Climate Change Risks, Stock Returns, and the Oil Sector

Michael Donadelli∗  Patrick Grüning†  Steffen Hitzemann‡

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Abstract

We develop a general equilibrium asset pricing model in which the emissions of fossil-fuel intensive firms lead to climate change, which negatively affects general economic output. The model allows us to analyze the effects of climate productivity risk and climate policy risk and to characterize related risk premia. We confront the model with the data by considering the stock market performance of climate sensitive vs. robust industries and dirty vs. clean industries. Our results are consistent with an increasing awareness of investors for climate change risks since the beginning of the 2000s. For the oil sector, the commodity price boom of the last decade temporarily masked the negative impact of climate risks.

Keywords: Oil market, General equilibrium, Risk premia

JEL: E2, E3, G12, Q43

∗Department of Economics, Ca’Foscari University and Research Center SAFE, Goethe University Frankfurt. Mailing address: Cannaregio 873, 30121 Venice, Italy. E-mail: donadelli.m@unive.it.

†Center for Excellence in Finance and Economic Research (CEFER), Bank of Lithuania, and Faculty of Economics, Vilnius University. Mailing address: Totoriu g. 4, 01121 Vilnius, Lithuania. E-mail: PGruening@lb.lt.

‡Department of Finance and Economics, Rutgers Business School. Mailing address: 100 Rockafeller Road, Piscataway, NJ 08854, United States. E-mail: hitzemann@business.rutgers.edu.

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1 Introduction

Climate change risks are identified by economic leaders and financial institutions among the most important types of macroeconomic risks going forward.\footnote{For example, the \textit{Global Risks Report 2018} of the World Economic Forum categorizes climate-change-related risks such as extreme weather events, natural disasters, and failure of climate-change mitigation and adaption as 3 of the top 5 most important risks with respect to both their likelihood and the extent of impact.} While there is obvious agreement that such substantial risks are a primary concern for financial investors, pricing these risks is a complex issue that is not yet precisely understood. A main reason for this complexity is that climate change risk comes in different facets, which may affect different firms in very different ways. Most importantly, some firms may be strongly exposed to the \textit{productivity risk} dimension of climate change, while others are mainly affected by the \textit{policy risk} dimension. Climate change risks are also distinct from standard weather risks that are rather short-term in nature.

The goal of this paper is to analyze the implications of climate change risks from an asset pricing perspective. We develop a macro-finance model that explicitly accounts for the different dimensions of climate change risk in general equilibrium. The model allows us to characterize the different types of climate risks and related risk premia, and yields a number of asset pricing predictions in the time-series and the cross-section. We explore the model predictions empirically by analyzing a large cross-section of firms that differ with respect to their greenhouse gas emissions intensity (\textit{dirty vs. clean}), their exposure to permanent temperature changes (\textit{sensitive vs. robust}), and their exposure to weather risk and other important risk factors, which we control for. An analysis of portfolio returns along the different dimensions disentangles the various dimensions of climate risk and quantifies the compensation that investors receive in the current state of the market.

Our climate change asset pricing model is based on a production economy in which firms’ output is negatively affected by permanent changes in temperature. The global temperature level, on the other hand, is influenced by the greenhouse emissions of the economy, and “dirty” firms have a higher
emissions intensity than “clean” firms. In the competitive equilibrium, dirty firms do not internalize the negative effect of their emissions on the rest of the economy, which gives rise to a climate change externality. To bring the economy closer to the social optimum, the regulator introduces a tax on greenhouse gas emissions. As in the real world, the regulator sets this tax between zero and the theoretically optimal level, driven by certain regulation shocks that are a result of political processes. The environmental regulation in form of a carbon tax thus reduces the amount of productivity risk originating from climate change, but also gives rise to policy risk due to the fact that the regulator’s actions are not fully predictable by market participants.

The model framework provides us with a detailed understanding of how temperature changes and policy shocks affect the economy and yields several predictions on climate change related risk premia from a general equilibrium perspective. In line with intuition, unpredicted temperature increases are bad news for the economy and lead to an increase in agents’ marginal rate of substitution due to the negative effect on firms’ output. As temperature-sensitive firms are more affected than firms that are robust to climate change, investors are compensated with a positive climate productivity risk premium on the sensitive-minus-robust portfolio. Increasing environmental regulation, on the other hand, mainly affects “dirty” industries with high carbon emissions in a negative way, while the effect on clean firms is positive. An important insight is, in addition, that a positive policy shock is positive for the overall economy and accordingly leads to a decline in the stochastic discount factor. We argue that this result has to obtain in basically any type of general equilibrium asset pricing model with rational expectations, as the positive regulation shock brings the economy closer to the social optimum by taking into account more of the negative climate externality. It directly follows that the climate policy risk premium on a dirty-minus-clean portfolio is predicted to be negative from a theoretical perspective.

We confront our model-based predictions with the data by constructing portfolios that load on the economy’s climate productivity risk and climate policy risk. For that, we measure different industries’ exposures to climate change along both dimensions and show, first, that the productivity
risk component can well be separated from the policy risk component in a cross-sectional setting. We furthermore show that in some cases, exposures to climate productivity risks can partly be explained by short-run weather risks, which we control for in the subsequence. Given the exposures along these dimensions, we sort industries and construct a climate sensitive-minus-robust portfolio and a dirty-minus-clean portfolio. An analysis of the corresponding portfolio returns over time shows that both portfolios exhibit negative returns overall, of which most of the negative performance is realized in the 2000s and later. The negative return is in line with the predicted climate policy risk premium, but not in accordance with the theoretical prediction on the climate productivity risk premium. Based on these results, we argue that the findings can be explained by a transition period during which investors start taking into account climate change related risks, which explains the negative returns along both dimensions.

An outstanding and particularly important industry in this context is the oil sector as a main producer of “dirty” fossil fuels. We find that the oil industry — relative to the overall market — also exhibits negative excess returns, in line with the performance of other dirty industries. The negative return is, however, much smaller in comparison to the dirty-minus-clean portfolio. A closer analysis of the oil-minus-market portfolio over time suggests that the negative effects of climate risks on the fossil fuel industry were temporarily masked by the commodity price boom from 2003 to 2008.

Our paper relates to a fast-growing literature on the effects of climate change on the macroeconomy and on asset prices. Several recent studies consider the exposure of equities to climate change risks and analyze related risk premia. Balvers, Du, and Zhao (2017) and Bansal, Kiku, and Ochoa (2017) investigate the effect of temperature shocks on the stock market and find evidence for positive temperature risk premia. On the other hand, Oestreich and Tsiakas (2015), Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2018), and In, Park, and Monk (2018) categorize firms by their carbon emission intensity and consider related portfolios over time, all focusing on sample periods of 10 years or less. While Oestreich and Tsiakas (2015) find higher returns for dirty firms in Europe between 2004 and 2009, which can be explained by a positive cash flow effect due to the free
allocation of carbon permits based on past emissions, Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2018) find that brown (“dirty”) firms have lower returns for the sample considered. This result could be due to a negative carbon risk premium, or as a transition phase to an economy in which these risks are priced with a positive premium. In, Park, and Monk (2018) also find lower returns for carbon inefficient firms compared to carbon efficient firms. Relatedly, Ilhan, Sautner, and Vilkov (2018) show that dirty firms exhibit increased downside risk as measured from out-of-the-money put options. Baker, Hollifield, and Osambela (2018) develop a portfolio allocation model with externalities, clean and dirty stocks, and households that are differently exposed to climate change.

