Financial Markets and Climate Change: Theory and Empirical Evidence of a Critical Return Threshold

Abstract

This article explores how financial market performance impacts climate change through pollution. It presents a theoretical framework analyzing the gap between private and social optima in asset allocation. Private investors focus on financial returns, neglecting environmental externalities, while social planners account for these costs to achieve sustainable outcomes. The analysis predicts a critical threshold for portfolio returns, beyond which higher returns reduce pollution due to the rising environmental costs of dirty assets. Empirical analysis examines whether investors or regulators have integrated social responsibility into their decisions, specifically if there's a critical point where increased returns lead to decreased emissions.

Using panel data from 43 countries (1990-2021), results show a nonlinear relationship between financial returns and pollution. Below a 23.8% return threshold, higher returns increase pollution; beyond this threshold, higher returns reduce pollution, indicating partial internalization of climate risks. High-income countries transition at lower returns (20.5%), while middle-income economies face higher barriers. G20 nations show a higher threshold (32.5%), whereas OECD policies have no significant effect.

Keywords: Financial market, pollution, return, volatility, environment, tax.

1 Introduction

In this article, we explore the relationship between financial market performance and pollution, a critical issue in contemporary economics and finance. Our study is set against the backdrop of a climate crisis marked by increasingly severe natural disasters, which demand the urgent attention of researchers, policymakers, and investors. Over the past few decades, the interactions between the environment and financial markets have garnered significant interest. Seminal studies, such as Flammer (2012), demonstrated that environmental initiatives can enhance firms' stock performance, while Pierpaolo Grippa (2019) highlighted the systemic risks that climate change poses to financial markets. More recently, Liang et al. (2024) analyzed the dynamic impacts of carbon markets and climate policy uncertainty on economic and financial stability in the United States, and Tedeschi et al. (2024) emphasized the rising importance of renewable energy in response to climate uncertainty in European markets.

Despite this growing body of literature, one crucial dimension remains underexplored: the direct link between financial market performance and pollution, particularly greenhouse gas (GHG) emissions. Our research seeks to fill this gap by examining the extent to which fluctuations in financial markets influence environmental degradation or improvement. Specifically, we aim to determine whether financial market performance acts as a driver of pollution reduction or, conversely, as a catalyst for its increase.

Building on the theoretical model, we now turn to empirical analysis to examine whether investors incorporate social responsibility or if regulatory mechanisms are already in place to account for the environmental impact of market returns. Specifically, we aim to analyze whether there exists a critical point of returns beyond which an increase in returns leads to a decrease in emissions. This would indicate that social responsibility is being integrated into investment decisions, although it may not necessarily be optimal. By comparing empirical results to the theoretical predictions, we aim to assess the extent to which financial markets internalize environmental externalities and the effectiveness of regulatory or voluntary mechanisms in aligning investment behavior with environmental goals.

Our empirical analysis reveals a significant nonlinear relationship between financial returns and pollution. For returns below an estimated threshold of 23.8%, increased financial returns lead to higher pollution. Beyond this threshold, higher returns result in reduced pollution levels. This finding supports the theoretical prediction of a critical threshold influencing the environmental impact of financial returns. Additionally, the disaggregated analysis provides key insights: high-income countries have a lower threshold for reducing pollution, middle-income countries require more efforts to decouple financial growth from environmental degradation, G20 countries' higher threshold highlights their significant influence on global environmental trends, and OECD countries show no significant relationship between financial performance and pollution, raising questions about the effectiveness of their policies.

This article is structured around three main sections. First, we provide a comprehensive literature review to contextualize the relationship between finance and the environment. Second, we conduct an empirical analysis that includes the specification of the econometric model, the presentation of the data and their sources, as well as the results and their discussion. Finally, we conclude by highlighting the policy implications of our findings and identifying future research opportunities.

2 Literature review

Climate change demands a profound reevaluation of economic and financial paradigms. Extreme climate events, such as persistent droughts, catastrophic floods, and devastating cyclones, are occurring with increasing frequency and intensity, threatening infrastructure stability and disrupting economic activities. These disruptions create significant systemic risks for financial markets, which manifest primarily in two forms, as highlighted by Grippa and Schmittmann (2019). Physical risks arise from direct damage to assets, infrastructure, and supply chains caused by extreme climate events. Transition risks are associated with changes in climate policies, technological innovations, and evolving consumer preferences in response to climate challenges. They are linked to the transition toward a low-carbon and resilient economy.

