*	0.15	0.06	0.04
$\hat{\lambda}_M$	0.042	0.034	0.034
(t-stat)	(1.00)	(0.96)	(0.80)
[t-stat*]	[1.95]	[1.65]	[1.54]
p-value*	0.02	0.06	0.07
$\hat{\lambda}_C$	0.003	0.004	0.005
(t-stat)	(1.68)	(2.03)	(2.95)
[t-stat*]	[1.25]	[1.73]	[2.16]
p-value*	0.12	0.04	0.01
$\bar{R}^2$	0.52	0.45	0.57

Table IX presents the estimates of the cross-sectional regression of average excess returns of 25 book-to-market and size sorted portfolios and 10 industry portfolios on their exposure to temperature risks and temperature risks scaled by the level of temperature. Temperature exposure is estimated by regressing portfolio excess returns on the change in one-, five- or ten-year moving average of temperature (ΔT_{t+1}) and the (de-meaned) change scaled by the level of temperature ($T_t \cdot \Delta T_{t+1}$) controlling for market and consumption growth risks. The upper panels show the estimates of the prices of temperature risks ($\hat{\lambda}_{\Delta T}$ and $\hat{\lambda}_{T\cdot\Delta T}$), the Fama and MacBeth (1973)-based t-statistics (t-stat in parentheses), and the Shanken (1992)-corrected t-statistics (t-stat* in brackets). P-value* is the fraction of Monte Carlo samples generated under the null that temperature risks have no effect on equity prices with a corrected t-statistic lower than the sample statistics. Similar statistics are reported for the cross-sectional estimates of the market and consumption risk prices ($\hat{\lambda}_M$ and $\hat{\lambda}_C$, respectively). For market and consumption risks, p-value* is the fraction of Monte Carlo samples with a corrected t-statistic greater than the sample counterpart. The bottom line reports the adjusted R-squared. The data are annual and cover the 1934-2014 period.

Table X

List of Countries

Argentina	Spain	Netherlands
Australia	Finland	Norway
Austria*	France	New Zealand
Belgium	U.K.	Peru
Brazil	Greece	Philippines
Canada	Indonesia	Portugal
Switzerland	India	Russia
Chile*	Italy	Sweden
China	Japan	Turkey*
Colombia	Korea, rep.	Taiwan*
Germany	Sri Lanka	U.S.A.
Denmark	Mexico	Venezuela*
Egypt	Malaysia	South Africa

Table X provides a list of countries in our data set. Due to missing country-specific controls, countries with asterisk are excluded from the panel regressions reported in Tables XI and XII.

Table XI

Elasticity of Equity Prices to Temperature Variations

Horizon	Sample	$\hat{\phi}_K$	t-stat
	1980 − 2000	−0.016	−1.51
$K = 1$yr	1980 − 2005	−0.043	−3.21
	1980 − 2009	−0.076	−4.41
	1980 − 2000	−0.040	−1.48
$K = 3$yr	1980 − 2005	−0.094	−3.40
	1980 − 2009	−0.138	−5.59
	1980 − 2000	0.058	1.79
$K = 5$yr	1980 − 2005	−0.023	−0.56
	1980 − 2009	−0.105	−3.33

Table XI reports the response of equity prices to temperature risks estimated in the following panel regression:

$$v_{i,t} = \bar{v}_i + \phi_K \, \overline{T}^K_{i,t} + \alpha'_x X_{i,t} + \alpha_v v_{i,t-1} + \varepsilon_{i,t} \ ,$$

where $v_{i,t}$ is the log of the price-dividend ratio of country i, $\bar{v}_i$ is the country-specific fixed effect, $\overline{T}^K_{i,t}$ is a K-year moving-average of local temperature, and $X_{i,t}$ is a set of global and local controls. The set of controls includes two common price-dividend ratio-based factors and country-specific inflation, unemployment, real interest rate, and gdp growth. The parameters are estimated using the Arellano and Bond (1991)'s GMM estimator applied to the first-differenced data. The table presents the estimates of the slope coefficient, ϕ_K, and the corresponding t-statistics based on the White (1980)'s robust estimator of the variance-covariance matrix. The panel comprises 34 countries over the 1980-2009 period.

