# When Growth Fuels Climate Risk and Climate Propels Decarbonization: A Model of Climate Feedback and Asset Pricing

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**Abstract**

Anthropogenic climate change is jointly driven by economic growth and emissions intensity. While growth raises emissions, we document that rising temperatures lead to subsequent reductions in emissions intensity, reflecting a feedback mechanism in which climate change spurs decarbonization through technology, behavior, and policy. We also find that rising temperatures lower financial analysts' long-term growth forecasts and depress equity valuations, particularly for firms with low adaptive capacity. To interpret these dynamics, we develop a structural model in which temperature evolves endogenously with economic activity and, in turn, affects emissions, growth risk and risk premia. The model, calibrated to observed macro and climate data, shows that adverse growth shocks of the emitting (brown) sector partially hedge climate risk by reducing future emissions. This helps explain the difficulty of identifying the impact of rising temperature on risk premia in the early stages of the climate transition, even as valuations fall. The hedging effect of brown-technology shocks also implies that, absent carbon taxation or other types of regulatory risk, the brown sector carries lower risk premia than the green sector.

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# Introduction

Climate change has emerged as one of the defining challenges of the 21st century, shaping contemporary policy, economic, and scientific discourse. There is broad scientific agreement that rising temperatures are not exogenous — they are endogenously driven by industrial carbon emissions resulting from economic activity. In response to rising temperatures and the growing recognition of their risks, governments and firms are advancing mitigation policies and technological solutions that, in turn, affect future climate trajectory and economic growth. While the endogenous nature of emissions and temperature is increasingly acknowledged in academic and policy circles, the financial implications of these joint dynamics, particularly the interplay between economic growth, technological progress, and climate change, are not yet fully understood. To address this gap, we provide new empirical evidence and develop a structural asset-pricing framework to examine how endogenously evolving climate risk is capitalized in asset markets and how it affects risk and risk premia.

We begin by documenting several empirical facts. First, we show that emissions intensity, defined as carbon emissions per unit of output, has been steadily declining over recent decades across much of the world. This trend has been especially pronounced in Europe and North America, where emissions intensity has fallen by approximately 52% over the past three decades. However, in many regions and at the global level, this decline has not been rapid enough to fully offset economic growth. As a result, total carbon emissions have increased by about 60% over the same period, driving a continued rise in atmospheric carbon concentrations and contributing to the ongoing increase in global temperatures. Importantly, we also find that the decline in emissions intensity is not entirely exogenous but is partly driven by rising temperatures. Quantitatively, a $1^{\circ}$C increase in regional temperature is associated with a 1% reduction in emissions intensity in the following year and a cumulative decline of approximately 3.2% over a three-year horizon. This evidence points to a dynamic feedback mechanism in which emissions raise temperatures, and in turn, elevated temperatures spur improvements in emissions efficiency through mitigation policies, technological innovation, and behavioral adaptation. That is, rising temperatures are not merely consequences of past emissions but also catalysts for future mitigation.

Second, we show that as temperatures continue to rise, capital markets have begun to recognize and factor in the risks associated with climate change. Specifically, using firm-level analyst forecast data, we find that, starting about two decades ago, financial analysts began revising their long-term earnings growth forecasts downward in response to temperature increases, especially for firms and sectors that are particularly vulnerable to global warming, such as those with low intangible capital and high exposure to heat.

We also show that equity valuations decline in response to rising temperatures, with the effect becoming statistically significant over the past decade — a period during which climate risks have gained greater public awareness and attention. Specifically, during the last ten years, a one standard deviation increase in temperature is associated with an approximately 1.2% fall in equity valuations. As with earnings growth forecasts, this effect is more pronounced among firms with limited adaptive capacity and industries with high exposure to climate-change risks. Taken together, this evidence demonstrates that analysts anticipate physical and transitional climate risks to adversely affect corporate cash flows, and that financial markets are increasingly internalizing and pricing the economic consequences of global warming.

While the data suggest that capital markets are beginning to incorporate temperature risks, they offer only a snapshot of the complex dynamics that are likely to unfold over many decades. To examine both the short- and long-run implications of climate change, we develop a structural model that endogenizes temperature dynamics and their feedback effects on future economic growth and policy decisions. In the model, economic growth driven by carbon-intensive (brown) technologies raises emissions, which in turn increase global temperatures. Once temperature crosses a tipping point, the economy begins to suffer output losses, with the probability of climate-driven damages rising as temperatures continue to increase. At the same time, higher temperatures accelerate decarbonization and the transition to a carbon-free production, reducing future emissions intensity. As a result, emissions evolves stochastically, declining more rapidly as temperature anomalies grow. Our modeling framework thus captures the documented negative temperature elasticity of expected growth and the interconnected dynamics of growth, temperature, and emissions intensity.

Our model generates a number of novel asset pricing implications. First, it shows that the endogeneity of temperature dynamics matters greatly for asset valuations. As long as temperature

variations are endogenous to economic activity, negative growth shocks in the emitting (brown) sector act as a hedge against rising climate risk. Holding all else constant, a decline in output of the brown sector raises marginal utility. However, it also reduces emissions, slowing the pace of climate change and thereby mitigating future climate-induced damages. This opposing channel lowers marginal utility, partially offsetting the direct effect of the negative growth shock. As a result, risk premia in a carbon-intensive economy may be lower than in a carbon-free economy, particularly in the early stages of the climate transition.

This finding challenges the conventional view that higher carbon emissions and temperatures must necessarily prompt an increase in market risk premia. As temperatures rise, the contribution of climate risk to risk premia does increase. However, because temperature dynamics are, for the most part, *endogenously* driven by economic growth, the hedging effect of adverse growth shocks of brown technologies may temper the overall impact of rising temperature on risk premia. As a result, despite the mounting threat of climate change, the overall model-implied risk premium thus far has remained essentially flat, which may help explain the difficulty in detecting and identifying the impact of carbon emissions and temperature on risk premia in the empirical data to date. Indeed, the empirical literature offers mixed evidence regarding the direction and magnitude of the relationship between carbon emissions and other climate risk measures and expected returns (e.g., Bolton and Kacperczyk (2021), Ilhan, Sautner, and Vilkov (2021), Pástor, Stambaugh, and Taylor (2022), Acharya, Johnson, Sundaresan, and Tomunen (2022), Aswani, Raghunundan, and Rajgopal (2024), Zhang (2025), Kruttli, Roth Tran, and Watugala (2025)).

Second, in the absence of carbon taxation or other forms of regulatory risk, brown-sector cash flows carry lower risk premia than green-sector cash flows. This "green" premium is driven by the hedging effect of brown shocks — negative shocks to brown output reduce emissions, slow the accumulation of atmospheric carbon, and thereby mitigate future climate-induced damages. As a result, brown shocks provide a partial hedge against future climate risk, making brown-sector cash flows less risky. The hedging channel is especially strong early in the transition, when emissions remain the primary driver of temperature fluctuations. This mechanism offers a potential explanation for recent empirical evidence in Jagannathan, Meier, and Sokolovski (2025), who find no evidence of a risk premium for high-emission firms in the U.S., where carbon pricing has remained

largely limited. Recently, Gârleanu and Pedersen (2025) show that a "green" premium may also emerge when carbon taxes are below their social optimum, as tax increases simultaneously reduce brown returns and lower marginal utility, making brown assets a hedge. Differently, in our model, the hedging value of brown assets is driven by the endogeneity of climate dynamics rather than by assumptions about policy.

The "green" premium reverses into a "brown" premium only once sufficiently strong carbon taxation is introduced. In particular, when carbon taxes adversely affect brown-sector growth and are expected to increase with temperature, after-tax brown cash flows become more exposed to climate risk and therefore require higher compensation than green cash flows.

Third, while the effect of rising temperature on risk premia may be subtle during the early stages of the climate transition, its impact on asset valuations is unequivocal — an increase in temperature, whether driven by exogenous or endogenous forces, leads to a decline in asset valuations. Based on the model-simulated data to date, a one-standard-deviation increase in temperature reduces asset valuations by approximately 0.2%, a magnitude that is qualitatively consistent with our empirical estimates. This elasticity is expected to increase over time as temperatures continue to rise.

Our paper contributes to a rapidly expanding literature at the intersection of climate economics, asset pricing, and policy design. The foundation for analyzing optimal climate policy under certainty was laid by Nordhaus (1994) and has since evolved to incorporate climate uncertainty, irreversibility, generalized risk preferences, and other relevant dimensions, with notable contributions from Pindyck (2007), Gollier (2012), Pindyck and Wang (2013), Lemoine and Traeger (2014), Golosov, Hassler, Krusell, and Tsyvinski (2014), Cai and Lontzek (2019), Brock and Hansen (2018). Complementary research has explored the role of ambiguity aversion, model uncertainty, and robust decision-making, e.g., Lemoine and Traeger (2012), Pindyck (2017), and Barnett, Brock, and Hansen (2020).

On the empirical front, a growing body of evidence points to the increasing impact of climate change on the macroeconomy and financial markets. Dell, Jones, and Olken (2012), Bansal and Ochoa (2012), and Colacito, Hoffmann, and Phan (2019) show that higher temperatures reduce economic growth. More recently, Huynh and Xia (2021), Bernstein, Gustafson, and Lewis (2019), Painter (2020), and Baldauf, Garlappi, and Yannelis (2020)) find that climate change risks and climete beliefs affect valuations of real estate and fixed income securities, especially in exposed sectors

and geographies. The relevance of these risks is further reflected in institutional investor behavior, as shown by survey evidence in Krueger, Sautner, and Starks (2020), and Stroebel and Wurgler (2021), who find that investors increasingly consider both physical and regulatory exposures in capital allocation decisions. Hsu, Li, and Tsou (2023) and Barnett (2019) explore the implications of climate policy for the pricing of transition risk, Engle, Giglio, Kelly, Lee, and Stroebel (2020) develop a mimicking portfolio strategy to hedge climate risk, and Jagannathan, Ravikumar, and Sammon (2018) show that integrating environmental concerns into portfolio design can reduce exposure to systematic risk.

In a comprehensive review, Giglio, Kelly, and Stroebel (2021) emphasize the importance of integrating physical climate risks, climate policy interventions, and financial market dynamics to improve our understanding of the economic consequences of climate change. Our paper advances this line of research by developing a structural asset-pricing framework in which economic growth and temperature reinforce each other, yielding new insights into the dynamic trade-offs and asset pricing implications of climate change and mitigation policies.

The rest of the paper is organized as follows. Section 1 analyzes the joint dynamics of carbon emissions and temperature; Section 2 examines the impact of rising temperatures on expected growth and asset valuations; Section 3 presents our structural model and explores its asset-pricing implications. Section 4 concludes.

# 1 Joint Dynamics of Carbon Emissions and Climate

In recent decades, the global dynamics of greenhouse gas (GHG) emissions intensity have undergone significant shifts, driven by heterogeneous pathways of economic development, technological adoption, and climate policy engagement around the world. Emissions are the primary driver of rising global temperatures, but the increasing risks associated with climate change have also spurred innovation in low-carbon technologies, energy systems, and adaptive responses. As such, temperature increases are not only consequences of past emissions but also catalysts for improved emissions efficiency. In this section, we briefly summarize the dynamic relationship between carbon emissions and temperature trends.

Our analysis draws on data from the Emissions Database for Global Atmospheric Research (EDGAR), maintained by the European Commission's Joint Research Centre, which provides harmonized annual GHG emissions estimates for each country. Economic data, particularly gross domestic product (GDP) measured in purchasing power parity (PPP) terms, are sourced from the World Bank's World Development Indicators. To evaluate trends and variations across regions, we aggregate country-level emissions and GDP data into seven broader world regions: East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa. For each region, we construct a measure of emissions intensity as GHG emissions (expressed in Mt $CO_2$-eq/year) per unit of economic output, equivalent to \$1,000 of GDP in PPP terms. Regional temperature data are obtained from the Berkeley Earth dataset.

Figure 1 presents the trajectory of carbon emissions intensity for seven world regions from 1990 to 2021. While carbon emissions intensity has declined globally over this period, there are notable regional differences in the pace and scale of improvement. The most substantial declines are observed in high-income economies, particularly in the European Union and North America. These reductions are driven by a combination of structural economic shifts towards service-based industries, the implementation of stringent environmental regulations (e.g., the EU Emissions Trading System), improvements in energy efficiency, and the gradual decarbonization of power systems through increased adoption of renewable energy. East Asia and the Pacific show a steady but considerably slower decline in emissions intensity. Countries in the Sub-Saharan Africa, Middle East and North Africa, and Latin America regions have made more limited progress in decarbonization and therefore exhibit significantly flatter trajectories. Quantitatively, over the last three decades, emissions intensity declined by approximately 52% in Europe and North America, compared to 40% in East Asia and the Pacific, 20% in Latin America and the Caribbean, and only 14% in Sub-Saharan Africa.

Yet improvements in emissions intensity have not been sufficient to offset the scale effects of sustained economic growth. As shown in Figure 2, absolute carbon emissions, driven by continued industrial expansion, rapid urbanization, and rising energy demand, have increased across most regions, particularly in East Asia and South Asia. While North America and Europe have achieved

reductions in total emissions, their cumulative decline has not been large enough to compensate for rising emissions elsewhere. As a result, global emissions have increased by nearly 60% over this period.

As emissions continue to rise, so do global temperatures. Figure 3 presents 10-year moving average trends in temperature anomalies across world regions. As shown, all regions experience substantial increases in average surface temperatures between 1990 and 2020, with anomalies exceeding 1°C in five out of the seven regions. These trends highlight the persistent and cumulative impact of greenhouse gas emissions: despite improvements in emissions intensity, both past and current emissions continue to drive temperature anomalies upward.

Notably, the simultaneous rise in temperatures and decline in emissions intensity across regions points to a potential feedback mechanism, whereby increasing climate stress may induce improvements in efficiency through technological adaptation, behavioral change, or policy responses. To explore this potential dynamic, we estimate the following panel regression model:

$$\Delta \log(Intensity)_{r,t+1\to t+k} = \bar{i}_r + \beta\, X_t + \Delta gdp_{r,t} + \epsilon_{r,t+1\to t+k}\ , \tag{1}$$

where $\Delta \log(Intensity)_{r,t+1\to t+k}$ denoted the cumulative change in log intensity over a $k$-year horizon in region $r$, $\Delta gdp_{r,t}$ is the GDP growth rate in region $r$ in year $t$, and $\bar{i}_r$ captures region-specific fixed effects. We consider two alternative specifications for the explanatory variable $X_t$: (i) the annual change in the log of global atmospheric carbon dioxide concentration, i.e., $X_t = \Delta \log(CO_2)_t$, and (ii) low-frequency variation in regional surface temperature anomalies, proxied by the 10-year change in temperature trends, i.e., $X_t \equiv \Delta_{10}\bar{T}_{r,t} = \Delta\bar{T}_{r,t-10\to t}$. The concentration data, measured in parts per million (ppm), are obtained from the National Oceanic and Atmospheric Administration (NOAA) Global Monitoring Laboratory.

