Do production frictions affect the impact of sustainable investing?

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Abstract

Prior studies focus on how investors' sustainability preferences incentivize firms to reallocate resources from dirty to clean physical capital. However, the impact of investors' preferences on capital allocation depends critically on whether clean capital and dirty capital are substitutable. I develop a novel empirical strategy showing that dirty capital and clean capital are highly complementary. Theoretically, I explore firms' investment decisions, assuming that investors dislike carbon emissions through both risk and nonpecuniary utility channels. Given the current level of complementarity, investors' preferences have a limited impact on investment decisions, underscoring the need for technological innovation to address this production friction.

JEL Codes: G11, G32, L21, C61

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1 Introduction

How effective is sustainable investment in making firms cleaner? Prior studies have focused on investors' nonpecuniary preferences for green stocks or risk aversion to climate change, increasing the costs of capital for dirty firms or production technologies (Pástor et al., 2021; Dangl et al., 2023; Hong et al., 2023). As a result of these increased costs, firms are expected to allocate more resources to clean technologies and reduce carbon emissions. An implicit assumption is a smooth or frictionless transition from dirty to clean capital, suggesting that firms' investment decisions should depend only on investors' sustainability demands. However, translating investors' sustainability demands into firm production is not straightforward, as the marginal value of dirty capital can be very high due to its high complementarity in the production process.

This paper explores the complementarity between dirty capital and clean capital in limiting the impact of sustainable investing as a real friction. "Dirty capital" refers to physical assets that contribute to a firm's production while generating carbon emissions, such as factories and machinery. Empirical estimates show that dirty capital remains highly complementary. A dynamic model is then employed to examine the realistic quantitative effects on capital allocation and to explore comparative statics with broader implications, such as carbon tax policies. The results demonstrate that the high complementarity between clean capital and dirty capital significantly limits the effectiveness of sustainable investing as a tool for mitigating climate change.

To illustrate complementarity versus substitutability, consider two examples. Tesla requires both clean gigafactories and dirty factories or supply chains to manufacture lithium for its electric car batteries. Without either the clean or dirty components, production halts, demonstrating high complementarity.[1] In contrast, consider an AI company that relies on supercomputers that generate carbon emissions (dirty) and machine learning algorithms (clean). With an ample supply

[1] This example illustrates complementarity and does not imply that Tesla is harmful to the environment or that electric cars should be abandoned. Rather, this example underscores that dirty capital is complementary to clean capital and thus vital to production across many industries and the entire economy. Therefore, investors' sustainability demands will be reflected only in firms' production if the complementarity issue is directly addressed (e.g., through R&D investments targeted at decreasing the complementarity between clean capital and dirty capital).

of clean energy, the AI company can easily switch to sources such as wind or water to power its supercomputers, demonstrating high substitutability between dirty capital and clean capital.

First, I build a two-period model of a typical firm to highlight the key economic mechanisms involved. Today, the firm makes investment decisions regarding dirty capital and clean capital. Dirty capital generates pollution, reducing the firm's total output through a damage function, similar to the setting in Barnett et al. (2023a). The damage function and the overall economic setting are specified to align with previous climate economics and finance models (Nordhaus and Sztorc, 2013; Nordhaus, 2014; Cai and Lontzek, 2019; Barnett et al., 2020). However, these models often include additional layers that link the damage function to an increased frequency or severity of natural disasters due to global warming. My model abstracts from those extra layers, simplifying the approach and allowing for a broader interpretation of the damage function. For instance, the damage function can also account for firm reputation, such as the possibility that consumers may have lower demand for products from firms perceived as environmentally harmful.

In the model, the firm maximizes the present value of its cash flows while incorporating sustainability concerns in its projected cash flows and pricing kernel. First, the firm includes a positive price of the damage shock in the pricing kernel, which may reflect climate change risk concerns or the direct cost of capital effects from investors' sustainability preferences. Second, the firm fully internalizes the damage function's impact on its cash flows. This naturally applies to immediate cash flow effects (e.g., the reputational cost of high carbon emissions). However, the environmental effect on productivity is better understood as an externality; thus, full internalization should be interpreted through the lens of shareholder welfare maximization with sustainable investors (see Hart and Zingales, 2017).[2] The results suggest that even in an ideal scenario where both investors and the firm align in terms of sustainability goals, the complementarity of dirty capital obstructs the firm's shift to clean capital.

[2] Hart and Zingales (2017) demonstrates that if profit and damage are inseparable, shareholder welfare is not equivalent to market value, making shareholder welfare the appropriate objective function in this context. I model this aspect in reduced form through the firm's full internalization of the damage function.

From the first-order conditions of a firm's investment decisions, marginal investment benefits and costs equate. Unlike clean capital, dirty capital generates pollution and damage, diminishing its marginal benefits. Shareholders' aversion to pollution and damage raises the cost of dirty capital, encouraging the firm to reduce its investment in it. However, the firm cannot invest exclusively in clean capital if dirty capital is complementary. For example, with a Cobb-Douglas production function, total output would drop to zero without dirty capital. When complementarity is high, the marginal benefits of dirty capital can be substantial, potentially offsetting the damage and shareholders' preferences for cleaner options.

Thus, a natural question arises: How complementary is dirty capital in the data? Building on the theoretical framework and the approach in Chirinko and Mallick (2017), a novel method is developed to empirically estimate the elasticity of substitution (ES) for dirty capital. The firm's production function follows a constant elasticity of substitution (CES) form, with dirty capital and clean capital as direct inputs.[3] First, theoretical assumptions are used to transform the CES function into a regression framework, where the relation between the dirty capital-to-output ratio and the marginal productivity of dirty capital reflects the ES. Second, given challenges in measuring absolute levels of dirty capital and clean capital, carbon emissions serve as a proxy for dirty capital and total assets for the combined capital stock.

The overall elasticity of substitution for dirty capital is estimated at approximately 0.3, aligning with the substitutability between capital and labor in the classical production function (Gechert et al., 2022). This estimate suggests a production function more complementary than Cobb-Douglas. Since Van der Beck (2023) highlights a significant increase in sustainable investing after 2012, I also consider a subsample analysis that starts in 2012. I find that dirty capital has become slightly more substitutable (with the ES increasing from approximately 0.15 to 0.3), indicating progress toward an economy with greater technological flexibility.

[3] Other economic inputs do not affect the estimation strategy, which relies on the partial derivative of output with respect to dirty capital, depending only on total output and dirty capital. See Appendix B for derivations. Notably, this model is consistent with the presence of costless adjustable labor as a production input, as labor would be embedded in firm-level total factor productivity in this case.

To arrive at the estimation, several assumptions are made along with corresponding robustness checks. First, total assets are used as a proxy for the sum of dirty capital and clean capital in the benchmark analysis. As robustness checks, total assets are replaced with physical capital only and with the sum of physical capital and intangible capital, yielding results that are consistent with the benchmark. Second, a linear relation between carbon emissions and dirty capital is assumed for simplicity. The estimation of ES does not rely on this specific linear functional form; alternative mathematical derivations for other functional forms lead to the same estimation equation. Third, following Chirinko and Mallick (2017), firm-level TFP is assumed to be captured by the sum of firm and time fixed effects, which removes the possibility of firm-specific variation in TFP. As additional robustness checks, the econometric method in Bai (2009) is employed to account for time-varying interactive fixed effects. The resulting estimates of ES are higher than the benchmark results but remain far from the perfect substitutability implicitly assumed in the literature. Overall, the results suggest that the current production function is more complementary than the Cobb-Douglas function.

After obtaining the elasticity of substitution, I back out the productivity share of dirty capital, which should be between zero and one.[4] The data-implied share of dirty capital is approximately 50%, which falls well within the theoretical range and validates the model assumption. I also present heterogeneous estimates of substitutability across ten industries as defined by Fama and French (1997). Industries that are more R&D intensive, such as the high-tech and health industries, exhibit lower complementarity of dirty capital. In contrast, traditional industries, such as the manufacturing and consumer goods industries, demonstrate greater complementarity.

Finally, to capture the more realistic dynamics and implications of climate change, the two-period model is extended to a dynamic model that examines the effects of carbon emissions on damage and temperature changes. This model integrates a standard investment-based asset pric-

[4] Specifically, two explicit assumptions are needed as follows: 1. the ratio of dirty capital to total assets is the same as the productivity share of dirty capital; and 2. there is a linear relationship between dirty capital and carbon emissions. Under these assumptions, the productivity share of dirty capital becomes a nonlinear function of the elasticity of substitution and other observable information. Note that the estimate of the productivity share (but not of the ES) heavily depends on the specific functional form relating carbon emissions to dirty capital (see Appendix B).

ing framework (Zhang, 2005) with a simplified version of the dynamic integrated climate–economy (DICE) model (Nordhaus and Sztorc, 2013). Pollution and subsequent temperature increases form a gradual process that can cause irreversible global damage. Because the two-period model cannot fully capture these progressive and long-term impacts, the dynamic model is developed with an infinite time horizon.

The economic mechanisms of the dynamic model are as follows. Similar to the two-period model, the firm maximizes the present value of cash flows while incorporating sustainability preferences into the projected cash flows and pricing kernel. Unlike the two-period model, sustainability preferences operate through concerns about carbon emissions, which lead to temperature increases and output damage, as described in Nordhaus and Sztorc (2013). Although the temperature changes and resulting damages are mild in each period, the cumulative loss is significant. Consequently, the firm opts for a much lower proportion of dirty capital when the two types of capital are perfectly substitutable, and when investors' climate concerns are substantial.

The dynamic model yields two main results. First, heightened investor sustainability demands related to climate change motivate firms to decrease their use of dirty capital, although this reduction is limited by the complementarity between clean capital and dirty capital. In the benchmark analysis, I assume that the two types of capital are equivalent except for climate concerns. With high sustainability demands, firms opt for as little as 20% dirty capital when it can be perfectly substituted by clean capital (ultimately, they opt for 0% dirty capital if the sustainability preference is further strengthened). However, when the capitals are complementary, productivity concerns outweigh sustainability demands, leading firms to maintain a more balanced allocation (near 50/50) despite investor pressures. I examine varying levels of complementarity, setting the elasticity of substitution from 0.3 to $+\infty$ (perfect substitution). An ES of 5 achieves only half the impact of sustainable investing under perfect substitution, underscoring the significant friction introduced by complementarity.[5]

[5]The firm might alter complementarity through R&D; however, I treat this parameter as exogenous to avoid significantly increasing model complexity. Currently, it is unclear whether firms are actively pursuing technological

Second, the magnitude of the "greenium" depends on the effectiveness of sustainable investing. I define the greenium as the difference between the one-period marginal expected returns of dirty and clean investments (dirty minus clean), which quantifies the short-term return that investors forego to mitigate the cumulative damage of climate change or the difference in the cost of capital. Here, investment return is defined as the marginal investment benefit divided by the cost. With higher substitutability, sustainable investing is more effective, prompting the firm to opt for a significantly lower level of dirty capital, which is associated with low marginal cost and high marginal benefit. This gap between benefits and costs drives up the return on dirty investments, resulting in a large positive greenium. In contrast, if sustainable investing is ineffective at reducing dirty capital, the greenium becomes close to zero. The greenium resulting from effective sustainable investing aligns with the findings of other models (Pástor et al., 2021), although it is derived here from an investment-based asset pricing perspective.[6]

Overall, my findings underscore the critical role of substitutability between the two types of capital, alongside the influence of investors' preferences. For sustainable investing to have a material effect on firms' investment in dirty capital, one needs to prioritize technological innovations that make clean capital a viable substitute for dirty capital. Simply pressuring firms to adopt greener practices may be ineffective if they are constrained by production requirements. In this sense, my findings are related to the point that other frictions, such as financial constraints, can counteract the intended impact of sustainable investing (see Hartzmark and Shue (2022) and Lanteri and Rampini (2023)).

shifts, as sustainability goals have only recently taken center stage. Some firms may simply divest from dirty assets under investor pressure rather than pursue structural changes. Nonetheless, this is an important question for future research.

[6]A positive greenium means that brown projects have a higher cost of capital than green projects. The current empirical literature on greenium presents mixed evidence and could reflect a world characterized by high complementarity and other economic forces. In practice, green firms experience higher average realized returns, which does not contradict a positive greenium, as the average realized return can be a poor proxy for the expected return in a short sample. Using alternative expected return measures, Yoo (2023) and Eskildsen et al. (2024) find higher brown expected returns, which is consistent with model predictions. A negative green premium could also arise from factors outside my model, such as rising ESG fund demand (Van der Beck, 2023) or future growth opportunities from intangible assets. Even if the greenium is negative, the goal of ESG is to make it positive, and my model examines the implications of achieving this objective.

Related Literature

My paper contributes to three strands of literature. First, it adds to the burgeoning literature on how sustainable investors impact firm value and corporate policies. Sustainable investors demonstrate preferences for green firms and construct portfolios on the basis of firms' environmental sustainability, thereby influencing firms' cost of equity through the required returns (Choi et al., 2020; Engle et al., 2020; Krueger et al., 2020; Ilhan et al., 2021; Pástor et al., 2021; Pedersen et al., 2021; Sautner et al., 2023). More specifically, my work contributes to the carbon premium and carbon emissions literature (Bolton and Kacperczyk, 2021; Gregory, 2021; Bartram et al., 2022; Bolton and Kacperczyk, 2023; Huij et al., 2023; Van der Beck, 2023; Zhang, 2024). I assume that the carbon risk price can be influenced by investors and focus on the implications of this risk price for firms' investment decisions and carbon emissions. Previous studies document that sustainable investors may or may not alter firm behaviors (Heinkel et al., 2001; Li et al., 2020; De Angelis et al., 2023; Heath et al., 2023). Favilukis et al. (2023) shows that the impact of portfolio mandates crucially depends on firms' demand elasticity of capital in a production economy. I demonstrate that sustainable investors have tangible effects on capital choices if clean capital and dirty capital are highly substitutable. Furthermore, my paper reveals the limitations of sustainable investors, emphasizing the importance of capital substitutability in firms' production processes.

The second contribution of my paper is to the literature on climate finance theories. Much of the literature in this area has focused on studying the interaction between social welfare and financial quantities and prices through macrofinance models (Daniel et al., 2016; Bansal et al., 2017; Donadelli et al., 2019; Barnett et al., 2020; Lemoine, 2021; Van den Bremer and Van der Ploeg, 2021; Barnett, 2023; Hong et al., 2023; Lontzek et al., 2023). Some recent models have examined the real effects of sustainable investors on firms (Hambel et al., 2020; Campbell and Martin, 2021; Pástor et al., 2021; Dangl et al., 2023; Lanteri and Rampini, 2023; Bustamante and Zucchi, 2024). These theories focus primarily on investor-side influences and explore how they can propagate to firms and the broader economy. In contrast, my model centers on firm-side decisions and the tradeoff between green and brown inputs in the production function. I emphasize the importance of technological innovation in capital substitutability, which aligns with the findings of Barnett et al. (2023b), who demonstrate the value of R&D investments.

Third, my paper contributes to the investment-based asset pricing literature (Zhang, 2005; Liu et al., 2009; Lin, 2012; Eisfeldt and Papanikolaou, 2013; Frank and Shen, 2016). This body of work has examined equity value and returns by considering endogenous investment decisions. Previous papers also highlight the implications of heterogeneous capital and labor sources (Belo et al., 2014; Belo et al., 2017; Gonçalves et al., 2020; Belo et al., 2022). I extend the standard investment-based model by incorporating both dirty capital and clean capital. Using an investment-based model with two types of capital, I highlight how the endogenous tradeoff between capital allocation and productivity limits the effect of sustainable investment, thereby addressing new questions in climate finance.

The remainder of this paper is organized as follows: Section 2 employs a two-period model to illustrate the key economic mechanisms. Section 3 reports the results of the empirical analysis concerning the substitutability of dirty capital. Section 4 outlines the full dynamic model. Section 5 presents and discusses the quantitative results. Finally, Section 6 provides concluding remarks.

2 Two-Period Model

In this section, I present a two-period model to illustrate key economic intuitions. The two-period model offers closed-form solutions for optimal investment decisions, enabling explicit descriptions of determinants for capital allocations.

Before delving into the model, I introduce three assumptions to simplify it without compromising economic insights. First, I assume full depreciation, meaning that investment I is equivalent to the next period's capital level K. Second, the two types of capital, clean K_C and dirty K_D, are assumed to be identical except for their contribution to damage, capturing the pure effects of sustainability preferences. Third, I set the initial economy with $K_C = K_D = 1$, implying that the share of dirty capital is 50%. The initial wealth today is denoted by W_0.

In a two-period model, tomorrow represents the end of the world. Unlike modeling climate risk as a long-run risk (Giglio et al., 2021b; Giglio et al., 2021a), I incorporate a natural disaster that causes significant damage in the next period.[7] For simplicity, I do not distinguish between pollution and damage. Since dirty capital causes more pollution, which translates into more damage, I assume that damage is an increasing function of dirty capital. This assumption is motivated by the increasing frequency and magnitude of natural disasters caused by carbon emissions and global warming (Cai and Lontzek, 2019). Alternatively, the postdamage profit can be viewed as shareholders' welfare, which the firm should maximize (Hart and Zingales, 2017). Since profit and damage are inextricably connected for technological reasons, shareholders' welfare is not equivalent to market value.

The damage function accounts for broad interpretations: cash flow losses due to lower consumer demand resulting from harmful environmental effects or shareholders' welfare losses from negative externalities, as in Hart and Zingales (2017). The economic setting of the damage function aligns with other standard climate economic models, where damage increases with more pollution and higher temperature (Nordhaus and Sztorc, 2013; Cai and Lontzek, 2019; Barnett et al., 2020).[8] In these models, production generates more carbon emissions, increasing temperatures, and therefore, causing more damage. Such realistic dynamics between temperature increase and dirty capital accumulation will be explored in the full dynamic model in Section 4, with an infinite time horizon.

The timeline of the model is as follows:

Investment Decisions with Adjustment Costs	Pricing kernel $M = \beta e^{-\gamma(x_1 - x_0) + \theta(z_1 - z_0)}$	Damage & Output
$t = 0$		$t = 1$
Observe $x_0 = z_0 = 0$		Climate disaster hits

[7] Long-run climate change has only mild effects each period, which would be negligible in a two-period setting, thereby blurring the economic mechanisms.

[8] There is debate about the specific functional form of the damage function. For example, it could be a smooth function, as used in Nordhaus's DICE model, or it could incorporate a tipping point and tail risks. However, it is widely accepted that temperature increases cause more damage. I make a simplifying assumption here, and the economic insights remain qualitatively the same.

The production output is given by

$$\Pi = (1 - D)X\Phi \tag{1}$$

where D represents the damage function, X denotes aggregate productivity, and Φ represents the constant elasticity of substitution (CES) production function. Specifically, the damage function increases with the level of dirty capital stock K_D:

$$D = \eta Z K_D \tag{2}$$

where η denotes the damage intensity, and Z represents a stochastic variable capturing the uncertainty of realized damage in the next period. The CES production function incorporates both types of capital:

$$\Phi = \left((1 - \alpha)(K_C)^{\omega} + \alpha(K_D)^{\omega}\right)^{\frac{1}{\omega}} \tag{3}$$

where α captures the productivity share of dirty capital, and ω represents the substitutability between clean and dirty technologies. I assume that both capital stocks have the same productivity share ($\alpha = 0.5$).

Consider two special cases: When $\omega = 1$, the two types of capital are perfectly substitutable, meaning that one marginal unit input of K_D can be perfectly substituted by one unit of K_C. Even if the economy completely eliminates K_D, it can still produce goods by relying solely on K_C. However, when $\omega = 0$, the production function becomes Cobb-Douglas. If the economy completely eliminates K_D, the output will become zero, indicating that the two types of capital are not substitutable.