Coming from a different angle, Engle, Giglio, Lee, Kelly, and Stroebel (2018) construct climate change hedging portfolios using a dynamic approach based on climate change news. Several other papers ask the question whether climate change risk is price in stock markets or other asset classes. Hong, Li, and Xu (2018) focus on food stocks and show that a publicly available index on drought time trends forecasts profits and stock returns for the food industry in the affected countries, consistent with a market-underreaction to these risks. Baldauf, Garlappi, and Yannelis (2018) show that real estate prices are affected only in regions where people believe in climate change. Bernstein, Gustafson, and Lewis (2018) and Murfin and Spiegel (2018) analyze the effect of sea level rises on the prices of coastal homes. Delis, de Greiff, and Ongena (2018) study the pricing of climate policy risks in bank loans given to fossil fuel firms.

The analysis of climate change on asset prices, empirically and within general equilibrium models, is motivated by the related macroeconomics literature. Important papers showing a significantly impact of higher temperatures on economic activity and growth rates include Nordhaus (2006) and Dell, Jones, and Olken (2012). Colacito, Hoffmann, and Phan (2016) and Donadelli, Jüppner, Riedel, and Schlag (2017) focus particularly on the United States and find a significantly negative effect of temperature shocks on economic growth. Deryugina and Hsiang (2017) and Lemoine (2018) discuss the relationship between climate and weather risks. General equilibrium models, such as
the well-known integrated assessment models developed Nordhaus (2008), are calibrated to match this empirical evidence in order to quantify the social cost of carbon as well as resulting optimal policies. Acemoglu, Aghion, Bursztyn, and Hemous (2012) develop a non-stochastic model featuring directed technical change and show that the optimal environmental policy involves both a carbon tax and research subsidies. Golosov, Hassler, Krusell, and Tsyvinski (2014), Cai, Judd, and Lontzek (2018), and Hambel, Kraft, and Schwartz (2018) build DSGE models that allow to compute the social cost of carbon under different types of modeling assumptions.

2 Model

We analyze the role of climate risks for asset prices within a general equilibrium asset pricing framework that features both the productivity risk dimension and the policy risk dimension of climate change. In our model, high temperature levels are assumed to have a negative effect on firms’ production output, making them subject to climate productivity risk. Future temperature levels are, on the other hand, driven by greenhouse gas emissions, which “dirty” firms emit as a by-product of their production process. As dirty firms do not fully account for the negative externality of their emissions on the rest of the economy in a competitive setting, it is optimal for the regulator to introduce a carbon tax. We assume that the carbon tax set by the regulator fluctuates between zero and the socially optimal tax level and is subject to regulation shocks, giving rise to climate policy risk in the model.

2.1 Setup

Production There are two intermediate goods production sectors in the economy, a clean and a dirty one. The final goods producers compose the output from the clean firms and the dirty firms
to a final good

\[ Y_t = \left( Y_{c,t}^{1-\frac{1}{\varepsilon}} + Y_{d,t}^{1-\frac{1}{\varepsilon}} \right)^{\frac{1}{1-\frac{1}{\varepsilon}}}, \]  

(1)

which is a constant elasticity of substitution aggregate with parameter \( \varepsilon \). Final goods producers are perfectly competitive and maximize

\[ E_t \sum_{t=0}^{\infty} M_t (Y_t - p_{c,t} Y_{c,t} - p_{d,t} Y_{d,t}), \]  

(2)

taking the prices \( p_{c,t} \) and \( p_{d,t} \) of the clean and dirty intermediate goods as given. We choose the final good to be the numeraire in our economy, such that it always trades at a price of 1. \( M_t \) is the stochastic discount factor.

The clean and dirty sectors differ in the amount of carbon emissions they generate as part of their production process, and also with respect to their temperature sensitivity of output. In particular, firms in the dirty sector emit \( \iota_d \) tons of greenhouse gas for each unit of produced output, and we assume for simplicity that \( \iota_c = 0 \). In both sectors, \( i \in \{c, d\} \), goods are produced according to a production function

\[ Y_{i,t} = (A_t L_{i,t})^{1-\alpha} K_{i,t}^{\alpha} \cdot (\bar{T} - T_t)^{\kappa_i}, \]  

(3)

such that output depends on the temperature level \( T_t \) in addition to the capital \( K_{i,t} \) and labor \( L_{i,t} \). The total factor productivity \( A_t \) of the economy follows the process

\[ \log A_{t+1} = \log A_t + \mu_A + \sigma_A \varepsilon^A_{t+1} \]  

(4)

with productivity shocks \( \varepsilon^A_{t+1} \).

Sectoral production output is negatively affected by rising temperature levels with a temperature sensitivity \( \kappa_i \), and we use a specification for temperature exposure in which \( \bar{T} \) is the hypothetical temperature level which would lead to an “armageddon” scenario with zero output. We focus on
the case that the clean sector is more temperature-sensitive than the dirty sector, $\kappa_c > \kappa_d$, which gives rise to a negative emissions externality through climate change. This externality is addressed by the regulator in form of a carbon tax of $\tau_t$ on each ton of greenhouse gas emissions, as specified below.

Overall, the perfectly competitive intermediate goods firms maximize

$$E_t \sum_{t=0}^{\infty} M_t \left( p_{i,t} Y_{i,t} - R_{i,t} K_{i,t} - w L_{i,t} - \tau_t t_i Y_{i,t} \right),$$

(5)

taking intermediate goods prices $p_{i,t}$, capital rental rates $R_{i,t}$, labor wages $w$, and the carbon tax $\tau_t$ as given.

**Emissions and temperature**  The production of the dirty firms increases the level of greenhouse gas emissions in the atmosphere, which evolve as

$$E_{t+1} = (1 - \eta) E_t + \iota_d Y_{d,t},$$

(6)

where $\eta$ specifies the rate at which the atmosphere recovers from greenhouse gases, and $\iota_d$ is the carbon intensity of the dirty firms’ production process (recall that we assume $\iota_c = 0$ for simplicity). The level of greenhouse gas emissions affects the global temperature level, which follows the dynamics

$$T_{t+1} = \nu T_t + \chi E_{t+1} + \sigma_T \varepsilon_{t+1}^T.$$  

(7)

Here, $\chi$ is the climate sensitivity to emissions and $\nu$ is the carbon retention rate similar to Bansal, Kiku, and Ochoa (2017), and we consider weather shocks $\varepsilon_{t+1}^T$. 
Carbon tax  We introduce a tax on greenhouse gas emissions into the model that is set by the regulator and evolves as

$$\tau_t = \theta_t \tau^*_t,$$  \hspace{1cm} (8)  

$$\theta_{t+1} = \zeta(1 - \mu\theta) + \zeta\theta_t + \sigma_\theta \varepsilon^\theta_{t+1},$$  \hspace{1cm} (9)  

where $\tau^*_t$ is the theoretically socially optimal tax level, and the process $\theta_t$ governs the extent of environmental regulation. The carbon tax accounts for the negative emissions externality in our model and narrows the wedge between the competitive equilibrium and the social planner’s solution.

While with an optimal carbon tax of $\tau^*_t$ the social optimum is attained under perfect competition, we assume that the implemented tax $\tau_t$ fluctuates between zero and the optimal level. The implemented carbon tax is subject to policy shocks $\varepsilon^\theta_{t+1}$, and a positive policy shock brings the carbon tax closer to the socially optimal level.