Table I presents evidence on the effect of unfolding climate change on cumulative changes in regional emissions intensity over 1-, 2-, and 3-year horizons. T-statistics reported in this and subsequent tables are based on standard errors clustered by region (or firm) and time, constructed using the approach in Thompson (2011). As shown in Panel A, a rise in carbon concentration is associated with significant subsequent improvements in emissions intensity. Similarly, Panel B

demonstrates that persistent increases in regional temperature also lead to a significant decline in emissions intensity. Specifically, a 1°C increase in regional temperature trend is associated with a 1.0% ($t = -4.74$) reduction in emissions intensity over the following year and approximately a 3.2% ($t = -2.47$) reduction over a three-year horizon. While the estimates are relatively small in magnitude, these findings suggest that rising global or regional temperatures trigger policy, behavioral, or technological responses aimed at promoting decarbonization. Taken together, this evidence points to a potentially important endogenous feedback mechanism through which climate change itself induces adaptive efforts to improve carbon efficiency, thereby contributing to its own mitigation.

## 2 Climate Change, Growth Expectations and Equity Valuations

In this section, we analyse the impact of rising temperature on market's expectations of future growth and equity prices. In contrast to the empirical economic literature that measures the effect of global warming on the macroeconomy by looking at the historical relationship between temperature and national income (e.g., Nordhaus (2006), Dell, Jones, and Olken (2012)), our approach leverages forward-looking information embedded in analysts' earnings forecasts and asset prices — information that may not be captured by past income or output data.

Our forward-looking analysis is based on monthly survey data of equity analysts' forecasts of long-term earnings growth obtained from the I/B/E/S files of the Thomson Reuters Database. To adjust for expected inflation, we convert nominal forecasts to real values using inflation expectations from the Survey of Professional Forecasters, maintained by the Federal Reserve Bank of Philadelphia. Standard accounting, equity price, and return data are obtained from the Compustat and CRSP databases. We supplement these with firm-level intangible capital series constructed by Peters and Taylor (2017) and made available through Wharton Research Data Services. Data on firm-level direct and indirect carbon emissions, as well as emissions intensity (carbon emissions scaled by firm revenue), are sourced from Truecost. We exclude firms in the financial section.

Macroeconomic indicators, including bond yields and the monthly Brave-Butters-Kelley series of real gross domestic product (GDP), are collected from the FRED database, maintained by the

Federal Reserve Bank of St. Louis. Climate-change risks are based on the monthly U.S. temperature anomaly series from the U.S. Climate Divisional Database. To isolate persistent climate trends and filter out short-term (weather) fluctuations, we focus on variations in a 12-month moving average temperature trend.

All accounting and financial data are deflated using the Consumer Price Index. While our full sample spans the period from 1983 to 2021, our primary analysis focuses on the more recent period beginning in 2000.

### 2.1 Temperature and Expected Long-Run Growth

To understand if markets' expectations of future long-term growth are affected by concerns about climate change we run the following panel regression:

$$Egrowth_{i,t} = a_i + \beta_T \, \Delta Temp_{t-4 \to t-1} + f' FC_{i,t-1} + m' MC_{t-1} + u_{i,t} \ , \tag{2}$$

where $Egrowth_{i,t}$ is the (log) median analysts' forecast of long-run earnings growth of firm $i$ in month $t$, $\Delta Temp_{t-4 \to t-1}$ is the change in the temperature trend over the quarter preceding month $t$, $FC_{i,t-1}$ and $MC_{t-1}$ are firm- and market-level controls, respectively, and $a_i$ captures firm fixed effects. Long-run growth forecasts, $Egrowth_{i,t}$, are expressed in annualized percentage terms.

In our baseline specification, temperature shocks are measured by the first difference in the temperature trend, which helps mitigate potential measurement errors in climate-change news. Our findings remain robust when temperature shocks are alternatively extracted using estimated time-series dynamics. To account for a potential lag in the market's reaction to climate-change news, we measure temperature shocks by the change in temperature trend over the previous quarter. Temperature shocks are standardized to facilitate the interpretation of their impact.

To absorb heterogeneity in firm characteristics, we include the following set of lagged controls: (log) market capitalization, (log) assets, (log) book-to-market ratio, return on assets, sales-to-assets ratio, gross profit to assets, and leverage.[1] To account for the persistence in analysts' forecasts, we

[1] We also consider additional firm-level controls, including the share of intangible capital, carbon emissions, and emissions intensity, but find no significant impact of these characteristics on earnings growth forecasts.

also include the lagged value of long-run earnings growth expectations. To control for the aggregate state of the economy, we include the (log) price-dividend ratio of the stock market portfolio, GDP growth, the one-year Treasury bond yield, the term spread (defined as the difference between ten- and one-year government bond yields), and the default spread (defined as the difference between BAA and AAA corporate bond yields). As with firm-level controls, all macroeconomic indicators are lagged by one month to ensure they reflect information available at the time forecasts are issued.

Panel A of Table II presents the impact of temperature on analysts' forecast of long-run earnings growth for the 2000–2021 sample. Based on the full panel (columns labeled "All"), we find that in response to a one standard deviation increase in temperature, analysts lower their expectations of long-run earnings growth by approximately 3.7 basis points. This effect is statistically significant, with a robust t-statistics of about $-4.7$. Although the magnitude of the estimated effect may appear modest, it is important to recognize that the cumulative impact of temperature is substantially larger due to the high persistence of expected growth.[2]

As Panel A of Table II further demonstrates, the impact of temperature on long-run earnings growth expectations is not driven by small firms or idiosyncratic analyst views. Even after excluding firms followed by only a few analysts, the estimated temperature elasticity remains statistically significant and of similar magnitude. For instance, in the subsample of firms covered by at least five analysts — typically larger and more closely monitored companies — the estimated elasticity is approximately $-0.031$, with a t-statistic of $-4.68$. This evidence suggests that the observed relationship is not driven by limited analyst coverage or firm size, and that risks associated with climate change affect expectations across the entire cross section of firms.

It is noteworthy that temperature risks have only recently begun to inform growth expectations. As Panel B of Table II shows, prior to 2000, analysts paid no attention to temperature variations. Since then, however, as markets have become more aware of and concerned about the potential economic consequences of climate change, rising temperatures have increasingly factored into analysts' expectations.

In Table III, we explore the cross-sectional variation in firms' expected growth exposure to climate-related risks by interacting temperature shocks in Equation (2) with dummy variables that

[2]Controlling for firm characteristics, the first-order autocorrelation of analysts' forecasts is about 0.9.

reflect firms' capital tangibility and their exposure to heat. Specifically, we sort firms into three portfolios based on the proportion of intangible capital in their total capital stock. We define the dummy variables $I_{\text{Intang-low}}$, $I_{\text{Intang-med}}$ and $I_{\text{Intang-high}}$ to indicate whether a firm falls into the bottom 25th percentile, the middle 50th percentile, or the top 25th percentile of the intangible capital share distribution, respectively.

Additionally, following the classification by the National Institute for Occupational Safety and Health (NIOSH) and Graff Zivin and Neidell (2014), we construct nine industry portfolios to capture differential exposure to heat. Industries that operate in hot and humid environments such as mining (including oil and gas extraction), construction, transportation, and utilities are classified as high heat-exposure sectors. The remaining sectors that include manufacturing, wholesale, retail trade, services, and communications are categorized as low heat-exposure sectors.[3] The dummy variables $I_{\text{Heat-Exposure-low}}$ and $I_{\text{Heat-Exposure-high}}$ take the value of one if a firm belongs to a low or high heat-exposure sector, respectively.

We find that the temperature elasticity of expected long-run earnings growth varies significantly with capital tangibility and heat exposure. As shown in Panel A of Table III, over the 2000–2021 sample period, in response to temperature shocks, firms with a low share of intangible capital experience a significant decline in expected earnings growth of about 5.4 basis points ($t = -4.02$) compared to only a 2.2 basis point decline ($t = -1.76$) for firms with high intangible capital. This evidence suggests that intangible capital — such as innovation capacity, digital infrastructure, and organizational know-how — tends to exhibit resilience against climate-change risks. In contrast, tangible capital appears significantly more vulnerable to such risks, likely due not only to direct physical exposure but also to the risk of asset stranding and tightened environmental regulations.

We also find that operational exposure to heat amplifies the adverse effects of rising temperature on growth expectations. In particular, firms operating in industries with high exposure to heat exhibit a more negative temperature elasticity of $-0.064$, relative to $-0.037$ for those in low heat-exposure sectors.

Panel B of Table III, which focuses on the more recent 2011–2021 period, documents an even larger degree of cross-sectional dispersion. The negative temperature elasticity of expected

[3]We omit the agricultural sector due to the limited number of publicly traded agricultural firms.

earnings growth for firms with a high share of tangible capital increases to approximately $-10$ basis points, while growth expectations of firms with high share of intangible capital appear largely unaffected by temperature variations. The difference in temperature sensitivity between the low- and high-intangible capital cohorts widens to roughly $-11$ basis points and is statistically significant with a t-statistic of about 2.57. A similar pattern emerges across industry groups: firms in high heat-exposed industries exhibit a temperature elasticity of $-0.12$ ($t = -2.88$), which is nearly four times greater in magnitude than the $-0.032$ ($t = -2.10$) elasticity observed among firms in less heat-sensitive sectors. This evidence suggests that financial analysts are becoming increasingly cognizant of the growing salience of climate risks, particularly for firms with greater operational vulnerability and tangible-heavy capital.

### 2.2 Temperature Elasticity of Equity Valuations

To complete our empirical analysis, we utilize an additional set of capital market data — equity valuations. Similar to analysts' forecasts, asset prices are forward-looking and reflect not only the market's expectations about future growth but also future returns. Therefore, if climate change is expected to affect either future growth and/or risk, such expectations should be reflected in current valuations.

We examine both the aggregate and cross-sectional impact of climate change on asset valuations using a set of 12 equity portfolios. We work with portfolios rather than individual firms because many firms do not pay dividends consistently; hence, constructing monthly valuations at the firm level is problematic, if not infeasible. Guided by the evidence in Table III, we select a cross section that is likely to exhibit significant variation in response to climate-change news. Specifically, our cross section comprises three portfolios constructed by sorting firms based on the ratio of intangible capital to total capital, along with nine industry-sorted portfolios used earlier in our analysis. The industry portfolios represent the mining, construction, transportation, utilities, manufacturing, wholesale, retail trade, services, and communications sectors.

To quantify the average response of equity valuations to temperature risks, we estimate the

following panel regression specification:

$$z_{p,t} \;=\; \bar{z}_p + \phi_T \, \Delta Temp_{t-3 \to t} + \rho z_{p,t-1} + f' PC_{p,t} + m' MC_t + \eta_{p,t} \;, \tag{3}$$

where $z_{p,t}$ is the log of the price-dividend ratio of portfolio $p$ in month $t$, $\bar{z}_p$ represents portfolio-specific fixed effects, $PC_{p,t}$ and $MC_t$ are portfolio-level and aggregate controls. We use the same set of macroeconomic controls as in the expected growth specification in Equation (2), and account for cross-sectional heterogeneity using the same characteristics as above, but measured at the portfolio rather than the firm level.

The estimated semi-elasticities of equity valuations with respect to temperature variations are presented in Table IV. We find that the response of equity valuations to temperature risk over the full 2000–2021 sample is negative but only marginally significant: $\hat{\phi}_T = -0.0048$, with a t-statistic of $-1.51$. However, in the second half of the sample (i.e., the 2011–2021 period), the temperature elasticity more than doubles to $-0.0117$ and becomes statistically significant at conventional levels, with a t-statistic of $-2.67$. This evidence reinforces the expected growth findings discussed above and suggests that capital markets have become sufficiently concerned with the potential ramifications of rising temperatures to begin pricing in those risks.

In Table V, we augment the regression specification in Equation (3) by including an interaction term between the temperature shock and a dummy variable that equals one for portfolios with a low fraction of intangible capital and those highly exposed to heat. Consistent with the expected-growth evidence, we find that the response of equity valuations to temperature is not uniform — sectors that are likely less adaptable to climate change exhibit greater sensitivity to temperature risks. In particular, during the recent 2011–2021 period, a one standard deviation increase in temperature is associated, on average, with a 1% decline in equity valuations ($t = -2.69$). However, firms with relatively low intangible capital and those operating in heat-sensitive sectors experience an additional valuation decline of approximately 0.41% ($t = -2.14$). Taken together, the evidence from Tables IV and V suggests that climate change risks are increasingly priced in equity markets, especially for firms and sectors with limited adaptive capacity or high exposure to heat-caused disruptions.

# 3 Climate Change Model

Motivated by the empirical evidence discussed above, we develop a quantitative model that links macroeconomic dynamics and climate change by endogenizing temperature-related risks and explicitly capturing the feedback effects of rising temperatures on decarbonization and the economy's transition towards emission-free production. We calibrate the model to match observed macroeconomic and climate trends discussed in Section 1 and the temperature elasticity of long-run growth expectations estimated in Section 2.1. We then use the calibrated framework to study the impact of rising temperatures on asset prices, as documented in Section 2.2, and to analyze the implications of climate risk and decarbonization dynamics for the evolution of risk and risk premia.

We begin by characterizing the production technologies available to firms and their implications for climate dynamics and long-run economic growth. We then set up a sectoral structure and describe how rising temperatures endogenously induce a gradual transition from carbon-intensive to emission-free production, generating feedback effects between economic activity, emissions, and climate risk.

## 3.1 Production Technologies

The aggregate output (consumption) in the economy is assumed to be produced by two types of production technologies: green technologies (labelled by the superscript $g$), which are emission-free, and brown technologies (labelled by the superscript $b$), which generate carbon emissions.[4] Let $Y_0^g$ and $Y_0^b$ denote the initial ($t = 0$) output produced using the green and brown technologies, respectively. The log growth rates of output produced by each type of technology evolve according to:

$$\Delta y_{t+1}^g \equiv \log(Y_{t+1}^g/Y_t^g) = \mu + \sigma_y \varepsilon_{y,t+1} + \sigma_g \varepsilon_{g,t+1} - \sigma_L L_{t+1}, \tag{4}$$

$$\Delta y_{t+1}^b \equiv \log(Y_{t+1}^b/Y_t^b) = \mu + \sigma_y \varepsilon_{y,t+1} + \sigma_b \varepsilon_{b,t+1} - \sigma_L L_{t+1}\,, \tag{5}$$

[4] For simplicity and tractability we abstract from investment and capital accumulation and work with an endowment economy in which aggregate output equals consumption.

where $\varepsilon_{y,t+1}$ represents a productivity shock common to both technologies, while $\varepsilon_{g,t+1}$ and $\varepsilon_{b,t+1}$ capture technology-specific innovations. The three shocks are assumed to be mutually orthogonal and follow i.i.d. standard normal distributions.

Consistent with our empirical evidence, we assume that rising temperatures adversely affect economic activity. Specifically, we assume that both production technologies in Equations (4) and (5) are subject to temperature-driven disruptions captures by the term $-\sigma_L L_{t+1}$, where $L_{t+1}$ is a Poisson process that counts the number of adverse climate shocks between $t$ and $t+1$, and the parameter $\sigma_L > 0$ represents the sensitivity of output growth to climate-driven losses. The perceived intensity of consumption losses, denoted by $\pi_t$, is assumed to increase with temperature:

$$\pi_t \;\equiv\; \mathbb{E}_t[L_{t+1}] \;=\; \ell_0 + \ell_T \max\left\{T_t - 1^{\circ}\mathrm{C}, 0\right\}, \tag{6}$$

where $\ell_0 > 0$ and $\ell_T > 0$ are parameters governing baseline and temperature-sensitive damage intensities, respectively, $T_t$ is the temperature anomaly (i.e., the deviation of temperature from its pre-industrial level), and $\mathbb{E}_t$ denotes agents' expectation conditional on information at time $t$. Our specification implies that, in normal times (i.e., absent climate change), output growth is subject to losses that occur with probability $\ell_0$. However, once the temperature anomaly exceeds the 1°C threshold, the expected frequency of losses increases proportionally with the degree of global warming.