The pricing kernel captures investors' preferences for less dirty capital or aversion to pollution or damage.[9] Following the investment-based asset pricing literature, I use an exogenous log-linear

[9] Investors may be willing to hold claims to clean capital at a lower expected return, while remaining risk-neutral to damage risk, meaning that the cost of capital wedge between dirty and clean assets is not necessarily risk-based. I do not take a stance on whether this wedge is due to risk or other factors. Under no-arbitrage conditions, any cost of capital effect can be represented by a stochastic discount factor (Kozak et al., 2018). Thus, the economic setup is equivalent whether I model damage as a priced factor or directly impose a wedge between the costs of dirty capital and those of clean capital.

pricing kernel.

$$\ln(M) = \ln(\beta) - \gamma(x_1 - x_0) + \theta(z_1 - z_0) \tag{4}$$

where $x_0 = \ln(X_0)$ represents the initial aggregate productivity, and $z_0 = \ln(Z_0)$ denotes the initial damage level at time $t = 0$. x_1 and z_1 are, respectively, the next period realized productivity and damage shocks. γ and θ measure the price of risk associated with aggregate productivity shocks and damage shocks, respectively. A higher θ can be interpreted as investors having stronger preferences for less pollution or damage.

To maintain simplicity, I model the shocks as a binomial tree. The productivity shock x_1 is as follows:

$$\ln(X_1) = x_1 = \begin{cases} x_0 + \Delta x, & \text{Prob } = \frac{1}{2} \\ x_0 - \Delta x, & \text{Prob } = \frac{1}{2} \end{cases} \tag{5}$$

and damage shock z_1 follows

$$\ln(Z_1) = z_1 = \begin{cases} z_0 + \Delta z, & \text{Prob } = \frac{1}{2} \\ z_0 - \Delta z, & \text{Prob } = \frac{1}{2} \end{cases} \tag{6}$$

The specific values of Δx and Δz do not change the qualitative results or the economic intuitions. The investment adjustment cost is

$$\phi^j = \frac{1}{2} I_j^2 \tag{7}$$

where $j \in \{C, D\}$. The net cash flow is thus

$$CF_0 = W_0 - I_C - I_D - \phi^C - \phi^D \tag{8}$$

$$CF_1 = \Pi_1 \tag{9}$$

where W_0 is the firm's initial wealth. The firm maximizes value

$$V = \max_{I_C, I_D} CF_0 + E[MCF_1] \tag{10}$$

The first-order conditions are therefore

$$
\begin{aligned}
[I_C] \quad 1 + I_C &= E\big[M(1-D)X_1 \frac{\partial \Phi}{\partial I_C}\big] && (11)\\
[I_D] \quad 1 + I_D &= \underbrace{E\big[M(1-D)X_1 \frac{\partial \Phi}{\partial I_D}\big]}_{\text{marginal contribution to production}} - \underbrace{E[M \frac{\partial D}{\partial I_D} X_1 \Phi]}_{\text{marginal contribution to damage}} && (12)
\end{aligned}
$$

To understand the economic intuitions more explicitly, consider two special cases. First, when $\omega = 1$, the two capital stocks are perfect substitutes for each other, and the first-order conditions become

$$
\begin{aligned}
1 + I_C &= E\big[M(1-D)X_1 \cdot 0.5\big] && (13)\\
1 + I_D &= E\big[M(1-D)X_1 \cdot 0.5\big] - E[M \frac{\partial D}{\partial I_D} X_1 \Phi] && (14)
\end{aligned}
$$

The wedge between the two types of investments is

$$
I_C - I_D = E[M \frac{\partial D}{\partial I_D} X_1 \Phi] \tag{15}
$$

which is driven purely by the potential damage generated by dirty capital. The greater the potential damage and aversion to it (θ), the less the firm invests in dirty capital. If the damage is sufficiently severe, the firm will rely solely on clean capital for production.

However, when $\omega = 0$, the production function simplifies to a Cobb-Douglas form. The first-order conditions thus become

$$
\begin{aligned}
1 + I_C &= E\big[M(1-D)X_1 \cdot 0.5(\frac{K_D}{K_C})^{0.5}\big] && (16)\\
1 + I_D &= E\big[M(1-D)X_1 \cdot 0.5(\frac{K_C}{K_D})^{0.5}\big] \quad - E[M \frac{\partial D}{\partial I_D} X_1 \Phi] && (17)
\end{aligned}
$$

If the economy entirely discards dirty capital ($I_D = K_D = 0$), it will not be able to produce. In this case, as shown in equations (16) and (17), the marginal return on dirty capital investment approaches infinity, whereas the marginal return on clean capital investment falls to zero.[10]

[10]Perfect substitutability implies a potentially wide wedge between clean and dirty investment but does not necessarily mean a zero share of dirty investment. Because the investment adjustment cost is convex, it is less

Given the optimal capital allocation, a natural question arises: How can different values of θ be economically interpreted? To provide more explicit economic explanations, I report the wedge between the expected one-period return of marginal dirty investment and clean investment. Specifically, following equations (16) and (17), the expected returns on dirty investment and clean investment are, respectively, as follows:

$$E[R^C] = \frac{E\big[(1-D)X_1 \cdot 0.5(\frac{K_D}{K_C})^{0.5}\big]}{1+I^C} \tag{18}$$

$$E[R^D] = \frac{E\big[(1-D)X_1 \cdot 0.5(\frac{K_C}{K_D})^{0.5}\big] \quad - E[M\frac{\partial D}{\partial I^D}X_1\Phi]}{1+I^D} \tag{19}$$

I define the wedge, $E[R^D]-E[R^C]$, as the "greenium." It quantifies the additional expected return required by investors for dirty investments, given a climate concern.[11]

The wedge between clean and dirty investments depends on two factors: marginal production and marginal damage. When the two types of capital are perfectly substitutable, clean capital can fully replace the marginal production of dirty capital, so damage and shareholder preferences largely disincentivize investment in dirty capital. If the potential damage is substantial or if investors place a very high concern on damage (high θ), the firm can achieve a very low (or even zero) share of dirty capital. However, when the two types of capital are complementary, production concerns dominate the damage and investor preference channels in firm investment decisions, making it challenging to attain a very low level of dirty capital.

Figure 1 illustrates the optimal ratio of dirty capital, $K_D/(K_C+K_D)$, across varying prices of damage shock, θ, under two scenarios of dirty capital substitutability ω. As θ increases, investor aversion to pollution risk intensifies, leading to a reduced share of dirty capital in the economy. This effect is concave due to the exponential form of the stochastic discount factor (SDF), with the marginal impact becoming more pronounced as θ increases.

costly to invest one dollar in each form of capital than to invest two dollars in clean capital.

[11] These investment returns can also be expressed in terms of the quantity and price of risk. From the first-order conditions for dirty and clean investments: $1 = E[MR^j]$, where $j \in \{C, D\}$. Following Cochrane (2009), $E[R^j] = R_f + \beta^j\lambda_m$, where $\beta^j = -Cov(R^j, M)/Var(M)$ represents the quantity of risk, and $\lambda_m = Var(M)/E(M)$ denotes the price of risk.

When the two types of capital are perfect substitutes ($\omega = 1$), the firm accumulates a significantly lower share of dirty capital, achieving a minimal share (i.e., 10%) when θ is sufficiently high. However, with a Cobb-Douglas production function ($\omega = 0$), the influence of θ on the share of dirty capital is far more constrained.

The greenium for different values of θ is presented in Figure 2. The economic insights of the "greenium" are straightforward. When the capital stock level is low, investment adjustment costs are also low due to the convexity of the adjustment function, meaning that the marginal cost of investment is low. Additionally, at low capital levels, the marginal benefit of investment is high (for Cobb-Douglas) or constant (for perfect substitution). Thus, the expected return, marginal benefit divided by marginal cost, on dirty capital is high, suggesting that firms can achieve higher returns by investing more in low-level capital. However, climate concerns lead investors to forgo these potential high returns. The greater the climate risk aversion is, the more returns they are willing to sacrifice, which drives the greenium patterns shown in Figure 2. This aligns with the high expected dirty (brown) premium seen in other models addressing climate change concerns (Pástor et al., 2021), albeit from an investment-based asset pricing perspective.

In summary, this section elucidates key economic intuitions through a simple two-period model. The model's closed-form solutions explicitly reveal the economic mechanisms governing optimal capital allocation decisions. The degree of substitutability between clean capital and dirty capital plays a pivotal role in these decisions. In a world characterized by a Cobb-Douglas production function, production concerns offset climate concerns. Consequently, the economy cannot achieve a very low level of dirty capital without substantially reducing output. Conversely, in a world where the two types of capital are perfect substitutes, production concerns are negligible, and climate concerns dominate. In this scenario, the economy can become as green as investors desire.

3 Empirical Analysis

The results from the two-period model highlight the importance of the substitution between dirty capital and clean capital. However, how high is the elasticity of substitution in the data? This study is the first to estimate the substitutability of dirty capital. Previous papers primarily focus on the elasticity of substitution between capital and labor, as capital and labor are classical production function inputs with relatively straightforward empirical measures. In this empirical literature, the substitutability parameter is often rewritten as $\omega = (\nu - 1)/\nu$ to simplify estimation. For capital and labor, Chirinko et al. (2011) and Chirinko and Mallick (2017) estimate an elasticity of $\nu = 0.4$ ($\omega = -1.5$). Similarly, Gechert et al. (2022) conducts a meta-analysis and finds an average elasticity of $\nu = 0.3$ ($\omega = -2.33$), conditional on the absence of publication bias. My estimates of the elasticity between dirty capital and clean capital suggest a similar magnitude to the elasticity between capital and labor.

In this section, I empirically estimate the value of ω (or ν) to demonstrate that the current economy is still far from achieving perfect substitution. The section begins with a detailed explanation of the empirical strategy, followed by a description of the dataset, and concludes with a discussion of the results.

3.1 Empirical Strategy

The empirical strategy combines the methods in Chirinko et al. (2011) and Chirinko and Mallick (2017) with the model presented in Section 2. Recall the CES production function in equation (3)

$$\Phi_{it} = \left((1-\alpha)(K_{C,it})^{\omega} + \alpha(K_{D,it})^{\omega}\right)^{\frac{1}{\omega}}$$

Consistent with the previous literature and for simplicity, I rewrite $\omega = (\nu - 1)/\nu$, where ν represents the elasticity of substitution. This functional form is common in empirical studies estimating the degree of substitution within the CES function, providing a regression equation that directly links the regression coefficient to the degree of substitution. Figure 3 illustrates the relationship between ω and ν, showing a positive correlation and similar qualitative implications.

Following Chirinko et al. (2011) and Chirinko and Mallick (2017), a firm-specific productivity, A_{it}, is added. Now, firm i has an output of

$$Y_{it} = A_{it}\big((1-\alpha)(K_{C,it})^{\frac{\nu-1}{\nu}} + \alpha(K_{D,it})^{\frac{\nu-1}{\nu}}\big)^{\frac{\nu}{\nu-1}} \tag{20}$$

Take the partial derivative with respect to K_{it}^D

$$\frac{\partial Y_{it}}{\partial K_{D,it}} = \alpha A_{it}^{\frac{\nu-1}{\nu}} Y_{it}^{\frac{1}{\nu}} K_{D,it}{}^{-\frac{1}{\nu}} \tag{21}$$

Rearranging the equation[12]

$$\frac{K_{D,it}}{Y_{it}} = \alpha^{\nu} A_{it}^{\nu-1}\left(\frac{\partial Y_{it}}{\partial K_{D,it}}\right)^{-\nu} \tag{22}$$

This equation does not rely on specific inputs in the production function. Although there may be other separately modeled inputs, such as labor and intangible capital, the equation above does not change because everything is included in the total output Y_{it} (see Appendix B for more details). Since carbon emissions are directly observable, I use them as a proxy for the dirty capital stock.

$$G_{it} = \eta K_{D,it} \tag{23}$$

where G_{it} represents carbon emissions, I assume a linear relationship between dirty capital stock and carbon emissions for simplicity and to remain consistent with my dynamic model assumption. This assumption aligns with the functional form in Barnett et al. (2023a) and Hong et al. (2023). The reasoning is that carbon emissions are a linear function of output (Nordhaus and Sztorc, 2013), and output can be assumed to be a linear function of capital, resulting in a linear relationship between carbon emissions and capital. This specific functional form does not affect the estimation strategy for ν (see Appendix B for more details), but it will affect the estimates of α. I plug the

[12] I rearrange the equation to place the partial derivative, $\partial Y_{it}/\partial K_{D,it}$, on the right-hand side because the firm-specific TFP is correlated with the dirty capital-to-output ratio, $K_{D,it}/Y_{it}$. In contrast, the partial derivative, which is a function of $\partial \ln Y_{it}/\partial \ln K_{D,it}$, does not depend on the firm-specific TFP by definition of the polynomial function used to approximate the nonlinear function, $\ln Y_{it}$.

equation above into equation (22), and obtain

$$\frac{G_{it}}{Y_{it}} = \alpha^{\nu}\eta^{1-\nu}A_{it}^{\nu-1}(\frac{\partial Y_{it}}{\partial G_{it}})^{-\nu} \tag{24}$$

Following Chirinko and Mallick (2017), the firm-specific productivity has the following functional form:

$$A_{it}^{\nu-1} = e^{u_i+u_t+u_{it}} \tag{25}$$

The portion of the firm TFP that is allowed to correlate with other firm variables is represented by the sum of firm and time fixed effects. While this simplified assumption could be overly restrictive and introduce bias into the estimates, a robustness check using the method proposed in Bai (2009) addresses this concern by incorporating time-varying interactive fixed effects. The approach leverages principal component analysis (PCA) to decompose the interactive fixed effects into time-varying factors and firm-specific loadings. The results are presented in Table D.6. Take the log on both sides and rearrange

$$\ln(\frac{G_{it}}{Y_{it}}) \triangleq a - \nu \cdot \ln(\frac{\partial Y_{it}}{\partial G_{it}}) + u_i + u_t + u_{it} \tag{26}$$

where $a = \nu \cdot \ln(\alpha) + (1-\nu)\cdot \ln(\eta)$ is the intercept. Taking the first difference eliminates the firm fixed effect

$$\Delta \ln(\frac{G_{it}}{Y_{it}}) = -\nu \cdot \Delta \ln(\frac{\partial Y_{it}}{\partial G_{it}}) + u_t + u_{it} \tag{27}$$

Equation (26) includes both firm and year fixed effects, whereas equation (27) includes only year fixed effects. The emission-to-output ratio, G_{it}/Y_{it}, is straightforward to calculate. However, calculating the firm-level marginal contribution of emissions to output, $\partial Y_{it}/\partial G_{it}$, is challenging. Therefore, I estimate it via sector-year regressions. Output Y is a nonlinear function of dirty capital, K_D, and clean capital, K_C, by definition. I use total assets, AT, as a proxy for total capital, $K_D + K_C$, and carbon emissions, G, as a proxy for K_D (an implication from equation (21)). Thus, for each sector j, I assume that output Y is a nonlinear function of emissions G and total assets

AT. I use cross-sectional firm data to estimate the nonlinear function within each sector. I then apply the sector-year-specific coefficients to calculate the firm-level $\partial Y_{it}/\partial G_{it}$. Motivated by Gala et al. (2022), the nonlinear function can be approximated by a polynomial function

$$\ln Y_{it} = c_{j0,t}+c_{j1,t}\cdot\ln G_{it}+c_{j2,t}\cdot(\ln G_{it})^2+c_{j3,t}\cdot\ln AT_{it}+c_{j4,t}\cdot(\ln AT_{it})^2+c_{j5,t}\cdot\ln G_{it}\times\ln AT_{it}+\epsilon_{it} \quad (28)$$

where AT_{it} is the total assets. The equation is estimated for each combination of sector j and time t, with coefficients that are specific for each sector-year combination.[13] Because the levels of output and emissions data are highly right skewed, the logarithmic form provides a more stable relationship. Using total assets as the primary independent variable is appropriate due to the functional form of the CES production function, where total output depends on dirty capital and clean capital stock. Total assets are most directly related to total capital stock.[14] Taking the partial derivative of (28), I obtain

$$\frac{\partial \ln Y_{it}}{\partial \ln G_{it}} = c_{j1,t} + 2\cdot c_{j2,t}\cdot \ln G_{it} + c_{j5,t}\cdot \ln AT_{it} \quad (29)$$

The partial derivative of the logarithm can be easily converted back to the original partial derivative in levels: $\partial Y_{it}/\partial G_{it} = (\partial \ln Y_{it}/\partial \ln G_{it})\cdot(Y_{it}/G_{it})$. Equations (26) and (27) are used to estimate ν.

The economic meaning of equation (26) is as follows: the marginal productivity of emissions to total output, $\partial Y/\partial G$, represents how productive carbon emissions are, indicating how much total output can be generated per marginal unit of carbon emissions. The specific relation between carbon emission intensity and the marginal productivity of carbon emissions can be quantified by the elasticity of substitution, ν, due to the functional form of the CES production function. Carbon emission intensity and the marginal productivity of carbon emissions are negatively correlated, reflecting diminishing returns to scale. If they are positively correlated, the firm continuously increases its carbon emission intensity as marginal productivity rises, without limits.

[13] By definition, the output Y_{it} is a function of firm-specific productivity, A_{it}, which depends on firm and time fixed effects. To estimate the polynomial function, I use sector and year combinations, which capture the year fixed effect. Because the variation within a sector comes from firm-level variables, I cannot include firm fixed effects.

[14] The results are robust if I replace total assets with physical capital (PPEGT or PPENT from COMPUSTAT,) or the sum of PPEGT and intangible capital. See Table D.3, Table D.4, and Table D.5 for more details.

3.2 Data

The data used for the empirical analysis are merged from the S&P Trucost Environmental and Compustat Fundamentals Annual (North America and Global) datasets from WRDS. The Trucost dataset covers global firm-level carbon emissions in tons of carbon dioxide equivalent (tCO2e) at an annual frequency, from 2002 to 2022. The Trucost data are merged with Compustat data via GVKEY and year. The sample is restricted to firms with positive total assets, carbon emissions, and total revenue. In the data, total revenue represents total output Y in the model. More detailed descriptions of the data variables are provided in Table D.1.

I study Scope 1, 2, and 3 carbon emissions. Scope 1 GHG emissions originate from sources owned or controlled by the company. Scope 2 GHG emissions result from the consumption of purchased electricity, heat, or steam by the company. Scope 3 GHG emissions (upstream and downstream) are indirect carbon emissions from other activities not covered in Scope 2.

The nonlinear function (28) is estimated at the 2-, 3-, and 4-digit SIC levels. To mitigate the impact of large firms, the regression is weighted by the inverse of the logarithm of total assets. Since there are six independent variables, for each combination of sector and year, samples with fewer than six observations are excluded. The corresponding control variables and estimates are winsorized at the 1st and 99th percentiles of the distribution.

3.3 Sample and Summary Statistics

The matched sample between Trucost and Compustat covers both developed and emerging markets at an annual frequency. Because Trucost did not update data for all countries in 2023, I use 2022 as the sample ending year. I drop countries with fewer than 20 observations and exclude financial firms (SIC codes between 6000 and 6999).[15] Table 1 reports the number of observations, start year, end year, and averages of the key variables used in the empirical analysis. The sample predomi-

[15] Financial firms might rely on polluting physical capital, such as buildings that use electricity. However, their production functions can fundamentally differ from those of other industries. I report estimates of ν with financial firms in Table D.2, which are quantitatively similar to estimates without financial firms but slightly higher overall.

nantly comprises developed markets, accounting for approximately 90% of the total observations. The leading countries are the U.S. (75%), Canada (5%), China (3%), and the United Kingdom (2%). The United States comprises the majority of the sample. I include the average log ratios of total revenue, Scope 1 carbon emissions, Scope 2 carbon emissions, and total assets. These are the critical variables used in estimating the marginal productivity of carbon emissions and dirty capital substitutability, ν.

Table 2 presents key summary statistics for firm-level carbon measures and fundamentals. Carbon emission measures in the U.S. do not differ substantially from those in the global sample. In the U.S. sample, across the three scopes of carbon emissions, Scope 3 has the highest intensity (4.88) compared with Scope 1 (2.28) and Scope 2 (2.56). Carbon intensity is measured by the logarithm of carbon emissions scaled by total revenue. Scope 1 has the highest standard deviation (2.02) compared with Scope 2 (1.36) and Scope 3 (1.36). For the logarithm of the carbon emission levels, Scope 3 has the highest value (11.52), which is higher than those of Scope 1 (8.92) and Scope 2 (9.20). Like carbon intensity, Scope 1 has the highest standard deviation (3.09), whereas Scope 2 (2.64) and Scope 3 (2.69) have similar standard deviations.