The magnitude of these risks threatens the viability of businesses and financial institutions, endangering global economic stability. Integrating climate risks into financial strategies and economic policies has thus become an urgent necessity. This integration enables economic and financial actors to anticipate the impacts of climate change, optimize risk management, and explore new investment opportunities in resilient and green growth sectors.

In this context, recent literature highlights the growing connection between the environment and financial markets. Liang et al. (2024) analyzed the impacts of the carbon market and climate policy uncertainty on economic and financial stability in the United States. Using a conditional network connectivity approach, their study revealed that the carbon market dynamically influences economic and financial stability, particularly through energy consumption and production structures as well as carbon emissions. While the impact of climate policy uncertainty on economic stability is generally weak, it can intensify in the long term and under extreme conditions, as observed before 2020.

Other research has also explored the effects of the carbon market and climate policy uncertainty on investor behavior. For example, Ramiah, Martin and Moosa (2013) examined the impact of environmental regulation announcements on the Australian stock market, finding that this market is particularly sensitive to the announcement of a carbon pollution reduction scheme. A similar sensitivity was observed in the French stock market, as shown in the study by Pham et al. [2020].

Moreover, Shang et al. (2022) evaluated the impact of climate policy uncertainty on the consumption of renewable and non-renewable energy in the United States using quarterly data from 2000Q1 to 2021Q3. They found that climate policy uncertainty positively affects renewable energy demand in the long term. Tedeschi et al. [2024] also investigated the impact of this uncertainty on European financial markets. Using a time-varying parameter Bayesian model (TVP-VAR), they identified a substitution relationship between fossil and renewable energy sectors: an increase in policy uncertainty leads to a rise in stock prices in the renewable energy sector and a decline in the fossil energy sector, suggesting that investors perceive climate uncertainty as a positive signal for renewable energy.

Bartolacci et al. (2018) focused on the relationship between good environmental practices and the financial performance of waste management companies in Italy. Their analysis of 45 companies showed a slight positive correlation between the rates of separate waste collection and financial performance, measured by return on assets. These findings suggest that responsible environmental practices can be compatible with enhanced financial viability.

Other studies further support these findings. Flammer (2012) found that companies adopting green initiatives experience positive stock returns. Clark et al. (2015) reviewed over 200 empirical studies, concluding that sustainable corporate management is generally positively correlated with financial performance. Thus, the literature highlights a complex but generally positive relationship between environmental initiatives and economic and financial performance. Climate policies and carbon markets play a crucial role in this relationship. Investors and policymakers must therefore consider these dynamics to promote sustainable practices while maintaining financial and economic stability.

3 Theoretical Framework

The problem of optimal asset allocation in an economy with environmental considerations can be modeled through the interaction of two types of assets in the financial market: ”dirty” assets and ”green” assets. These assets not only offer returns to the investor but also carry environmental implications, particularly in terms of emissions and pollution. This section presents a framework that incorporates these environmental externalities while accounting for the investor’s risk preferences and the social cost of pollution.

3.1 Model Setup

Let us assume that in the economy, there are two types of assets available for investment. A dirty asset (d) which are investments in firms that produce goods and services with a negative environmental impact, and green assets, which are investments in firms that produce goods and services with very low or no impact on the environment. For the sake of simplification, we will assume that investment in green assets does not generate any damage to society.

Suppose that the returns on dirty and green assets, denoted by $\tilde{R}_d$ and $\tilde{R}_g$, follow a joint distribution. The expected returns are μ_d and μ_g, respectively. The variances of the returns are σ_d^2 for dirty assets and σ_g^2 for green assets. The covariance between the returns is $\rho\sigma_d\sigma_g$. The subscripts d and g stand for dirty and green assets, respectively.

Let $w > 0$ represent the initial wealth of an investor. Let $0 \leq x \leq 1$ be the portion of the portfolio invested in dirty assets. The final wealth of the investor, denoted by $\tilde{w}$, is then a random variable given by $\tilde{w} = xw\tilde{R}_d + (1-x)w\tilde{R}_g = w\tilde{R}_w$ where $\tilde{R}_w$ is the portfolio return. Thus,

$$\tilde{R}_w = x\tilde{R}_d + (1-x)\tilde{R}_g \tag{1}$$

From Equation (1), the initial portfolio w can be normalized to 1. We assume a risk-averse investor whose utility for wealth is described by the mean-variance utility function $U(R) = E[R] - \frac{1}{2}Var(R)$, as defined by Levy and Markowitz (1979). Here, R represents the random variable for the portfolio return. The parameter $A > 0$ denotes the risk aversion coefficient. The risk aversion coefficient, A, measures the investor's tolerance for risk. A higher value of A indicates greater risk aversion, meaning the investor prefers less risk even if it results in lower expected returns.