### 3.2 Emissions, Carbon Concentration and Temperature

We assume that the temperature anomaly is driven by anthropogenic carbon emissions, which arise as a by-product of brown production technologies. Specifically, aggregate emissions at time $t$ are proportional to brown output:

$$E_t \;=\; \alpha\, Y_t^b, \qquad \alpha > 0\,. \tag{7}$$

Consequently, aggregate emissions intensity, $\frac{E_t}{Y_t}$, is determined by the emissions intensity of the brown production ($\alpha$) and the allocation of production between green and brown technologies.

As emissions accumulate, they raise atmospheric carbon concentration, which in turn increases

global temperatures. In particular, atmospheric carbon concentration, denoted by $\mathbb{C}_t$, and the temperature anomaly evolve according to:

$$\mathbb{C}_{t+1} = (1-\nu)\mathbb{C}_0 + \nu\mathbb{C}_t + cE_{t+1} + \sigma_{\mathbb{C}}\varepsilon_{\mathbb{C},t+1}\,, \tag{8}$$

$$T_{t+1} = \phi\big(\mathbb{C}_{t+1} - \mathbb{C}^*\big)\,, \tag{9}$$

where the parameters $c > 0$ and $\phi > 0$, $\varepsilon_{\mathbb{C},t+1} \sim i.i.d.\ N(0,1)$ is an exogenous shock to atmospheric carbon concentration, and $\mathbb{C}^*$ denotes the pre-industrial baseline level of atmospheric carbon concentration. Consistent with findings in climate science, the long-run temperature trend is assumed to be proportional to the deviation of atmospheric carbon concentration from its pre-industrial level.

Note that our specification explicitly links economic growth, technological transition, and climate dynamics. In particular, temperature is modeled as being driven by both an *exogenous component*, represented by innovations $\varepsilon_{\mathbb{C},t+1}$ to atmospheric carbon concentration, and an *endogenous component*, captured by emissions $E_{t+1}$. Endogenous variations in temperature arise from economic growth driven by brown production and shifts in the technological composition of output. Holding all else constant, growth in brown output increases emissions and thereby raises temperature, whereas reallocation towards green technologies mitigates this effect by slowing the rate of temperature increase. We next describe the transition to a carbon-free economy.

### 3.3 Aggregate Output along the Transition Path to a Carbon-Free Economy

Aggregate output at time $t = 0$ is determined by the initial allocation of production across the two technologies, $Y_0 = Y_0^g + Y_0^b$. We assume that over time, in response to rising climate risk, regulatory pressure, and shifts in market sentiment, the economy gradually transitions away from brown production towards green technologies. Specifically, at the end of period $t$, a fraction $\omega_t$ of the remaining brown output is converted into green production. As a result, production at the beginning of period $t+1$ starts with $(1-\omega_t)\,Y_t^b$ of brown output and with $Y_t^g + \omega_t Y_t^b$ of green

output. Aggregate output at the end of period $t+1$ is therefore given by

$$Y_{t+1} = (1-\omega_t)\, Y_t^b\, e^{\Delta y_{t+1}^b} + \left(Y_t^g + \omega_t Y_t^b\right) e^{\Delta y_{t+1}^g}\,. \tag{10}$$

The transition rate $\omega_t$ is assumed to follow a persistent process that increases endogenously with temperature, in particular:

$$\omega_t = \frac{1}{1+e^{\lambda_t}}, \tag{11}$$

$$\lambda_t = (1-\rho_\lambda)\lambda_0 + \rho_\lambda \lambda_{t-1} + \chi\, T_{t-1} - \sigma_\lambda \varepsilon_{\lambda,t}, \tag{12}$$

where $\varepsilon_{\lambda,t} \sim i.i.d.\ \mathcal{N}(0,1)$ and $\sigma_\lambda > 0$. We set $\chi < 0$, which means that higher temperatures accelerate decarbonization of the economy due to tighter regulation, stronger political pressure and more stringent abatement policies. The negative sign in front of the innovation implies that a positive $\varepsilon_{\lambda,t}$ shock lowers $\lambda_t$, increases $\omega_t$, and thereby speeds up the transition towards emission-free production. We refer to $\varepsilon_{\lambda,t}$ as a decarbonization shock. The logistic specification ensures that $0 < \omega_t < 1$ and captures the gradual and irreversible nature of technological reallocation.

Note that aggregate output growth is approximately a convex combination of brown- and green-technology growth rates:

$$\Delta y_{t+1} \approx \theta_t\, \Delta y_{t+1}^b + (1-\theta_t)\, \Delta y_{t+1}^g, \tag{13}$$

where

$$\theta_t \equiv \frac{(1-\omega_t) Y_t^b}{Y_t} \tag{14}$$

denotes the share of output that remains carbon-intensive. Accordingly, along the transition path, aggregate output is a portfolio of brown and green cash flows whose composition changes over time as the economy shifts away from carbon-intensive production — the weight on green production increases, while the contribution of brown technology declines. In the limit, as $\theta_t \to 0$, the economy completes its transition to carbon-free production, and aggregate consumption growth is driven entirely by the dynamics of green technologies.

Note that our model features important dynamic feedbacks between economic activity and climate risk. High economic growth when driven by brown production generates emissions, raises temperatures, and increases future growth risk. Higher temperatures, in turn, accelerate the transition away from brown technologies, reducing future emissions and mitigating climate risk. The net welfare effect of these opposing forces depends on the speed of the technological transition relative to the accumulation of carbon in the atmosphere.

### 3.4 Cross-Section of Brown and Green Firms

To understand the cross-sectional implications of endogenous climate-change risks, we consider two representative sectors (firms) in the economy: the brown sector and the green sector. Let $Y_t^B$ and $Y_t^G$ denote the time-$t$ output (cash flow) of the brown and green sectors, respectively; and let $D_t^B$ and $D_t^G$ denote their respective dividends. We use uppercase superscripts ($G$ and $B$) to distinguish sectors from production technologies, which are denoted by lowercase superscripts ($g$ and $b$).

We define the green sector (or a representative green firm) as a sector that starts with entirely green output $Y_0^G = Y_0^g$ and grows at the green-technology rate $\Delta y_t^g$ as defined in Equation (4); that is,

$$\Delta y_{t+1}^G \;\equiv\; \log\left(Y_{t+1}^G / Y_t^G\right) \;=\; \Delta y_{t+1}^g \,. \tag{15}$$

All cash flows generated by the green firm are distributed as dividends to its shareholders, i.e., $D_t^G = Y_t^G$.

The brown sector differs from the green sector in two respects. First, it starts with cash flows produced using brown technologies ($Y_0^B = Y_0^b$) which are decarbonized over time at the rate given by Equations (11) and (12). That is, each period a fraction $\omega_t$ of its remaining brown output becomes emission-free and subsequently grows at the green-technology rate. Therefore, the growth of the brown sector cash flows is approximately given by

$$\Delta y_{t+1}^B \;\equiv\; \log\left(Y_{t+1}^B / Y_t^B\right) \;\approx\; \widehat{\theta}_t \, \Delta y_{t+1}^b + (1 - \widehat{\theta}_t) \, \Delta y_{t+1}^g \,, \tag{16}$$

where

$$\widehat{\theta}_t \equiv \frac{(1-\omega_t)Y_t^b}{Y_t^B} \tag{17}$$

is the emitting share of brown sector output at time $t$.

Second, the brown sector may be subject to climate policy (regulatory) risk in the form of carbon taxation. Because climate regulations are likely to create persistent distortions to the marginal profitability of carbon-intensive production, we model the carbon tax as a reduction in the growth rate of brown-sector dividends. In particular, we assume that dividends paid by the brown sector, $D_t^B$, grow at the rate

$$\Delta d_t^B \;\equiv\; \log\left(D_{t+1}^B/D_t^B\right) \;=\; \Delta y_t^B - \tau_t, \tag{18}$$

where $\tau_t$ captures the effective tax burden imposed on brown-sector production. The tax rate $\tau_t$ depends on the prevailing carbon price and the current emissions intensity of the brown sector. In particular, we assume that

$$\tau_t \;=\; p_t \frac{E_t}{Y_t^B}\,, \tag{19}$$

$$p_t \;=\; p_{t-1} + \sigma_p L'_{t+1}\,. \tag{20}$$

Here, $E_t/Y_t^B$ is the emissions intensity of the brown sector at time $t$, and $p_t$ denotes the carbon price per unit of emissions intensity. We assume that the carbon price is subject to periodic upward adjustments, captured by the shock $\sigma_p L'_{t+1}$, with $\sigma_p > 0$, reflecting regulatory tightening in response to rising temperatures. Specifically, $L'_{t+1}$ is assumed to follows a Poisson process with intensity governed by Equation (6), but with $\ell_0 = 0$, so that carbon-price jumps occur only in response to high temperatures and not otherwise.

Note that aggregate output (consumption) in our framework is simply the sum of outputs in the two sectors,

$$Y_t = Y_t^B + Y_t^G\,, \tag{21}$$

and, in evaluating the pricing implications of climate change, we consider four cash flows: aggregate consumption $Y_t$, dividends paid by the green sector $D_t^G$, and the pre- and after-tax cash flows of the brown sector, $Y_t^B$ and $D_t^B$, respectively.

### 3.5 Preferences

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

$$U_t = \left\{ (1-\delta) C_t^{1-\frac{1}{\psi}} + \delta \left( \mathbb{E}_t \left[ U_{t+1}^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}}, \tag{22}$$

where $U_{t+1}$ is the continuation value of the consumption plan starting in period $t+1$, $\delta$ is the rate of time preference, $\gamma$ is the coefficient of relative risk aversion, and $\psi$ denotes the intertemporal elasticity of substitution (IES). The maximized life-time utility in this setting is proportional to the wealth-consumption ratio provided that $\psi \neq 1$. Specifically, the value function normalized by current consumption is given by:

$$\frac{U_t}{C_t} = \left[ (1-\delta) Z_t \right]^{\frac{\psi}{\psi-1}}, \tag{23}$$

where $Z_t \equiv \frac{W_t}{C_t}$ is the aggregate wealth-consumption ratio.[5]

Note that climate risks are inherently long-run — they unfold slowly and are expected to persist over many decades. Therefore, following the long-run risks literature (Bansal and Yaron (2004)), we assume a preference for early resolution of uncertainty, which arises when $\gamma > 1/\psi$. Unlike the standard expected utility framework commonly used in integrated assessment models, where the timing of risk resolution is irrelevant, recursive preferences explicitly reflect agents' concerns about risks that realize in the distant future — precisely the kind of uncertainty that defines climate change. Preferences for early resolution therefore offer a coherent and theoretically plausible way to capture concerns about climate risks. In contrast, expected utility can accommodate such concerns only by embedding climate outcomes directly into the utility function (for example, as in Barnett, Brock, and Hansen (2020)).[6]

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

[6] Prior work including Bansal, Kiku, and Ochoa (2017), Daniel, Litterman, and Wagner (2018), and Cai and Lontzek (2019) has explored the implications of risk preferences for the social cost of carbon and optimal abatement policies.

### 3.6 Calibration and Model's Dynamics

To quantitatively assess the asset pricing and welfare implications of our framework, we calibrate the model parameters to match key moments of output, emissions, carbon concentration, and temperature dynamics observed over the past three decades.

Table VI reports the baseline parameter values. To match the mean and standard deviation of global real GDP growth over the 1990–2021 sample, we set the growth rate parameter to $\mu = 0.034$, and the volatility parameters to $\sigma_y = 0.0179$ and $\sigma_g = \sigma_b = 0.0089$. These values imply an overall standard deviation of Gaussian growth shocks of 2%, with the common productivity shocks accounting for 80% of the variation in sectoral output growth and sector-specific shocks accounting for the remaining 20%. We set the initial allocation of production to 25% green technologies and 75% brown technologies, consistent with evidence that fossil fuels accounted for roughly three-quarters to four-fifths of global primary energy consumption over the early part of our sample period.

The loss magnitude ($\sigma_L = -0.05$) and the baseline arrival rate of damage shocks ($\ell_0 = 0.05$) are chosen to replicate the observed skewness and kurtosis in output growth based on historical data, which so far largely reflect non-climate-related sources of macroeconomic risk. The temperature sensitivity of the loss arrival rate, $\ell_T = 0.05$, is calibrated to account for the sample elasticity of long-run earnings expectations to variations in temperature.

To account for the observed level and declining trend in emissions intensity, as well as the feedback effect of temperature on emissions, we set $\alpha = 0.725$, $\rho = 0.986$, $\chi = -0.017$, and $\sigma_\lambda = 0.03$.

We calibrate $\nu = 0.9938$, $c = 0.05$ and $\phi = 0.015$ to match historical trends in carbon concentration and global temperature. The initial atmospheric carbon concentration is set to $\mathbb{C}_0 = 354.45$ ppm, corresponding to its empirical value in 1990, and the pre-industrial baseline is fixed at $\mathbb{C}^* = 325$ ppm.

We set the initial carbon price to $p_0 = 0.0001$ and $\sigma_p = 0.015$. Together with the calibration of the decarbonization dynamics, this specification implies that the reduction in brown-sector dividend growth is effectively zero before the temperature anomaly exceeds the 1°C threshold and reaches a peak of about 0.4% on average.

Because our model abstracts from other quantitatively important sources of long-run risk to focus explicitly on climate change, we adopt a relatively high coefficient of risk aversion of 15, and we set the intertemporal elasticity of substitution to 1.5 to ensure plausible dynamics of the risk-free rate and risk premia.

To solve the calibrated model, we assume that the wealth-consumption ratio is an exponentially affine function of the state variables: $Z_t = e^{\Phi_t' \mathbb{S}_t}$, where $\mathbb{S}_t = \{T_t, E_t, \omega_t, \lambda_t\}$, and solve for the solution coefficients $\Phi_t$ numerically using Monte Carlo simulations by exploiting the Euler equation:

$$1 = \mathbb{E}_t \left[ M_{t+1} R_{c,t+1} \right], \tag{24}$$

where $M_{t+1}$ is the stochastic discount factor (SDF) and $R_{c,t+1}$ is the return of the wealth portfolio. The valuation of sectoral claims is obtained in the same way by imposing their respective pricing conditions.[7] Because the model features non-stationary dynamics along the transition path and the solution coefficients are time-varying, we employ a backward solution algorithm. Starting from a terminal date 500 years in the future — when climate-change risks are effectively no longer present — we recursively solve for the coefficients at each point in time back to notional time 0, which corresponds to the year 1990 in the sample data.[8]

Table VII presents the distribution of model-implied moments over the first 30 years of simulated data, alongside their empirical counterparts. As the table indicates, the sample moments of output growth, emissions intensity, and carbon concentration fall well within the respective model-implied distributions.[9] Figure 4 further demonstrates that the model calibration successfully replicates the historical trends in cumulative output growth, emissions intensity, carbon concentration, and temperature.