Capital  The capital stock in each of the two sectors follows a law of motion of the form

$$K_{i,t+1} = (1 - \delta)K_{i,t} + I_{i,t} - G_{i,t}K_{i,t},$$  \hspace{1cm} (10)  

where $\delta$ is the capital depreciation rate and $G_{i,t}$ is a Jermann (1998) adjustment cost function:

$$G_{i,t}(I_{i,t}/K_{i,t}) = I_{i,t}/K_{i,t} - (a_{0,i} + \frac{a_{1,i}}{1 - \xi} (I_{i,t}/K_{i,t})^{1-\xi}).$$  \hspace{1cm} (11)  

The capital depreciation rate $\delta$ and the adjustment cost parameter $\xi$ are assumed to be the same for both sectors.
Households and market clearing Finally, the households in our model consume final goods $C_t$ and maximize Epstein and Zin (1991) utility

$$V_t = \left[(1 - \beta)C_t^{1 - \psi} + \beta E_t \left[V_{t+1}^{1-\gamma}\right]^{\frac{1}{1-\gamma}}\right]^{\frac{1}{1 - \psi}}$$

(12)

with risk aversion $\gamma$ and intertemporal elasticity of substitution $\psi$. As usual, final goods are both consumption and investment goods, and the market has to clear according to the condition

$$Y_t = C_t + I_{c,t} + I_{d,t}.$$  

(13)

2.2 Equilibrium

We derive the household’s and the firms’ first order conditions in order to solve for the model equilibrium. For the former, we define the pricing kernel as

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}} \left(\frac{V_{t+1}}{E_t \left[V_{t+1}^{1-\gamma}\right]^{\frac{1}{1-\gamma}}}\right)^{\frac{1}{\psi} - \gamma}$$

(14)

and obtain that the Euler equation

$$E_t [M_{t+1} R_{t+1}] = 1$$

(15)

holds for the assets traded in the economy, with return $R_{t+1}$.

From the firms’ side, we obtain that (15) holds for the investment returns in the two sectors,

$$R_{i,t+1} = \frac{R^K_{i,t+1} + ((1 - \delta) + G_{i,t+1}'\frac{L_{i,t+1}}{K_{i,t+1}} - G_{i,t+1})Q_{i,t+1}}{Q_{i,t}},$$

(16)
with marginal products of capital $R_{i,t}^K$ as well as $Q_{i,t}$ given as

$$R_{c,t}^K = \alpha_{c,t} \frac{Y_{c,t}}{K_{c,t}}, \quad R_{d,t}^K = \alpha_{d,t} (p_{d,t} - \tau_t) \frac{Y_{d,t}}{K_{d,t}}, \quad Q_{i,t} = \frac{1}{1 - G_{i,t}}. \quad (17)$$

We furthermore obtain the condition

$$Y_{i,t} = p_{i,t}^e Y_t. \quad (18)$$

Finally, we show in Appendix A.3 that the socially optimal carbon tax is

$$\tau_t^* = \epsilon_{c,t}, \quad (19)$$

where $\epsilon_{c,t}$ is a Lagrange multiplier describing the negative externality of the dirty firms on the clean sector as defined in Appendix A.

With these conditions as well as the laws of motion at hand, we can solve for the model equilibrium. In particular, we use a numerical a second-order approximation computed by perturbation methods as provided by the dynare package. We apply the pruning scheme proposed by Andreasen, Fernández-Villaverde, and Rubio-Ramírez (2018), which allows us to compute impulse response functions in closed form.

We furthermore compute the risk-free rate, the market return, and the equity premium based on the model solution, as defined by:

$$R_t^f = \frac{1}{E_t[M_{t+1}]}, \quad (20)$$

$$R_{t+1}^M = \frac{K_{c,t}Q_{c,t}R_{c,t+1} + K_{d,t}Q_{d,t}R_{d,t+1}}{K_{c,t}Q_{c,t} + K_{d,t}Q_{d,t}}, \quad (21)$$

$$R_{i,x,t}^{LEV} = (1 + \overline{DE})(R_{t}^M - R_{t-1}^f). \quad (22)$$

We assume an average debt-to-equity ratio $\overline{DE}$ of 1, in line with Croce (2014).
2.3 Calibration and Model Predictions

We calibrate the model in order to investigate the role and pricing of climate change risks within our framework. In line with the long-run risk asset pricing literature (e.g., Bansal and Yaron 2004; Croce 2014), we choose a risk aversion of 10 and an intertemporal elasticity of substitution of 2. This parametrization yields a preference for early resolution of uncertainty, such that long-run risks are particularly meaningful for households and command large risk premia. The parameters describing the production sector in our economy such as the capital share of production, the depreciation rate of capital, and others, are chosen in line with Croce (2014). These parameters are set to identical values for the clean and the dirty sector. We furthermore set the elasticity of substitution between clean and dirty sector output to 3, following Acemoglu, Aghion, Bursztyn, and Hemous (2012). The intuition is that clean sector technology should be a substitute for dirty sector technology.

The clean and the dirty sector differ along two dimensions. First, the dirty sector generates a significant amount of greenhouse gas emissions as part of the production process, $\iota_d = 0.5$, while the clean sector’s emissions intensity is 0. Second, we assume that the dirty sector is also the temperature-robust sector according to a temperature sensitivity $\kappa_d$ of 0, while the clean sector is temperature-sensitive with a parameter $\kappa_c$ of 0.25. Further parameters driving the overall emissions in the atmosphere as well as the global temperature dynamics are chosen in line with Bansal, Kiku, and Ochoa (2017). All parameter values are summarized in Table 1.