The expected portfolio return $\mu_w = E[\tilde{R}_w]$ and the portfolio volatility $\sigma_w^2 = Var(\tilde{R}_w)$ are given after simplification by:

$$\mu_w = E[\tilde{R}_w] = x(\mu_d - \mu_g) + \mu_g \tag{2}$$

$$\sigma_w^2 = x^2(\sigma_d^2 + \sigma_g^2 - 2\rho\sigma_d\sigma_g) + 2x(\rho\sigma_d\sigma_g - \sigma_g^2) + \sigma_g^2 \tag{3}$$

The expected utility of the investor is $E[U(\tilde{R}_w)] = \mu_w - A\sigma_w^2/2$ substituting μ_w and σ_w^2 from (2) and (3) we get:

$$E[U(\tilde{R}_w)] = -\frac{1}{2}A(\sigma_d^2 + \sigma_g^2 - 2\rho\sigma_d\sigma_g)x^2 + (\mu_d - \mu_g - A(\rho\sigma_d\sigma_g - \sigma_g^2))x + \mu_g - \frac{1}{2}A\sigma_g^2. \quad (4)$$

The environmental cost of pollution is assumed to be quadratic in the level of emissions e, with the following functional form: $C(e) = \frac{1}{2}a_0 e^2$, where a_0 is a positive constant and e denotes the emissions levels, which are assumed to be proportional to the amount invested in dirty assets. For simplicity, let's assume that one dollar invested in a dirty asset generates one unit of emissions.

Let θ be a dichotomous parameter that reflects the social concern for the external cost of pollution. Specifically, $\theta = 0$ represents the private scenario where no attention is given to the externality, while $\theta = 1$ represents the social optimum, where either the regulator internalizes the external cost of pollution or private investors consider pollution and incorporate social responsibility into their objective function.

Therefore, the objective of each economic agent is to maximize the expected utility return of wealth, minus the external cost of pollution resulting from investments in dirty assets. The optimization problem can be expressed as:

$$\max_{0\leq x\leq 1} E[U(\tilde{R}_w)) - \theta C(x\tilde{R}_d)] = V(x).$$

The expected external cost is $E[C(x\tilde{R}_d)] = \frac{1}{2}a_0(\sigma_d^2 + \mu_d^2)x^2$. The optimization problem can now be expressed as:

$$\max_{0\leq x\leq 1} V(x) = -\frac{1}{2}[A(\sigma_d^2+\sigma_g^2-2\rho\sigma_d\sigma_g)+\theta a_0(\sigma_d^2+\mu_d^2)]x^2+[\mu_d-\mu_g-A(\rho\sigma_d\sigma_g-\sigma_g^2)]x+\mu_g-\frac{1}{2}A\sigma_g^2. \quad (5)$$

3.2 Results under Certainty

To fix ideas, let us briefly analyze the problem when there is no uncertainty. That means $\sigma_g^2 = \sigma_d^2 = 0$. Therefore, under private optimum, the investor will invest all their money in the asset with the higher return. Let us then assume for complexity that $\mu_d > \mu_g$. Indeed, if $\mu_g \leq \mu_d$, the solution is straightforward. It is optimal for the investor to allocate all their portfolio value to the green asset in both private and social optimum ($x^p = x^s = 0$), thus there will be no emissions.

If $\mu_d > \mu_g$, then under private optimum, $x^p = 1$, meaning that the investor invests all their money in the dirty asset. While in the social optimum, we have that: $x^s = \frac{\mu_d - \mu_g}{a_0 \mu_d^2}$. The social allocation x^s satisfies $0 < x^s < 1$ if and only if:

$$\mu_d - \mu_g < a_0 \mu_d^2. \tag{6}$$

We will assume this condition. The economic intuition is as follows: The difference $\mu_d - \mu_g$ represents the excess return of dirty assets over green assets. A larger excess return increases the incentive to invest in dirty assets. The environmental cost a_0 acts as a penalty on dirty assets. A higher a_0 reduces the attractiveness of dirty assets, pushing the social planner to allocate more investment to green assets. If a_0 is small, the environmental cost is low, and the social planner may allocate the entire portfolio to dirty assets ($x^s = 1$) because the financial return μ_d dominates. If a_0 is large, the environmental cost is high, and the social planner will limit investment in dirty assets ($x^s < 1$) to reduce pollution. Condition (6) ensures that the environmental cost a_0 is large enough to limit investment in dirty assets.