The average trajectories and the 95% confidence bands for key economic and climate indicators along the transition path are displayed in Figure 5. As Panel (a) shows, under current dynamics,

[7] When solving for the equilibrium price of the after-tax dividend stream of the brown sector, we augment the state vector with the tax rate $\tau_t$.

[8] Expectations are computed using 3 million simulated paths. The solution is robust to increasing the number of simulations, allowing for non-linear state dynamics, or extending the terminal horizon beyond 500 years.

[9] A notable exception is the volatility of temperature changes, which the model does not aim to match. Our focus is on capturing the long-run trend in temperature, whereas observed volatility is largely driven by short-term (i.e., weather) fluctuations that are not representative of climate change risk.

atmospheric carbon concentration is projected to rise steadily over the next century. As a result, the temperature anomaly is expected to increase persistently, peaking at around 3°C on average before gradually declining as emissions abate. This sustained rise in temperature leads to a sharp increase in the probability of output losses — from a baseline of 5% to approximately 14% at its peak (Panel (c)). As losses compound, average economic growth declines by about 0.5 percentage point at its trough, before recovering as mitigation efforts build up and begin to pay off (Panel (d)).

The projected temperature path implied by our calibration is consistent with the long-run projections outlined in the IPCC (2023)'s Sixth Assessment Report. As shown in Figure 6, the model-implied average temperature trajectory over the next century falls well within the IPCC's range of long-run scenarios, aligning closely with the "intermediate" pathway both in terms of levels and growth rates.

To better understand the model's dynamics, Figure 7 presents the cumulative impulse responses of expected consumption growth to the fundamental sources of risk. Since time 0 in the model corresponds to the year 1990, we evaluate the responses to shocks realized in model year 30, which approximately corresponds to the present. Panel (a) shows the response to three growth shocks — a common productivity shock ($\sigma_y \varepsilon_{y,t+1}$), a green-technology innovation ($\sigma_g \varepsilon_{g,t+1}$), and a brown-technology innovation ($\sigma_b \varepsilon_{b,t+1}$). First, note that shocks to green-technology growth are i.i.d. and have no effect on future climate conditions; consequently, they have no impact on expected future growth. In contrast, positive shocks to brown-technology growth — whether common or brown-specific — reduce cumulative expected growth. These shocks generate persistent negative effects through their endogenous impact on the climate: higher current growth in brown technologies leads to higher emissions, raises temperatures, and thereby amplifies future economic damages.

As shown in Panel (b) of Figure 7, an increase in decarbonization intensity has a positive cumulative effect on expected growth. A positive shock $\sigma_\lambda \varepsilon_{\lambda,t}$ accelerates the pace of technological reallocation towards emission-free production, thereby mitigating climate-change risks and increasing future growth.

Notably, an exogenous temperature shock ($\phi \sigma_{\mathbb{C}} \varepsilon_{\mathbb{C},t+1}$) has a non-monotonic effect on expected growth — as shown in Panel (c), an increase in temperature significantly lowers cumulative expected growth in the short and medium run, but this effect is effectively reversed in the long run. The

U-shaped pattern reflects both the direct and indirect (feedback) effects of temperature on the macroeconomy — an increase in temperature raises the probability of economic losses, thereby depressing growth, but it also triggers policy and technological responses that accelerate the transition away from brown production (see Equations (11–12)). The former effect dominates in the near and medium term, while the latter prevails in the long run.

Figure 8 presents the impulse responses of temperature to the structural shocks. Both common and brown-specific growth shocks increase temperatures by raising emissions over the next century, with the effect gradually tapering off in the long run (Panel (a)). An increase in decarbonization intensity lowers future emissions and reduces temperature by accelerating the reallocation of production towards emission-free technologies (Panel (b)). The impact of an exogenous temperature shock is initially positive. However, it leads to a decline in temperature in the medium and long run due to the endogenous feedback effect of temperature, which speeds up the transition toward green production (Panel (c)).

### 3.7 Evolution of Aggregate and Sectoral Wealth

Figure 9 presents the model-implied average trajectories of valuation ratios and risk premia for aggregate consumption and sectoral claims along the transition path. Recall that model time 0 corresponds to the year 1990 in real time; thus, year 30 (represented by the dashed line) approximately corresponds to the present day.

As shown in Panel (a), the wealth-to-consumption ratio declines steadily over the next few decades as global temperatures rise. This decline reflects the cumulative impact of climate-induced output losses and elevated macroeconomic uncertainty, both of which reduce the present value of future consumption. The downward trend begins to reverse once emissions start to decline and the temperature anomaly begins to subside. As climate risks diminish and economic damages are gradually mitigated, the wealth-to-consumption ratio rebounds and eventually surpasses its initial level. In the long run, when temperature risks effectively disappear, the wealth-to-consumption ratio exceeds its present-day value by approximately 30%.

Panel (b) shows that valuation ratios of the green sector and the pre-tax brown sector follow a

similar trajectory to that of the wealth-to-consumption ratio. In contrast, the valuation of after-tax brown-sector cash flows is initially substantially lower, reflecting both weaker expected growth and higher risk of the rising tax burden driven by rising temperatures.

As expected, the trajectory of the risk premium on the consumption claim, shown in Panel (c), closely tracks the evolution of the temperature anomaly, rising as climate-change risks intensify and declining as the anomaly disappears. Quantitatively, the risk premium increases from approximately 0.45% today to around 1.4% at the peak of the temperature anomaly, before declining to about 0.9% in the long-run limit.

What is perhaps surprising is that, at the onset of the transition, the risk premium declines, and that in the long run it remains higher than its current level, despite the fact that temperature risk is substantially greater today than in the carbon-free long-run equilibrium, where such risk is effectively nil. Furthermore, as shown in Panel (d), as long as the brown sector continues to emit carbon, the risk premium on its pre-tax cash flows remains lower than that of the green sector. We explore these puzzling results in detail next.

### 3.8 Evolution of Risk and Risk Prices

To understand the evolution of risk and risk premia, consider the dynamics of the stochastic discount factor, which can be approximated by:

$$\begin{aligned} m_{t+1} \equiv \log(M_{t+1}) \;\approx\; \mathbb{E}_t\big[m_{t+1}\big] \quad &- \quad \gamma_{t,y}\sigma_y\varepsilon_{y,t+1} - \gamma_{t,g}\sigma_g\varepsilon_{g,t+1} - \gamma_{t,b}\sigma_b\varepsilon_{b,t+1} \\ &- \quad \gamma_{t,\lambda}\sigma_\lambda\varepsilon_{\lambda,t+1} - \gamma_{t,T}\sigma_T\varepsilon_{T,t+1} - \gamma_{t,L}\big(-\sigma_L[L_{t+1}-\pi_t]\big)\,, \end{aligned} \tag{25}$$

where $\sigma_T\varepsilon_{T,t+1} \equiv \phi\sigma_{\mathbb{C}}\varepsilon_{\mathbb{C},t+1}$ denotes the exogenous innovation to temperature, and $\gamma_{t,\cdot}$ represent the time-$t$ prices of the corresponding risks plotted in Figure 10.

First, consider the price of the green technology shock ($\gamma_{t,g}$) represented by the green dashed line in Panel (a). A positive shock to the green sector increases output without generating any climate externality and therefore raises consumption without affecting future climate risk. Hence, a positive green-technology shock lowers marginal utility and carries a positive price. The magnitude

of its price increases over time, reflecting a compositional effect: as the economy transitions toward emission-free production, the share of green output rises, increasing the exposure of aggregate consumption to green shocks. In the long-run carbon-free equilibrium, when all output is produced using green technologies, their price converges to the coefficient of relative risk aversion.

In contrast, the price of brown-technology shocks ($\gamma_{t,b}$) is determined not only by their effect on current consumption but also by their impact on temperature and, consequently, future aggregate growth. A positive brown shock is good news in the short run, as it raises immediate consumption and thus lowers marginal utility. At the same time, it is bad news in the long run, as it increases emissions, temperatures, and the likelihood of future climate-related damages, thereby increasing marginal utility. Due to these offsetting effects, all else equal, marginal utility is less sensitive to brown shocks than to green shocks.

In other words, when climate change is anthropogenic, a negative brown shock provides a hedge against future climate risk: it reduces output today (thus raising marginal utility) while simultaneously slowing the pace of climate change (thus lowering marginal utility). Early in the transition, when the economy remains heavily carbon-intensive, the hedging channel is particularly strong, resulting in a relatively low and even negative price of brown risk. Over time, as the share of brown production declines and its impact on future climate diminishes, the hedging effect weakens, and the price of brown risk converges to zero as the economy approaches a carbon-free equilibrium.

Because common productivity shock affects both green and brown production, its risk price ($\gamma_{t,y}$) reflects the combined effects of green and brown shocks. On the one hand, it raises current output by increasing production in both sectors. On the other hand, by boosting brown production, it also increases emissions and future climate risks. As a result, the price of common risk inherits both the pricing effect associated with green shocks and the hedging effect associated with brown shocks. Over time, as the economy transitions toward emission-free production and the share of brown output declines, the price of common risk gradually converges toward that of green risk. The price of climate-damage shocks ($\gamma_{t,L}$), presented in Panel (d), follows a similar trajectory as these shocks are also common to both sectors.

Panel (b) plots the price of exogenous temperature shocks ($\gamma_{t,T}$). Positive temperature shocks directly increase climate risk by raising expected damages. At the same time, higher temperatures

induce mitigation efforts, partially offsetting their adverse effects and dampening their impact on marginal utility. This offsetting channel is particularly strong in the early stages of the transition, when temperature has not yet breached the loss threshold, resulting in a slightly positive price. As temperatures continue to rise, however, the adverse effect becomes increasingly dominant, leading to a negative price. As the economy gradually decarbonizes and temperature risks subside, the price of temperature risk converges to zero.

Panel (c) shows the price of decarbonization shocks ($\gamma_{t,\lambda}$). A positive decarbonization shock accelerates the transition toward emission-free production, reducing future emissions and mitigating climate risk. Because these shocks improve future consumption outlook, they lower marginal utility and carry a positive price of risk. The magnitude of their price is particularly high during the transition period, when marginal changes in the speed of decarbonization have large implications for future climate dynamics. As the economy approaches the carbon-free steady state, the importance of this channel diminishes, and the price of decarbonization shocks declines to zero.

Taken together, Figure 10 highlights several important features of the evolution of risks and their prices. First, the price of brown-technology shocks it typically much lower than that of green-technology shocks, reflecting both the hedging effect of negative brown shocks against future climate risk and the compositional effect of the declining share of brown production over the transition. Second, common productivity shocks also carry a hedging component through their effect on emissions and temperature, but their hedging value declines over time as emissions intensity falls. As green production becomes dominant, both the weakening of the hedging channel of common shocks and the increasing exposure to green risk drive up their prices and, consequently, the overall risk premium (as shown in Panel (c) of Figure 9). Third, even though an exogenous increase in temperature lowers expected future growth, temperature risk can carry a positive price, particularly at the onset of the transition, due to its endogenous feedback on decarbonization.

### 3.9 Growth Risks Betas

To further understand the cross-sectional variation in sectoral risk and risk premia, in Figure 11 we plot the evolution of betas of the green and brown sectors, as well as aggregate consumption, with respect to three growth shocks — common, green, and brown — along the transition to a

carbon-free economy.[10]

As Panel (a) shows, exposure to common productivity shocks generates no cross-sectional variation, as these shocks affect both sectors symmetrically. What is important, however, is that the betas with respect to the common shock increase in the long run. This pattern reflects the diminishing hedging effect of common productivity shocks. At the onset of the transition, a negative common shock reduces current output in both sectors and, in the absence of climate effects, would imply unit exposure. However, by lowering emissions and reducing the likelihood of future climate-driven losses, it also improves future growth prospects, thereby mitigating sectoral risk exposure. This hedging channel becomes stronger as temperature rises, but eventually weakens as the economy decarbonizes and climate dynamics become decoupled from growth. As a result, the betas converge to one in the long run.

Panel (b) presents the betas with respect to green technology shocks. By construction, the green sector always has unit exposure to its own shock. In contrast, the brown sector's loading on green shocks is initially zero as green technologies are not yet part of the brown sector's production mix. As the brown sector is gradually decarbonized, its exposure to green shocks increases and eventually converges to one once the transition to emission-free production is complete.

Panel (c) shows the betas with respect to brown technology shocks. Note that the brown sector's initial exposure to its own shock is positive but below one, as negative brown shocks, similar to common shocks, provide a hedge against future climate risks by reducing emissions and mitigating expected damages. This exposure declines over time as the brown sector progressively shifts away from carbon-intensive production. In contrast, the green sector's exposure to brown shocks is initially negative, particularly early in the transition, since positive brown shocks increase emissions and exacerbate climate risks, generating a negative externality for the green sector. As emissions from brown technologies diminish, this channel weakens and the green sector's brown beta converges to zero.

The growth betas of aggregate consumption are effectively a convex combination of the sectoral betas, with weights reflecting the sectors' shares in aggregate output. As the economy transitions

[10]For brevity, we focus on betas with respect to growth shocks only, as these are the primary drivers of the cross-sectional variation in risk premia. Exposure of the green and (pre-tax) brown sectors to other shocks is very similar and therefore does not contribute meaningfully to differences in their risk premia.

toward emission-free production, these shares shift from the brown to the green sector, causing aggregate consumption risk exposures to increasingly resemble those of the green sector.

While it is challenging to disentangle growth shocks in the data and thus to construct empirical counterparts to all model-implied betas, we adopt a reduced-form approach and focuses on sectoral exposure to the primary source of climate risk — the brown shock. As shown in Figure 11, both common and green-technology shocks have positive effects on sectoral returns. In contrast, brown-technology shocks generate asymmetric responses. Brown shocks increase future climate risk for the entire economy, but they also boost output in the brown sector sufficiently enough to make its exposure positive. The green sector, however, does not benefit from these productivity gains and therefore exhibits negative exposure to brown shocks.

We define the brown sector as firms operating in the most emission-intensive industries. Specifically, we classify firms in electric power generation, transmission and distribution, oil and gas extraction and mining, chemicals, petroleum and plastics manufacturing, and transportation as brown firms. As defined, the brown sector accounts for approximately 90% of total direct (Scope 1) emissions on average. The green sector comprises all remaining (non-financial) firms. For each sector, we construct time series of annual value-weighted returns and aggregate sales growth over the 1990–2021 period.

We identify brown-specific shocks by regressing sales growth in the brown sector on the growth in GDP and sales growth in the green sector. The residual from this regression captures innovations in the brown sector that are orthogonal to both aggregate (common) shocks and green-technology shocks. We then estimate sectoral exposure to brown shocks by regressing the returns of the brown and green sectors on the extracted shocks. To reduce measurement noise and capture the low-frequency dynamics consistent with the model, all regressions are conducted using three-year cumulative growth rates and returns. To trace the evolution of brown-shock betas, we estimate them using expanding windows ending in 2000, 2005, 2010, 2015, and 2021, and plot the resulting estimates together with their confidence bands in Figure 12.

Consistent with the model's predictions, the green sector in the data exhibits a significantly negative exposure to brown-technology shocks. Over the full 1990–2021 sample, the estimated brown beta of the green sector is $-0.97$, with a robust t-statistic of $-2.73$. Moreover, the

green-sector exposure to growth in the brown sector becomes more negative over time. Although the trend is not statistically significant, its direction is consistent with the model's mechanism: early in the transition, growth in the brown sector amplifies future climate risk and expected losses, strengthening the negative externality for the green sector and leading to lower valuations and returns. In contrast, the brown sector displays a muted exposure to its own shock, as the negative effect of higher climate risk and the positive effect of stronger current growth offset each other. While the statistical precision of these estimates is limited, the overall patterns are nonetheless in line with the trajectories implied by the model.