We analyze the effects of different shocks in the model by inspecting the corresponding impulse response functions. In particular, we are interested in the effect of temperature shocks and of policy shocks as well as in the respective risk premia. Figure 1 illustrates impulse responses to a positive temperature shock $\varepsilon_{T_{t+1}}$. In line with intuition, the plots reveal that the temperature increase is a negative shock to the overall economy, as reflected by an increase of the stochastic discount factor. Especially the output of the clean, temperature-sensitive sector is strongly negatively affected due to the direct negative impact through the production function. The effect on the dirty, temperature-
Table 1: Model parameters. This table reports parameters describing the production sector, the emissions and temperature dynamics, the carbon tax set by the regulator, as well as the household’s preferences in the model. The model is calibrated at an annual frequency.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Preferences</strong></td>
<td></td>
</tr>
<tr>
<td>Subjective discount factor ( \beta )</td>
<td>0.96</td>
</tr>
<tr>
<td>Relative risk aversion ( \gamma )</td>
<td>10</td>
</tr>
<tr>
<td>Intertemporal elasticity of substitution ( \psi )</td>
<td>2</td>
</tr>
<tr>
<td><strong>Production Sector</strong></td>
<td></td>
</tr>
<tr>
<td>Elasticity of substitution between clean and dirty sector ( \varepsilon )</td>
<td>3</td>
</tr>
<tr>
<td>Capital share of production ( \alpha )</td>
<td>0.34</td>
</tr>
<tr>
<td>Depreciation rate of capital ( \delta )</td>
<td>0.06</td>
</tr>
<tr>
<td>Average growth rate ( \mu )</td>
<td>1.8%</td>
</tr>
<tr>
<td>Capital adjustment costs ( \xi )</td>
<td>3.94</td>
</tr>
<tr>
<td>Volatility of productivity risk ( \sigma_A )</td>
<td>3.35%</td>
</tr>
<tr>
<td><strong>Emissions and Temperature</strong></td>
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</tr>
<tr>
<td>Climate sensitivity to emissions ( \chi )</td>
<td>0.4</td>
</tr>
<tr>
<td>Emissions intensity of clean sector ( \iota_c )</td>
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</tr>
<tr>
<td>Emissions intensity of dirty sector ( \iota_d )</td>
<td>0.5</td>
</tr>
<tr>
<td>Carbon retention rate ( \nu )</td>
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<tr>
<td>Atmosphere recovery rate ( \eta )</td>
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</tr>
<tr>
<td>Temperature-sensitivity of clean sector ( \kappa_c )</td>
<td>0.25</td>
</tr>
<tr>
<td>Temperature-sensitivity of dirty sector ( \kappa_d )</td>
<td>0.00</td>
</tr>
<tr>
<td>Volatility of temperature shocks ( \sigma_t )</td>
<td>0.1</td>
</tr>
<tr>
<td><strong>Carbon Tax</strong></td>
<td></td>
</tr>
<tr>
<td>Average carbon tax relative to optimal tax ( \mu_\theta )</td>
<td>0.3</td>
</tr>
<tr>
<td>Persistence of carbon tax ( \zeta )</td>
<td>0.98</td>
</tr>
<tr>
<td>Volatility of policy shocks ( \sigma_\theta )</td>
<td>0.025</td>
</tr>
</tbody>
</table>
robust sector is even positive, as agents reallocate both capital and labor to this sector. As a result, the equity return of temperature-sensitive firms responds negatively due to a decline in the price of related sector-specific capital, while the return is positive for temperature-robust firms. The figures furthermore show that in a model variant with no carbon tax, all described effects are more pronounced, in line with the notion that a carbon tax dampens the negative effect of increasing temperatures. We summarize these findings in the following prediction:

**Prediction 1** (Climate Productivity Risk). *Positive temperature shocks lead to an increase of the economy’s stochastic discount factor, i.e., they are “bad” shocks for the economy. Stock returns of temperature-sensitive firms react negatively to increasing temperatures, while robust firms’ stock returns respond positively.*

Figure 2 shows impulse responses to a positive climate policy shock $\theta_{t+1}$, i.e., an increase of the carbon tax towards the socially optimal level. A direct and important observation from our plots is that such a shock is a positive shock to the overall economy and leads to a decline in the stochastic discount factor. Economically, this is the case because the negative externality of the dirty firms’ emissions is internalized to a greater extent through a higher carbon tax, provided that the tax does still not exceed the socially optimal level, which is warranted in our calibration. As a result, emissions and temperature levels decrease over time. In terms of sectoral output, the dirty sector is naturally negatively affected by the climate policy shock, while the clean sector responds positively due to both the reduction of global temperatures as well as the capital and labor reallocation towards clean technologies. These findings and the corresponding effect on equity returns are summarized as follows:

**Prediction 2** (Climate Policy Risk). *Positive carbon tax shocks lead to a decrease of the economy’s stochastic discount factor, i.e., they are “good” shocks for the economy. Stock returns of dirty firms react negatively to an increasing carbon tax, while clean firms’ stock returns respond positively.*
Figure 1: Impact of temperature shocks. This figure shows impulse response functions of quantities and prices to a positive one-standard-deviation temperature shock materializing at $t = 1$. Parameters are chosen according to Table 1. Lowercase letters refer to log variables.
Figure 2: Impact of carbon tax shocks. This figure shows impulse response functions of quantities and prices to a positive one-standard-deviation policy shock materializing at $t = 1$. Parameters are chosen according to Table 1. Lowercase letters refer to log variables.
The model responses to temperature shocks and to policy shocks have direct implications for the pricing of the corresponding climate productivity risks and climate policy risks in terms of risk premia. More precisely, the related risk premia follow from the covariance of sector-specific equity returns with the stochastic discount factor in response to the respective shocks. Our model results therefore directly yield the following implications:

**Prediction 3 (Climate Change Risk Premia).** *There is a positive climate productivity risk premium in general equilibrium, i.e., a portfolio that goes long temperature-sensitive firms and short temperature-robust firms generates positive excess returns. The climate policy risk premium is negative in general equilibrium, i.e., a portfolio that goes long dirty firms and short clean firms generates negative excess returns.*

### 3 Measuring Exposures to Climate Change Risks

To confront our model predictions with the data, we need to measure different industries’ exposures to the productivity and policy risk dimension of climate change. For that, we build on data on the average temperature level in the United States as well as on the amount of overall CO₂ emissions. We furthermore use industry output data provided by the BEA, and Fama-French industry portfolios as provided by Kenneth French’s data library. Our sample period runs from 1960 to 2015.

#### 3.1 Climate Productivity Risk Exposures

We analyze the exposures of different industries to climate productivity risk, i.e., the risk of permanent temperature changes affecting future output. As a benchmark approach, we follow Bansal, Kiku, and Ochoa (2017) and measure an industry’s exposure by their stock return exposure to 5-year temperature changes. The intuition for using 5-year temperature changes is that these reflect
longer-term climate changes better than 1-year temperature changes, for example, which could be affected by relatively short-run weather fluctuations. Furthermore, using stock return exposures — as opposed to output exposures, for example — takes into account negative productivity effects of climate change in the remote future, which are priced into stock prices but not yet reflected by current changes in output. Nevertheless, we also consider the industries’ exposures to such alternative measures, which allows us to evaluate the robustness of our approach and to analyze in particular to what extent long-run climate risks can be distinguished from short-term weather fluctuations. We compute in particular the stock return exposures of the different industries to 1-year temperature changes and to the temperature level. Motivated by Colacito, Hoffmann, and Phan (2016), we also consider the stock return exposures to 1-year temperature changes in each of the separate quarters of a calendar year. Finally, we compute the industries’ current output growth exposure to 1-year temperature changes, which we consider as fundamental weather risk exposure.

Table 2 reports the different exposures. We find that the industries with the strongest negative exposure to climate productivity risk are Textiles, Apparel, and Footware, Transportation, as well as Banks, Insurance Companies, and Other Financials. While we do not have a clear prior on which industries’ productivity will be most influenced by climate change, it seems reasonable that transportation and financials are very strongly affected. A comparison with these industries’ stock return and output exposure to 1-year temperature changes reveals to what extent these are longer-term climate productivity risks or just short-run weather risks. For both transportation and financials, the stock return exposure to 1-year temperature changes is very similar to the benchmark measure; however, the output exposure to temperature changes is only slightly negative or even positive. The second finding indicates that the climate productivity risks these sectors are exposed to are distinct from current operational weather risks, while the first result suggests that it is not important to consider 5-year temperature changes instead of 1-year changes when measuring climate risks. Considering the exposures for different quarters, we also find for both sectors that the negative climate productivity risk exposure is attributed to all quarters (except for one), which
Table 2: Stock return and output exposures to temperature factors. This table reports the exposures (betas) of the Fama-French 17 industry portfolio excess returns with respect to a number of different temperature factors in the first seven columns headed “Stock return exposure to”. The last column headed “Output exposure to” reports exposures (betas) of the log output growth rates of the industries to 1-year temperature growth. We control for excess market returns and the two-year average per capita U.S. consumption growth in the stock return regressions, and for the lagged output growth rate in the output regression. The temperature factors used are 5-year U.S. temperature change $\Delta_5 T_t$, 1-year U.S. temperature change $\Delta_1 T_t$, and U.S. temperature $T_t$. Moreover, we report exposures to the 1-year change of the four quarterly U.S. temperature levels, implying four exposures (betas) $\Delta_1 T_{Q1}^t$, $\Delta_1 T_{Q2}^t$, $\Delta_1 T_{Q3}^t$, and $\Delta_1 T_{Q4}^t$ computed in one more regression. The last regression for output exposures uses the 1-year U.S. temperature change $\Delta_1 T_t$ as temperature factor. The sample period is 1960–2015 in all regressions.