Table XII

Equity Response to Long- and Short-Run Temperature Risks

	Estimate	t-stat
$K = 3$yr		
ϕ_{LR}	-0.138	-4.78
ϕ_{SR}	-0.026	-1.00
$K = 5$yr		
ϕ_{LR}	-0.135	-3.37
ϕ_{SR}	-0.028	-1.05

Table XII reports the response of equity valuations to long- and short-run temperature risks estimated in the following panel regression:

$$v_{i,t} = \bar{v}_i + \phi_{LR}\, LR^K_{i,t} + \phi_{SR}\, SR_{i,t} + \alpha'_x X_{i,t} + \alpha_v v_{i,t-1} + \varepsilon_{i,t}\ ,$$

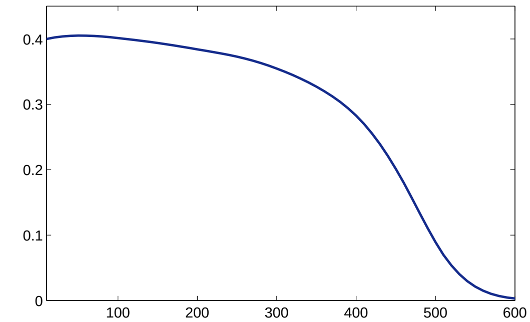
where $v_{i,t}$ is the log of the price-dividend ratio of country i, $\bar{v}_i$ is the country-specific fixed effect, $LR^K_{i,t}$ proxies for low-frequency temperature risks and is measured by the three- or five-year moving-average of local temperature, $SR_{i,t}$ is annual temperature orthogonalized with respect to long-run fluctuations, and $X_{i,t}$ is a set of global and local controls. The set of controls includes two common price-dividend ratio-based factors and country-specific inflation, unemployment, real interest rate, and gdp growth. The parameters are estimated using the Arellano and Bond (1991)'s GMM estimator applied to the first-differenced data. The table presents the estimates of the slope coefficients, ϕ_{LR} and ϕ_{SR}, and the corresponding t-statistics based on the White (1980)'s robust estimator of the variance-covariance matrix. The panel comprises 34 countries over the 1980-2009 period.

Table XIII

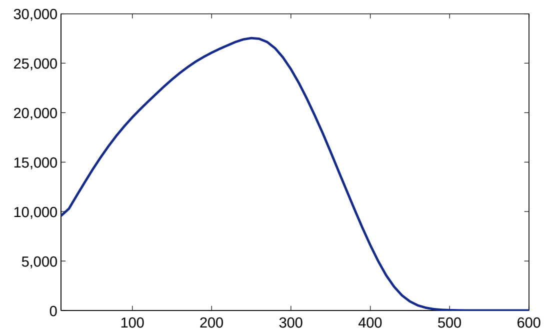
VAR Dynamics of Equity Prices and Temperature

	$\overline{T}^8_{i,t}$	$T_{i,t}$	$v_{i,t}$
$\overline{T}^8_{i,t-1}$	0.921	0.385	−0.093
	[107.1]	[7.06]	[−2.29]
$T_{i,t-1}$	0.026	0.158	−0.017
	[5.44]	[5.19]	[−0.73]
$v_{i,t-1}$	0.014	0.076	0.520
	[3.15]	[2.65]	[24.41]
$\bar{R}^2$	0.96	0.31	0.67

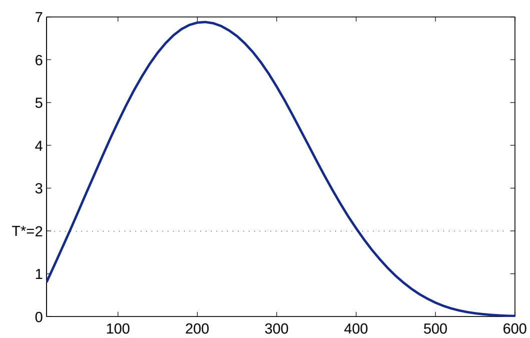
Table XIII shows the estimates of the first-order panel VAR for equity prices and temperature. $\overline{T}^8_{i,t}$ denotes the eight-year moving-average of local temperature, $T_{i,t}$ is annual temperature series, and $v_{i,t}$ is the log of the price-dividend ratio of country i. The exogenous variables included in the VAR comprise two price-dividend ratio factors that control for common macro-economic risks and country-specific fixed effects. T-statistics are reported in brackets. The panel consists of 39 countries over the 1970-2012 period.