### 3.10 Risk Premia

The model's dynamics presented in Figures 10 and 11 imply that, in the absence of carbon taxation, the brown sector carries a lower risk premium than the green sector. The gap in risk premia is driven by the hedging effect of brown technology shocks. Because emissions generated by brown production increase future climate risk, brown shocks have offsetting effects: a positive brown shock raises current consumption but worsens future climate outcomes, while a negative shock lowers current consumption but mitigates future damages. As a result, brown shocks provide a partial hedge against future climate risk, which lowers the price of brown risk and, consequently, the risk premium on brown-sector cash flows as shown in Panel (d) of Figure 9.

The hedging effect is strongest early in the transition, when most variations in temperature are endogenously driven by brown production. As the economy decarbonizes and the link between growth and temperature weakens, this hedging effect diminishes and the premia of the two sectors converge. However, as long as emissions remain positive, brown shocks retain their hedging value, resulting in lower premia on pre-tax brown cash flows.

The gap in risk premia is also reflected in differences in average performance. Figure 13 plots the average realized returns of the two sectors, where returns at each point in time are computed as cross-simulation averages across multiple model paths. As the figure shows, over the first 30 years of the transition, the green sector outperforms the brown sector on average. This pattern is consistent with the empirical evidence that, in an environment with limited direct carbon taxation of brown firms — such as the United States in recent decades — green assets have delivered stronger

performance than brown assets (Pástor, Stambaugh, and Taylor (2022)). Our model shows that, in the absence of substantial carbon pricing, the hedging characteristics of brown-sector cash flows lead to lower required returns and weaker average performance relative to the green sector.

As Panel (d) of Figure 9 further shows, the wedge in risk premia reverses once the brown sector becomes subject to carbon taxation. Carbon taxes in our specification impose downside regulatory risk on brown-sector growth and, because the tax burden rises with temperature, make brown cash flows more exposed to climate-driven risk and therefore require higher compensation. As a result, after-tax brown cash flows become riskier than green cash flows and carry higher premia.

Finally, note that both sectoral and aggregate risk premia are much smaller at the onset of the transition than in the long-run carbon-free state. As the economy decarbonizes, the hedging effect of brown and common growth shocks disappears, as these shocks no longer affect future climate risk. Consequently, all growth shocks become purely adverse when they reduce consumption, without offering any offsetting long-run benefits thereby leading to higher long-run premia for all claims, even as climate risk itself vanishes.

Note that the increase in risk premia in the long run (relative to their level at the onset of the transition) is driven by the erosion and eventual disappearance of the hedging effect of emitting growth shocks. It is important to emphasize that this pattern does not imply that climate risk commands a negative premium. On the contrary, climate risk carries a positive compensation.

To isolate the contribution of climate risk to overall risk premia, we conduct the following counterfactual exercise. Starting from the benchmark economy, we hold fixed the prices of growth risks as implied by the stochastic discount factor except we eliminate the adverse impact of climate change — namely, temperature-driven damages — while leaving all other features of the economy unchanged. The difference between the risk premia in the benchmark economy and those in this counterfactual economy provides a measure of the climate risk premium. The evolution of the climate premium for the consumption claim is presented in Figure 14. As the figure shows, the climate premium — that is, the contribution of climate risk to overall risk premia — is positive throughout, rising from about 0.1% at the onset of the transition to a peak of approximately 0.8% at the height of the temperature anomaly.

### 3.11 Temperature Elasticities

To quantify the model-implied response of expected growth and asset prices to variations in temperature, we estimate a panel regression specification that parallels the one used in our empirical analysis:

$$y_{t,i} \;=\; \bar{y}_i + \theta\, \Delta T_t + u_{t,i}\ , \tag{26}$$

where $y_{t,i}$ represents either long-run expected growth, valuation ratio, or excess return of asset $i$, and $\Delta T_t$ denotes the one-year change in temperature. As in our empirical analysis, we normalize the temperature change to have mean zero and unit standard deviation, and express the expected growth in percentages. We estimate the regression using a three-asset panel consisting of claims to aggregate consumption, green and brown sectors, based on the first 30 years of simulated data across multiple simulations, and report the distribution of the estimated elasticities in Table VIII.

Higher temperature in the model lowers future consumption growth. Therefore, the model is expected to generate a negative elasticity of expected growth with respect to temperature changes. Quantitatively, a one-standard-deviation increase in annual temperature leads, on average, to a significant 1.3 basis point decline in long-run expected consumption growth, a magnitude comparable with our empirical estimates.

The expected decline in future growth translates into a decline in asset valuations. As shown in Panel B, a one-standard-deviation increase in temperature lowers asset valuations by a significant 0.2%, on average, which is broadly consistent with the (unlevered) empirical estimates reported in Table V.

In contrast to valuations, the temperature elasticity of returns, reported in Panel C, is, on average, insignificant. Note that increases in temperature early in the transition are largely driven by common and brown productivity shocks which, while raising future climate risks and thereby lowering prices, also boost current growth and thus have a positive effect on returns. These opposing effects seem to offset each other on average, which might help explain why it is empirically challenging to identify the impact of temperature on asset returns and to estimate its risk premium.

Figure 9 further illustrates the difficulty of detecting temperature effects on risk premia during

the early stages of the climate transition. As Panels (c) and (d) show, the risk premium remains essentially flat (if not declining) for the first 30 years, even as temperatures rise. This stems from the hedging effect of emitting common and brown shocks. In contrast, Panels (a) and (b) show a pronounced and steady decline in asset valuations, reflecting the anticipated impact of climate-induced output losses and rising uncertainty. Thus, early in the transition, return-based measures may obscure the effect of climate risk, even as asset valuations already begin to reflect it.

# 4 Conclusion

This paper analyzes the implications of the dynamic relationship between economic growth, climate change, and financial markets. Empirically, we show that rising temperatures, endogenously driven by carbon emissions, induce subsequent reductions in emissions intensity, reflecting an adaptive feedback mechanism that supports climate mitigation. We also show that financial markets respond to rising temperatures by revising long-run earnings growth expectations downward, thereby lowering asset valuations, particularly for firms with low intangible capital and those in heat-sensitive sectors.

To interpret these dynamics and their long-run consequences, we develop a structural model in which temperature evolves endogenously with economic activity and feeds back into emissions intensity and output risk. The model is calibrated to match observed trends in emissions, temperature, economic growth, and asset prices. We show that the endogeneity of temperature risk alters the risk characteristics of emitting growth shocks relative to a carbon-free economy. When temperature is driven by economic activity, adverse growth shocks of brown technologies reduce future emissions and, hence, partially hedge climate risk. This mechanism helps explain both the empirical difficulty of identifying the impact of rising carbon emissions and temperature on risk premia and the emergence of a "green" premium when carbon taxation, or its effective burden, is low.

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**Table I**
**Dynamics of Emission Intensity Growth**

**Panel A**: Carbon Concentration Impact

| | **1-year** | | **2-year** | | **3-year** | |
|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\boldsymbol{\Delta \log(CO_2)_t}$ | $-1.682$ | $-2.24$ | $-3.507$ | $-2.50$ | $-6.158$ | $-3.23$ |
| $\Delta \text{gdp}_{r,t}$ | $-0.052$ | $-0.92$ | $-0.120$ | $-0.95$ | $-0.140$ | $-0.89$ |
| Region FE | ✓ | | ✓ | | ✓ | |

**Panel B**: Regional Temperature Impact

| | **1-year** | | **2-year** | | **3-year** | |
|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\boldsymbol{\Delta_{10}\bar{T}_{r,t}}$ | $-0.010$ | $-4.74$ | $-0.024$ | $-4.13$ | $-0.032$ | $-2.47$ |
| $\Delta \text{gdp}_{r,t}$ | $-0.158$ | $-1.83$ | $-0.358$ | $-1.52$ | $-0.401$ | $-1.20$ |
| Region FE | ✓ | | ✓ | | ✓ | |

Table I presents the estimates from panel regressions of cumulative log growth in future emissions intensity over 1-, 2-, and 3-year horizons on current growth in global atmospheric carbon dioxide concentration (Panel A) and ten-year change in regional temperature trends (Panel B), controlling for regional GDP growth and fixed effects. The analysis is based on annual data spanning the 1990–2021 period.

**Table II**

**Temperature and Long-Run Earnings Growth Expectations**

**Panel A**: 2000–2021 Sample

| | **All** | | **Analysts≥3** | | **Analysts≥5** | |
|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\mathbf{\Delta_3 Temp_{t-1}}$ | −0.037 | −4.69 | −0.044 | −5.20 | −0.031 | −4.68 |
| Firm & Mrk Controls | ✓ | | ✓ | | ✓ | |
| Firm FE | ✓ | | ✓ | | ✓ | |
| # of obs | 311,667 | | 155,663 | | 81,805 | |

**Panel B**: 1983–1999 Sample

| | **All** | | **Analysts≥3** | | **Analysts≥5** | |
|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| $\mathbf{\Delta_3 Temp_{t-1}}$ | 0.001 | 0.13 | 0.001 | 0.07 | −0.001 | 0.09 |
| Firm & Mrk Controls | ✓ | | ✓ | | ✓ | |
| Firm FE | ✓ | | ✓ | | ✓ | |
| # of obs | 252,984 | | 147,886 | | 93,451 | |

Table II shows the estimates of panel regressions of the (log) median analysts' forecasts of long-run earnings growth on the lagged quarterly change in temperature ($\Delta_3 \text{Temp}_{t-1}$), controlling for firm characteristics and aggregate market, as detailed in Section 2.1. The first set of columns reports the estimates based on the whole panel, the second and third use firms that are followed by at least three and five analysts, respectively. Growth forecasts are expressed as annualized percentages, and temperature changes are standardized. The data are monthly and cover the 2000–2021 time period (Panel A) and the 1983–1999 sample (Panel B).

**Table III**

**Temperature and Long-Run Earnings Growth Expectations: Cross-Sectional Variation**

**Panel A**: 2000–2021 Sample

| | Coeff | t-stat | Coeff | t-stat |
|---|---|---|---|---|
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Intang-low}}$ | −0.054 | −4.02 | | |
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Intang-med}}$ | −0.032 | −4.24 | | |
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Intang-high}}$ | −0.022 | −1.76 | | |
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Heat-Exposure-low}}$ | | | −0.037 | −5.13 |
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Heat-Exposure-high}}$ | | | −0.064 | −3.06 |

**Panel B**: 2011–2021 Sample

| | Coeff | t-stat | Coeff | t-stat |
|---|---|---|---|---|
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Intang-low}}$ | −0.108 | −2.88 | | |
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Intang-med}}$ | −0.027 | −1.62 | | |
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Intang-high}}$ | 0.003 | 0.13 | | |
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Heat-Exposure-low}}$ | | | −0.032 | −2.10 |
| $\Delta_3 \text{Temp}_{t-1} \cdot \text{I}_{\text{Heat-Exposure-high}}$ | | | −0.122 | −2.88 |

Table III shows the variation of the temperature elasticity of the expected long-run earnings growth across firms that differ in their intangible capital fraction and heat exposure. The estimates are based on a panel regression of (log) analysts' forecasts on the lagged quarterly change in temperature ($\Delta_3 \text{Temp}_{t-1}$) interacted with dummy variables that reflect if a firm is the bottom 25-percentile (low), the middle 50-percentile (med) or the top 25-percentile (high) of the distribution of the fraction of intangible-to-total capital, or dummy variables that reflect if a firm belongs to industries that have low or high exposure to heat. Each panel regression includes the same set of controls as in Table II. Growth forecasts are expressed as annualized percentages, and temperature changes are standardized. The data are monthly and cover the 2000–2021 time period in Panel A and 2011-2021 period in Panel B.

**Table IV**
**Temperature and Asset Valuations**

| | **2000–2021** | | **2011–2021** | |
|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat |
| $\mathbf{\Delta_3 Temp_t}$ | $-0.0048$ | $-1.51$ | $-0.0117$ | $-2.67$ |
| Portfolio & Mrk Controls | ✓ | | ✓ | |
| Portfolio FE | ✓ | | ✓ | |
| # of obs | $3,120$ | | $1,536$ | |

Table IV presents the elasticity of asset valuations to temperature estimated in a panel regression of (log) price-dividend ratios on the standardized quarterly change in temperature ($\Delta_3 \text{Temp}_t$). The panel data consist of three portfolios constructed by sorting firms on the fraction of intangible-to-total capital, and nine industry sorted portfolios. The three panels present estimates using monthly data over different time periods.

**Table V**

**Temperature and Asset Valuations: Cross-Sectional Variation**

| | **2000–2021** | | **2011–2021** | |
|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat |
| $\mathbf{\Delta_3 Temp_t}$ | $-0.0036$ | $-0.98$ | $-0.0099$ | $-2.69$ |
| $\mathbf{\Delta_3 Temp_t} \cdot \mathbf{I}_{\text{Low-Intang \& High-Heat}}$ | $-0.0029$ | $-0.77$ | $-0.0041$ | $-2.14$ |
| Portfolio & Mrk Controls | ✓ | | ✓ | |
| Portfolio FE | ✓ | | ✓ | |
| # of obs | $3,120$ | | $1,536$ | |

Table V presents the elasticity of asset valuations to temperature estimated in a panel regression of (log) price-dividend ratios on the standardized quarterly change in temperature ($\Delta_3 \text{Temp}_t$) and the interaction of temperature shock with the dummy variable that is equal to one for portfolios with low fraction of intangible capital and portfolios that are highly exposed to heat. The panel data consist of three portfolios constructed by sorting firms on the fraction of intangible-to-total capital, and nine industry sorted portfolios. The three panels present estimates using monthly data over different time periods.

**Table VI**
**Calibration**

| Parameter | Value |
|---|---|
| $\mu$ | 0.034 |
| $\sigma_y$ | 0.0179 |
| $\sigma_g$ | 0.0089 |
| $\sigma_b$ | 0.0089 |
| $\sigma_L$ | 0.05 |
| $\ell_0$ | 0.05 |
| $\ell_T$ | 0.05 |
| $\alpha$ | 0.725 |
| $\lambda_0$ | 4.32 |
| $\rho$ | 0.986 |
| $\chi$ | $-0.018$ |
| $\sigma_\lambda$ | 0.03 |
| $\mathbb{C}_0$ | 354.45 |
| $\nu$ | 0.9938 |
| $c$ | 0.05 |
| $\sigma_\mathbb{C}$ | 0.5 |
| $\phi$ | 0.015 |
| $\mathbb{C}^*$ | 325 |
| $p_0$ | 0.0001 |
| $\sigma_p$ | 0.015 |
| Time-discount | 0.99 |
| IES | 1.5 |
| RA | 15 |

Table VI reports the parameter values used in the model calibration.