<table>
<thead>
<tr>
<th>Industry</th>
<th>$\Delta_5 T_t$</th>
<th>$\Delta_1 T_t$</th>
<th>$\Delta_1 T_{Q1}^t$</th>
<th>$\Delta_1 T_{Q2}^t$</th>
<th>$\Delta_1 T_{Q3}^t$</th>
<th>$\Delta_1 T_{Q4}^t$</th>
<th>$T_t$</th>
<th>$\Delta_1 T_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>-0.66</td>
<td>-2.13</td>
<td>1.21</td>
<td>-3.71</td>
<td>1.18</td>
<td>-0.79</td>
<td>-1.40</td>
<td>-0.46</td>
</tr>
<tr>
<td>Mining and Minerals</td>
<td>-2.08</td>
<td>0.44</td>
<td>-0.27</td>
<td>1.02</td>
<td>6.25</td>
<td>-1.46</td>
<td>-2.04</td>
<td>0.52</td>
</tr>
<tr>
<td>Oil and Petroleum Products</td>
<td>-1.99</td>
<td>-0.35</td>
<td>1.26</td>
<td>0.23</td>
<td>3.20</td>
<td>-4.91</td>
<td>-2.31</td>
<td>-4.11</td>
</tr>
<tr>
<td>Textiles, Apparel, and Footware</td>
<td>-3.62</td>
<td>-3.79</td>
<td>0.06</td>
<td>-0.96</td>
<td>-9.44</td>
<td>-1.17</td>
<td>-2.18</td>
<td>-0.48</td>
</tr>
<tr>
<td>Consumer Durables</td>
<td>-0.75</td>
<td>-2.17</td>
<td>-0.60</td>
<td>-2.80</td>
<td>-2.32</td>
<td>4.85</td>
<td>-2.54</td>
<td>0.38</td>
</tr>
<tr>
<td>Chemicals</td>
<td>-0.75</td>
<td>0.23</td>
<td>0.51</td>
<td>0.00</td>
<td>-0.93</td>
<td>0.84</td>
<td>0.31</td>
<td>-0.06</td>
</tr>
<tr>
<td>Drugs, Soap, Parfums, Tobacco</td>
<td>0.86</td>
<td>1.14</td>
<td>2.93</td>
<td>-1.46</td>
<td>3.39</td>
<td>-0.46</td>
<td>0.35</td>
<td>—</td>
</tr>
<tr>
<td>Construction and Construction Materials</td>
<td>1.15</td>
<td>2.33</td>
<td>0.67</td>
<td>1.70</td>
<td>-1.95</td>
<td>1.53</td>
<td>1.92</td>
<td>0.48</td>
</tr>
<tr>
<td>Steel Works Etc</td>
<td>1.57</td>
<td>-0.89</td>
<td>-0.33</td>
<td>3.54</td>
<td>-3.34</td>
<td>-3.80</td>
<td>1.84</td>
<td>0.10</td>
</tr>
<tr>
<td>Fabricated Products</td>
<td>-2.06</td>
<td>-1.62</td>
<td>-0.51</td>
<td>1.66</td>
<td>-3.06</td>
<td>0.43</td>
<td>-1.49</td>
<td>0.24</td>
</tr>
<tr>
<td>Machinery and Business Equipment</td>
<td>0.94</td>
<td>0.78</td>
<td>-0.95</td>
<td>1.78</td>
<td>-0.66</td>
<td>0.79</td>
<td>0.12</td>
<td>0.15</td>
</tr>
<tr>
<td>Automobiles</td>
<td>-0.22</td>
<td>-1.88</td>
<td>-1.81</td>
<td>0.58</td>
<td>-0.73</td>
<td>0.69</td>
<td>-1.85</td>
<td>0.23</td>
</tr>
<tr>
<td>Transportation</td>
<td>-2.81</td>
<td>-4.77</td>
<td>-0.72</td>
<td>-3.97</td>
<td>-0.71</td>
<td>0.14</td>
<td>-2.96</td>
<td>0.63</td>
</tr>
<tr>
<td>Utilities</td>
<td>-2.12</td>
<td>-1.66</td>
<td>2.08</td>
<td>-2.31</td>
<td>1.66</td>
<td>-1.43</td>
<td>-0.92</td>
<td>-1.67</td>
</tr>
<tr>
<td>Retail Stores</td>
<td>0.88</td>
<td>-1.40</td>
<td>-0.13</td>
<td>-5.59</td>
<td>-2.82</td>
<td>1.03</td>
<td>-0.38</td>
<td>0.83</td>
</tr>
<tr>
<td>Banks, Insurance, and Other Financials</td>
<td>-2.18</td>
<td>-1.70</td>
<td>2.05</td>
<td>-0.76</td>
<td>-2.48</td>
<td>-1.84</td>
<td>-1.92</td>
<td>-0.16</td>
</tr>
<tr>
<td>Other</td>
<td>1.78</td>
<td>0.12</td>
<td>-0.97</td>
<td>-0.53</td>
<td>0.03</td>
<td>1.14</td>
<td>0.69</td>
<td>0.70</td>
</tr>
</tbody>
</table>
additionally indicates that it does not measure specific weather risk.

For the textiles industry, on the other hand, the picture is different: The negative stock return exposure to 5-year temperature changes is also reflected by considerably negative exposures of both stock returns and output to 1-year temperature changes, suggesting that our benchmark measure is partly picking up weather risk. The quarter-wise exposures particularly indicate that the textiles industry is negatively affected by warmer temperatures in the third and fourth quarters, presumably due to lower sales of winter clothes. On the other side of the spectrum, there are several industries with positive stock return exposures to 5-year temperature changes, in particular Steel Works, Construction and Construction Materials, Machinery and Business Equipment, and Retail Stores.

A close look at the Oil and Petroleum Products industry reconfirms that a strong exposure to 5-year temperature changes can also be due to current weather-related cash-flow effects, making it important to control for these factors when analyzing the impact of climate productivity risk. For the oil industry, the negative stock return exposure to 5-year temperature changes is in line with negative stock return and output exposures to 1-year temperature changes. Furthermore, the analysis of different quarters reveals that the negative exposure is completely due to the fourth quarter, while stock returns in all other quarters are actually positively exposed to higher temperatures. This is in line with intuition, as warmer temperatures in winter lead to lower petroleum and gas consumption for heating, while warmer summer temperatures increase the electricity consumption for air conditioning. The results therefore show that particularly for the oil sector, a good amount of the negative exposure to 5-year temperature changes can be attributed concrete weather-related cash flow effects.