The impact of μ_d on the portfolio and thus the level of emission is given by:

$$\frac{\partial e^s}{\partial \mu_d} = \frac{\partial x^s}{\partial \mu_d} = \frac{-\mu_d + 2\mu_g}{a_0 \mu_d^3}$$

$$\frac{\partial e^s}{\partial \mu_w} = \frac{\partial x^s}{\partial \mu_w} = \frac{-\mu_d + 2\mu_g}{a_0 \mu_d^3 (\mu_d - \mu_g)}.$$

Therefore, there is a threshold value $\bar{\mu}_d = 2\mu_g$ and $\bar{\mu}_w = \mu_g + \frac{1}{4a}$ such that:

- When $\mu_d < 2\mu_g$ or $\mu_w < \bar{\mu}_w$, an increase in the portfolio return μ_w leads to an increase in the fraction invested in dirty assets (x^s). This is because the return on dirty assets is not sufficiently high to outweigh the environmental cost, so the social planner increases investment in dirty assets as the portfolio return grows.

- When $\mu_d > 2\mu_g$, an increase in the portfolio return μ_w leads to a decrease in the fraction invested in dirty assets (x^s). This is because the return on dirty assets is already high, and further increases make the environmental cost a_0 more significant, leading the social planner to reduce investment in dirty assets.

This threshold, absent in the private optimum, reflects the social planner's consideration of environmental sustainability alongside financial performance.

3.3 Results under uncertainty

Now, let's analyze the solution when the investor faces uncertainty in both assets ($\sigma_g^2 > 0$ and $\sigma_d^2 > 0$).

$V(x)$ is a quadratic and strictly concave function of x. Therefore, the first-order condition is sufficient for an interior optimal solution and is given by:
$V'(x) = -\left[A(\sigma_d^2 + \sigma_g^2 - 2\rho\sigma_d\sigma_g) + \theta a_0(\sigma_d^2 + \mu_d^2)\right] x + \left[\mu_d - \mu_g - A(\rho\sigma_d\sigma_g - \sigma_g^2)\right] = 0.$
The interior solution exists under the following condition[1]

$$A(\rho\sigma_d\sigma_g - \sigma_g^2) < \mu_d - \mu_g < A(\sigma_d^2 - \rho\sigma_d\sigma_g). \tag{7}$$

The condition (7) means the excess return of dirty assets must be at least $A(\rho\sigma_d\sigma_g - \sigma_g^2)$. If the difference $\mu_d - \mu_g$ is too small, the investor will fully allocate to green assets ($x^p = 0$) because the additional return from dirty assets does not compensate for their higher risk. The excess return must not exceed $A(\sigma_d^2 - \rho\sigma_d\sigma_g)$. If it does, the investor will fully allocate to dirty assets ($x^p = 1$), since the return is so high that the risk penalty does not outweigh the financial gain.

Now let analyze the optimal portfolio allocation. The solution under private optimum

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[1] This condition is derived by assuming that in the private optimum when $\theta = 0$, the solution x^p satisfies $0 < x^p < 1$.

$(\theta = 0)$ and the efficient portfolio allocation $(\theta = 1)$ are respectively given by

$$x^p = \frac{\mu_d - \mu_g - A(\rho\sigma_d\sigma_g - \sigma_g^2)}{A(\sigma_d^2 + \sigma_g^2 - 2\rho\sigma_d\sigma_g)} \tag{8}$$

$$x^s = \frac{\mu_d - \mu_g - A(\rho\sigma_d\sigma_g - \sigma_g^2)}{A(\sigma_d^2 + \sigma_g^2 - 2\rho\sigma_d\sigma_g) + a_0(\sigma_d^2 + \mu_d^2)} \tag{9}$$

The superscripts p and s denote the private optimum and social optimum, respectively. The optimal emissions at the private optimum and social optimum are $e^p = x^p$ and $e^s = x^s$, respectively. It follows from (8) and (9) that $x^p < x^s$. Therefore, we can state the following result,

Proposition 1 *The investment in dirty assets is higher at the private optimum than at the social optimum.*

Indeed, at the private optimum, investors do not consider the external costs of pollution. They allocate their portfolio based solely on the expected returns and risks of the assets, leading to a higher investment in dirty assets because the environmental externalities are ignored. In contrast, at the social optimum, the external costs of pollution are internalized, either through regulation or by investors incorporating social responsibility into their decision-making. This results in a lower investment in dirty assets.