**Table VII**
**Distribution of Model-Implied Moments**

**Panel A**: Output Growth (log)

| | **Data** | 2.5% | 5% | 50% | 95% | 97.5% |
|---|---|---|---|---|---|---|
| Mean | 0.031 | 0.023 | 0.024 | 0.031 | 0.038 | 0.039 |
| Std | 0.017 | 0.015 | 0.016 | 0.022 | 0.028 | 0.030 |
| Skewness | −1.42 | −1.65 | −1.40 | −0.37 | 0.45 | 0.61 |
| Kurtosis | 6.37 | 1.97 | 2.08 | 3.09 | 6.03 | 7.14 |

**Panel B**: Emission Intensity Growth (log)

| | **Data** | 2.5% | 5% | 50% | 95% | 97.5% |
|---|---|---|---|---|---|---|
| Mean | −0.016 | −0.019 | −0.018 | −0.015 | −0.013 | −0.013 |
| Std | 0.009 | 0.004 | 0.004 | 0.005 | 0.008 | 0.009 |
| Skewness | 0.33 | −1.21 | −1.03 | −0.25 | 0.50 | 0.67 |
| Kurtosis | 2.92 | 1.91 | 2.01 | 2.81 | 4.71 | 5.35 |

**Panel C**: Carbon Concentration Growth (log)

| | **Data** | 2.5% | 5% | 50% | 95% | 97.5% |
|---|---|---|---|---|---|---|
| Mean | 0.005 | 0.004 | 0.004 | 0.005 | 0.006 | 0.006 |
| Std | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 |
| Skewness | −0.10 | −0.87 | −0.72 | −0.03 | 0.65 | 0.79 |
| Kurtosis | 3.39 | 1.86 | 1.96 | 2.65 | 4.14 | 4.61 |

**Panel D**: Temperature Change

| | **Data** | 2.5% | 5% | 50% | 95% | 97.5% |
|---|---|---|---|---|---|---|
| Mean | 0.030 | 0.024 | 0.025 | 0.029 | 0.034 | 0.035 |
| Std | 0.214 | 0.006 | 0.006 | 0.008 | 0.010 | 0.011 |
| Skewness | −0.12 | −0.81 | −0.66 | 0.01 | 0.68 | 0.82 |
| Kurtosis | 1.93 | 1.86 | 1.95 | 2.63 | 4.07 | 4.52 |

Table VII shows the distribution of model-implied moments over the first 30 years of simulated data, alongside the sample statistics.

**Table VIII**
**Model-Implied Temperature Elasticities**

**Panel A**: Expected Growth

| | 10% | 50% | 90% |
|---|---|---|---|
| Elasticity | −0.0461 | −0.0125 | 0.0038 |
| t-stat | −5.56 | −2.27 | 0.70 |

**Panel B**: Valuation Ratio

| | 10% | 50% | 90% |
|---|---|---|---|
| Elasticity | −0.0103 | −0.0022 | 0.0024 |
| t-stat | −6.65 | −1.99 | 2.23 |

**Panel C**: Excess Return

| | 10% | 50% | 90% |
|---|---|---|---|
| Elasticity | −0.0042 | 0.0005 | 0.0052 |
| t-stat | −2.22 | 0.29 | 2.80 |

Table VIII shows the distribution of the model-implied temperature elasticities estimated using the first 30 years of simulated data.

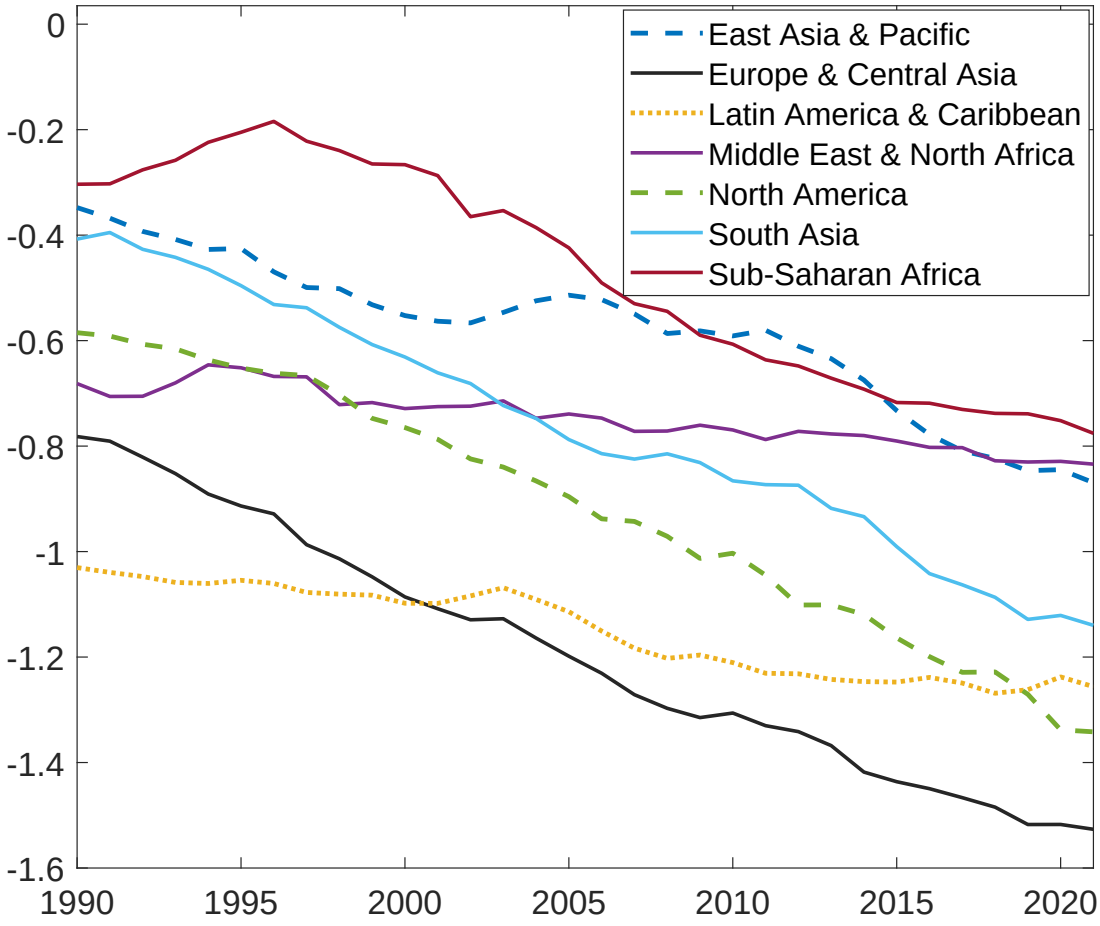



**Figure 1.** Emissions Intensity (log)

Figure 1 shows the trajectory of log carbon emissions intensity for seven world regions from 1990 to 2021.

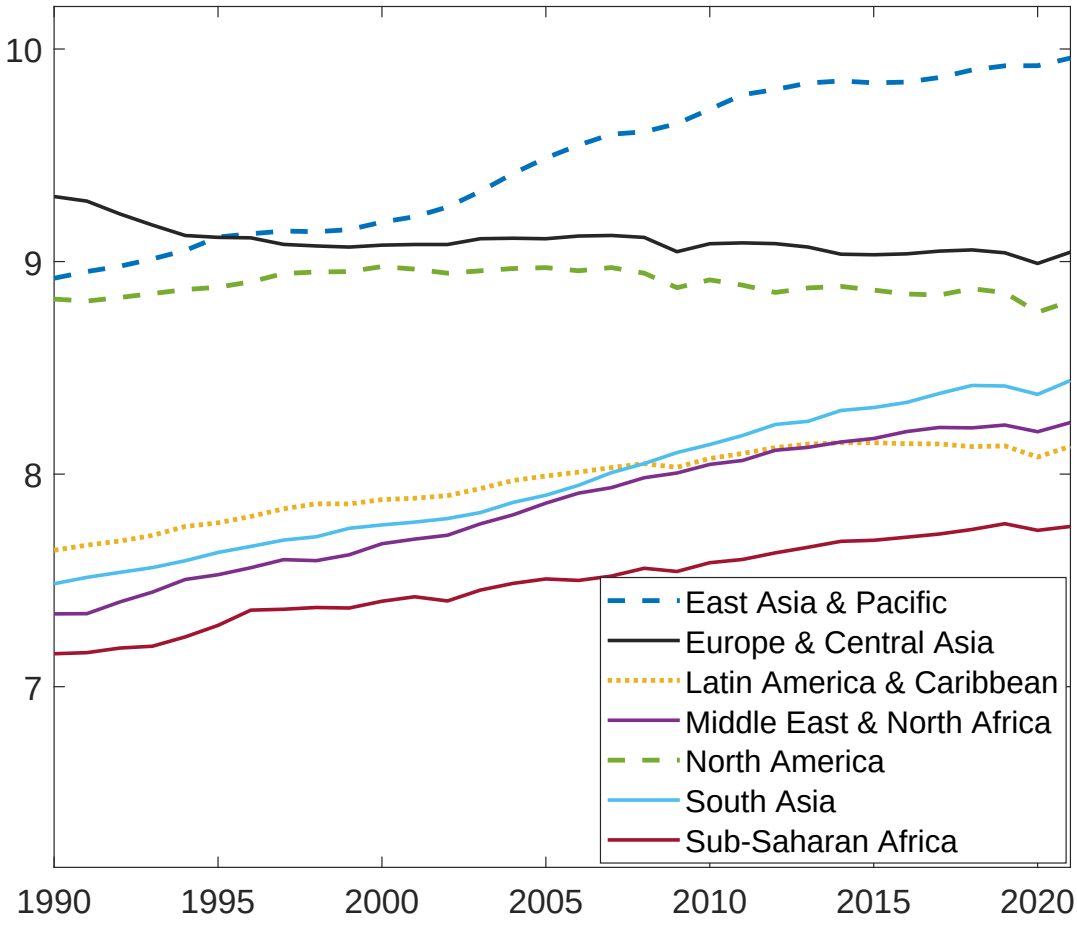



**Figure 2.** Carbon Emissions (log)

Figure 2 presents the trajectory of (log) greenhouse gas emissions for seven world regions from 1990 to 2021.

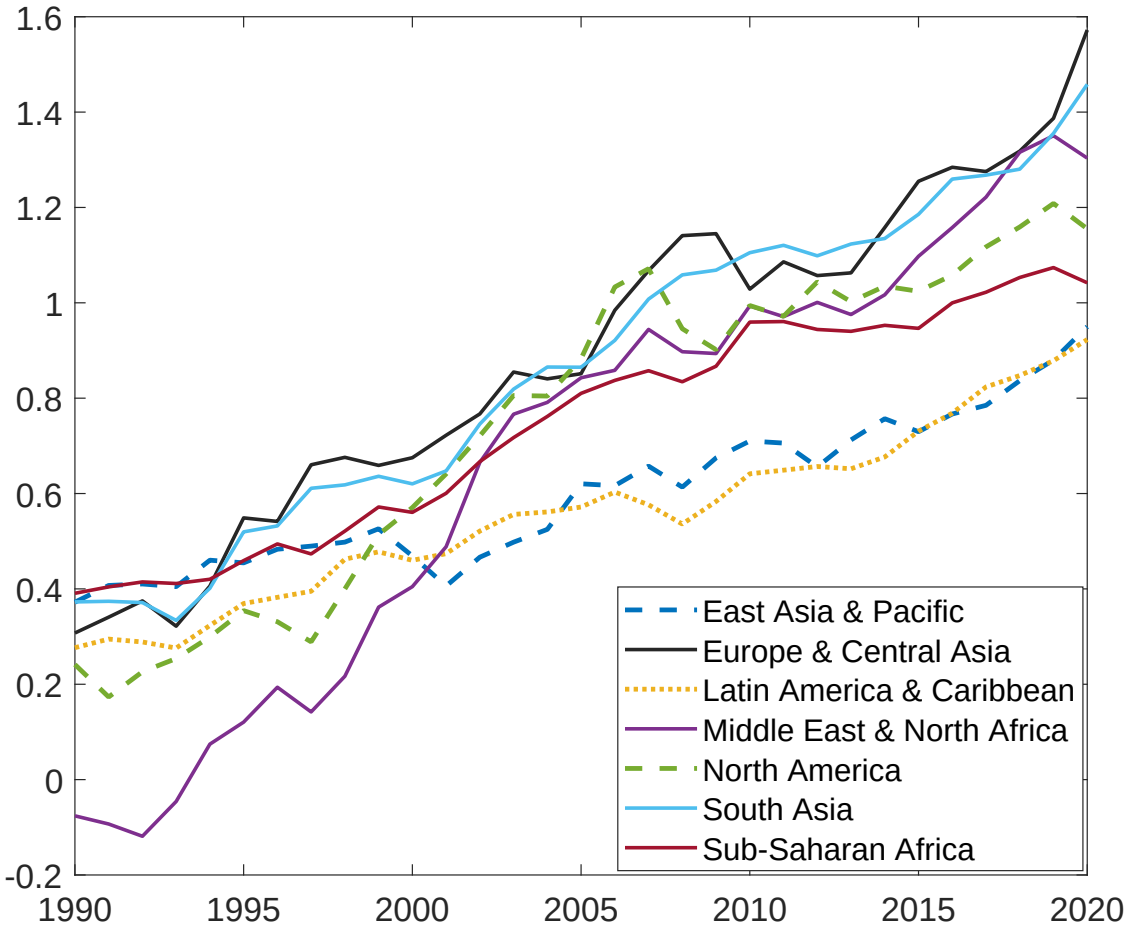
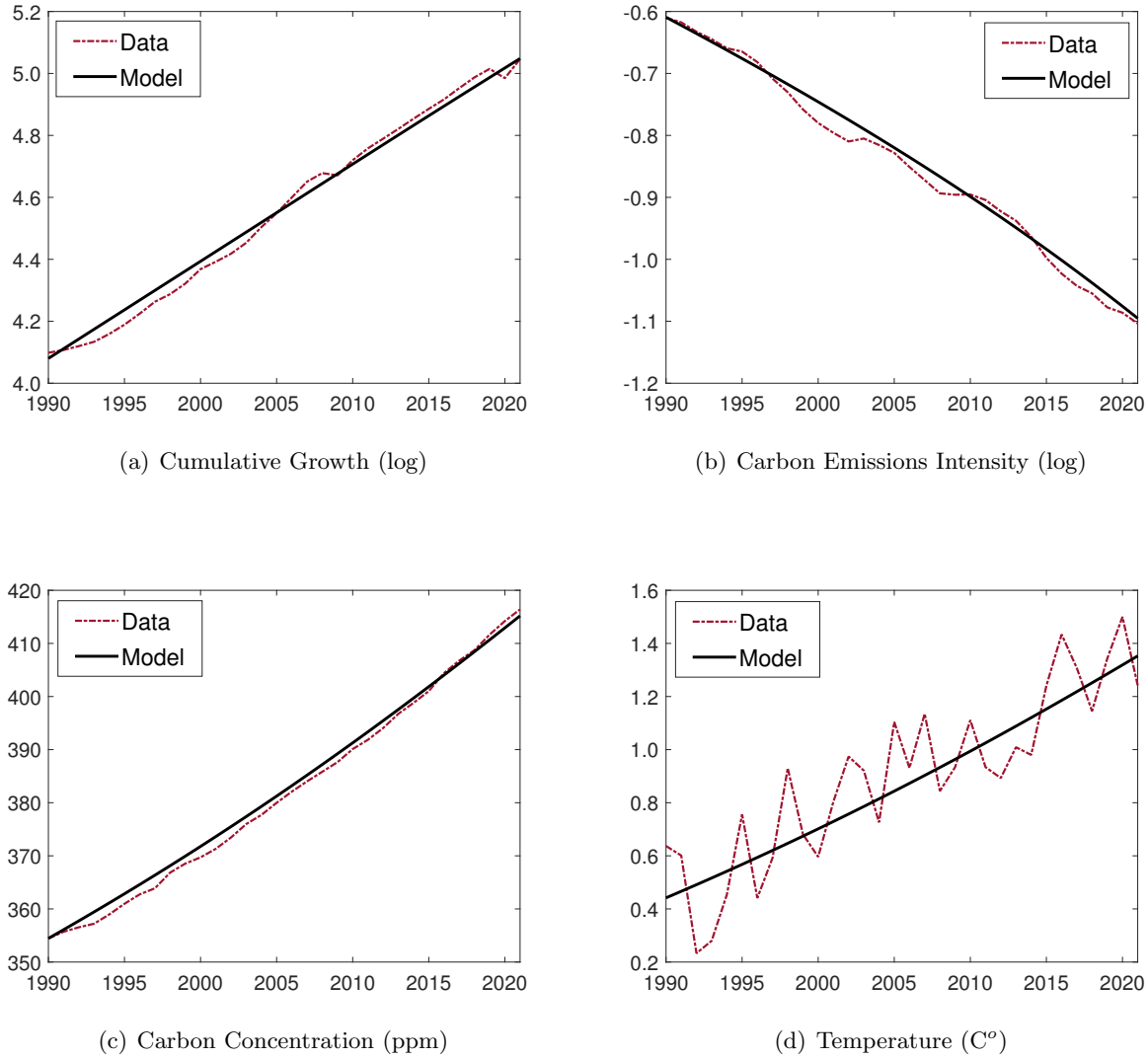



**Figure 3.** Temperature Trends (°C)

Figure 3 presents 10-year moving average trends in temperature anomalies for seven world regions from 1990 to 2021.