Table 3 extends our analysis by considering portfolio sorts. In particular, we sort industry portfolios by their stock return exposure to 5-year temperature changes, which is estimated over a rolling window of 20 years length. We construct five portfolios from low to high exposures and rebalance the portfolios every year. The average exposures are reported in the second column of the table, showing considerable cross-sectional variation between negatively and positively affected
Table 3: Average exposures and returns of portfolios sorted by stock return exposure to 5-year U.S. temperature changes. We sort industries by their stock return exposure to 5-year U.S. temperature changes estimated over the previous 20 years in a rolling-window fashion. Portfolios are rebalanced every year. We report the average exposures for the 5 quintile portfolios, as well as other temperature factor exposures for the same portfolios, namely to the 1-year U.S. temperature change, 1-year changes in quarterly U.S. temperatures (one regression with four quarterly temperature growth rates), and the U.S. temperature level. The second-last column reports the exposures of output growth rates to the 1-year U.S. temperature change, and the last column the average stock market return of the respective portfolios. The sample runs from 1960 to 2015.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>$\Delta_5 T_t$</th>
<th>$\Delta_1 T_t$</th>
<th>$\Delta_1 T_{t1}$</th>
<th>$\Delta_1 T_{t2}$</th>
<th>$\Delta_1 T_{t3}$</th>
<th>$\Delta_1 T_{t4}$</th>
<th>$\Delta_1 T_{t5}$</th>
<th>Average return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>-5.29</td>
<td>-4.00</td>
<td>-1.27</td>
<td>-0.69</td>
<td>-0.05</td>
<td>-1.82</td>
<td>-4.88</td>
<td>8.84</td>
</tr>
<tr>
<td>2</td>
<td>-3.17</td>
<td>-3.34</td>
<td>-0.33</td>
<td>-1.51</td>
<td>1.28</td>
<td>-2.57</td>
<td>-2.38</td>
<td>8.56</td>
</tr>
<tr>
<td>3</td>
<td>-1.46</td>
<td>-2.45</td>
<td>-0.91</td>
<td>-1.01</td>
<td>1.37</td>
<td>-0.68</td>
<td>-1.11</td>
<td>7.21</td>
</tr>
<tr>
<td>4</td>
<td>0.76</td>
<td>0.28</td>
<td>-0.04</td>
<td>1.05</td>
<td>1.02</td>
<td>-0.54</td>
<td>0.83</td>
<td>11.22</td>
</tr>
<tr>
<td>High</td>
<td>3.30</td>
<td>2.24</td>
<td>0.81</td>
<td>1.36</td>
<td>0.63</td>
<td>1.50</td>
<td>2.83</td>
<td>6.66</td>
</tr>
<tr>
<td>5-1</td>
<td>8.59</td>
<td>6.23</td>
<td>2.07</td>
<td>2.05</td>
<td>0.68</td>
<td>3.32</td>
<td>7.71</td>
<td>-2.18</td>
</tr>
</tbody>
</table>
industries.

The other columns report the average exposures of the exact same sorted portfolios with respect to alternative measurement approaches. Confirming the evidence from Table 2, we find that stock return exposures to 5-year temperature changes are very much reflected also by exposures to 1-year temperature changes, suggesting that the longer time interval does not significantly contribute to a better identification of longer-term climate risks. On the other hand, the output exposures to 1-year temperature changes show a much weaker pattern across the sorted portfolios and are also non-monotonic, indicating that portfolios sorted by stock return exposures to 5-year temperature changes do not just pick up variations in current output caused by fluctuating weather conditions. Finally, the stock return exposures to temperature changes in different quarters are broadly in line with the whole-year exposures and do not exhibit any notable additional patterns.

Overall, the analysis of the different portfolios strongly suggests that for identifying long-run climate productivity risks, one should use stock return exposures to 5-year temperature changes and control for those industries’ output exposures to temperature changes at the same time.

3.2 Climate Policy Risk Exposures

We further categorize industries along the second important dimension of climate change risks, which materializes as climate policy risk. Naturally, relevant climate policies regulate the emission of greenhouse gases (GHGs), such that “dirty” firms with a high GHG emissions intensity are much more exposed to climate policy risks compared to clean firms. Our goal is therefore to sort industries by their contribution to the overall amount of GHG emissions in the United States. For that purpose, we define our benchmark measure for an industry’s climate policy risk exposure as the exposure of the US-wide CO\(_2\) emissions growth rate (per capita) to the industry’s change in output, as computed from a univariate regression for each industry.

Table 4 presents the inferred greenhouse gas intensity, and thus our measure of climate policy
Table 4: U.S. CO\textsubscript{2} per capita emission exposures to industry output growth rates. This table reports the exposures (betas) of the growth rate of U.S. CO\textsubscript{2} per capita emissions to the growth rate of output in the 17 Fama-French industries. The sample runs from 1961 to 2014.

<table>
<thead>
<tr>
<th>Industry</th>
<th>U.S. CO\textsubscript{2} per capita emission exposure to industry output growth rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>0.00243</td>
</tr>
<tr>
<td>Mining and Minerals</td>
<td>0.00086</td>
</tr>
<tr>
<td>Oil and Petroleum Products</td>
<td>0.00018</td>
</tr>
<tr>
<td>Textiles, Apparel, and Footwear</td>
<td>0.00196</td>
</tr>
<tr>
<td>Consumer Durables</td>
<td>0.00238</td>
</tr>
<tr>
<td>Chemicals</td>
<td>0.00185</td>
</tr>
<tr>
<td>Drugs, Soap, Parfums, Tobacco</td>
<td>—</td>
</tr>
<tr>
<td>Construction and Construction Materials</td>
<td>0.00216</td>
</tr>
<tr>
<td>Steel Works Etc</td>
<td>0.00104</td>
</tr>
<tr>
<td>Fabricated Products</td>
<td>0.00222</td>
</tr>
<tr>
<td>Machinery and Business Equipment</td>
<td>0.00228</td>
</tr>
<tr>
<td>Automobiles</td>
<td>0.00079</td>
</tr>
<tr>
<td>Transportation</td>
<td>0.00313</td>
</tr>
<tr>
<td>Utilities</td>
<td>0.00050</td>
</tr>
<tr>
<td>Retail Stores</td>
<td>0.00025</td>
</tr>
<tr>
<td>Banks, Insurance Companies, and Other Financials</td>
<td>0.00212</td>
</tr>
<tr>
<td>Other</td>
<td>-0.00036</td>
</tr>
</tbody>
</table>
Table 5: Average exposures and returns of portfolios sorted according to exposures from regressions of U.S. CO₂ per capita emission changes on industry output growth rates. We sort industries by the United States’ CO₂ emissions exposure to the industries’ output growth rates, estimated over the previous 20 years in a rolling-window fashion. The oil sector is considered separately and thus excluded from this analysis. Portfolios are rebalanced every year. We report the average exposures for the 5 quintile portfolios, as well as the temperature factor exposures considered in Tables 2 and 3, namely the stock return exposure to the 1-year U.S. temperature change, 1-year changes in quarterly U.S. temperatures (one regression with four quarterly temperature growth rates), and the U.S. temperature level, as well as the exposures of output growth rates to the 1-year U.S. temperature change. The last column reports the average stock market return of the sorted portfolios. The sample runs from 1960 to 2015.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Avg. CO₂ exp. to Output growth</th>
<th>Average stock return exposure to</th>
<th>Avg. output exp. to</th>
<th>Average return</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Avg. Carbon Dioxide exposure</td>
<td>1-year change</td>
<td>1-quarter change</td>
<td>2-quarter change</td>
</tr>
<tr>
<td>Low</td>
<td>-0.0019</td>
<td>-2.18</td>
<td>-2.71</td>
<td>-0.43</td>
</tr>
<tr>
<td>2</td>
<td>-0.0008</td>
<td>-1.13</td>
<td>-1.67</td>
<td>-0.96</td>
</tr>
<tr>
<td>3</td>
<td>0.0000</td>
<td>-0.32</td>
<td>-1.37</td>
<td>-0.48</td>
</tr>
<tr>
<td>4</td>
<td>0.0009</td>
<td>-2.04</td>
<td>-2.26</td>
<td>-0.88</td>
</tr>
<tr>
<td>High</td>
<td>0.0022</td>
<td>-1.10</td>
<td>-1.96</td>
<td>0.03</td>
</tr>
<tr>
<td>5-1</td>
<td>0.0041</td>
<td>1.08</td>
<td>0.75</td>
<td>0.47</td>
</tr>
</tbody>
</table>
risk exposure, for the different industries. We find the highest intensity for the Transportation sector, followed by the Food industry and Consumer Durables, which makes economic sense. Particularly low exposures are found for Retail Stores and Other industries, for example. Clearly a special role in our analysis is taken by the Oil and Petroleum Products sector: It is actually very sensible that this sector itself, which includes oil drilling and refineries, for example, does not generate a lot of greenhouse gas emissions. It is, however, the consumption of oil and petroleum products by other sectors which produces large amounts of CO\textsubscript{2}. Therefore this industry is clearly negatively exposed to climate policy risks, as restrictions on CO\textsubscript{2} emissions reduce the demand for oil-related goods. We also argue that this is the only industry that stands out in this perspective, as all other industries are consumers of fossil fuels, at a higher or lower intensity. As a consequence, we consider the oil sector separately in the subsequent analysis and do not include it in our portfolio sorts.