Total revenue and total assets are important components in the empirical analysis. In the U.S. sample, the average log of total revenue (in millions) is 6.66, and the average log of total assets (in millions) is 7.83. The summary statistics of the estimated marginal productivity of carbon emissions, $\partial Y/\partial G$, are calculated via Scope 1 carbon emissions and industry proxies on the basis of 3-digit SIC codes. I also include the ratio of carbon emissions to total assets, as this ratio is used to back out the model-implied α in later analysis. The logarithm of the Scope 3 emissions-to-total-asset ratio is the highest (3.70), followed by Scope 2 (1.37) and Scope 1 (1.10) in the U.S. sample.

3.4 Empirical Results

The baseline empirical analysis follows regression equations (26) and (27). Equation (26) regresses the logarithm of carbon emissions scaled by total revenue, $\ln(G/Y)$, on the logarithm of the marginal productivity of carbon emissions, $\ln(\partial Y/\partial G)$. As suggested by the model, firm and year fixed effects are included. Equation (27) employs the first-difference estimator based on equation (26), which eliminates the firm fixed effect and includes only the year fixed effect.

Table 3 panels A, B, and C use Scope 1, 2, and 3 carbon emissions respectively, as proxies for G. Within each carbon emission proxy, I estimate the marginal productivity of carbon emissions using 2-, 3-, and 4-digit SIC codes as the sector classifications. For example, equation (28) is estimated by industries classified by 4-digit SIC codes. After obtaining the industry-level coefficients, I use them to estimate firm-level $\partial Y/\partial G$ before the final pooled firm-level regressions. Because industries with fewer than 6 observations per industry-year are filtered out, the number of observations is lower in regressions using 4-digit SIC codes for industry classification.

Overall, the estimates suggest a high level of complementarity for dirty capital. Table 3 presents the average estimates of ν. In Panel A, Scope 1 carbon emissions suggest that ν is between 0.146 and 0.350, depending on industry classifications. The 2-digit SIC code yields the highest ν, with 0.350 using equation (26) and 0.212 using equation (27). The 4-digit SIC code yields a relatively lower ν, with 0.244 using equation (26) and 0.146 using equation (27). In Panel B, Scope 2 carbon emissions suggest similar levels of ν as those using Scope 1, with the highest at 0.398 for the 2-digit SIC code and the lowest at 0.153 for the 4-digit SIC code. Panel C, Scope 3, indicates an overall higher level of ν than Scopes 1 and 2 do, with the highest ν at 0.458 for the 2-digit SIC code and the lowest at 0.245 for the 4-digit SIC code. First difference estimators indicate an overall lower level of ν.[16]

Different specifications yield varying estimates of ν. However, the message is consistent across all specifications: dirty capital is highly complementary. Recall from Figure 3 that the production function is Cobb-Douglas if $\nu = 1$. The higher the ν, the more substitutable dirty capital and clean capital are. To achieve perfect substitution, ν would need to approach $+\infty$. In Table 3, the highest ν is 0.458, which is obtained when Scope 3 and the 2-digit SIC code are used to proxy for carbon

[16]The ES ν is heterogeneous across industries because of the different technologies used in each industry. An alternative way to estimate the average ν is to calculate it at the industry level and then average it across industries. The results are qualitatively the same, as shown in Table D.8.

emissions and industry. This estimate is still substantially lower than one, suggesting even higher complementarity than the Cobb-Douglas production function.

One caveat of the empirical framework is that using separable firm and time fixed effects to capture firm-specific TFP could bias the estimates of ν. Therefore, I use the methodology proposed in Bai (2009) to capture time-varying interactive fixed effects via PCA. The number of principal components may affect the estimates, so I report results with 1, 5, and 10 factors. The results are shown in Table D.6. Because the fixed effects are interactive between firm and time, I cannot use the first-difference regression equation (27), so I focus on the results from equation (26). Compared with the benchmark results, the estimates are overall higher, ranging from 0.450 to 0.729, depending on industry and carbon emission specifications. These results indeed indicate potential bias from the original estimation strategy with separable fixed effects. However, the results still suggest a more complementary production function than a Cobb-Douglas function.

The dependence on dirty capital in the overall production function can vary over time. Van der Beck (2023) suggests the emergence of sustainable investors after 2012, which is also the midpoint of my data period. Therefore, I split the sample using 2012 as the threshold and examine whether the elasticity of dirty capital changes over time.[17]

Although clean capital and dirty capital remain highly complementary both before and after 2012, the elasticity of dirty capital is greater in the later period. This result is qualitatively consistent across different specifications. Table 4 presents the subsample estimates. For simplicity, I report only the results for Scope 1 and Scope 2 with industry classifications using 3- and 4-digit SIC codes. The results for the 2-digit SIC code and Scope 3 are qualitatively similar.

Following equation (26), Scope 1 carbon emissions and the 3-digit SIC industry classification suggest that ν increases from 0.143 to 0.289, and the 4-digit SIC suggests an increase from 0.119 to 0.270. Scope 2 and 3-digit SIC indicate that ν increases from 0.260 to 0.318, whereas the 4-digit SIC suggests an increase from 0.279 to 0.293. The first-difference estimators produce an overall lower

[17] An alternative approach is to split the sample in 2016, the year of the Paris Agreement. The results are qualitatively similar, as shown in Table D.9.

ν, but the increase before and after 2012 is consistent with the original estimators. These results show a positive trend toward transitioning to clean technologies. To statistically test the difference between subsample estimates of ν before and after 2012, I report the z statistics and p-values for the difference between subsample estimates. For most specifications, there is a statistically significant increase in ν after 2012.

The model has broader implications beyond the elasticity parameter. To support the theoretical framework, I calculate the implied α on the basis of empirical estimates. However, additional assumptions are required to derive α, including the specific functional form between carbon emissions and dirty capital, as well as the relationship between α and η. Recall that in equation (26), the intercept a can be decomposed as $a = \nu \cdot \ln(\alpha) + (1 - \nu) \cdot \ln(\eta)$. If we assume that the productivity share of dirty capital, α, is the same as its proportion in total assets, K_D/AT, then α can be calculated.[18] Given that $G = \eta K_D$, we have $\alpha = K_D/AT = (G/\eta)/AT$. Plugging everything in, I get

$$\ln(\alpha) = \frac{a - (1 - \nu)\ln(G/AT)}{2\nu - 1} \tag{30}$$

Table 5 presents the results under various carbon emission and industry specifications. For simplicity, I focus on Scope 1 and Scope 2 emissions with 3- and 4-digit SIC classifications. The average $\ln(G/AT)$ is used to derive α. The intercept estimates, a, and elasticity estimates, ν, are taken from Table 3 with matching specifications.

The implied α falls within the range of zero to one, which is consistent with the model assumption. The implied α is approximately 50%, indicating that, on average, 50% of assets are dirty capital, or that dirty capital contributes to 50% of total production. The estimate varies slightly across specifications: Scope 2 emissions and the 3-digit SIC industry classification produce the highest α at 55%, whereas Scope 2 and the 4-digit SIC yield the lowest α at 42%.

[18] The proportion of dirty capital relative to total assets may differ from its contribution share in total productivity if productivity efficiency is not exactly one. Here, I make a simplified assumption to uniquely derive α.

Finally, I split the sample by industry and estimate the heterogeneous elasticity parameter within each industry. I follow Fama and French's definition of ten industries, using the 4-digit SIC codes to divide the sample.[19] Table 6 presents the results across different specifications, focusing on Scope 1 and 2 emissions and 3- and 4-digit SIC industry classifications. Similar to the results in Table 3, the first-difference estimator generally produces a lower ν. The results are reasonably consistent across different specifications.

Compared with other industries, the high-tech, utilities, and health industries have relatively greater elasticity of dirty capital. For example, when Scope 1 emissions and the 3-digit SIC classification are used, the elasticity of the high-tech industry is 0.418, which is significantly greater than the average across industries of 0.277. The high ν of the high-tech and health industries could be because R&D- and intangible-intensive industries rely less on dirty capital or have a better chance of finding substitutes for it. The high ν in the utilities industry could result from the transition to renewable energy, as renewable energy can perfectly substitute for polluting energy when generating electricity.

In contrast, the consumer goods (durables and nondurables), manufacturing, telecom, and shops industries have relatively lower elasticity of dirty capital. These are traditional industries with limited room for innovations in their production functions and are also less active in finding replacements for existing dirty technologies. This may be due to lower R&D investments or a lack of affordable and viable alternatives. For example, the manufacturing industry relies on long equipment lifespans, making it costly to transition to clean technologies before the end of their useful life.

In summary, this section proposes a strategy to estimate the elasticity of dirty capital and empirically explores both overall and heterogeneous elasticity parameters. Since measuring the absolute levels of dirty capital and clean capital is challenging, I rely on a method that maps the elasticity parameter into a regression-based framework and uses observed carbon emission and accounting data for estimation. The results suggest that dirty capital and clean capital are highly

[19]For more details, see Kenneth French's data library.

complementary, although they have become less complementary in recent years, implying a transition to a world with better technology flexibility. Additionally, dirty capital is less complementary in R&D-intensive industries than in traditional industries.

4 The Quantitative Model

The two-period model and empirical results highlight the importance of the substitutability between dirty capital and clean capital, as well as the fact that dirty capital remains highly complementary. In this section, I propose a more realistic dynamic model that combines elements of the classical investment-based model with an exogenous log-linear SDF (Zhang, 2005) and standard elements from the dynamic integrated climate economy (DICE) model (Nordhaus and Sztorc, 2013; Cai and Lontzek, 2019). The model incorporates climate concerns into the pricing kernel, capturing investors' worries or preferences regarding climate change. Unlike the two-period model, this model uses a more realistic representation of temperature change as a proxy for climate concerns (Nordhaus and Sztorc, 2013; Balvers et al., 2017; Bansal et al., 2017; Hugon and Law, 2019). Investors' preferences regarding climate change are captured by the positive price of a carbon emission shock in the pricing kernel, as a positive carbon emission shock translates into a greater temperature increase and greater damage to total output. Firms make optimal dirty and clean investment decisions in response to the exogenous pricing kernel. Time is discrete and infinite.

4.1 The Firm

As in the DICE model (Nordhaus and Sztorc, 2013), the firm's total output is

$$\Pi_t = (1 - D_t) X_t \Phi_t \tag{31}$$

Similar to Section 2, D_t is the damage function, X_t represents aggregate productivity, and Φ_t is the CES production function, with the following functional form:

$$\Phi_t = \left((1-\alpha)(K_{C,t})^{\frac{\nu-1}{\nu}} + \alpha(K_{D,t})^{\frac{\nu-1}{\nu}}\right)^{\mu\cdot\frac{\nu}{\nu-1}} \tag{32}$$

where ν governs the substitutability between clean capital and dirty capital, and μ governs the degree of homogeneity of the production function. K_C and K_D denote clean capital and dirty capital, respectively. I assume that the degree of substitution, ν, is fixed and exogenous to the firm. In reality, firms can increase R&D investment to develop new technologies, reducing the complementarity between dirty capital and clean capital. In this case, ν would be an endogenous decision variable rather than an exogenous parameter. I take a simplified approach because endogenizing innovation would substantially increase model complexity. Because R&D takes a long time to fundamentally change a firm's technology, it is reasonable to assume an exogenous production function with respect to the degree of complementarity. That said, this could be an interesting direction for future research.

I follow the climate economics literature in introducing a damage function for total output. This damage function can be interpreted as either real damage to total output due to the increasing frequency and magnitude of natural disasters caused by carbon emissions and global warming (Cai and Lontzek, 2019) or as shareholders' welfare loss from negative externalities, as in Hart and Zingales (2017).[20] As in previous studies, the damage increases with increasing temperature compared with preindustrial levels to capture the harmful consequences of global warming.[21] Temperature rises further if the firm generates more carbon emissions. Unlike previous models, I consider two types of capital, dirty and clean, to study the effect of substitutability between them. Since clean capital does not produce pollution, carbon emissions depend solely on dirty capital.

[20] If global warming passes certain thresholds, the climate system may enter an irreversible state with significantly more severe disasters. According to the Federal Emergency Management Agency (FEMA), the most frequent natural disasters are fires, severe storms, and floods, all of which are directly linked to global warming. Alternatively, the damage can be seen as a negative externality internalized in shareholder welfare. As in Hart and Zingales, 2017, the firm should maximize welfare rather than market value if profit and damage are inseparable, especially when firms can pollute but individuals cannot offset pollution by themselves.

[21] For example, in Cai and Lontzek (2019): It is recognized that temperature increases may cause substantial, irreversible damage to the climate. Some studies use the possibility of severe damage caused by low-probability catastrophic events to advocate for aggressive mitigation policies. Moreover, the IAM (Integrated Assessment Model) literature has recently emphasized climate tipping points, which refer to "a critical threshold at which a tiny perturbation can qualitatively alter the state or development of the climate system." Examples of tipping processes include the irreversible melting of the Greenland ice sheet, the collapse of the West Antarctic ice sheet, and the weakening of the Atlantic thermohaline circulation.

The specific functional form of the damage is

$$D_t = 1 - \frac{1}{1 + a_1 \Delta T_t + a_2 \Delta T_t^2} \tag{33}$$

in which ΔT_t is the temperature at time t relative to its preindustrial level. This is a classical functional form for damage, following Nordhaus and Sztorc (2013) and Nordhaus (2014). Capital allocation is standard, and investment adjustment is costly:

$$K_{j,t+1} = (1 - \delta_j) K_{j,t} + I_{j,t} \tag{34}$$

$$\psi^j(I_{j,t}, K_{j,t}) = \frac{\phi^j I_{j,t}^2}{2K_{j,t}} \tag{35}$$

where $j \in \{C, D\}$, $I_j \geq 0$. ϕ^j captures the adjustment cost. The firm's production generates CO_2. The carbon (greenhouse gas) emission function is

$$G_t = \eta K_{D,t} Z_t \tag{36}$$

where η represents the intensity of emissions, and Z_t captures the uncertainty of emissions. I introduce a shock to carbon emissions to capture investors' preferences for fewer emissions in the pricing kernel. The modeling strategy is similar to the inclusion of an aggregate productivity shock. A positive carbon emission shock is considered bad news by investors, who, therefore, impose a positive price on the carbon emission shock. A higher positive price on the emission shock indicates stronger investor aversion to increased carbon emissions. Following the approach of Matthews et al. (2009) and Barnett et al. (2020), I model temperature increases as proportional to carbon emissions. Specifically,

$$\Delta T_{t+1} = \Delta T_t + \lambda G_t \tag{37}$$

The aggregate productivity, $x_t = \ln(X_t)$, follows an AR(1) process

$$x_{t+1} = (1 - \rho_x)\bar{x} + \rho_x x_t + \sigma_x {\epsilon^x}_{t+1} \tag{38}$$

Similarly, the firm's emission shock, $z_t = \ln(Z_t)$, follows an AR(1) process

$$z_{t+1} = (1 - \rho_z)\bar{z} + \rho_z z_t + \sigma_z {\epsilon^z}_{t+1} \tag{39}$$

where ρ_x and ρ_z capture the persistence of the shock, and $\bar{x}$ and $\bar{z}$ are unconditional means. ϵ^x_{t+1} and ϵ^z_{t+1} are uncorrelated independently and identically distributed (i.i.d.) random variables that follow a standard normal distribution. σ_x and σ_z are the standard deviations of the i.i.d. shocks. The contemporaneous cash flow is therefore

$$CF_t = \Pi_t - \tau_D G_t - I_t - \Psi_t \tag{40}$$

in which total investment is denoted as $I_t = I_{C,t} + I_{D,t}$, and the total investment adjustment cost is $\Psi_t = \psi^C_t + \psi^D_t$. τ_D represents the carbon tax charged proportionally to total emissions. Because the carbon tax usually captures the social welfare loss from carbon emissions, it enters shareholders' welfare value and the firm's objective function if the firm maximizes shareholders' welfare, as in Hart and Zingales (2017).[22] Introducing the carbon tax allows me to explore how capital substitutability interacts with carbon tax policies. Additionally, as more countries start to implement carbon taxes, this setting is consistent with real-world practice. Taking the pricing kernel as given, the firm's Bellman equation is as follows:

$$V(X_t, K_{C,t}, K_{D,t}, \Delta T_t, Z_t) = \max_{K_{C,t+1}, K_{D,t+1}} \Big\{ CF_t + E\big[M_{t+1} V(X_{t+1}, K_{C,t+1}, K_{D,t+1}, \Delta T_{t+1}, Z_{t+1})\big] \Big\} \tag{41}$$

subject to dirty capital and clean capital accumulation

Similar to the two-period model, the greenium is defined as the wedge between the expected

[22] I opt for a reduced-form approach to model the carbon tax and assume it is exogenous for the firm. In papers focusing on determining the optimal carbon tax, it is typically defined as the "social cost of carbon," which represents the social welfare loss from carbon emissions (Weitzman, 2014; Bansal et al., 2017; Cai and Lontzek, 2019; Lemoine, 2021; Olijslagers and van Wijnbergen, 2024).

one-period marginal returns on dirty and clean investments, $E_t[R^D_{t+1}] - E_t[R^C_{t+1}]$. Specifically,

$$E_t[R^C_{t+1}] = \frac{E[\frac{\partial V_{t+1}}{\partial K_{C,t+1}}]}{1+\frac{\partial \psi^C_t}{\partial I_{C,t}}} \tag{42}$$

$$E_t[R^D_{t+1}] = \underbrace{\frac{E[\frac{\partial V_{t+1}}{\partial K_{D,t+1}}]}{1+\frac{\partial \psi^D_t}{\partial I_{D,t}}}}_{\text{marginal contribution to } V} + \underbrace{\frac{E[\frac{\partial V_{t+1}}{\partial \Delta T_{t+1}} \times \frac{\partial \Delta T_{t+1}}{\partial K_{D,t+1}}]}{1+\frac{\partial \psi^D_t}{\partial I_{D,t}}}}_{\text{marginal contribution to } \Delta T} \tag{43}$$

The returns can be decomposed into two channels: firm value and temperature change. Both expected returns rely on the marginal investment contribution to firm value. Low investment incurs low adjustment costs but high marginal benefits, leading to high expected returns. However, unlike clean investment, the return on dirty investment also depends on its effects on climate change. High dirty investment leads to more temperature increases, thereby generating more damage to the total output and lowering firm value. Because temperature change is a gradual process and its impact is mild each period, the first channel typically dominates the second channel when dirty investment is very low, resulting in a positive greenium.

4.2 The Pricing Kernel

The exogenous log-linear SDF, or pricing kernel, has the following form:

$$\ln M_t = \ln \beta - \gamma(x_{t+1} - x_t) + \theta(z_{t+1} - \bar{z}) \tag{44}$$

where β is the time discount factor, γ is the aggregate risk aversion, and θ is the emission aversion. To better understand the economic intuition, consider three states of emissions

$$z = \begin{cases} z_L, & \text{Low emission state} \\ \bar{z}, & \text{Normal state} \\ z_H, & \text{High emission state} \end{cases} \tag{45}$$

Because a positive emission shock is bad news for the firm, it should correlate positively with M_t. Unlike aggregate productivity shocks, where the price of risk is typically tied to the growth of aggregate productivity, I assume that the investor is concerned with deviations in emissions from the unconditional mean (the normal state). The rationale is as follows: suppose that we are currently in a high emission state and that tomorrow's emissions are also expected to be high. An investor focused solely on the growth of emissions would view this as neutral news since emissions are not increasing. However, in reality, more pollution is always undesirable, and investors continuously seek to mitigate it.

Similar to the economic interpretation of γ as the price of aggregate risk, θ represents the price of emission risk. A higher θ indicates that investors place a higher price on emission risk, or that they are more averse toward emissions. Consequently, we should expect the firm to choose a smaller portion of dirty capital as θ increases.