(a) Carbon Intensity



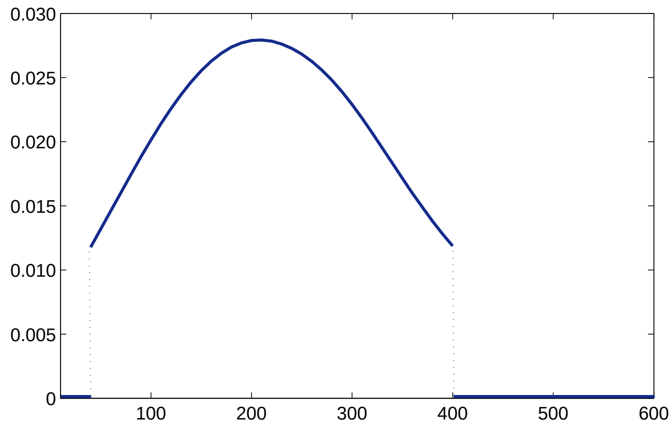
(b) Expected Path of Carbon Emissions



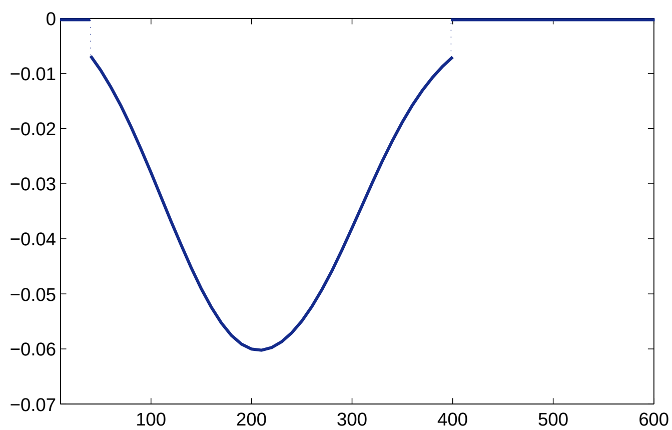
(c) Expected Path of Temperature Anomaly

Figure 1. Dynamics under the BAU Scenario

Figure 1 illustrates the business-as-usual scenario. Panel (a) shows the evolution of carbon intensity; Panel (b) presents the projected path of carbon emissions; Panel (c) shows the projected path of temperature anomaly (temperature relative to its pre-industrial level). Emissions are measured in millions of metric ton of carbon per annum, and temperature is in degrees Celsius. The dotted line in Panel (c) represents the tipping point of global warming. The horizontal axis is the time-line measured in years from today.



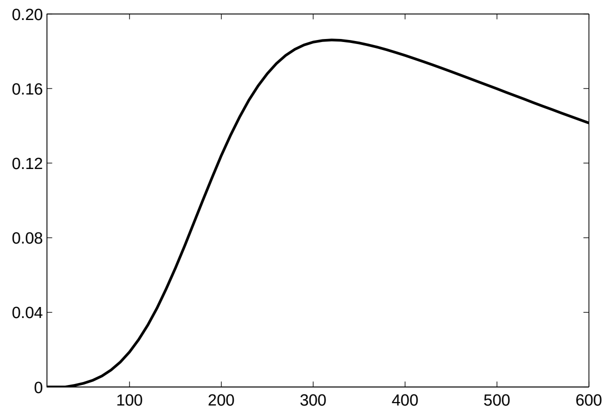
(a) Disaster Intensity



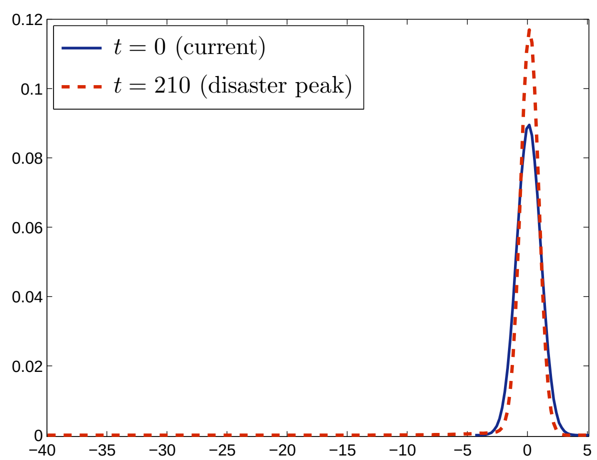
(b) Disaster Size

Figure 2. Global Warming Disasters under the BAU policy

Figure 2 shows the consequences of global warming in the business-as-usual case. Panel (a) plots the expected intensity of climate change disasters per annum; Panel (b) shows the average annual size of disasters ($-d_t$). The horizontal axis is the time-line measured in years from today.