(a) Cumulative Growth (log)

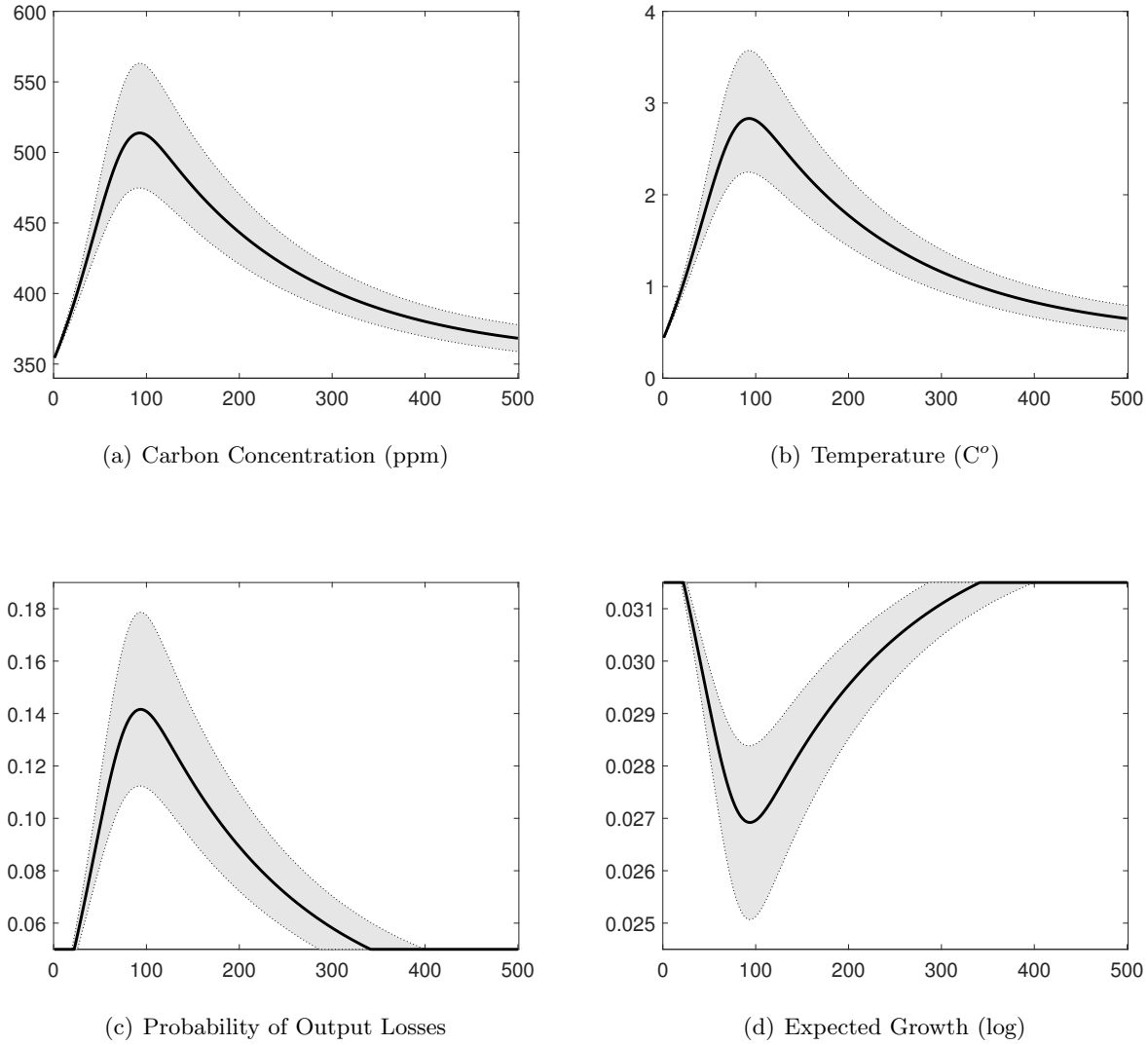
(b) Carbon Emissions Intensity (log)

(c) Carbon Concentration (ppm)

(d) Temperature ($C^o$)

**Figure 4.** Growth, Emissions and Climate Trends

Figure 4 presents global (log) output, (log) emissions intensity, carbon concentration, and temperature in the data, alongside the average trends implied by the calibrated model.




(a) Carbon Concentration (ppm)

(b) Temperature ($C^o$)

(c) Probability of Output Losses

(d) Expected Growth (log)

**Figure 5.** Distribution of Future Model Dynamics

Figure 5 shows the average trajectories of carbon concentration, temperature, the probability of output losses, and expected log output growth, with shaded areas representing the 95% confidence intervals.

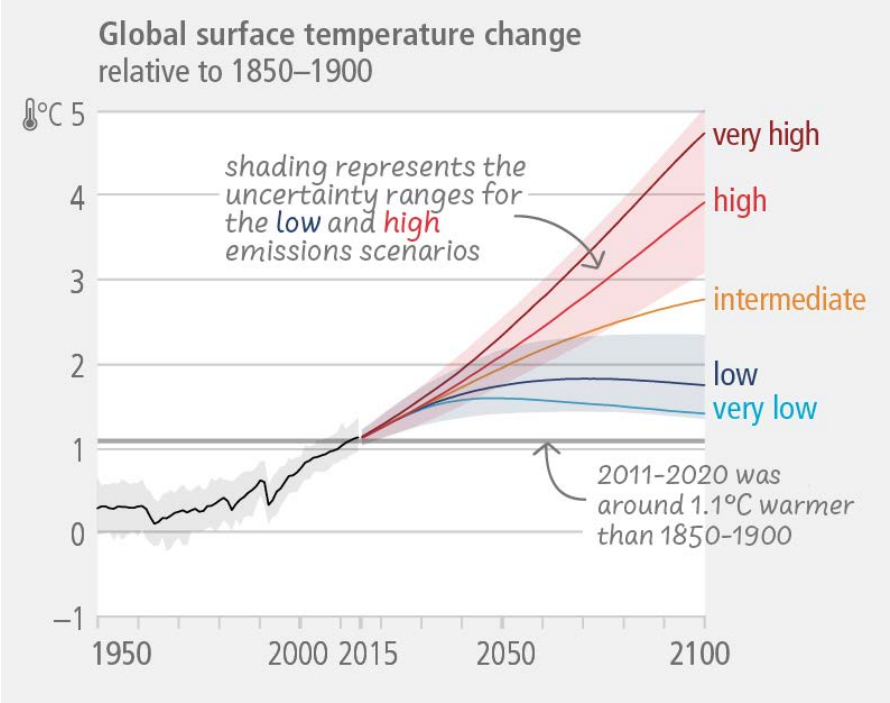
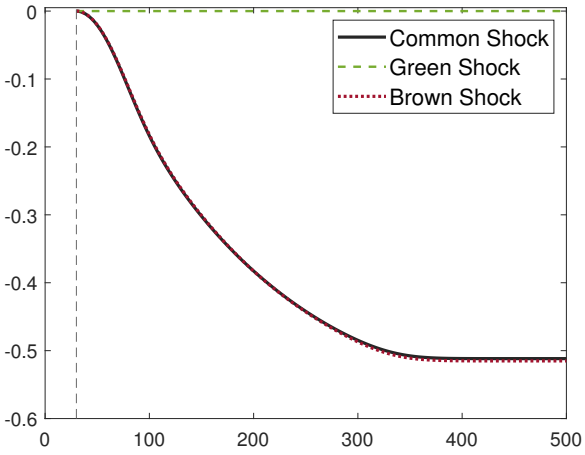
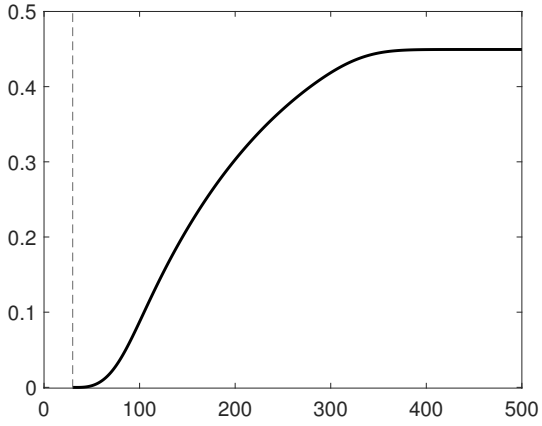



**Figure 6.** IPCC Global Temperature Projections

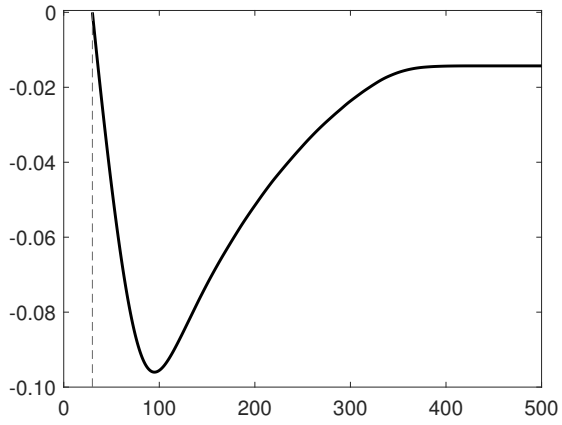
Figure 6 shows global temperature projection outlined in the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.




(a) Growth Shocks



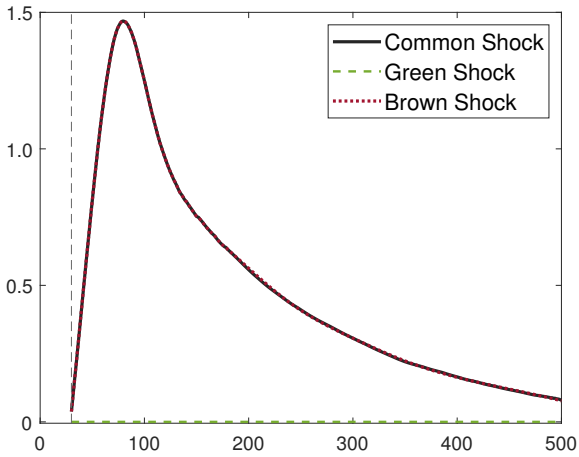

(b) Decarbonization Shock



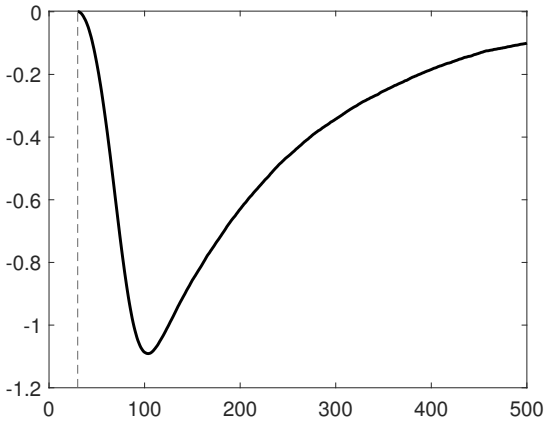

(c) Temperature Shock

**Figure 7.** Cumulative Impulse Response of Expected Growth

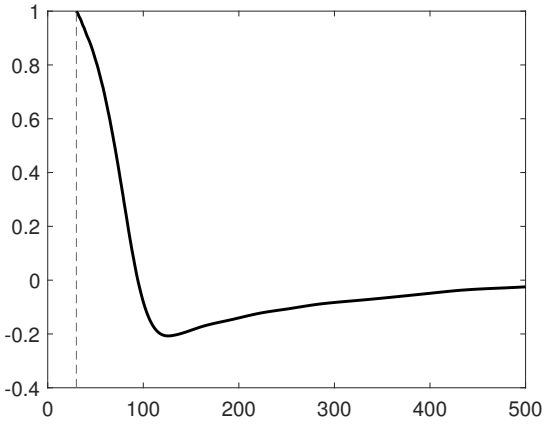
Figure 7 presents the cumulative impulse responses of expected (log) consumption growth to three growth shocks, a decarbonization shock, and an exogenous innovation in temperature. Shocks are realized in model year 30 (marked by the dashed line), which approximately corresponds to the present day in real time.