The economic intuitions remain consistent with those of the two-period model. As temperature increases, it inflicts more damage on output, thereby decreasing firm value. Because temperature increases are driven by emissions and dirty capital stock, the firm opts to accumulate more clean capital when θ is high. However, the optimal allocation depends on the substitutability between the two types of capital. When they exhibit high complementarity, the firm cannot produce anything without dirty capital. Consequently, production concerns are nonnegligible, even if emission aversion is very strong. Conversely, if the two types of capital are perfectly substitutable, climate change concerns dominate. In this case, the firm can choose a very low share of dirty capital if emission aversion is sufficiently strong.

In summary, in this section, I introduce a dynamic model that integrates carbon emission risk and climate change to analyze firms' endogenous decisions regarding clean and dirty investments. The presence of emission risk and climate change concerns tends to reduce dirty investments. However, the complementarity in production offsets these effects. Consequently, lower levels of dirty capital result in a positive greenium.

5 Quantitative Results

In this section, I begin by reporting parameter values and discussing my calibration strategies. Next, I present the quantitative results derived from the dynamic model and comparative statics.

5.1 Calibration

The model is solved and simulated at a quarterly frequency over 100 years. To illustrate the benchmark results, I maintain uniform characteristics for both clean capital and dirty capital, except climate change and the cost of capital channels. Specifically, both types of capital contribute equally to production, have the same depreciation rate, and entail the same adjustment costs. However, dirty capital diverges by generating carbon emissions and temperature changes and incurring negative cash flow shocks due to carbon taxes.

During the model calibration process, I pursue two primary goals: first, to maintain the average temperature increase between $1.5°C$ and $2°C$; second, to keep the level of aggregate risk, measured by the equity premium, approximately 8% annually. Using the calibrated model, I examine the implications for firms' capital allocations. I adjust the substitution parameter in the CES production function to study the impact of capital substitutability. Simultaneously, I explore the effects of investors' climate concerns by varying the price of carbon emission risk.

Table 7 reports the parameter values and their meanings. The subjective discount factor, $\beta = 0.99$, is chosen on the basis of the literature. The parameter values governing climate change and the damage function are calibrated to generate a reasonable temperature change path. Setting values too high for the damage function coefficients, a_1 and a_2, results in excessively negative output shocks, making it difficult to invest in both capitals. Consequently, the linear coefficient a_1 is set to zero following previous papers, whereas the quadratic coefficient a_2 is calibrated to 0.08. Additionally, parameters governing the contribution of emissions to temperature change, $\lambda = 0.05$ and $\eta = 0.01$, are selected to achieve a temperature increase of around $1.5°C$. Setting λ and η too high results in unrealistically high temperature increases.

The benchmark carbon tax rate τ_D is set to zero because, in the U.S., most states do not have a carbon tax. I explore the implications of adding a carbon tax in the comparative statics section. The productivity share of dirty capital α, depreciation rates δ, and adjustment costs ϕ are chosen to maintain equivalence between the two types of capital. I follow previous studies to set the values of depreciation rates, while adjustment cost values are set to ensure stable capital levels within the simulation grid boundaries.

The persistence $\rho_x = 0.9$ and volatility $\sigma_x = 0.03$ of the aggregate productivity shock are comparable to those in Belo et al. (2023). The unconditional mean $\bar{x} = -2.6$ is calibrated in conjunction with adjustment costs to maintain stable capital levels in simulations. The unconditional mean of the emission shock $\bar{z}$ is set to zero so that, on average, the shock has no effect, which is consistent with models featuring only constant emission intensity. Similarly, to ensure minimal average effects, I choose a relatively small standard deviation of the emission shock $\sigma_z = 0.005$ and an arbitrary value for its persistence $\rho_z = 0.5$.

5.2 Benchmark Results

Similar to the section on the two-period model, I focus on the effects on optimal capital allocation and greenium, considering different levels of emission aversion θ and production substitutability ν. The simulation begins with both capitals at the same level and a temperature change of $\Delta T = 1$. The ratio of dirty capital is defined as $K_D/(K_C+K_D)$. The economy is simulated for 100 years (400 quarters), independently for 1000 times. To calculate the variables of interest, the first 10 years of the simulation are excluded, and averages are calculated for the remaining simulation period.

I examine the effects on the ratio of dirty capital and greenium by maintaining a constant equity premium. Specifically, for each value of θ, I choose the optimal γ that generates an annualized equity premium closest to 8%. Different optimal ratios of dirty capital in the economy are associated with varying equity premium levels. Dirty capital is perceived as riskier because emission risk is priced in the pricing kernel. Therefore, a lower ratio of dirty capital corresponds to a lower equity premium, assuming that the aggregate productivity aversion γ is fixed. With the SDF in equation (34), higher values of γ result in higher equity premiums. To counteract the negative impact of higher θ on the equity premium, a higher γ is selected.

Figure 4 displays the optimal γ with respect to θ under two scenarios of capital substitutability. $\nu = +\infty$ indicates perfect substitution between the two types of capital, whereas $\nu = 0.3$ represents higher capital complementarity, as observed in the data. Because a higher θ results in a lower ratio of dirty capital and, therefore, a lower equity premium, a higher optimal γ is selected to keep the equity premium fixed. This pattern holds qualitatively across both substitutability scenarios. Since the share of dirty capital decreases faster in the perfect substitution scenario as θ increases, this scenario requires an overall higher optimal γ.[23]

Figure 5 illustrates the average ratio of dirty capital and greenium after selecting the optimal γ to maintain a constant equity premium. In Panel (a), the results for the dirty capital ratio align with those of the two-period model and scenario $\gamma = 5$. Higher levels of emission aversion θ and capital substitutability ν correspond to lower ratios of dirty capital. Investor emission aversion has only limited effects when the two types of capital are more complementary due to productivity concerns. However, if the two types of capital are perfectly substitutable, climate change concerns dominate, resulting in a significantly lower ratio of dirty capital.

Figure 5, Panel (b), presents the results for the greenium. Higher levels of emission aversion and greater substitutability lead to a greater greenium, driven by a lower ratio of dirty capital and reduced dirty investments. Because of the concavity of the production function, lower investment incurs lower marginal adjustment costs but yields higher marginal expected benefits, consequently resulting in higher marginal expected returns. When dirty capital is highly complementary, $\nu = 0.3$, the greenium is slightly negative. This is because the firm holds almost the same amount of dirty capital and clean capital. When the dirty capital and clean capital levels are similar, the marginal

[23]Figure E.1 illustrates the optimal ratio of dirty capital and annualized equity premium with respect to different levels of emission aversion θ, while maintaining a fixed aggregate risk aversion $\gamma = 5$. Higher values of θ result in a lower portion of dirty capital in the economy and, consequently, a lower equity premium. Similarly, perfect substitution between clean capital and dirty capital yields a lower ratio of dirty capital and a lower equity premium.

investment costs (denominator of the investment return) are similar. However, dirty investment generates lower marginal benefits because of the potential temperature increase and damage, lowering the numerator of the investment return. As a result, the expected dirty investment return is slightly lower than the clean investment return, yielding a slightly negative greenium.[24]

Then, I show how capital allocation varies across different levels of substitutability. Figure 6 shows the relation between the ratio of dirty capital and different prices of the carbon emission shock, θ, under various values of ν. Starting with $\nu = 0.3$, as suggested by the empirical estimates, I incrementally increase it to 1 (Cobb-Douglas), 2, 5, 10, and $+\infty$ (perfect substitution). The real effects of sustainability demand on the firm's ratio of dirty capital become stronger as ν increases. When the production function is Cobb-Douglas ($\nu = 1$), the effects are not substantial, and the lowest ratio of dirty capital is approximately 47%. In contrast, if $\nu = 5$, the ratio of dirty capital decreases to approximately 33%, which is half the effect compared with perfect substitution. The results suggest that to achieve better effectiveness of sustainable investing, perfect substitution might not be mandatory, but the high complementarity between dirty capital and clean capital must be addressed. Moreover, the results indicate that even a high ν of 5 achieves only half the effect of the perfect substitution scenario, showing that this implicit assumption in prior studies may be overly optimistic.

The implications for temperature change are straightforward. Increased production using dirty capital results in increased CO_2 emissions, which exacerbates climate change. Although investor concerns about climate change help to alleviate temperature increases, this effect is limited when the two types of capital are highly complementary.

Figure 7 depicts the average simulated temperature change over the next 100 years, with θ set at 13 and γ at the optimal value that maintains a constant equity premium.[25] The temperature increase is significantly lower when the two types of capital are perfect substitutes ($\nu = +\infty$) than

[24]When $\nu = +\infty$, the production function is linear and the marginal benefit is constant.

[25]I report only the result with the highest θ and the corresponding γ that yields an annualized equity premium approximately 8%. The choice of the maximum value of θ in its grid is due to algorithm convergence limitations, as the model fails to converge if θ is too high.

when they are highly complementary ($\nu = 0.3$).

5.3 Comparative Statics

The benchmark assumptions can differ from real-world conditions. In this section, I explore the comparative statics of how sustainable investors affect dirty capital allocation and the greenium under different scenarios while holding all other factors constant. Specifically, I focus on economic forces that can affect green investments, including carbon tax rates, investment adjustment costs, and the relative productivity of dirty capital compared with that of clean capital. Other comparative statics are reported in Appendix C.

5.3.1 Carbon Tax

In the benchmark results, I set the carbon tax value to zero because most states in the U.S. do not have a carbon tax. In reality, the carbon tax varies across countries and has increased in recent years.[26] Therefore, in this section, I explore results with all else equal but a higher carbon tax.

Figure 8 shows the results. The effects of sustainable investors are qualitatively the same. A high carbon tax reduces the optimal portion of dirty capital, as a higher carbon tax generates lower cash flow each period, given a certain level of emission aversion (θ). Because the firm maximizes its equity value, it rationally reduces the share of dirty capital. As a result, the optimal share of dirty capital is lower in both the complementarity and perfect substitution scenarios than in the benchmark results.

The effect of a higher carbon tax is stronger when the two types of capital are perfect substitutes, because it is easier to replace dirty capital with clean capital in production. The results suggest that the policy of raising the carbon tax is more effective under perfect substitution, highlighting the importance of technological innovation in substitution.

The results for the greenium are consistent with the capital allocation decisions. When the two types of capital are perfect substitutes, a significantly lower share of dirty capital generates a high marginal equity value per unit of dirty investment, leading to a much greater greenium. In the

[26] For more details, see the cross-country time series of carbon tax data from the World Bank: https://carbonpricingdashboard.worldbank.org/compliance/price

case of complementarity, the effect of a higher carbon tax on capital allocation is limited, resulting in fewer effects on the greenium. The slightly negative effects on the greenium are also due to the lesser marginal contribution to the equity value of dirty investments, as a higher carbon tax generates larger negative impacts on the firm's cash flow.

5.3.2 Costly Clean Investment

Clean capital could be more costly to adjust than dirty capital, which differs from my benchmark assumption (Lin et al., 2020). For example, new technologies may require large R&D investments and high costs for training labor with the necessary human capital. This feature can be reflected in a higher clean investment adjustment cost (higher ϕ^C). In the comparative statics, I set the clean investment adjustment cost to be twice that of the dirty investment adjustment cost and explore the implications. For practical implications, we can imagine that we currently have a higher clean investment adjustment cost than dirty investment does, and we want to decrease the cost to at least match the dirty investment adjustment cost.

Figure 9 shows the results. The effects of sustainable investors remain qualitatively the same. Doubled clean investment adjustment costs reduce overall cash flows, leading to lower optimal levels of both dirty capital and clean capital. Intuitively, the share of clean capital decreases compared with the benchmark results. The effects are more significant when there is less emission aversion. However, the investment adjustment cost is not the game changer. Although investing in clean capital is substantially more costly, sustainability motivations can still lead to a much lower allocation toward dirty capital. There is minimal effect from changing clean investment adjustment costs if dirty capital is highly complementary, suggesting that reducing the investment adjustment cost is not the key. Sustainable investing can yield real, tangible effects only after the complementarity problem is addressed.

The effects on the greenium are stronger than those on capital allocation. These results are driven by much higher expected marginal returns on clean investments. The higher investment adjustment cost substantially discourages the accumulation of clean capital. The significantly lower level of clean capital generates much higher marginal expected investment returns, even though the overall ratio of clean capital is higher than the benchmark results. The higher marginal clean investment returns consequently lower the greenium.

5.3.3 Relative Productivity Share

Although growing rapidly, current clean technology investment is still in progress. According to the United Nations, renewable energy cannot completely replace fossil fuels, and fossil fuels still play a larger role in global energy production.[27] It may be overly optimistic to assume that clean capital and dirty capital contribute equally to total production ($\alpha = 0.5$). Therefore, I explore the comparative statics with lower productivity shares of dirty capital and examine the implications. The results for cases where dirty capital has a higher productivity share are reported in Appendix C.

Figure 10 plots the results when dirty capital plays a smaller role in the production function. Intuitively, a lower share of dirty capital leads to reduced accumulation of dirty capital. The effects are significantly stronger when dirty capital and clean capital are perfect substitutes. The effects of sustainable investors are qualitatively similar. Stronger emission aversion and climate concerns lead to a lower share of dirty capital. Even when there is no emission aversion, $\theta = 0$, a lower productivity share results in a substantially reduced portion of dirty capital in the perfect substitution scenario.

The greenium aligns with the dirty capital accumulation. A substantially lower level of dirty capital generates larger marginal returns on dirty investments in the perfect substitution scenario. In the complementarity scenario, the productivity channel is influential. When the productivity share α is lower, the marginal benefit of dirty investment decreases, reducing the marginal investment return. When the levels of dirty capital and clean capital are similar, the lower marginal benefit results in lower returns on dirty investments, and, consequently, a lower expected greenium.

In summary, this section elaborates on the calibration strategy and presents quantitative outcomes derived from the model outlined in Section 4. Comparative statics are also explored to

[27] https://www.un.org/en/climatechange/raising-ambition/renewable-energy

reflect different aspects of reality. The impacts of sustainable investors remain qualitatively similar, although effects under different comparative statics are more pronounced when dirty capital and clean capital are perfect substitutes. More importantly, climate policies, such as a carbon tax, achieve better results with greater substitutability.

6 Conclusion

In this paper, I elucidate the complexities involved in transitioning to a cleaner economy amid investors' climate change concerns. The findings underscore the significant impact of production frictions in limiting the effects of investors' nonpecuniary preferences and climate risk aversion on firm behavior and capital allocation decisions. While sustainable investors exert influence through the cost of equity and nonpecuniary utility channels, the high complementarity between clean capital and dirty capital introduces production friction, hindering the economy's ability to achieve net-zero emissions. The comparative statics suggest that complementarity is also crucial for the effectiveness of other environmental forces, such as a carbon tax. The empirical estimates of the parameter governing the substitutability of dirty capital indicate a still strongly complementary production function, although dirty capital is becoming more substitutable in recent years.

This study emphasizes the importance of investing in technological innovations that make clean capital a better substitute for dirty capital to effectively mitigate climate change and achieve sustainability goals. Simply forcing firms to become cleaner through the cost of capital may not suffice, especially when strong production complementarities are present. A holistic approach that combines financial incentives with technological advancements is therefore essential for a successful transition to a cleaner economy.

The model can be extended to study richer testable implications. First, capital substitutability can be an endogenously chosen variable with associated costs. Specifically, the firm can enhance substitutability by investing more in R&D. Innovative investments are costly and risky, but they can assist the firm in successfully phasing out dirty investments and achieving the net-zero emission goal. Endogenous technological innovation will lead to richer theoretical predictions about the firm's clean innovation and investments in greener projects. This direction will open the door for both theoretical and empirical research in the future.

Second, the model can be extended to study green bonds or loans. Numerous ongoing studies examine the cost of financing channels for green bonds and their real effects. By incorporating green bonds, the model will elucidate the capital structure implications. For example, how many green bonds should a firm use, and how can green bonds play a different role in incentivizing firms' clean investments? More broadly, the model can be expanded to explore the interaction between climate change and capital structure dynamics.

The empirical findings can be extended in several ways for further practical implications. First, should capital complementarity be considered an important input in a firm's ESG scores? Improving capital substitutability in the production function leads to more effective sustainable mandates. If a high ESG score reflects a greater likelihood that the firm can transition to clean, sustainable investing that targets high ESG score firms will be more effective. This raises an empirical question: does the current ESG rating system consider capital complementarity?

Second, substitutability has significant implications for climate policies. For example, the effectiveness of a carbon tax depends on how substitutable dirty capital is, as predicted by the model's comparative statics. These testable implications can reveal whether real-world decisions are optimal and effective on the basis of the substitutability of dirty capital.

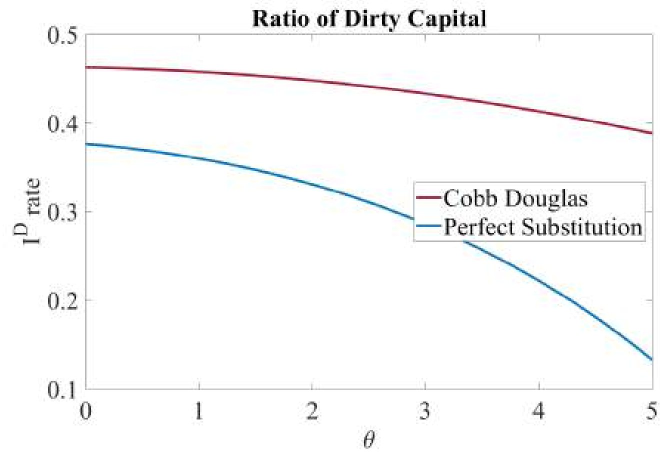


Figure 1: Optimal ratio of dirty capital in the two-period model. Dirty investment is denoted by I^D, and clean investment is denoted by I^C. The ratio is defined as $I^D/(I^C + I^D)$. Because of full depreciation, investment I is equivalent to capital stock K. This figure shows the optimal ratio in relation to different prices of the carbon emission shock, θ, under two scenarios of substitutability.

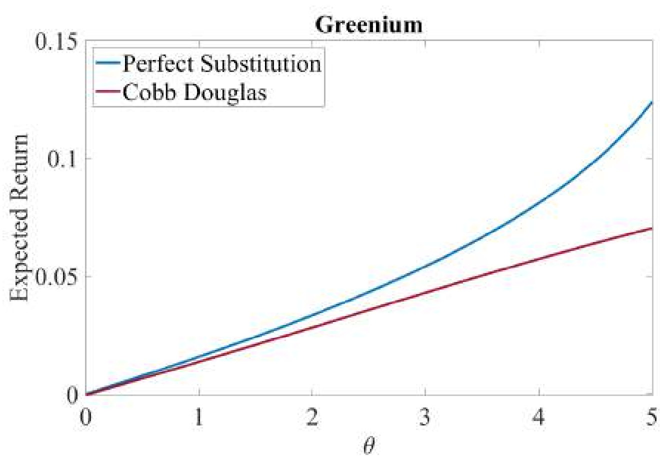


Figure 2: The greenium in the two-period model. The greenium is defined according to equations (18) and (19). This figure shows the greenium in relation to different prices of the carbon emission shock, θ, under two scenarios of substitutability.

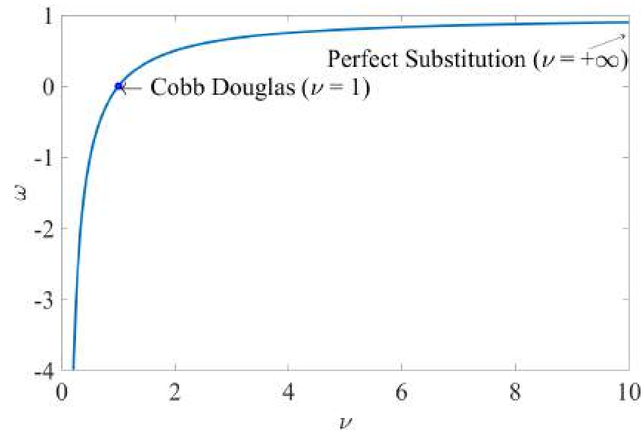


Figure 3: Relation between ω and ν, the parameters that govern the substitutability between dirty capital and clean capital, where $\omega = \frac{\nu-1}{\nu}$. This figure shows how different values of ω correspond to ν. When $\nu = 1$, the production function is Cobb-Douglas. When ν approaches $+\infty$, dirty capital and clean capital are perfectly substitutable.