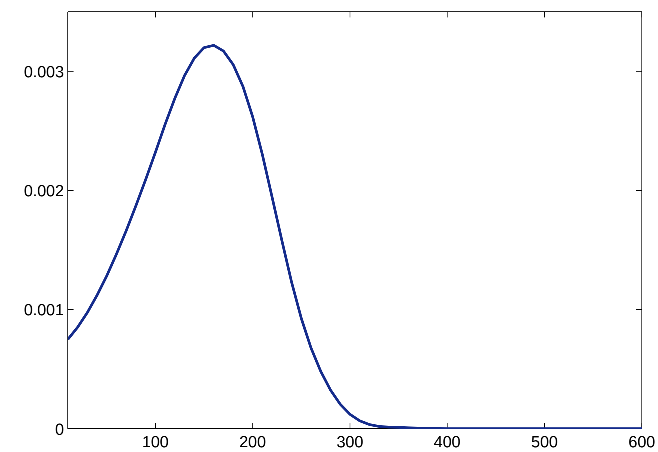
(a) Change in Ex-Ante Volatility



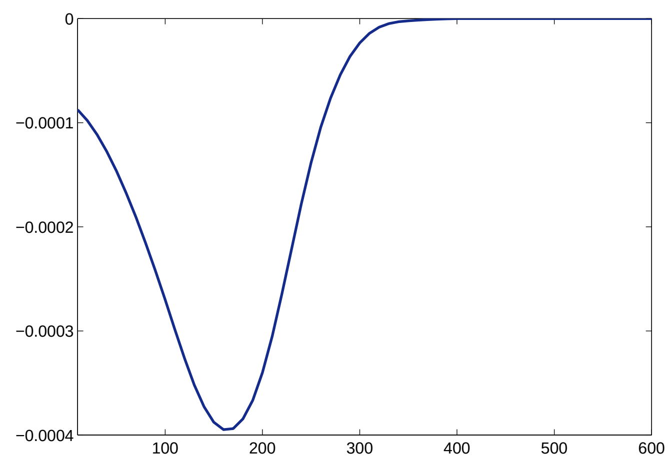
(b) Distribution of Consumption Growth

Figure 3. Implications of Global Warming for Consumption Growth

Figure 3 shows the implications of global-warming disasters for consumption growth. Panel (a) plots the difference between ex-ante volatility of cumulative log consumption growth under the business-as-usual scenario and the conditional volatility absent temperature disasters. Volatility is annualized and expressed in percentage terms. The horizontal axis is the time-line measured in years from today. Panel (b) presents the distribution of normalized consumption growth at time-0 (when disasters are absent) and 210 years from now (at the peak of global-warming disasters).



(a) Elasticity of SDF



(b) Elasticity of W/C

Figure 4. Elasticity of the SDF and Wealth-Consumption Ratio to Emissions

Panel (a) of Figure 4 presents the elasticity of the stochastic discount factor (SDF) to a one-percent increase in time-0 emissions implied by the LRR-T model. Panel (b) presents the corresponding elasticity of the wealth-consumption ratio (W/C). The horizontal axis is the time-line measured in years from today.