In Table 5, we sort industries by their carbon intensity, following a similar procedure as in Table 3, and analyze how the related portfolios behave along the climate productivity risk dimension. This analysis provides insights into whether climate policy risks and climate productivity risks can well be separated empirically, which would not be the case if the cleanest firms in the sample were also the most temperature-sensitive ones, or the other way round. Our results show that this is not the case: Clean firms tend to be more temperature-sensitive overall, but across the different portfolios the relationship is weak and also non-monotonic. When it comes to weather risk, as measured by output exposures to temperature changes, it is even the case that dirty firms tend to have a larger negative exposure to weather fluctuations than clean firms, but this relation is not monotonic either. Therefore, our results confirm that it is very well possible to separate the policy risk and the productivity risk dimensions of climate change empirically by considering appropriate portfolios. In the next section, we apply these findings in order to construct portfolios that load on the different climate risks, and analyze the behavior of their respective returns.
4 Climate Risk Portfolio Returns

We analyze the returns of two main portfolios over time: one that loads heavily on climate productivity risk, and one that takes on a large exposure to climate policy risk. The past performance of these portfolios provides insights into the question whether the market prices the different dimensions of climate change risk in line with theory. Our analysis is complemented by studying the return of a weather risk portfolio, which is only exposed to short-run temperature risks, and of the oil sector portfolio as the main producer of oil as an input factor for “dirty” industries.

4.1 Climate Sensitive vs. Robust

First, we construct a portfolio that is strongly exposed to long-run climate productivity risks. To this end, we apply our findings from Section 3 and sort portfolios according to the industries’ stock return exposure to 5-year temperature changes. Figure 3 shows the cumulative excess return of the corresponding high-minus-low climate productivity risk portfolio, representing the difference between the climate-sensitive and climate-robust firms’ stock returns. Prediction 3 of our model states that from a general equilibrium asset pricing point of view, this portfolio should deliver significant positive excess returns on average as a compensation for investors being exposed to climate productivity risks. The cumulative returns in the figure reveal that historically, there is no evidence for a positive average return corresponding to the prediction — rather, the sensitive-minus-robust portfolio return is clearly negative overall at an average of $-2.18\%$ per year (see also Table 3). As we discuss in Section 5, this negative return, most of which is realized in the 2000s and later, could instead stand for a transition period in which investors have increasingly taken into account the climate risks for climate-sensitive firms, leading to negative realized returns as a result of lower expected cash-flows and larger expected future returns.

The results of Section 3 strongly suggest that one should compare the performance of the climate sensitive-minus-robust portfolio to a portfolio that loads heavily on weather risks, in order to identify
Figure 3: Cumulative excess return of the climate sensitive-minus-robust portfolio. Portfolios are sorted into quintiles based on the industries’ stock return exposures to 5-year temperature changes, with yearly rebalancing. The chart shows the return of the portfolio with the highest exposure minus the return of the portfolio with the lowest exposure. The sample period runs from 1980 to 2015.

Figure 4: Cumulative excess return of the weather risk portfolio. Portfolios are sorted into quintiles based on the industries’ output growth exposures to 1-year temperature changes, with yearly rebalancing. The chart shows the return of the portfolio with the highest exposure minus the return of the portfolio with the lowest exposure. The sample period runs from 1980 to 2015.
a potential short-term component. Accordingly, Figure 4 illustrates the cumulative excess return of a high-minus-low portfolio constructed by the industries’ output exposure to 1-year temperature changes, which we interpret as weather exposure. The figure shows that the cumulative excess return is fluctuating around zero, without any clear direction towards negative or positive returns. This shows, first, that the returns realized by the climate sensitive-minus-robust portfolio are not explained by short-term weather risks. Secondly, there is no evidence for risk premia — neither in realized form or in form of a transition period — for weather risks, which makes sense due to their short-run and possibly idiosyncratic nature.

4.2 Dirty vs. Clean

Second, we construct a portfolio that loads heavily on climate policy risk. We use our measure from Section 3, the exposure of CO₂ emissions growth in the U.S. to the industries’ output change, to construct portfolios of dirty and clean industries. Figure 5 plots the cumulative returns of the dirty-minus-clean portfolio over time. Prediction 3 of our model predicts that this portfolio should exhibit significant risk premia, which should be negative in sign due to the positive effect of stricter environmental policies on the overall economy. We see that, indeed, the dirty-minus-clean portfolio yields clearly negative returns, with an average excess return of $-2.01\%$ per year, most of which is attributable to the time after year 2000, similar to the climate sensitive-minus-robust returns. We would, however, like to raise caution regarding the direct interpretation of these negative returns as risk premia, because this would mean that investors priced climate policy risks in line with theory, while they did not take climate productivity risks into account properly. In contrast, the notion of a transition period, which could explain the realized returns of the climate sensitive-minus-robust portfolio, is also consistent with the observed dirty-minus-clean portfolio returns.

Finally, we analyze the historical returns of the oil and petroleum goods industry, which we have classified as dirty firms per se, relative to the market return. Figure 6 reveals that the return of the
Figure 5: Cumulative excess return of the dirty-minus-clean portfolio. Portfolios are sorted into quintiles based on the United States’ CO\textsubscript{2} per capita exposure to the industries’ output growth, with yearly rebalancing. The chart shows the return of the portfolio with the highest exposure minus the return of the portfolio with the lowest exposure. The sample period runs from 1980 to 2015.