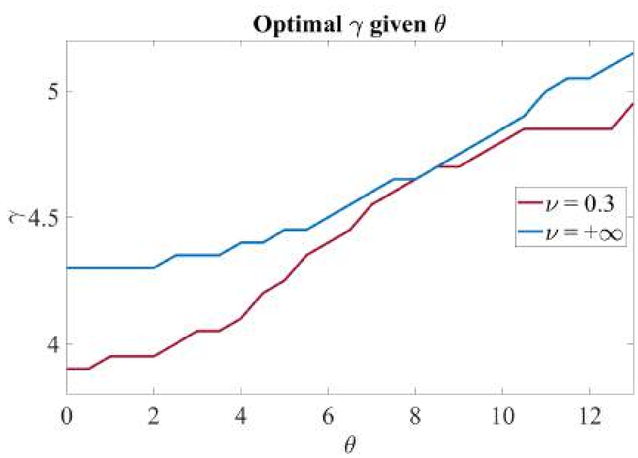
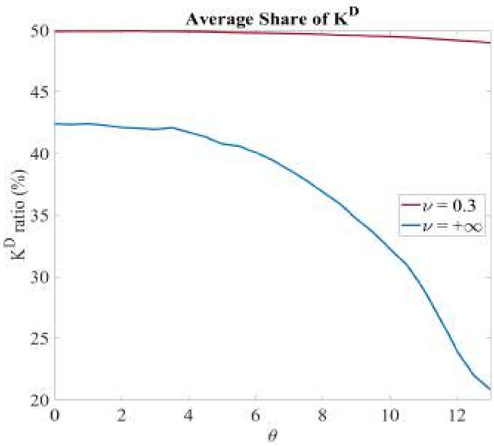
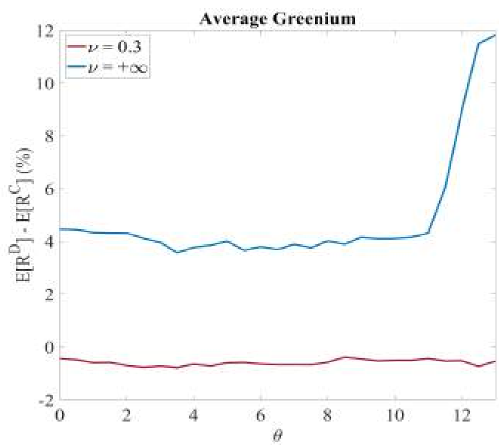


Figure 4: Optimal price of productivity shock, γ, with respect to the price of carbon emission shock, θ. For each θ, I report the optimal γ that yields an average annualized equity premium closest to 8%. When the two types of capital are complementary, $\nu = 0.3$. When the two types of capital are perfectly substitutable, $\nu = +\infty$.



(a) Ratio of Dirty Capital



(b) Greenium

Figure 5: Ratio of dirty capital and the greenium. This figure shows the ratio of dirty capital and the greenium with respect to different prices of the carbon emission shock, θ, under two scenarios of substitutability. For each θ, the price of the productivity shock, γ, is selected to yield an average annualized equity premium closest to 8%. The ratio is defined as the level of dirty capital scaled by the total capital level (clean plus dirty), $K_D/(K_C + K_D)$. When the two types of capital are complementary, $\nu = 0.3$. When the two types of capital are perfectly substitutable, $\nu = +\infty$.

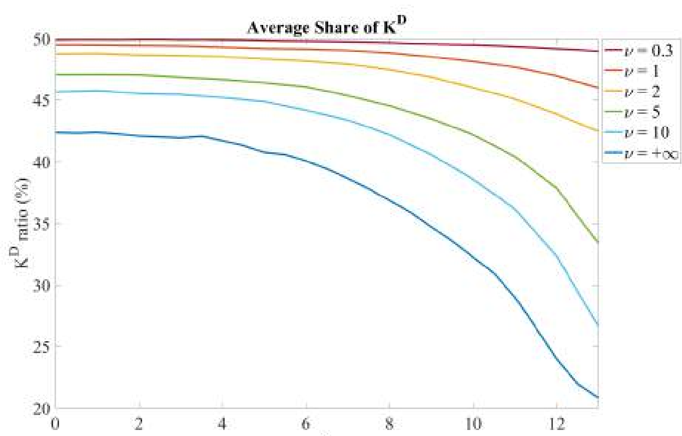


Figure 6: Ratio of dirty capital with respect to different levels of substitutability, ν. For each θ, the price of the productivity shock, γ, is selected to yield an average annualized equity premium closest to 8%. The ratio is defined as the level of dirty capital scaled by the total capital level (clean plus dirty), $K_D/(K_C+K_D)$. When the two types of capital are complementary, as in the data, $\nu = 0.3$. When the production function is Cobb-Douglas, $\nu = 1$. When the two types of capital are perfectly substitutable, $\nu = +\infty$.

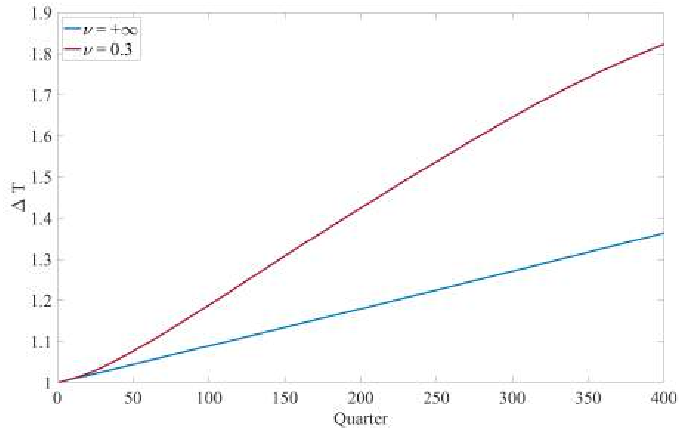
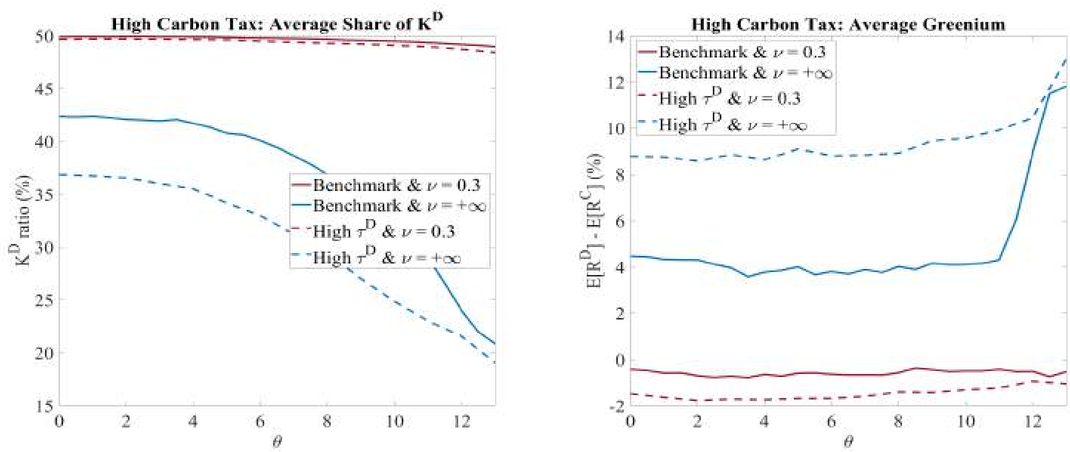


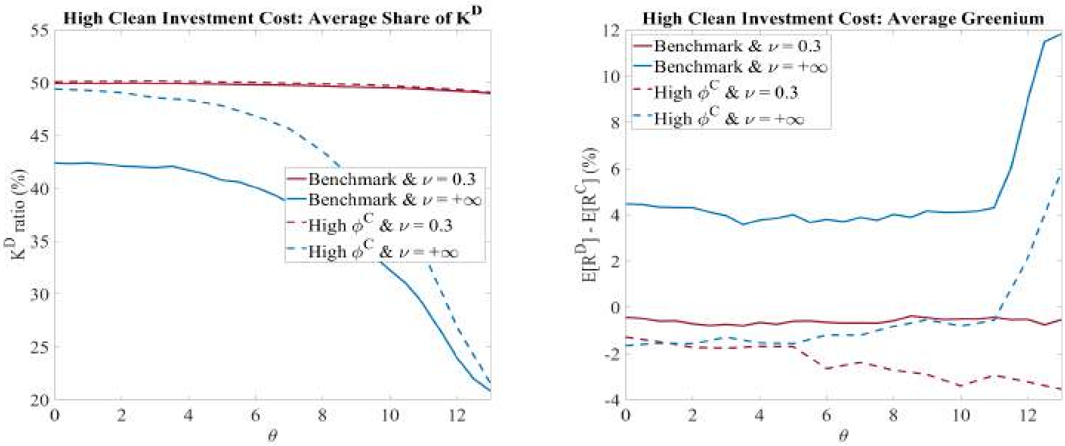
Figure 7: Average temperature change compared with the preindustrial period, ΔT, over the next 100 years. The price of the carbon emission shock, θ, is set to 13, and the price of the productivity shock, γ, is adjusted to maintain an excess equity return of approximately 8%. Other parameter values are reported in Table 7. When clean capital and dirty capital are complementary, $\nu = 0.3$. When clean capital and dirty capital are perfectly substitutable, $\nu = +\infty$.



(a) Ratio of Dirty Capital

(b) Greenium

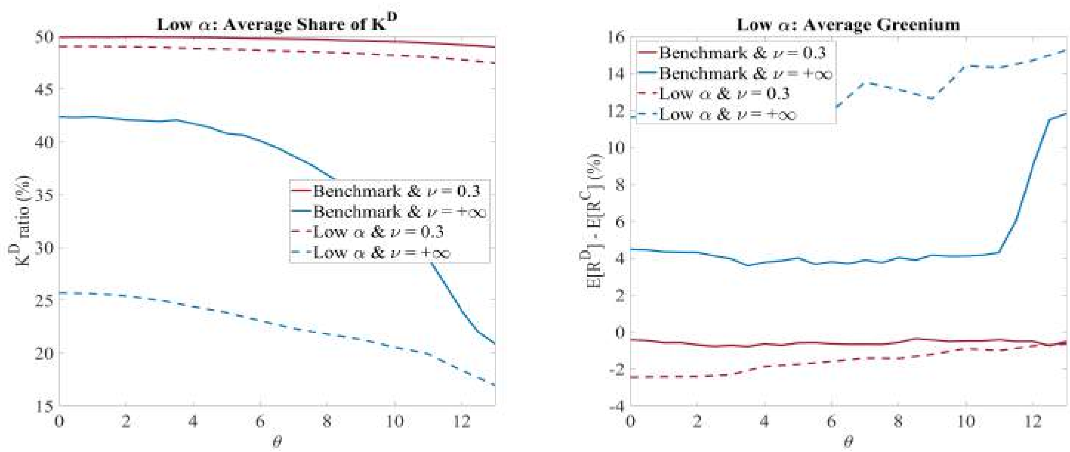
Figure 8: Ratio of dirty capital and the greenium with a high carbon tax ($\tau_D = 0.6$). This figure shows the ratio of dirty capital and the greenium with respect to different prices of the carbon emission shock, θ, under two scenarios of substitutability. For each θ, the price of the productivity shock, γ, is selected to generate an average annualized equity premium closest to 8%. The ratio is defined as the level of dirty capital scaled by total capital (clean plus dirty), $K_D/(K_C + K_D)$. When the two types of capital are complementary, $\nu = 0.3$. When the two types of capital are perfectly substitutable, $\nu = +\infty$. The benchmark results are plotted with solid lines, and the results with a high carbon tax are plotted with dashed lines.



(a) Ratio of Dirty Capital

(b) Greenium

Figure 9: Ratio of dirty capital and the greenium with high clean investment adjustment cost ($\phi^C = 2$). This figure shows the ratio of dirty capital and the greenium with respect to different prices of the carbon emission shock, θ, under two scenarios of substitutability. For each θ, the price of the productivity shock, γ, is selected to generate an average annualized equity premium closest to 8%. The ratio is defined as the level of dirty capital scaled by the total capital (clean plus dirty), $K_D/(K_C + K_D)$. When the two types of capital are complementary, $\nu = 0.3$. When the two types of capital are perfectly substitutable, $\nu = +\infty$. The benchmark results are plotted with solid lines, and the results with high clean investment adjustment costs are plotted with dashed lines.



(a) Ratio of Dirty Capital

(b) Greenium

Figure 10: Ratio of dirty capital and the greenium with a low productivity share of dirty capital ($\alpha = 0.45$). This figure shows the ratio of dirty capital and the greenium with respect to different prices of the carbon emission shock, θ, under two scenarios of substitutability. For each θ, the price of the productivity shock, γ, is selected to generate an average annualized equity premium closest to 8%. The ratio is defined as the level of dirty capital scaled by the total capital (clean plus dirty), $K_D/(K_C + K_D)$. When the two types of capital are complementary, $\nu = 0.3$. When the two types of capital are perfectly substitutable, $\nu = +\infty$. The benchmark results are plotted with solid lines, and the results with a low productivity share of dirty capital are plotted with dashed lines.

Table 1: Summary Statistics by Country

This table presents the number of observations, sample time range, and averages of key variables by country. Ln(Y) is the log ratio of the total revenue, where the total revenue is measured in million U.S. dollars. Ln(GHG1) and Ln(GHG2) are the log ratios of Scope 1 and Scope 2 GHG emissions, respectively, with carbon emissions measured in tCO2e. Ln(AT) is the log ratio of the total assets, with the total assets measured in million U.S. dollars.

Country	Observations	Start Year	End Year	Ln(Y)	Ln(GHG1)	Ln(GHG2)	Ln(AT)
Panel A: Developed Markets							
Australia	52	2004	2022	7.06	10.46	10.69	8.94
Belgium	47	2005	2022	6.82	10.70	9.52	8.28
Canada	1073	2002	2022	7.18	10.94	10.56	8.62
Denmark	46	2002	2022	6.78	8.99	9.45	7.96
France	152	2002	2022	8.13	11.26	11.25	9.00
Germany	114	2002	2022	7.99	10.25	10.61	9.19
Hong Kong	93	2002	2022	8.08	10.05	10.68	9.18
Ireland	256	2002	2022	7.78	10.34	10.38	8.86
Israel	346	2005	2022	5.52	7.89	8.08	6.48
Italy	44	2002	2022	10.04	13.81	12.64	10.64
Japan	164	2002	2022	9.78	11.17	12.64	10.93
Netherlands	136	2002	2022	7.74	9.33	10.27	8.93
Norway	31	2002	2022	9.28	13.25	11.69	9.89
Singapore	63	2005	2022	6.03	9.04	8.43	6.81
Spain	42	2002	2022	9.97	11.34	12.41	11.67
Sweden	46	2002	2022	7.86	9.84	10.96	8.44
Switzerland	150	2002	2022	8.06	10.18	10.63	9.32
United Kingdom	423	2002	2022	8.54	11.20	11.33	9.74
United States	16133	2002	2022	6.66	8.94	9.28	7.83
Panel B: Emerging Markets							
Argentina	42	2005	2022	7.99	10.32	9.89	9.01
Bermuda	165	2002	2022	7.47	9.01	9.18	8.94
Brazil	175	2002	2022	8.90	12.59	11.44	9.88
Cayman Islands	42	2010	2022	5.87	9.04	8.49	7.09
Chile	89	2005	2022	7.75	11.14	9.68	9.10
China	681	2002	2022	6.83	9.25	9.50	7.57
Colombia	21	2008	2022	8.24	13.60	10.75	9.02
Greece	114	2002	2022	7.99	10.25	9.05	9.19
India	99	2002	2022	7.85	9.57	10.06	8.92
Indonesia	31	2002	2022	8.37	10.03	11.02	9.00
Jersey	23	2002	2022	5.86	10.68	9.56	6.73
Luxembourg	83	2002	2022	8.09	11.30	11.95	8.40
Mexico	63	2003	2022	8.58	11.34	11.60	9.29
Monaco	37	2014	2022	5.65	13.16	8.62	7.52
Peru	21	2005	2022	7.22	9.55	10.39	9.11
Russia	33	2005	2021	8.53	12.32	12.11	8.85
South Africa	89	2004	2022	7.46	12.12	13.44	8.00
South Korea	78	2002	2022	9.07	11.27	11.77	10.87
Taiwan	103	2002	2022	7.97	11.34	12.46	8.55

Table 2: Summary Statistics

This table presents summary statistics of the key variables. SD represents the standard deviation. Scope 1 Intensity, Scope 2 Intensity, and Scope 3 Intensity are the logarithms of GHG1, GHG2, and GHG3 emissions divided by the total revenue, respectively. Ln(G) is the logarithm of carbon emissions. Ln(Y) is the log ratio of the total revenue, and Ln(AT) is the log ratio of the total assets. Ln($\frac{\partial Y}{\partial G}$) represents the log ratio of the marginal productivity of emissions, estimated using the 3-digit SIC codes as the sector classification. GHG1/AT, GHG2/AT, and GHG3/AT are ratios of Scope 1, Scope 2, and Scope 3 emissions to the total assets, respectively. The total assets and revenue are reported in nominal U.S. dollars.

	US				Global			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Scope 1 Intensity	2.28	2.02	-9.37	10.04	3.15	1.89	-6.89	10.35
Scope 2 Intensity	2.56	1.36	-6.42	8.47	2.97	1.14	-6.42	8.64
Scope 3 Intensity	4.88	1.36	2.68	13.79	5.23	1.30	2.84	13.79
Scope 1 ln(G)	8.92	3.09	-3.47	19.51	10.05	3.22	-3.47	19.78
Scope 2 ln(G)	9.20	2.64	-3.65	16.92	9.87	2.68	-3.08	17.62
Scope 3 ln(G)	11.52	2.69	-2.21	20.73	12.13	2.87	-1.65	21.12
Ln(Y)	6.66	2.12	0.37	11.72	6.92	2.28	0.37	11.72
Ln(AT)	7.83	1.91	3.72	13.49	7.65	1.90	3.72	13.49
Ln($\frac{\partial Y}{\partial G}$)	-3.14	2.35	-15.89	9.14	-4.11	2.23	-16.33	7.13
GHG1/AT	62.25	291.39	0.00	7704.66	105.25	425.24	0.00	12718.73
Ln(GHG1/AT)	1.10	2.78	-10.88	8.95	2.42	2.15	-8.35	9.45
GHG2/AT	18.64	46.81	0.00	2304.09	27.83	81.49	0.00	3078.91
Ln(GHG2/AT)	1.37	2.23	-9.53	7.74	2.24	1.60	-8.22	8.03
GHG3/AT	451.65	5292.29	0.00	658896.60	547.95	5541.43	0.00	658896.60
Ln(GHG3/AT)	3.70	2.19	-6.23	13.40	4.49	1.83	-6.23	13.40

Table 3: Estimates of ν

This table presents the estimates of ν, representing the degree of substitution of dirty capital, derived from equations (26) and (27). Proxies for carbon emissions, G, include Scope 1, Scope 2, and Scope 3 emissions. The 2-, 3-, and 4-digit SIC codes are used for sector classification in estimating equation (28) and calculating the marginal productivity of carbon emissions, $\frac{\partial Y}{\partial G}$. When the independent variable is $\Delta \ln(\frac{\partial Y}{\partial G})$, the dependent variable is $\Delta \ln(G/Y)$. Conversely, if the independent variable is $\ln(\frac{\partial Y}{\partial G})$, the dependent variable is $\ln(G/Y)$. The estimates and standard errors (in parentheses) are bootstrapped from 10,000 iterations.