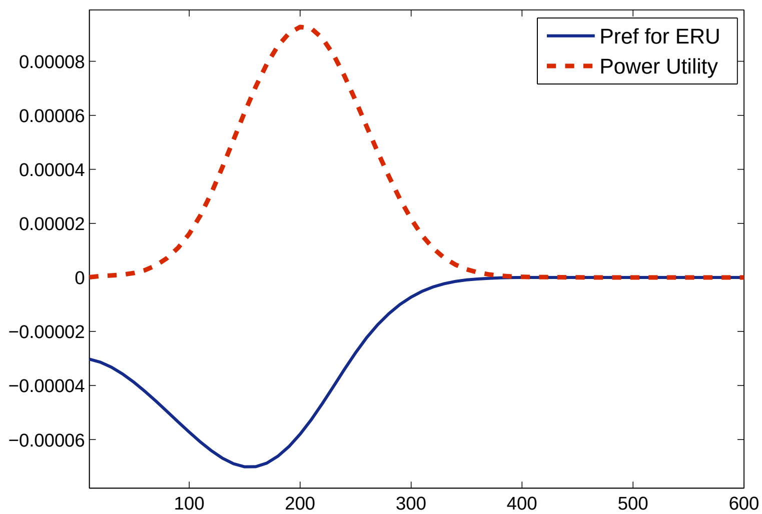
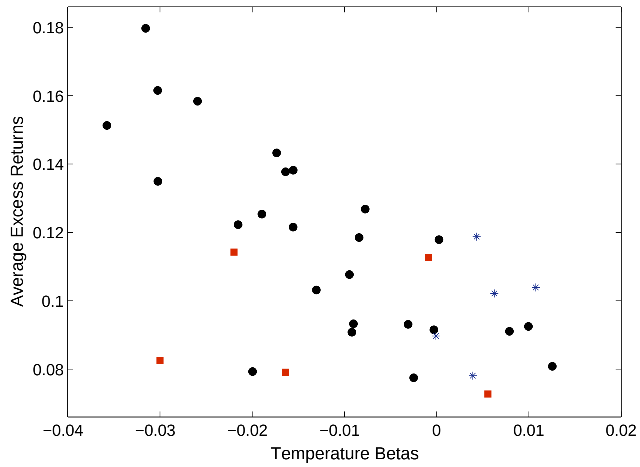
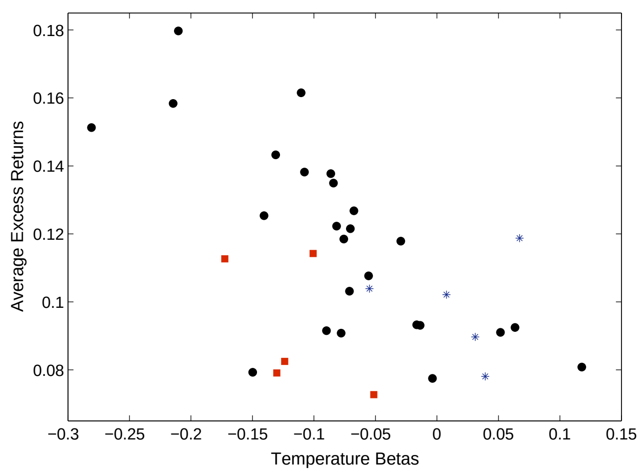


Figure 5. Sensitivity to Emissions

Figure 5 shows the elasticity of the wealth-consumption ratio to a one-percent increase in time-0 emissions for two alternative specifications of preferences: preferences for early resolution of uncertainty (Pref for ERU) and CRRA preferences (Power Utility). The horizontal axis is the time-line measured in years from today.



(a) Exposure to Variation in Annual Temperature



(b) Exposure to Variation in 5-year MA of Temperature

Figure 6. Exposure to Temperature

Figure 6 presents scatter plots of average excess returns and exposure to temperature variations of 25 book-to-market and size sorted portfolios and 10 industry portfolios. Panel (a) shows exposure to the annual change in temperature; Panel (b) presents exposure to the change in the five-year moving-average (MA) of temperature. Circles represent BM/size sorted portfolios; squares and asterisks correspond to high and low heat-exposed industries, respectively. Temperature betas are computed controlling for market and consumption growth risks; the data are annual and cover the 1934-2014 period.

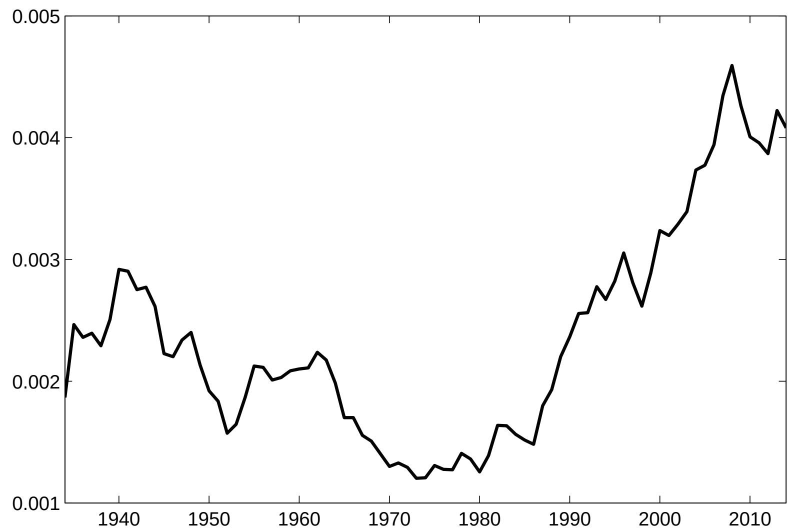


Figure 7. Temperature Premia

Figure 7 plots the premium for a (negative) one-standard deviation shock to temperature trend based on the cross-sectional estimates reported in Table IX that correspond to the 10-year horizon.