Figure 6: Cumulative excess return of the oil-minus-market portfolio. The chart shows the stock return of the Oil and Petroleum Products portfolio minus the return of the market portfolio. The sample period runs from 1980 to 2015.
oil-minus-market portfolio is also negative, in line with the dirty-minus-clean portfolio, although still very close to zero over the sample period. It is eye-catching that the commodity price boom between 2003 and 2008 has also driven up the returns of the oil sector, potentially overlaying stronger negative returns due to climate change related effects.

5 Conclusion

This paper develops a general equilibrium asset pricing model that provides us with a foundation for understanding climate-related risk factors, in particular climate productivity risk and climate policy risk. We confront the model predictions with the data and find that the corresponding portfolio returns do not indicate a completely consistent pricing of climate change risks in line with theory. In particular, both the climate productivity risk portfolio of climate sensitive-minus-robust firms and the climate policy risk portfolio (“dirty-minus-clean”) exhibit negative returns, while asset pricing theory predicts opposite signs of the risk premia of these two portfolios. A large part of the negative return for both portfolios is realized within and after the 2000s. An interpretation that is fully consistent with these observations is that the stock market is undergoing a transition period, which started in the 2000s, in which investors start taking climate productivity risks and climate policy risks into account. This leads to negative realized returns for both portfolios, whereas the negative effect on the sensitive-minus-robust portfolio is larger as both lower cash flows and higher discount rates lead to lower stock returns, while for the dirty-minus-clean portfolio the negative cash flow effect is partly counteracted by lower discount rates, due to negative future risk premia. For the oil sector as a particularly “dirty” industry, it seems that the commodity price boom of the last decade temporarily masked the negative impact of climate risks.
References


A Model Equilibrium Conditions

A.1 Competitive Equilibrium with Carbon Tax

Final goods producer The final goods firm in the model solves the problem

$$
\max_{Y_{i,t}} E_t \sum_{t=0}^{\infty} M_t (Y_t - p_{c,t}Y_{c,t} - p_{d,t}Y_{d,t}), \quad (A.1)
$$

which leads to the equilibrium condition

$$
Y_{i,t} = p_{i,t}^c Y_t, \quad (A.2)
$$

in line with equation (18).

Intermediate goods firms The clean and dirty intermediate goods producers, $i \in \{c, d\}$, optimize (5) subject to the laws of motion (3), (6), and (7), leading to the problem

$$
\max_{Y_{i,t}, L_{i,t}, K_{i,t}, T_{t+1}, \epsilon_{t+1}} E_t \sum_{t=0}^{\infty} M_t (p_{i,t}Y_{i,t} - R_{i,t}K_{i,t} - wL_{i,t} - \tau t_i Y_{i,t} \\
- \lambda_{i,t}(Y_{i,t} - (A_t L_{i,t})^{1-\alpha} K_{i,t}^{\alpha} \cdot (\bar{T} - T_t)^{\kappa}) \\
- \phi_{i,t}(\nu T_t + \chi \epsilon_{t+1} + \sigma T_0^T \epsilon_{t+1} - T_{t+1}) - \epsilon_{i,t}(\epsilon_d Y_{d,t} + (1-\eta)\epsilon_t - \epsilon_{t+1}) \quad (A.3)
$$

with Lagrange multipliers $\lambda_{i,t}$, $\phi_{i,t}$, and $\epsilon_{i,t}$.

Setting the first derivative by $Y_{i,t}$ to zero yields

$$
p_{i,t} - \tau t_i - \lambda_{i,t} - \epsilon_{i,t} t_i = 0. \quad (A.4)
$$
We set the first derivative by $T_{t+1}$ to zero and obtain

$$-E_t M_{t+1} \lambda_{i,t+1} \kappa_i \frac{Y_{i,t+1}}{T - T_{t+1}} - E_t M_{t+1} \phi_{i,t+1} \nu + \phi_{i,t} = 0. \quad (A.5)$$

Setting the first derivative by $E_{t+1}$ to zero yields

$$-\phi_{i,t} \chi - (1 - \eta) E_t M_{t+1} \epsilon_{i,t+1} + \epsilon_{i,t} = 0. \quad (A.6)$$

Finally, setting the first derivative by $L_{i,t}$ to zero gives us

$$\lambda_{i,t} (1 - \alpha) \frac{Y_{i,t}}{L_{i,t}} = w, \quad (A.7)$$

and the first order condition with respect to $K_{i,t}$ is

$$\lambda_{i,t} \alpha \frac{Y_{i,t}}{K_{i,t}} = R_{i,t}. \quad (A.8)$$

### A.2 Social Planner Solution

The social planner considers the production sector as a whole and optimizes

$$\max_{Y_{i,t}, L_{i,t}, K_{i,t}, T_{t+1}, \epsilon_{t+1}} \mathbb{E}_t \sum_{t=0}^{\infty} M_t \left( Y_t - \sum_{i \in \{c,d\}} (R_{i,t} K_{i,t} - w L_{i,t}) ight) - \omega_t(Y_t - p_c Y_{c,t} - p_d Y_{d,t}) - \sum_{i \in \{c,d\}} \lambda_{i,t} (Y_{i,t} - (A_{i,t} L_{i,t})^{1-\alpha} K_{i,t}^\alpha (T - T_t)^{\kappa_i}) - \phi_t(\nu T_t + \chi \epsilon_{t+1} + \sigma_T \epsilon_{t+1}^T - T_{t+1}) - \epsilon_t \left( \sum_{i \in \{c,d\}} \iota_i Y_{i,t} + (1 - \eta) \epsilon_t - \epsilon_{t+1} \right). \quad (A.9)$$
We obtain the first order condition with respect to $Y_{i,t}$, which (noting that $\omega_t = 1$) is

$$p_{i,t} - \lambda_{i,t} - \epsilon_{t} \iota = 0,$$  \hspace{1cm} (A.10)

as well as with respect to $E_{t+1}$,

$$-\phi_t \chi - (1 - \eta) E_t M_{t+1} \epsilon_{t+1} + \epsilon_t = 0,$$  \hspace{1cm} (A.11)

and $T_{t+1}$, which yields

$$-E_t M_{t+1} \left( \sum_{i \in \{c,d\}} \lambda_{i,t+1} \kappa_i \frac{Y_{i,t+1}}{T - T_{t+1}} \right) - E_t M_{t+1} \phi_{t+1} \nu + \phi_t = 0.$$  \hspace{1cm} (A.12)

The main difference to the FOCs for the competitive equilibrium is that there are joint Lagrange multipliers $\epsilon_t$ and $\phi_t$ instead of individual ones, such that the effects of emissions and temperatures are internalized, in line with intuition.

### A.3 Optimal Carbon Tax

Given the competitive equilibrium and the social planner solution, we obtain the optimal carbon tax as follows. In our model specification, we have $\kappa_d = 0$ and $\iota_c = 0$, which leads to $\epsilon_{d,t} = 0$ and $\epsilon_{c,t} = \epsilon_t$, and we have

$$p_{c,t} = \lambda_{c,t} \quad \text{and} \quad p_{d,t} = \lambda_{d,t} + \tau_{t} \iota_d$$  \hspace{1cm} (A.13)

in the competitive equilibrium and

$$p_{c,t} = \lambda_{c,t} \quad \text{and} \quad p_{d,t} = \lambda_{d,t} + \epsilon_{t} \iota_d$$  \hspace{1cm} (A.14)
in the social planner solution. Therefore, for a carbon tax of $\tau_t^* = \epsilon_t$, the social optimum is achieved in a competitive setting.