Panel A: Scope 1						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.211		0.162		0.146	
	(0.007)		(0.007)		(0.006)	
$\ln(\frac{\partial Y}{\partial G})$		0.349		0.277		0.245
		(0.007)		(0.007)		(0.008)
Constant	-0.052	1.608	-0.048	2.019	-0.046	2.249
	(0.002)	(0.032)	(0.003)	(0.032)	(0.003)	(0.033)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Panel B: Scope 2						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.218		0.168		0.154	
	(0.006)		(0.006)		(0.007)	
$\ln(\frac{\partial Y}{\partial G})$		0.400		0.356		0.352
		(0.007)		(0.008)		(0.009)
Constant	-0.046	1.351	-0.048	1.597	-0.048	1.617
	(0.002)	(0.030)	(0.002)	(0.033)	(0.003)	(0.355)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Panel C: Scope 3						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.334		0.278		0.246	
	(0.007)		(0.007)		(0.009)	
$\ln(\frac{\partial Y}{\partial G})$		0.457		0.453		0.441
		(0.006)		(0.008)		(0.009)
Constant	0.017	2.475	0.029	2.621	0.031	2.689
	(0.006)	(0.033)	(0.003)	(0.043)	(0.003)	(0.048)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y

Table 4: Estimates of ν Before and After Year 2012

This table presents the subsample estimates of ν, the degree of substitution of dirty capital, derived from equations (26) and (27). The sample is split by the year 2012, with time periods before 2012 denoted by <=2012 and those after 2012 by >2012. Proxies for carbon emissions, G, include Scope 1 and Scope 2 emissions. The 3- and 4-digit SIC codes are used for sector classification in estimating equation (28) and calculating the marginal productivity of carbon emissions, $\frac{\partial Y}{\partial G}$. When the independent variable is $\Delta\ln(\frac{\partial Y}{\partial G})$, the dependent variable is $\Delta\ln(G/Y)$; otherwise, if the independent variable is $\ln(\frac{\partial Y}{\partial G})$, the dependent variable is $\ln(G/Y)$. The estimates and standard errors (in parentheses) are bootstrapped from 10,000 iterations, while the z-statistics and p-values are derived from the original pooled regressions.

Panel A: Scope 1

	SIC3				SIC4			
	<=2012	>2012	<=2012	>2012	<=2012	>2012	<=2012	>2012
$\Delta\ln(\frac{\partial Y}{\partial G})$	0.080	0.193			0.074	0.174		
	(0.007)	(0.008)			(0.008)	(0.009)		
$\ln(\frac{\partial Y}{\partial G})$			0.144	0.299			0.121	0.279
			(0.009)	(0.009)			(0.104)	(0.010)
Constant	-0.052	-0.046	2.924	1.839	-0.048	-0.044	3.221	2.009
	(0.004)	(0.003)	(0.046)	(0.040)	(0.005)	(0.003)	(0.057)	(0.042)
Firm Fixed	N	N	Y	Y	N	N	Y	Y
Time Fixed	Y	Y	Y	Y	Y	Y	Y	Y
z-stats	9.272		8.390		7.623		7.867	
p-value	0.000		0.000		0.000		0.000	

Panel B: Scope 2

	SIC3				SIC4			
	<=2012	>2012	<=2012	>2012	<=2012	>2012	<=2012	>2012
$\Delta\ln(\frac{\partial Y}{\partial G})$	0.115	0.188			0.124	0.166		
	(0.010)	(0.008)			(0.012)	(0.008)		
$\ln(\frac{\partial Y}{\partial G})$			0.263	0.311			0.278	0.293
			(0.015)	(0.010)			(0.017)	(0.012)
Constant	-0.043	-0.049	1.944	1.775	-0.037	-0.051	1.879	1.842
	(0.004)	(0.003)	(0.063)	(0.040)	(0.005)	(0.003)	(0.069)	(0.045)
Firm Fixed	N	N	Y	Y	N	N	Y	Y
Time Fixed	Y	Y	Y	Y	Y	Y	Y	Y
z-stats	5.414		2.088		3.291		0.443	
p-value	0.000		0.037		0.001		0.658	

Table 5: Estimates of α

This table presents the estimates of the share of dirty capital, α, calculated as a function of $\ln(G/AT)$ and the degree of substitution, ν. Scope 1 and Scope 2 emissions are used to proxy carbon emissions G. The 3- and 4-digit SIC codes are applied to classify sectors to estimate equation (28) and to determine the marginal productivity of carbon emissions, $\frac{\partial Y}{\partial G}$. The "Average ln(G/AT)" row provides the mean logarithm of carbon emissions divided by total assets. Implied α is derived from equation (26).

	Scope 1		Scope 2	
	3-digit SIC	4-digit SIC	3-digit SIC	4-digit SIC
Average ln(G/AT)	2.42	2.43	2.22	2.10
Implied α	0.54	0.44	0.55	0.42

Table 6: Estimates of ν By Industry

This table presents the estimates of ν, the degree of substitution of dirty capital, across different industries. Panel A provides estimates from the original equation (26), while Panel B presents estimates from the first difference equation (27). Scope 1 and Scope 2 emissions are used as proxies for carbon emissions G. The 3- and 4-digit SIC codes are applied to classify sectors for estimating equation (28) and to calculate the marginal productivity of carbon emissions, $\frac{\partial Y}{\partial G}$. The industry classification follows the ten-industry classification available at Ken French's Website.

Panel A: Original Equation (26)				
	Scope 1		Scope 2	
	3-digit SIC	4-digit SIC	3-digit SIC	4-digit SIC
1 Consumer Nondurables	0.125	0.088	0.146	0.150
2 Consumer Durables	0.176	0.148	0.189	0.156
3 Manufacturing	0.184	0.164	0.135	0.098
4 Energy	0.266	0.270	0.356	0.312
5 Hightech	0.418	0.360	0.378	0.288
6 Telecom	0.142	0.180	0.249	0.202
7 Shops	0.162	0.165	0.119	0.135
8 Health	0.400	0.342	0.418	0.374
9 Utilities	0.359	0.290	0.592	0.624
10 Others	0.220	0.152	0.241	0.254
Panel B: First Difference (27)				
	Scope 1		Scope 2	
	3-digit SIC	4-digit SIC	3-digit SIC	4-digit SIC
1 Consumer Nondurables	0.037	0.010	0.075	0.107
2 Consumer Durables	0.093	0.101	0.134	0.085
3 Manufacturing	0.088	0.090	0.071	0.076
4 Energy	0.155	0.159	0.227	0.176
5 Hightech	0.307	0.207	0.266	0.180
6 Telecom	0.053	0.060	0.117	0.105
7 Shops	0.064	0.080	0.070	0.082
8 Health	0.276	0.261	0.322	0.276
9 Utilities	0.229	0.196	0.439	0.445
10 Others	0.125	0.105	0.109	0.104

Table 7: Benchmark Parameter Values

This table lists the benchmark parameter values used to solve and simulate the model at a quarterly frequency. Each parameter includes its notation, value, and explanation.

Parameter	Value	Meaning
β	0.99	Subjective discount factor
a_1	0	Damage function coefficient (linear)
a_2	0.1	Damage function coefficient (square)
λ	0.05	Contribution of emission to temperature change
η	0.01	Emission intensity coefficient
τ^D	0	Carbon tax rate
α	0.5	Productivity share of dirty capital
μ	1	Degree of homogeneity of the production function
δ^D	0.03	Dirty capital depreciation rate
δ^C	0.03	Clean capital depreciation rate
ϕ^D	1	Dirty investment adjustment cost
ϕ^C	1	Clean investment adjustment cost
ρ_x	0.9	Persistence of aggregate productivity
σ_x	0.03	Volatility of aggregate productivity
$\bar{x}$	-2.6	Average aggregate productivity
ρ_z	0.5	Persistence of emission shock
σ_z	0.005	Volatility of emission shock
$\bar{z}$	0	Average emission shock

References

Bai, Jushan. (2009) Panel data models with interactive fixed effects. *Econometrica*, *77*(4), 1229–1279.

Balvers, Ronald, Du, Ding, and Zhao, Xiaobing. (2017) Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking & Finance*, *77*, 18–34.

Bansal, Ravi, Ochoa, Marcelo, and Kiku, Dana. (2017) *Climate change and growth risks* (tech. rep.). National Bureau of Economic Research.

Barnett, Michael. (2023) Climate change and uncertainty: An asset pricing perspective. *Management Science*, *69*(12), 7562–7584.

Barnett, Michael, Brock, William, and Hansen, Lars Peter. (2020) Pricing uncertainty induced by climate change. *The Review of Financial Studies*, *33*(3), 1024–1066.

Barnett, Michael, Brock, William, Hansen, Lars Peter, Hu, Ruimeng, and Huang, Joseph. (2023a) A deep learning analysis of climate change, innovation, and uncertainty. *arXiv preprint arXiv:2310.13200*.

Barnett, Michael, Brock, William A, Hansen, Lars Peter, and Zhang, Hong. (2023b) How should climate change uncertainty impact social valuation and policy? *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2023-140).

Bartram, Söhnke M, Hou, Kewei, and Kim, Sehoon. (2022) Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics*, *143*(2), 668–696.

Basu, Susanto and Fernald, John G. (1997) Returns to scale in us production: Estimates and implications. *Journal of Political Economy*, *105*(2), 249–283.

Belo, Frederico, Donangelo, Andres, Lin, Xiaoji, and Luo, Ding. (2023) What drives firms' hiring decisions? an asset pricing perspective. *The Review of Financial Studies*, *36*(9), 3825–3860.

Belo, Frederico, Gala, Vito D, Salomao, Juliana, and Vitorino, Maria Ana. (2022) Decomposing firm value. *Journal of Financial Economics*, *143*(2), 619–639.

Belo, Frederico, Li, Jun, Lin, Xiaoji, and Zhao, Xiaofei. (2017) Labor-force heterogeneity and asset prices: The importance of skilled labor. *The Review of Financial Studies*, *30*(10), 3669–3709.

Belo, Frederico, Lin, Xiaoji, and Vitorino, Maria Ana. (2014) Brand capital and firm value. *Review of Economic Dynamics*, *17*(1), 150–169.

Bolton, Patrick and Kacperczyk, Marcin. (2021) Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517–549.

Bolton, Patrick and Kacperczyk, Marcin. (2023) Global pricing of carbon-transition risk. *The Journal of Finance*, *78*(6), 3677–3754.

Bustamante, Maria Cecilia and Zucchi, Francesca. (2024) Dynamic carbon emission management.

Cai, Yongyang and Lontzek, Thomas S. (2019) The social cost of carbon with economic and climate risks. *Journal of Political Economy*, *127*(6), 2684–2734.

Campbell, John Y and Martin, Ian. (2021) *Sustainability in a risky world* (tech. rep.). National Bureau of Economic Research.

Chirinko, Robert S, Fazzari, Steven M, and Meyer, Andrew P. (2011) A new approach to estimating production function parameters: The elusive capital–labor substitution elasticity. *Journal of Business & Economic Statistics*, *29*(4), 587–594.

Chirinko, Robert S and Mallick, Debdulal. (2017) The substitution elasticity, factor shares, and the low-frequency panel model. *American Economic Journal: Macroeconomics*, *9*(4), 225–253.

Choi, Darwin, Gao, Zhenyu, and Jiang, Wenxi. (2020) Attention to global warming. *The Review of Financial Studies*, *33*(3), 1112–1145.

Cochrane, John H. (2009) *Asset pricing: Revised edition.* Princeton university press.

Dangl, Thomas, Halling, Michael, Yu, Jin, and Zechner, Josef. (2023) Social preferences and corporate investment. *Available at SSRN 4470567.*

Daniel, Kent D, Litterman, Robert B, and Wagner, Gernot. (2016) Applying asset pricing theory to calibrate the price of climate risk.

De Angelis, Tiziano, Tankov, Peter, and Zerbib, Olivier David. (2023) Climate impact investing. *Management Science*, *69*(12), 7669–7692.

Donadelli, Michael, Grüning, Patrick, and Hitzemann, Steffen. (2019) Understanding macro and asset price dynamics during the climate transition. *Bank of Lithuania Discussion Paper*, (18).

Eisfeldt, Andrea L and Papanikolaou, Dimitris. (2013) Organization capital and the cross-section of expected returns. *The Journal of Finance*, *68*(4), 1365–1406.

Engle, Robert F, Giglio, Stefano, Kelly, Bryan, Lee, Heebum, and Stroebel, Johannes. (2020) Hedging climate change news. *The Review of Financial Studies*, *33*(3), 1184–1216.

Eskildsen, Marc, Ibert, Markus, Jensen, Theis Ingerslev, and Pedersen, Lasse Heje. (2024) In search of the true greenium. *Available at SSRN.*

Fama, Eugene F and French, Kenneth R. (1997) Industry costs of equity. *Journal of financial economics*, *43*(2), 153–193.

Favilukis, Jack, Garlappi, Lorenzo, and Uppal, Raman. (2023) How effective are portfolio mandates? *Available at SSRN 4572588.*

Frank, Murray Z and Shen, Tao. (2016) Investment and the weighted average cost of capital. *Journal of Financial Economics*, *119*(2), 300–315.

Gala, Vito D, Gomes, Joao F, and Liu, Tong. (2022) Marginal q. *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper.*

Gechert, Sebastian, Havranek, Tomas, Irsova, Zuzana, and Kolcunova, Dominika. (2022) Measuring capital-labor substitution: The importance of method choices and publication bias. *Review of Economic Dynamics*, *45*, 55–82.

Giglio, Stefano, Kelly, Bryan, and Stroebel, Johannes. (2021a) Climate finance. *Annual Review of Financial Economics*, *13*, 15–36.

Giglio, Stefano, Maggiori, Matteo, Rao, Krishna, Stroebel, Johannes, and Weber, Andreas. (2021b) Climate change and long-run discount rates: Evidence from real estate. *The Review of Financial Studies*, *34*(8), 3527–3571.

Gonçalves, Andrei S, Xue, Chen, and Zhang, Lu. (2020) Aggregation, capital heterogeneity, and the investment capm. *The Review of Financial Studies*, *33*(6), 2728–2771.

Gregory, Richard P. (2021) The pricing of global temperature shocks in the cost of equity capital. *Journal of International Financial Markets, Institutions and Money*, *72*, 101319.

Hambel, Christoph, Kraft, Holger, and van der Ploeg, Frederick. (2020) *Asset pricing and decarbonization: Diversification versus climate action*. Department of Economics, University of Oxford.

Hart, Oliver and Zingales, Luigi. (2017) Companies should maximize shareholder welfare not market value. *ECGI-Finance Working Paper*, (521).

Hartzmark, Samuel M and Shue, Kelly. (2022) Counterproductive sustainable investing: The impact elasticity of brown and green firms. *Available at SSRN 4359282*.

Heath, Davidson, Macciocchi, Daniele, Michaely, Roni, and C. Ringgenberg, Matthew. (2023) Does socially responsible investing change firm behavior? *Review of Finance*, *27*(6), 2057–2083.

Heinkel, Robert, Kraus, Alan, and Zechner, Josef. (2001) The effect of green investment on corporate behavior. *Journal of Financial and Quantitative Analysis*, *36*(4), 431–449.

Hong, Harrison, Wang, Neng, and Yang, Jinqiang. (2023) Welfare consequences of sustainable finance. *The Review of Financial Studies*, *36*(12), 4864–4918.

Hugon, Artur and Law, Kelvin. (2019) Impact of climate change on firm earnings: Evidence from temperature anomalies. *Available at SSRN 3271386*.

Huij, Joop, Laurs, Dries, Stork, Philip A, and Zwinkels, Remco CJ. (2023) Carbon beta: A market-based measure of climate transition risk exposure. *Available at SSRN 3957900*.

Ilhan, Emirhan, Sautner, Zacharias, and Vilkov, Grigory. (2021) Carbon tail risk. *The Review of Financial Studies*, *34*(3), 1540–1571.

Kozak, Serhiy, Nagel, Stefan, and Santosh, Shrihari. (2018) Interpreting factor models. *The Journal of Finance*, *73*(3), 1183–1223.

Krueger, Philipp, Sautner, Zacharias, and Starks, Laura T. (2020) The importance of climate risks for institutional investors. *The Review of Financial Studies*, *33*(3), 1067–1111.

Lanteri, Andrea and Rampini, Adriano A. (2023) *Financing the adoption of clean technology* (tech. rep.). Mimeo.

Lashkari, Danial, Bauer, Arthur, and Boussard, Jocelyn. (2024) Information technology and returns to scale. *American Economic Review*, *114*(6), 1769–1815.

Lemoine, Derek. (2021) The climate risk premium: How uncertainty affects the social cost of carbon. *Journal of the Association of Environmental and Resource Economists*, *8*(1), 27–57.

Li, Qing, Shan, Hongyu, Tang, Yuehua, and Yao, Vincent. (2020) Corporate climate risk: Measurements and responses. *Available at SSRN 3508497*.

Lin, Xiaoji. (2012) Endogenous technological progress and the cross-section of stock returns. *Journal of Financial Economics*, *103*(2), 411–427.

Lin, Xiaoji, Palazzo, Berardino, and Yang, Fan. (2020) The risks of old capital age: Asset pricing implications of technology adoption. *Journal of Monetary Economics*, *115*, 145–161.

Liu, Laura Xiaolei, Whited, Toni M, and Zhang, Lu. (2009) Investment-based expected stock returns. *Journal of Political Economy*, *117*(6), 1105–1139.

Lontzek, Thomas, Pohl, Walt, Schmedders, Karl, Thalhammer, Marco, and Wilms, Ole. (2023) Asset pricing with disagreement about climate risks. *Available at SSRN 4473164*.

Matthews, H Damon, Gillett, Nathan P, Stott, Peter A, and Zickfeld, Kirsten. (2009) The proportionality of global warming to cumulative carbon emissions. *Nature*, *459*(7248), 829–832.

Nordhaus, William. (2014) Estimates of the social cost of carbon: Concepts and results from the dice-2013r model and alternative approaches. *Journal of the Association of Environmental and Resource Economists*, *1*(1/2), 273–312.

Nordhaus, William and Sztorc, Paul. (2013) Dice 2013r: Introduction and user's manual. *Yale University and the National Bureau of Economic Research, USA*.

Olijslagers, Stan and van Wijnbergen, Sweder. (2024) Discounting the future: On climate change, ambiguity aversion and epstein–zin preferences. *Environmental and Resource Economics*, 1–48.

Pástor, L'uboš, Stambaugh, Robert F, and Taylor, Lucian A. (2021) Sustainable investing in equilibrium. *Journal of Financial Economics*, *142*(2), 550–571.

Pedersen, Lasse Heje, Fitzgibbons, Shaun, and Pomorski, Lukasz. (2021) Responsible investing: The esg-efficient frontier. *Journal of Financial Economics*, *142*(2), 572–597.

Sautner, Zacharias, Van Lent, Laurence, Vilkov, Grigory, and Zhang, Ruishen. (2023) Pricing climate change exposure. *Management Science*, *69*(12), 7540–7561.

Van den Bremer, Ton S and Van der Ploeg, Frederick. (2021) The risk-adjusted carbon price. *American Economic Review*, *111*(9), 2782–2810.

Van der Beck, Philippe. (2023) Flow-driven esg returns. *Swiss Finance Institute Research Paper*, (21-71).

Weitzman, Martin L. (2014) Fat tails and the social cost of carbon. *American Economic Review*, *104*(5), 544–546.

Yoo, Paul Chinwang. (2023) *Esg investing: A tale of two preferences* [Doctoral dissertation, The University of North Carolina at Chapel Hill].

Zhang, Lu. (2005) The value premium. *The Journal of Finance*, *60*(1), 67–103.

Zhang, Shaojun. (2024) Carbon returns across the globe. *The Journal of Finance*.

Appendix A Additional Examples

To better illustrate the meanings of dirty capital and clean capital, as well as complementarity versus substitutability, this section provides real-world examples from various industries.

A.1 Complementarity

Steel Manufacturing:

This industry uses two main types of assets: blast furnaces and electric arc furnaces. Blast furnaces emit significant amounts of carbon but produce the high-purity steel required in sectors such as aerospace. Electric arc furnaces are cleaner but have limitations in controlling steel purity because of their reliance on scrap steel. These two furnace types complement each other by producing steel with different purity levels necessary for diverse end products.