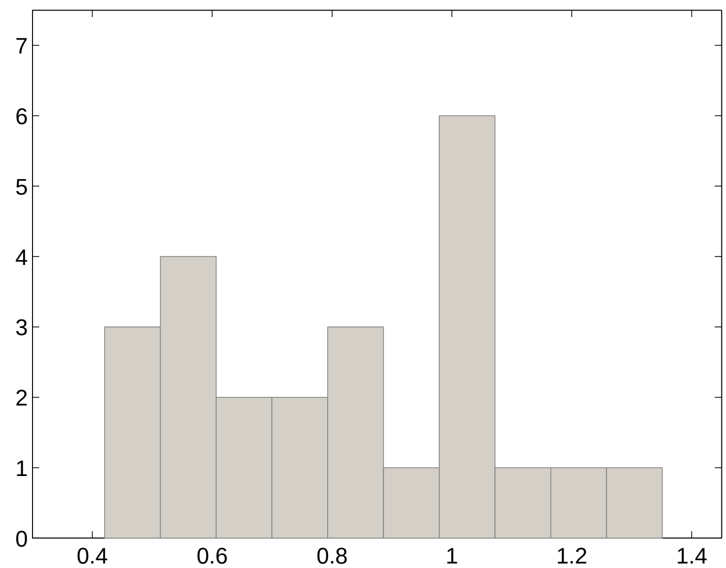
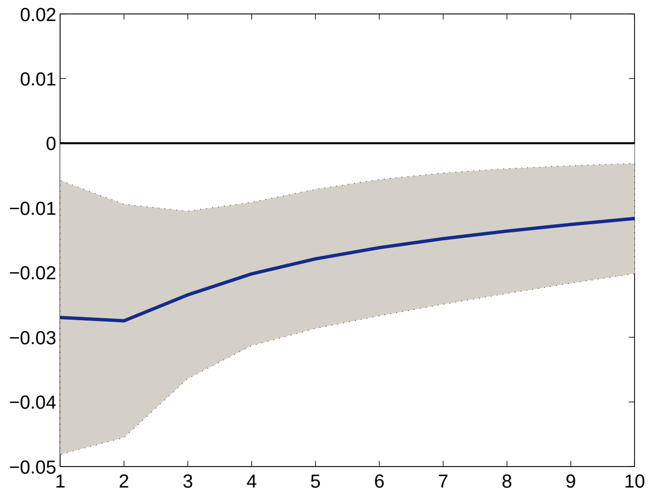
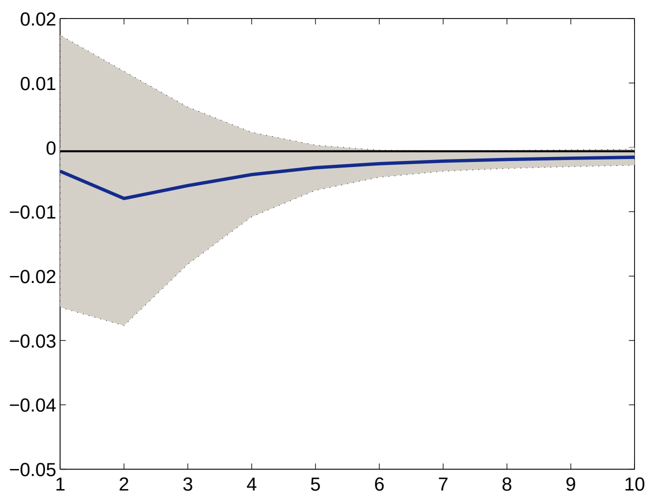


Figure 8. Histogram of the Trend in Local Temperature

Figure 8 shows the histogram of the trend in local temperature measured by the change in average temperature over the 2003-2012 period relative to the 1951-1980 average. The cross-sectional data comprise 39 countries; temperature is measured in degrees Celsius.



(a) Response to Long-Run Shock



(b) Response to Short-Run Shock

Figure 9. Impulse Responses of Equity Prices to Long- and Short-Run Temperature Risks

Figure 9 presents impulse responses of the price-dividend ratio to long- and short-run temperature risks implied by a first-order VAR. The estimated responses are represented by the solid lines, the shaded areas show the two standard-error bands. Time-horizon on the horizontal axes is measured in years.