(a) Growth Shock



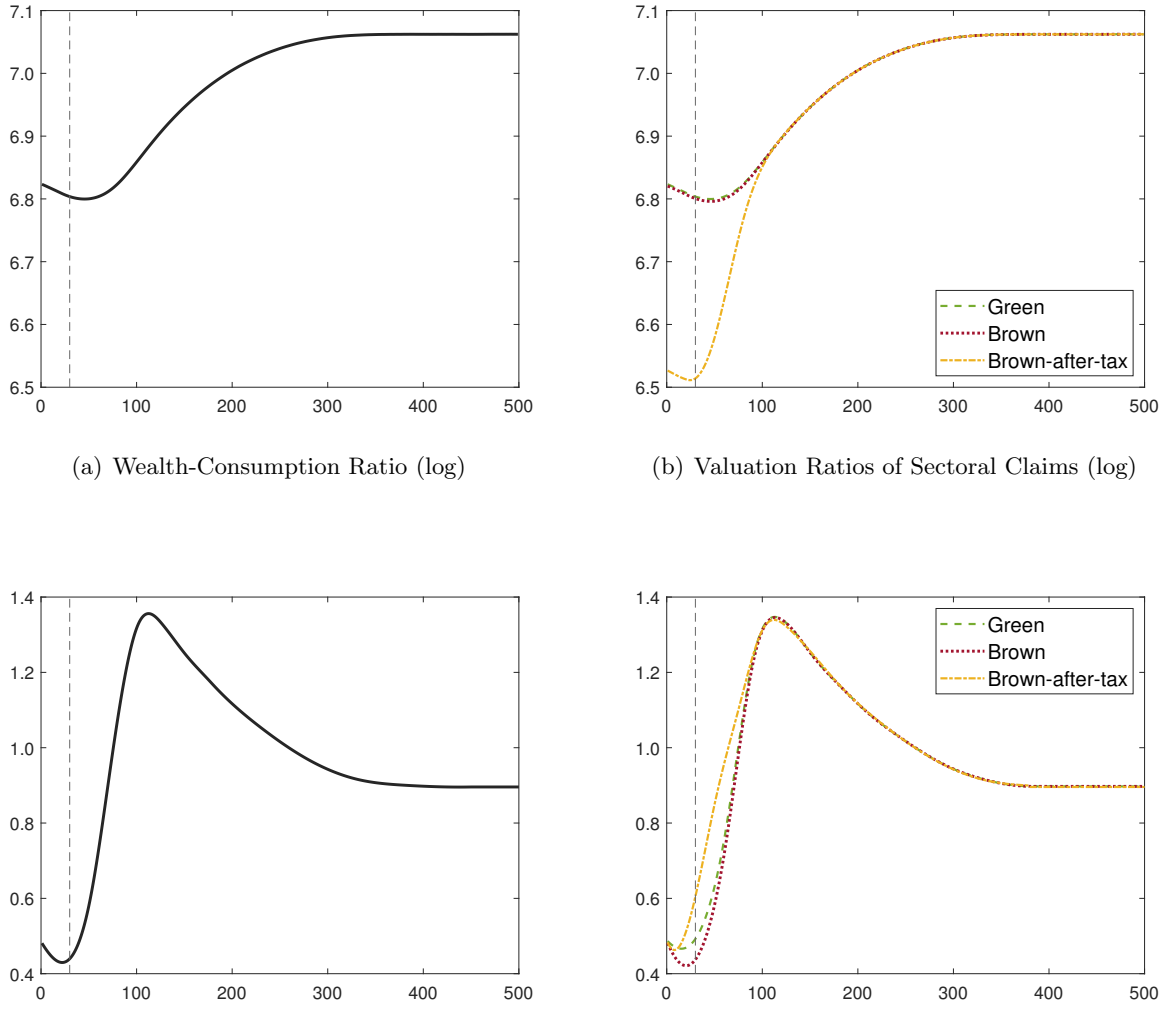

(b) Decarbonization Shock




(c) Temperature Shock

**Figure 8.** Impulse Response of Temperature

Figure 8 presents the impulse responses of temperature to three growth shocks, a decarbonization shock, and an exogenous innovation in temperature. Shocks are realized in model year 30 (marked by the dashed line), which approximately corresponds to the present day in real time.




(a) Wealth-Consumption Ratio (log)

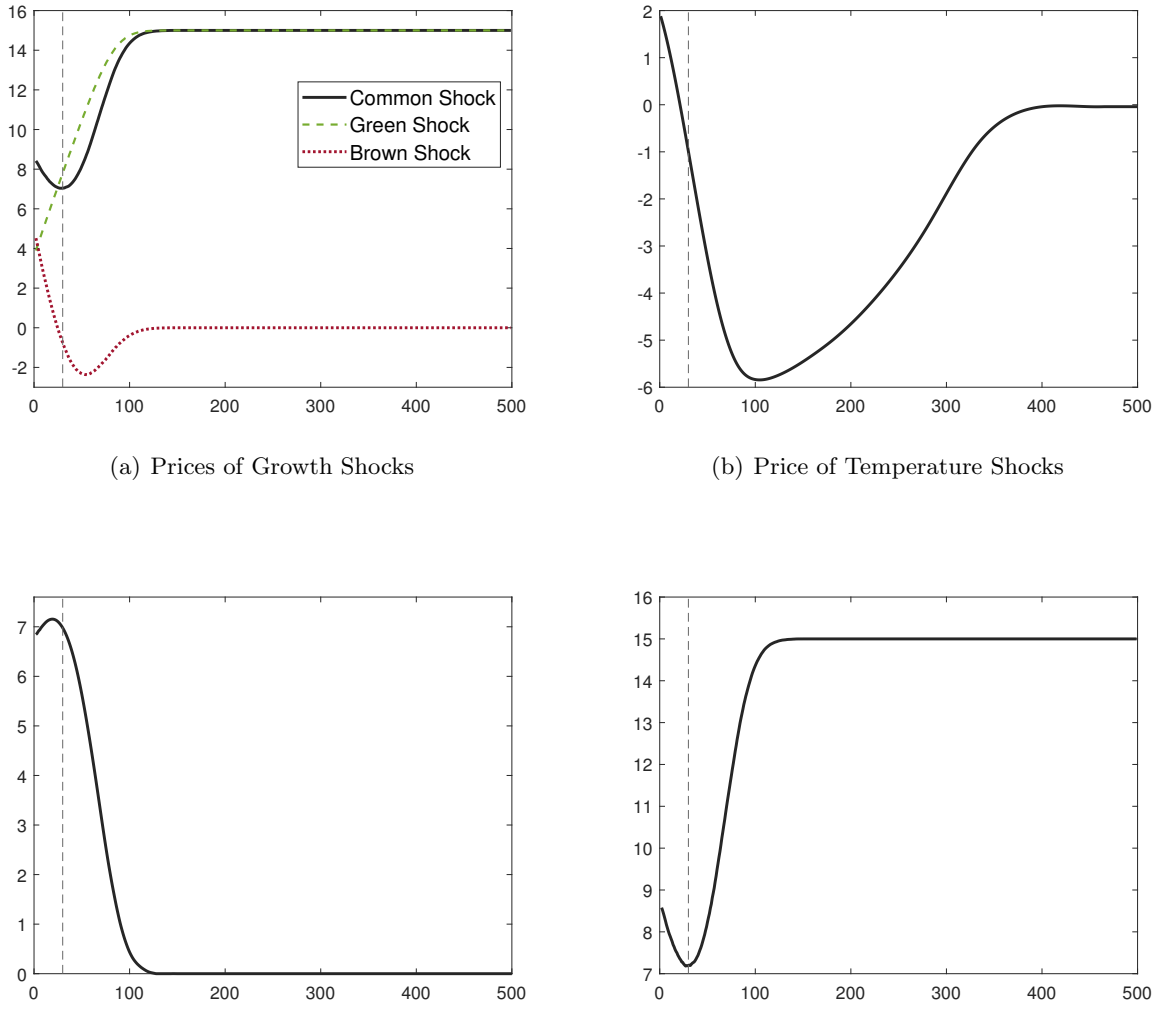
(b) Valuation Ratios of Sectoral Claims (log)

(c) Risk Premia of Consumption Claim (%)

(d) Risk Premia of Sectoral Claims (%)

**Figure 9.** Evolution of Valuation Ratios and Risk Premia

Figure 9 shows the evolution of the model-implied average valuation ratios of consumption and sectoral claims, and their risk premia. In the model, time 0 corresponds to the year 1990 in real time, and the dashed line in the figure marks year 30, which approximately represents the present day.




(a) Prices of Growth Shocks

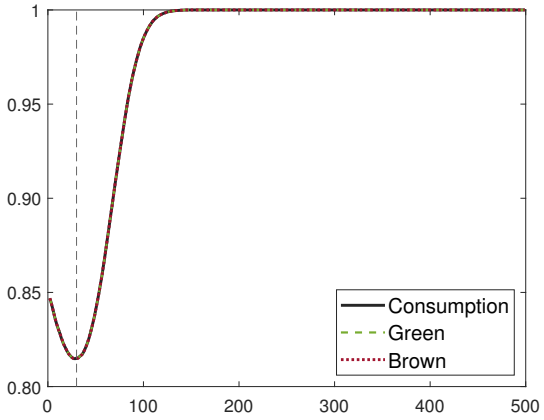
(b) Price of Temperature Shocks

(c) Price of Decarbonization Shocks

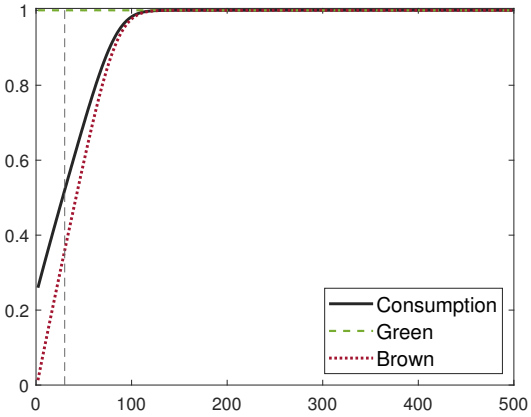
(d) Price of Jump Shocks

**Figure 10.** Evolution of Risk Prices

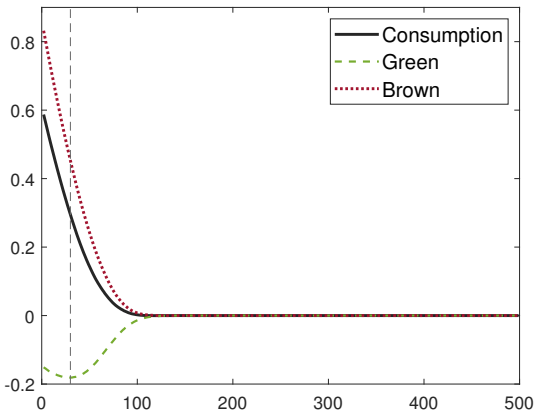
Figure 10 shows the evolution of risk prices over the transition path to a carbon-free economy. In the model, time 0 corresponds to the year 1990 in real time, and the dashed line in the figure marks year 30, which approximately represents the present day.




(a) Common Shock



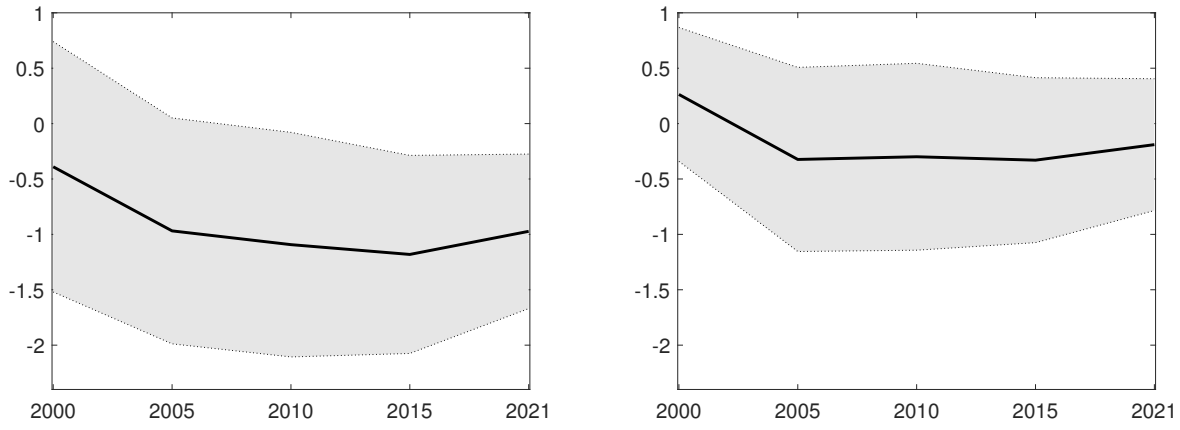

(b) Green Shock




(c) Brown Shock

**Figure 11.** Consumption and Sectoral Betas with respect to Growth Risks

Figure 11 shows the evolution of consumption and sectoral betas with respect to three growth risks over the transition path to a carbon-free economy. In the model, time 0 corresponds to the year 1990 in real time, and the dashed line in the figure marks year 30, which approximately represents the present day.




(a) Green Sector

(b) Brown Sector

**Figure 12.** Sectoral Exposure to Brown-Technology Shocks

Figure 12 shows estimates of brown-shock betas for the green (Panel (a)) and brown (Panel (b)) sectors. The betas are estimated using expanding windows over samples beginning in 1990 and ending in 2000, 2005, 2010, 2015, and 2021. Shaded areas represent the 95% confidence intervals.

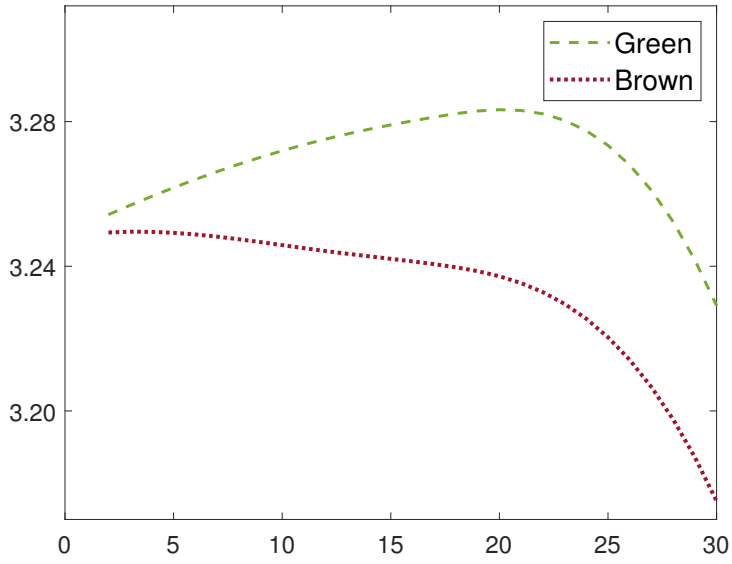



**Figure 13.** Average Returns of the Green and Brown Sectors (%)

Figure 13 presents the average returns of the green and brown sectors during the initial 30 years of the model transition.

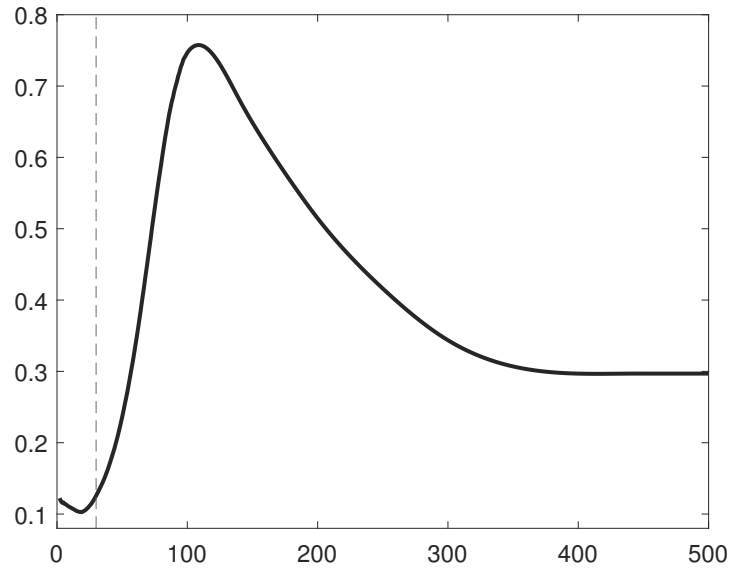



**Figure 14.** Climate Premium

Figure 14 shows the evolution of the climate premium for the consumption claim. In the model, time 0 corresponds to the year 1990 in real time, and the dashed line in the figure marks year 30, which approximately represents the present day.