Wind Turbine Manufacturing:

Producing renewable energy equipment, such as wind turbines, depends on steel mills and smelting facilities for turbine materials (dirty) and renewable energy facilities to power the manufacturing process (clean). Without either steel production or renewable energy inputs, turbine production is infeasible.

Semiconductor Manufacturing:

Semiconductor production relies on ”dirty” fabrication tools, such as lithography machines, and ”clean” facilities, such as cleanrooms. Fabrication equipment is necessary for processing silicon wafers, while cleanrooms prevent dust and temperature fluctuations from damaging microcircuitries. Production cannot proceed without either capital type.

A.2 Substitutability

Steel Manufacturing:

As noted in complementarity, blast and electric arc furnaces both produce steel. For products that do not need high-purity steel, electric arc furnaces can fully substitute for blast furnaces, resulting in reduced emissions. However, the industry continues to use blast furnaces because of factors such as installation costs and economies of scale.

Utilities:

Utility companies can use wind, water, coal, or gas to generate electricity, substituting energy sources on the basis of availability. However, high reliance on coal and gas persists due to supply constraints. For example, solely using wind energy to power New York City is infeasible because of limited local wind resources.

Transportation:

Transportation companies such as UPS and Amazon use diesel trucks (dirty) and electric trucks (clean), which can substitute each other to fulfill the same transportation function.

Building Construction:

Green building projects employ sustainable materials such as cross-laminated timber, recycled steel, and low-carbon cement alternatives to replace traditional concrete, which relies on CO_2-intensive cement production.

Appendix B Robustness of the Empirical Strategy

B.1 Other Economic Inputs

This subsection demonstrates that the empirical strategy is not contingent upon specific economic inputs within the production function. Consider a more general production function with N additional economic inputs apart from the dirty capital K_D. For simplicity, the firm and time indicators i and t are omitted. The firm's output is

$$Y = A\big(\alpha(K_D)^{\frac{\nu-1}{\nu}} + \sum_{j=1}^{N} \alpha_j K_j^{\frac{\nu-1}{\nu}}\big)^{\frac{\nu}{\nu-1}}$$

where the total production shares satisfy $\alpha + \sum_{j=1}^{N} \alpha_j = 100\%$. Taking the partial derivative with respect to K_D yields:

$$\begin{aligned}
\frac{\partial Y}{\partial K_D} &= A \cdot \frac{\nu}{\nu-1} \cdot \big(\alpha(K_D)^{\frac{\nu-1}{\nu}} + \sum_{j=1}^{N} \alpha_j K_j^{\frac{\nu-1}{\nu}}\big)^{\frac{1}{\nu-1}} \cdot \alpha \cdot \frac{\nu-1}{\nu} \cdot K_D{}^{-\frac{1}{\nu}} \\
&= A \cdot \big(\alpha(K_D)^{\frac{\nu-1}{\nu}} + \sum_{j=1}^{N} \alpha_j K_j^{\frac{\nu-1}{\nu}}\big)^{\frac{1}{\nu-1}} \cdot \alpha \cdot K_D{}^{-\frac{1}{\nu}} \\
&= A^{\frac{\nu-1}{\nu}} \cdot Y^{\frac{1}{\nu}} \cdot \alpha \cdot K_D{}^{-\frac{1}{\nu}} \\
&= \alpha \cdot A^{\frac{\nu-1}{\nu}} \cdot \big(\frac{K_D}{Y}\big)^{-\frac{1}{\nu}}
\end{aligned}$$

Rearranging both sides, I obtain equation (22) again:

$$\frac{K_D}{Y} = \alpha^{\nu} A^{\nu-1} \big(\frac{\partial Y}{\partial K_D}\big)^{-\nu}$$

B.2 Other Functional Forms of Dirty Capital

This subsection shows that the estimation strategy of ν does not rely on the specific functional form between dirty capital and carbon emissions. For simplicity, I omit firm and time indicators. Consider the dirty capital as a function of carbon emissions as follows:

$$K_D = f(G)$$

Take the derivative with respect to G:

$$\frac{\partial K_D}{\partial G} = f'(G)$$

Plugging into equation (22), I obtain

$$\begin{aligned}\frac{f(G)}{Y} &= \alpha^{\nu} A^{\nu-1} \left(\frac{\partial Y}{\partial K_D}\right)^{-\nu} \\ &= \alpha^{\nu} A^{\nu-1} \left(\frac{\partial Y}{\partial G}\frac{\partial G}{\partial K_D}\right)^{-\nu} \\ &= \alpha^{\nu} A^{\nu-1} \left(\frac{\partial Y}{\partial G} \cdot \frac{1}{f'(G)}\right)^{-\nu}\end{aligned}$$

The left-hand side can be rewritten as

$$\frac{f(G)}{Y} = \frac{G}{Y} \cdot \frac{f(G)}{G}$$

Then, I obtain

$$\frac{G}{Y} = \frac{G}{f(G)} \alpha^{\nu} A^{\nu-1} \left(\frac{\partial Y}{\partial G} \cdot \frac{1}{f'(G)}\right)^{-\nu}$$

Take the log on both sides, add back the firm and time indicators, and assume that $A^{\nu-1}$ can be captured by firm and time fixed effects

$$\ln\left(\frac{G_{it}}{Y_{it}}\right) = a - \nu \cdot \ln\left(\frac{\partial Y_{it}}{\partial G_{it}}\right) + u_i + u_t + u_{it} \tag{46}$$

where $a = \ln(G_{it}) - \ln(f(G_{it})) + \nu \ln(\alpha) + \nu \ln(f'(G_{it}))$

Equation (46) shows that the specific functional form of $f(\cdot)$ does not affect the estimation of the coefficient ν, but affects the information in the intercept a. The intercept is a nonlinear function of other parameters and carbon emissions. In the next two subsections, I show how the results change given different functional forms of $f(\cdot)$.

B.2.1 Linear Function

In Section 3, I assume $G = \eta K_D$. Equivalently, $K_D = \frac{G}{\eta}$. Then, plugging the functional form into equation (46), I obtain

$$\begin{aligned} a &= \ln(G_{it}) - \ln\left(\frac{G_{it}}{\eta}\right) + \nu \ln(\alpha) + \nu \ln\left(\frac{1}{\eta}\right) \\ &= \nu \ln(\alpha) + (1-\nu)\ln(\eta) \end{aligned}$$

In this case, the intercept is a function of the elasticity of substitution ν, the productivity share of dirty capital α, and the carbon emission intensity η.

B.2.2 Power Function

Suppose that $K_D = G^b$. Then, plugging the functional form into equation (46), I obtain

$$\begin{aligned} a &= \ln(G_{it}) - \ln(G_{it}^b) + \nu \ln(\alpha) + \nu \ln(b \cdot G_{it}^{b-1}) \\ &= (1-\nu)(1-b)\ln(G_{it}) + \nu \ln(\alpha) + \nu \ln(b) \end{aligned}$$

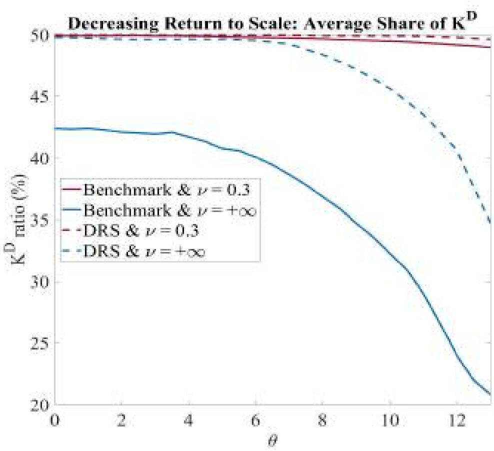
In this case, the intercept is a function of the elasticity of substitution ν, the productivity share of dirty capital α, the carbon emission intensity η, the parameter b that governs the functional form of $f(\cdot)$, and the carbon emissions G.

Appendix C Other Comparative Statics

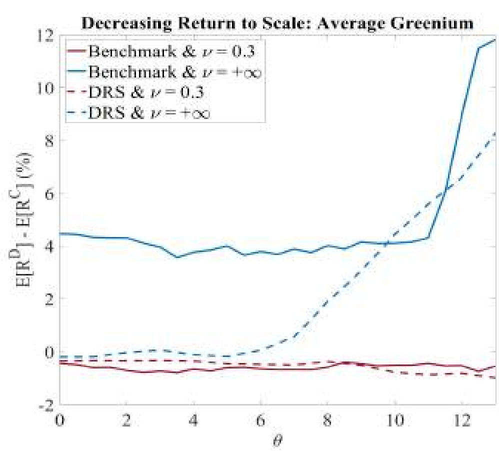
This section reports other comparative statics that are not reported in the main text. The goal is to show how other economic forces interact with the complementarity between dirty capital and clean capital, and how this interaction affects the ratio of dirty capital and the greenium.

C.1 Decreasing Return to Scale

In the benchmark results, the CES production function Φ_t has constant returns to scale ($\mu = 1$). However, previous studies have documented evidence of production functions with decreasing returns to scale (Basu and Fernald, 1997; Lashkari et al., 2024). In this comparative static analysis, I report results with a lower degree of homogeneity of the production function, $\mu = 0.9$. The results are qualitatively the same when μ is even lower. Alternatively, this exercise shows the effects of increasing returns to scale, if the benchmark is when $\nu = 0.9$.



(a) Ratio of Dirty Capital



(b) Greenium

Figure C.1: Ratio of dirty capital and the greenium with decreasing return to scale ($\mu = 0.9$). This figure shows the ratio of dirty capital and the greenium with respect to different prices of the carbon emission shock, θ, under two scenarios of substitutability. For each θ, the price of the productivity shock, γ, is selected to generate an average annualized equity premium that is closest to 8%. The ratio is defined as the dirty capital level scaled by the total capital level (clean plus dirty), $K_D/(K_C + K_D)$. When the two types of capital are complementary, $\nu = 0.3$. When the two types of capital are perfect substitutes, $\nu = +\infty$. The benchmark results are plotted as solid lines, and the results with decreasing return to scale are plotted as dashed lines.

Figure C.1 shows the impacts of sustainable investors on the ratio of dirty capital (Panel (a)) and the greenium (Panel (b)). The results with perfect substitution (complementarity) are plotted in blue (red). The benchmark results are plotted as solid lines, and results with decreasing returns to scale are plotted as dashed lines.

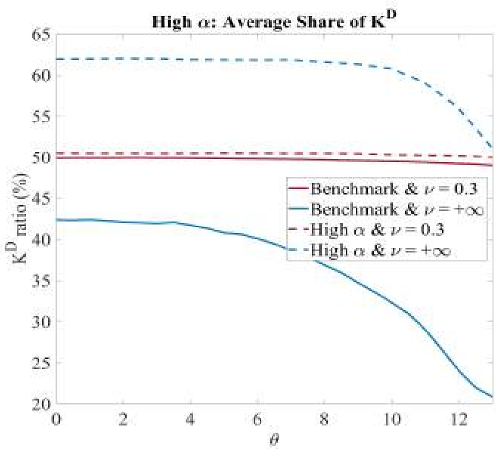
The effects of sustainable investors are qualitatively the same. Higher emission concern (higher θ) is associated with less allocation toward dirty capital (lower K_D ratio) and a greater greenium. However, the feature of decreasing returns to scale discourages the accumulation of clean capital. The intuition is straightforward. Conditional on a certain level of emission aversion (θ), marginally more clean capital generates less output when the production function has decreasing returns to scale. Because the firm maximizes its equity value, it rationally increases the share of dirty capital compared with the scenario with constant returns to scale. As a result, the optimal share of dirty capital is greater in both the complementarity and perfect substitution scenarios. The effect is especially salient when there is no emission aversion ($\theta = 0$). The firm almost chooses a balanced allocation between clean capital and dirty capital.

A higher ratio of dirty capital reduces the greenium. According to equation (33), the expected marginal return on dirty investment depends on its marginal contribution to equity value. With decreasing returns to scale, the marginal contribution to equity value becomes lower when there is a higher level of dirty capital. Additionally, more dirty capital reduces the expected return by increasing the temperature. Taken together, this reduces the greenium compared with the benchmark results.

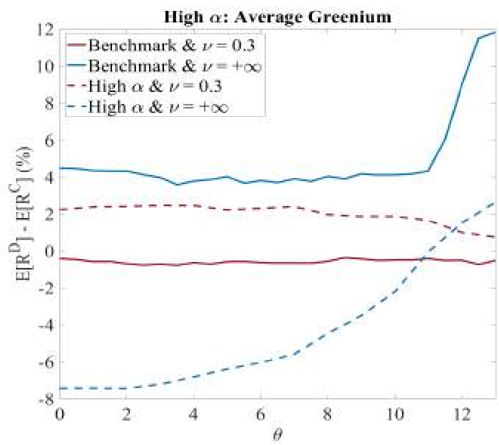
C.2 Higher Productivity Share of Dirty Capital

In Section 5, I show the effects when we lower the productivity share of dirty capital. In this section, I explore the effects on the ratio of dirty capital and the greenium if we increase the share of dirty capital.

Figure C.2 shows the results when dirty capital plays a smaller role. The economic mechanisms are the same, but the results are the opposite of those in the case in which dirty capital is less productive. When dirty capital is more productive than clean capital, the optimal share of dirty capital becomes greater. Because of the flexibility to substitute between clean capital and dirty capital, productivity motivation dominates if the sustainability concern is not strong enough. Similar to the results in Section 5, the effects are stronger when the two types of capital are perfect substitutes.



(a) Ratio of Dirty Capital



(b) Greenium

Figure C.2: Ratio of dirty capital and the greenium with a high productivity share of dirty capital ($\alpha = 0.55$). This figure shows the ratio of dirty capital and the greenium with respect to different prices of the carbon emission shock, θ, under two scenarios of substitutability. For each θ, the price of the productivity shock, γ, is selected to generate an average annualized equity premium that is closest to 8%. The ratio is defined as the dirty capital level scaled by the total capital level (clean plus dirty), $K_D/(K_C + K_D)$. When the two types of capital are complementary, $\nu = 0.3$. When the two types of capital are perfect substitutes, $\nu = +\infty$. The benchmark results are plotted as solid lines and the results with high productivity share of dirty capital are plotted as dashed lines.

The results for the greenium follow similar economic intuitions as those of the previous comparative statics in Section 5. In the perfect substitution scenario, a significantly higher level of dirty capital lowers the expected marginal return on dirty investment, dragging down the greenium. The results in the complementarity scenario are more complicated. There are two contradicting channels: a higher level of dirty capital is associated with lower marginal dirty investment returns, whereas a higher productivity share generates higher marginal investment benefits and returns. The results indicate that the productivity channel dominates and produces a greater greenium because the level of dirty capital when $\alpha = 0.55$ is not very different from that in the scenario where $\alpha = 0.5$.

Appendix D Additional Tables

Table D.1: Data Variable Definition

This table lists the data variable names, sources, identifiers in the original data source (ID), and descriptions.

Name	Source	ID	Description
GHG Scope 1	Trucost	di_319413	Greenhouse gas (GHG) emissions from sources that are owned or controlled by the company (categorised by the greenhouse gas protocol)
GHG Scope 2	Trucost	di_319414	Greenhouse gas (GHG) emissions from the consumption of purchased electricity, heat, or steam by the company (categorized by the greenhouse gas protocol). Emissions are calculated using a location-based methodology i.e. using grid emission factors for each region.
GHG Scope 3 Upstream	Trucost	di_319415	Greenhouse gas (GHG) emissions from other upstream activities not covered in scope 2 (categorised by the greenhouse gas protocol)
GHG Scope 3 Downstream	Trucost	di_326737	Total downstream indirect greenhouse gas (GHG) emissions associated with the use of sold goods and services
Total Revenue	Trucost	di_319522	For holding companies, revenue is calculated by apportioning each subsidiary's revenue plus adding dividend, share of equity profits and gain on derivatives. For all other companies the value derives from CIQ data.
Total Asset	Compustat	AT	Total value of assets reported on the Balance Sheet
Property, Plant and Equipment (Gross)	Compustat	PPEGT	The cost and/or valuation of tangible fixed assets used in the production of revenue
Property, Plant and Equipment (Net)	Compustat	PPENT	The cost, less accumulated depreciation, of tangible fixed property used in the production of revenue
Intangible Capital	Peters & Taylor	K_INT	Replacement cost of firms intangible capital

Table D.2: Estimates of ν with Financial Firms

Estimates of ν, the degree of substitution of dirty capital, including financial firms (SIC code 6000 - 6999). The estimates follow equations (26) and (27). Proxies for carbon emissions, G, include Scope 1, 2, and 3. The 2-, 3-, and 4-digit SIC codes are used to classify sectors to estimate equation (28) and the marginal productivity of carbon emission, $\frac{\partial Y}{\partial G}$. The dependent variable is $\Delta\ln(G/Y)$ if the independent variable is $\Delta\ln(\frac{\partial Y}{\partial G})$; the dependent variable is $\ln(G/Y)$ if the independent variable is $\ln(\frac{\partial Y}{\partial G})$. Standard errors are clustered by firm and reported in parentheses.

	2-digit SIC		3-digit SIC		4-digit SIC	
Panel A: Scope 1						
$\Delta\ln(\frac{\partial Y}{\partial G})$	0.232***		0.169***		0.151***	
	(0.006)		(0.005)		(0.005)	
$\ln(\frac{\partial Y}{\partial G})$		0.383***		0.296***		0.263***
		(0.010)		(0.010)		(0.010)
Constant	-0.049***	1.111***	-0.046***	1.437***	-0.044***	1.571***
	(0.001)	(0.036)	(0.001)	(0.032)	(0.002)	(0.032)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.29	0.96	0.21	0.97	0.18	0.97
N	28650	35436	22685	29194	19575	25633
Panel B: Scope 2						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta\ln(\frac{\partial Y}{\partial G})$	0.232***		0.179***		0.164***	
	(0.006)		(0.005)		(0.005)	
$\ln(\frac{\partial Y}{\partial G})$		0.421***		0.369***		0.362***
		(0.011)		(0.012)		(0.013)
Constant	-0.045***	1.128***	-0.048***	1.343***	-0.048***	1.349***
	(0.001)	(0.041)	(0.001)	(0.042)	(0.001)	(0.045)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.36	0.92	0.31	0.92	0.30	0.92
N	30832	37332	24438	30737	20556	26528
Panel C: Scope 3						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta\ln(\frac{\partial Y}{\partial G})$	0.418***		0.397***		0.368***	
	(0.006)		(0.008)		(0.008)	
$\ln(\frac{\partial Y}{\partial G})$		0.507***		0.513***		0.500***
		(0.007)		(0.010)		(0.010)
Constant	0.022***	2.081***	0.034***	2.150***	0.040***	2.205***
	(0.001)	(0.037)	(0.002)	(0.052)	(0.002)	(0.054)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.64	0.93	0.62	0.91	0.59	0.90
N	32420	38662	26266	32204	22498	28117

Table D.3: Estimates of ν using PPEGT

This table presents the estimates of ν, the degree of substitution of dirty capital, following equations (26) and (27). In equation (28), the total asset is replaced by property, plant, and equipment (gross). Proxies for carbon emissions, G, include Scope 1, 2, and 3. The 2-, 3-, and 4-digit SIC codes are used to classify sectors to estimate equation (28) and the marginal productivity of carbon emissions, $\frac{\partial Y}{\partial G}$. The dependent variable is $\Delta \ln(G/Y)$ if the independent variable is $\Delta \ln(\frac{\partial Y}{\partial G})$. The dependent variable is $\ln(G/Y)$ if the independent variable is $\ln(\frac{\partial Y}{\partial G})$. Standard errors are clustered by firm and reported in parentheses.

	Panel A: Scope 1					
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.200***		0.161***		0.132***	
	(0.006)		(0.006)		(0.006)	
$\ln(\frac{\partial Y}{\partial G})$		0.356***		0.284***		0.253***
		(0.017)		(0.013)		(0.014)
Constant	-0.047***	1.738***	-0.043***	2.160***	-0.039***	2.385***
	(0.001)	(0.073)	(0.002)	(0.053)	(0.002)	(0.059)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.23	0.95	0.19	0.95	0.15	0.96
N	25194	31497	19860	25902	16523	22279
	Panel B: Scope 2					
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.269***		0.183***		0.165***	
	(0.007)		(0.006)		(0.006)	
$\ln(\frac{\partial Y}{\partial G})$		0.462***		0.373***		0.357***
		(0.015)		(0.015)		(0.015)
Constant	-0.044***	1.214***	-0.041***	1.565***	-0.041***	1.634***
	(0.001)	(0.057)	(0.002)	(0.054)	(0.002)	(0.056)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.36	0.87	0.27	0.88	0.26	0.87
N	27856	33767	21618	27537	17970	23572
	Panel C: Scope 3					
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.402***		0.332***		0.290***	
	(0.007)		(0.008)		(0.008)	
$\ln(\frac{\partial Y}{\partial G})$		0.559***		0.530***		0.512***
		(0.009)		(0.012)		(0.012)
Constant	0.016***	2.000***	0.034***	2.261***	0.040***	2.371***
	(0.001)	(0.053)	(0.002)	(0.066)	(0.002)	(0.070)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.64	0.93	0.58	0.91	0.54	0.90
N	30523	36174	24606	30069	20690	25879

Table D.4: Estimates of ν using PPENT

This table presents the estimates of ν, the degree of substitution of dirty capital, following equations (26) and (27). In equation (28), the total asset is replaced by property, plant, and equipment (net). Proxies for carbon emissions, G, include Scope 1, 2, and 3. The 2-, 3-, and 4-digit SIC codes are used to classify sectors to estimate equation (28) and the marginal productivity of carbon emissions, $\frac{\partial Y}{\partial G}$. The dependent variable is $\Delta \ln(G/Y)$ if the independent variable is $\Delta \ln(\frac{\partial Y}{\partial G})$. The dependent variable is $\ln(G/Y)$ if the independent variable is $\ln(\frac{\partial Y}{\partial G})$. Standard errors are clustered by firm and reported in parentheses.

	2-digit SIC		3-digit SIC		4-digit SIC	
Panel A: Scope 1						
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.235***		0.178***		0.145***	
	(0.006)		(0.006)		(0.006)	
$\ln(\frac{\partial Y}{\partial G})$		0.395***		0.311***		0.254***
		(0.015)		(0.011)		(0.012)
Constant	-0.047***	1.588***	-0.044***	2.046***	-0.040***	2.388***
	(0.001)	(0.065)	(0.002)	(0.046)	(0.002)	(0.048)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.28	0.96	0.22	0.95	0.18	0.96
N	26807	33005	20460	26578	17197	23031
Panel B: Scope 2						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.284***		0.185***		0.176***	
	(0.007)		(0.006)		(0.006)	
$\ln(\frac{\partial Y}{\partial G})$		0.489***		0.387***		0.387***
		(0.014)		(0.014)		(0.015)
Constant	-0.045***	1.136***	-0.043***	1.516***	-0.042***	1.522***
	(0.001)	(0.053)	(0.001)	(0.052)	(0.002)	(0.055)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.38	0.88	0.28	0.88	0.28	0.88
N	28744	34707	22183	28154	18272	23945
Panel C: Scope 3						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.459***		0.358***		0.330***	
	(0.007)		(0.008)		(0.008)	
$\ln(\frac{\partial Y}{\partial G})$		0.603***		0.549***		0.537***
		(0.007)		(0.011)		(0.012)
Constant	0.011***	1.768***	0.030***	2.169***	0.034***	2.233***
	(0.001)	(0.044)	(0.002)	(0.064)	(0.002)	(0.069)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.68	0.94	0.60	0.92	0.58	0.91
N	30890	36511	24976	30429	20902	26158

Table D.5: Estimates of ν using PPEGT and Intangible

This table presents the estimates of ν, the degree of substitution of dirty capital, following equations (26) and (27). In equation (28), the total asset is replaced by the sum of property, plant, and equipment (gross) and intangible capital. Proxies for carbon emissions, G, include Scope 1, 2, and 3. The 2-, 3-, and 4-digit SIC codes are used to classify sectors to estimate equation (28) and the marginal productivity of carbon emissions, $\frac{\partial Y}{\partial G}$. The dependent variable is $\Delta \ln(G/Y)$ if the independent variable is $\Delta \ln(\frac{\partial Y}{\partial G})$. The dependent variable is $\ln(G/Y)$ if the independent variable is $\ln(\frac{\partial Y}{\partial G})$. Standard errors are clustered by firm and reported in parentheses.

Panel A: Scope 1						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.182***		0.148***		0.128***	
	(0.006)		(0.006)		(0.006)	
$\ln(\frac{\partial Y}{\partial G})$		0.356***		0.282***		0.252***
		(0.016)		(0.016)		(0.018)
Constant	-0.042***	1.702***	-0.037***	2.169***	-0.031***	2.396***
	(0.002)	(0.071)	(0.002)	(0.070)	(0.002)	(0.079)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.23	0.95	0.17	0.96	0.16	0.96
N	22569	28582	17242	22894	14356	19552
Panel B: Scope 2						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.225***		0.157***		0.146***	
	(0.007)		(0.006)		(0.006)	
$\ln(\frac{\partial Y}{\partial G})$		0.435***		0.368***		0.349***
		(0.015)		(0.015)		(0.016)
Constant	-0.022***	1.269***	-0.013***	1.588***	-0.014***	1.681***
	(0.001)	(0.061)	(0.002)	(0.059)	(0.002)	(0.062)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.28	0.87	0.21	0.87	0.19	0.87
N	24913	30588	19059	24611	15365	20553
Panel C: Scope 3						
	2-digit SIC		3-digit SIC		4-digit SIC	
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.339***		0.293***		0.259***	
	(0.007)		(0.007)		(0.007)	
$\ln(\frac{\partial Y}{\partial G})$		0.490***		0.508***		0.483***
		(0.009)		(0.013)		(0.014)
Constant	0.024***	2.314***	0.042***	2.335***	0.046***	2.491***
	(0.001)	(0.051)	(0.002)	(0.073)	(0.002)	(0.077)
Firm Fixed	N	Y	N	Y	N	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.63	0.93	0.58	0.90	0.56	0.89
N	27177	32443	21501	26548	17985	22761

Table D.6: Estimates of ν with Time-Varying Interactive Fixed Effect

This table presents the estimates of ν, the degree of substitution of dirty capital, following equation (26). The benchmark setting, the separate firm and time fixed effects are replaced by time-varying interactive fixed effects, following Bai (2009). Proxies for carbon emissions, G, include Scopes 1, 2, and 3. The 2-, 3-, and 4-digit SIC codes are used to classify sectors to estimate equation (28) and the marginal productivity of carbon emissions, $\frac{\partial Y}{\partial G}$. The dependent variable is $\ln(G/Y)$, and the independent variable is $\ln(\frac{\partial Y}{\partial G})$. The estimates and standard errors (in parentheses) are bootstrapped from 10,000 iterations.

	2-digit SIC			3-digit SIC			4-digit SIC		
Panel A: Scope 1									
	1	5	10	1	5	10	1	5	10
$\ln(\frac{\partial Y}{\partial G})$	0.682	0.676	0.685	0.709	0.710	0.729	0.716	0.717	0.721
	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)	(0.009)	(0.004)	(0.006)	(0.012)
Constant	0.156	0.213	0.212	0.249	0.275	0.240	0.337	0.356	0.388
	(0.015)	(0.020)	(0.029)	(0.017)	(0.024)	(0.038)	(0.018)	(0.026)	(0.055)
Panel B: Scope 2									
	2-digit SIC			3-digit SIC			4-digit SIC		
	1	5	10	1	5	10	1	5	10
$\ln(\frac{\partial Y}{\partial G})$	0.548	0.542	0.534	0.543	0.547	0.541	0.545	0.553	0.546
	(0.005)	(0.010)	(0.013)	(0.006)	(0.011)	(0.016)	(0.006)	(0.009)	(0.018)
Constant	0.741	0.766	0.771	0.886	0.851	0.856	0.908	0.852	0.865
	(0.020)	(0.046)	(0.056)	(0.023)	(0.050)	(0.067)	(0.023)	(0.044)	(0.070)
Panel C: Scope 3									
	2-digit SIC			3-digit SIC			4-digit SIC		
	1	5	10	1	5	10	1	5	10
$\ln(\frac{\partial Y}{\partial G})$	0.597	0.562	0.526	0.610	0.535	0.466	0.598	0.519	0.450
	(0.003)	(0.005)	(0.008)	(0.005)	(0.008)	(0.013)	(0.006)	(0.008)	(0.015)
Constant	1.629	1.826	2.046	1.711	2.088	2.474	1.798	2.162	2.574
	(0.019)	(0.027)	(0.045)	(0.027)	(0.040)	(0.073)	(0.031)	(0.041)	(0.079)

Table D.7: Estimates of ν by Country

This table presents the estimates of ν by country. GHG1 and GHG2 represent Scope 1 and Scope 2 carbon emissions, respectively. SIC3 and SIC4 correspond to the 3-digit and 4-digit SIC codes, respectively. The average column shows the average across four different carbon emissions and SIC code classifications.

Panel A: Developed Markets					
Country	GHG1 SIC3	GHG1 SIC4	GHG2 SIC3	GHG2 SIC3	Average
Australia	0.441	0.503	0.291	0.119	0.338
Canada	0.308	0.275	0.457	0.454	0.374
Denmark	0.459	0.397	0.637	0.524	0.504
France	0.592	0.120	0.176	0.309	0.299
Germany	0.286	0.326	0.304	0.209	0.281
Hong Kong	0.273	0.135	0.626	0.467	0.375
Ireland	0.207	0.139	0.218	0.108	0.168
Israel	0.396	0.287	0.207	0.176	0.267
Italy	0.312	0.372	0.329	0.213	0.307
Japan	0.023	0.016	0.110	0.044	0.048
Netherlands	0.275	0.324	0.310	0.284	0.298
Norway	0.251	0.198	0.063	0.063	0.144
Singapore	0.085	0.115	0.087	0.124	0.103
Spain	0.207	0.134	0.158	0.126	0.156
Sweden	0.099	0.152	0.258	0.233	0.186
Switzerland	0.311	0.133	0.370	0.357	0.293
United Kingdom	0.293	0.233	0.374	0.390	0.323
United States	0.276	0.246	0.330	0.326	0.295
Panel B: Emerging Markets					
Argentina	0.379	0.350	0.520	0.504	0.438
Bermuda	0.286	0.327	0.362	0.377	0.338
Brazil	0.301	0.378	0.626	0.677	0.496
Chile	0.047	0.008	0.424	0.502	0.245
China	0.327	0.313	0.373	0.356	0.342
Greece	0.330	0.330	1.328	1.328	0.829
India	0.329	0.116	0.264	0.131	0.210
Indonesia	-0.001	-0.006	-0.044	-0.019	-0.017
Jersey	1.106	0.737	0.841	1.370	1.014
Luxembourg	0.493	0.527	0.494	0.396	0.478
Mexico	0.450	0.540	0.236	0.224	0.363
Peru	0.182	0.173	-0.532	-0.515	-0.173
Russia	-0.177	0.281	0.469	0.027	0.150
South Africa	0.359	0.329	0.611	0.563	0.465
South Korea	0.206	0.045	0.568	0.572	0.348
Taiwan	0.241	0.041	0.343	0.345	0.243

Table D.8: Estimates of ν By Industry

This table presents the estimates of ν, the degree of substitution of dirty capital, by industries. Panel A presents estimates from the original equation (26). Panel B presents estimates from the first difference equation (27). The carbon emissions of Scope 1 (GHG1), Scope 2 (GHG2), and Scope 3 (GHG3) are used to proxy carbon emissions G. The 2-, 3-, and 4-digit SIC codes (SIC2, SIC3, SIC4) are used to classify sectors to estimate equation (28) and the marginal productivity of carbon emissions $\frac{\partial Y}{\partial G}$. Industry classification follows the ten industry classifications from Ken French's Website. The ID column indicates the industry ID: 1-consumer nondurables, 2-consumer durables, 3-manufacturing, 4-energy, 5-hightech, 6-telecom, 7-shops, 8-health, 9-utilities, 10-others. The average column (row) represents the average across different carbon emissions and industry classifications (industries).

Panel A: Original Equation (26)										
ID	GHG1 SIC2	GHG1 SIC3	GHG1 SIC4	GHG2 SIC2	GHG2 SIC3	GHG2 SIC4	GHG3 SIC2	GHG3 SIC3	GHG3 SIC4	Average
1	0.33	0.13	0.09	0.13	0.15	0.15	0.17	0.07	0.08	0.14
2	0.26	0.18	0.15	0.23	0.19	0.16	0.31	0.30	0.15	0.21
3	0.32	0.18	0.16	0.27	0.14	0.10	0.39	0.21	0.16	0.21
4	0.13	0.27	0.27	0.36	0.36	0.31	0.59	0.68	0.67	0.40
5	0.54	0.42	0.36	0.43	0.38	0.29	0.60	0.50	0.40	0.44
6	0.32	0.14	0.18	0.41	0.25	0.20	0.54	0.22	0.15	0.27
7	0.23	0.16	0.17	0.21	0.12	0.14	0.41	0.34	0.25	0.22
8	0.54	0.40	0.34	0.48	0.42	0.37	0.43	0.56	0.47	0.45
9	0.49	0.36	0.29	0.63	0.59	0.62	0.44	0.31	0.31	0.45
10	0.32	0.22	0.15	0.34	0.24	0.25	0.36	0.29	0.29	0.27
Average	0.35	0.25	0.22	0.35	0.28	0.26	0.42	0.35	0.29	
Panel B: First Difference (27)										
1	0.16	0.04	-0.01	0.11	0.08	0.11	0.12	0.02	0.01	0.07
2	0.21	0.09	0.10	0.17	0.13	0.09	0.32	0.24	0.13	0.16
3	0.17	0.09	0.09	0.19	0.07	0.08	0.30	0.14	0.09	0.13
4	0.05	0.16	0.16	0.19	0.23	0.18	0.11	0.55	0.53	0.24
5	0.40	0.31	0.21	0.35	0.27	0.18	0.53	0.44	0.36	0.34
6	0.17	0.05	0.06	0.22	0.12	0.11	0.48	0.14	0.08	0.16
7	0.09	0.06	0.08	0.10	0.07	0.08	0.33	0.25	0.19	0.14
8	0.38	0.28	0.26	0.39	0.32	0.28	0.46	0.47	0.40	0.36
9	0.33	0.23	0.20	0.46	0.44	0.45	0.33	0.20	0.19	0.31
10	0.18	0.13	0.11	0.18	0.11	0.10	0.25	0.17	0.16	0.15
Average	0.21	0.14	0.12	0.23	0.18	0.16	0.32	0.26	0.21	

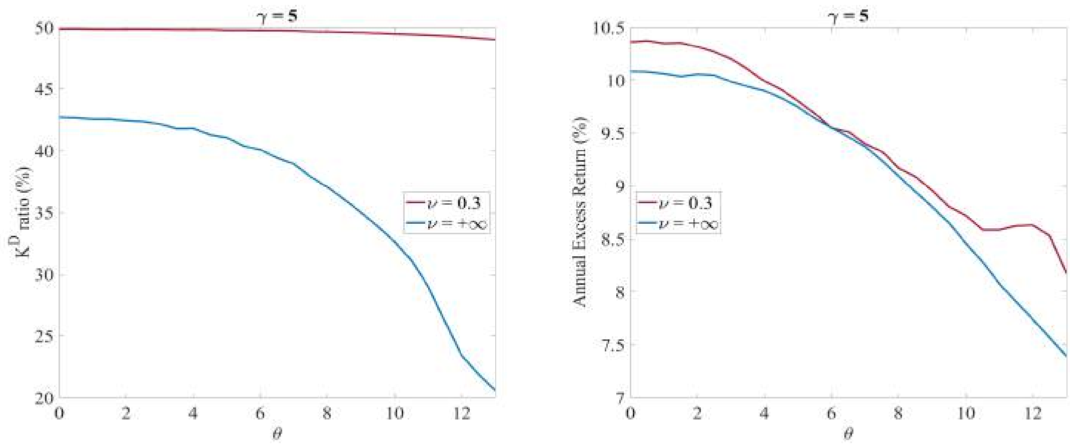
Table D.9: Estimates of ν Before and After the Year 2016

This table presents the subsample estimates of ν, the degree of substitution of dirty capital, following equations (26) and (27). The sample is split by the year 2016. The time period before the year 2016 is denoted by ≤ 2016. The time period after the year 2016 is denoted by > 2016. Proxies for carbon emissions, G, include Scope 1 and 2. The 3- and 4-digit SIC codes are used to classify sectors to estimate equation (28) and the marginal productivity of carbon emissions, $\frac{\partial Y}{\partial G}$. The dependent variable is $\Delta \ln(G/Y)$ if the independent variable is $\Delta \ln\left(\frac{\partial Y}{\partial G}\right)$. The dependent variable is $\ln(G/Y)$ if the independent variable is $\ln\left(\frac{\partial Y}{\partial G}\right)$. Standard errors are clustered by firm and reported in parentheses.

Panel A: Scope 1								
	3-digit SIC				4-digit SIC			
	<=2016	>2016	<=2016	>2016	<=2016	>2016	<=2016	>2016
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.081***	0.219***			0.078***	0.191***		
	(0.007)	(0.008)			(0.007)	(0.009)		
$\ln(\frac{\partial Y}{\partial G})$			0.175***	0.335***			0.155***	0.308***
			(0.012)	(0.014)			(0.013)	(0.016)
Constant	-0.036***	-0.052***	2.663***	1.663***	-0.029***	-0.052***	2.900***	1.849***
	(0.003)	(0.002)	(0.055)	(0.056)	(0.003)	(0.003)	(0.058)	(0.062)
Firm Fixed	N	N	Y	Y	N	N	Y	Y
Time Fixed	Y	Y	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.10	0.29	0.96	0.96	0.11	0.24	0.97	0.96
N	5859	10231	8927	12417	4492	8845	7173	11011
z-stats	12.710		8.385		10.001		7.391	
p-value	0.000		0.000		0.000		0.000	

Panel B: Scope 2								
	3-digit SIC				4-digit SIC			
	<=2016	>2016	<=2016	>2016	<=2016	>2016	<=2016	>2016
$\Delta \ln(\frac{\partial Y}{\partial G})$	0.108***	0.211***			0.107***	0.184***		
	(0.008)	(0.008)			(0.009)	(0.008)		
$\ln(\frac{\partial Y}{\partial G})$			0.318***	0.345***			0.339***	0.316***
			(0.022)	(0.017)			(0.025)	(0.019)
Constant	-0.017***	-0.065***	1.758***	1.631***	-0.012***	-0.066***	1.682***	1.735***
	(0.002)	(0.002)	(0.088)	(0.061)	(0.003)	(0.002)	(0.096)	(0.066)
Firm Fixed	N	N	Y	Y	N	N	Y	Y
Time Fixed	Y	Y	Y	Y	Y	Y	Y	Y
Adj-R-squared	0.15	0.36	0.88	0.90	0.16	0.33	0.89	0.89
N	6819	11086	9810	13129	4993	9417	7682	11486
z-stats	8.992		0.957		6.443		-0.714	
p-value	0.000		0.339		0.000		0.475	

Appendix E Additional Figures



(a) Ratio of Dirty Capital **(b)** Annual Excess Equity Return

Figure E.1: Optimal ratio of dirty capital and the annualized equity premium given the price of the productivity shock, $\gamma = 5$. This figure shows the optimal ratio of dirty capital and the annualized excess equity returns with respect to different prices of the carbon emission shock, θ, under two scenarios of substitutability. The ratio is defined as the dirty capital level scaled by the total capital level (clean plus dirty), $K_D/(K_C + K_D)$. Excess equity return is the difference between the realized equity return and the risk-free rate. When the two types of capital are complementary, $\nu = 0.3$. When the two types of capital are perfect substitutions, $\nu = +\infty$.