Now let's analyze the characteristics of the portfolio at the optimum. We show in the appendix that

$$\frac{\partial x^p}{\partial \mu_g} < 0 \quad \text{and} \quad \frac{\partial x^s}{\partial \mu_g} < 0 \quad \Longrightarrow \quad \frac{\partial e^p}{\partial \mu_g} < 0 \quad \text{and} \quad \frac{\partial e^s}{\partial \mu_g} < 0.$$

This result shows that as the expected return of green assets (μ_g) increases, the share of investment in dirty assets (x^p and x^s) decreases. Similarly, the emissions (e^p and e^s) associated with dirty assets also decrease. A higher μ_g makes green assets more attractive, reducing the demand for dirty assets. From a societal perspective, this aligns with environmental goals as higher returns for green assets incentivize cleaner investments, thereby lowering pollution. It also follows from our result that

$$\frac{\partial x^p}{\partial \mu_d} > 0 \quad \text{and} \quad \frac{\partial e^p}{\partial \mu_d} > 0.$$

This means that, as the expected return of dirty assets (μ_d) increases, the portfolio share allocated to dirty assets (x^p) rises. This is because higher returns on dirty assets make them more financially appealing, despite their environmental costs. Consequently, emissions associated with dirty assets (e^p) also increase. This result highlights a trade-off: financial incentives can drive environmentally harmful investments unless green assets offer competitive returns. The result is different at the social optimum. It is shown in the appendix that there exist $\bar{\mu}_d$ such that $\frac{\partial x^s}{\partial \mu_d} = 0$ at $\mu_d = \bar{\mu}_d$. The sign of $\frac{\partial x^s}{\partial \mu_d}$ depends on whether $\bar{\mu}_d$ satisfies condition (7). Meaning that $\mu_{d1} = \mu_g + A(\rho\sigma_d\sigma_g - \sigma_g^2) < \bar{\mu}_d < \mu_{d2} = \mu_g + A(\sigma_d^2 - \rho\sigma_d\sigma_g)$. It is proved in the appendix that $\bar{\mu}_d > \mu_{d1}$. Notice that $\mu_{d2} - \mu_{d1} = Var((\tilde{R}_d - \tilde{R}_g)/\sqrt{A})$ with represents the variance of excess return. Now,

- If $\bar{\mu}_d < \mu_{d2}$, meaning that $Var((\tilde{R}_d - \tilde{R}_g)/\sqrt{A})$ is large

For $\mu_d < \bar{\mu}_d$, $\frac{\partial x^s}{\partial \mu_d} > 0$, an increase in μ_d leads to a higher allocation to dirty assets. For $\mu_d > \bar{\mu}_d$, $\frac{\partial x^s}{\partial \mu_d} < 0$, an increase in μ_d leads to a lower allocation to dirty assets.

- If $\bar{\mu}_d > \mu_{d2}$ meaning that $Var((\tilde{R}_d - \tilde{R}_g)/\sqrt{A})$ is small

$\frac{\partial x^s}{\partial \mu_d} > 0$ for all μ_d: An increase in μ_d always leads to a higher allocation to dirty assets. The intuition is as follows: When the variance of the excess return is large, the social planner faces significant uncertainty about the relative performance of dirty and green assets. As μ_d increases, the social planner initially increases x^s to take advantage of the higher return. However, once μ_d exceeds $\bar{\mu}_d$, the environmental cost a_0 becomes more significant, and the social planner reduces x^s to mitigate pollution. When the variance of the excess return is small, the social planner faces less uncertainty about the relative performance of dirty and green assets. As μ_d increases, the financial return dominates, and the social planner always increases x^s to maximize returns, regardless of the environmental cost.

Let now analyze the impact of market return (μ_w)on both the efficient market portfolio and efficient emissions. If μ_w increases due to a rise in μ_g, we have $\frac{\partial x^s}{\partial \mu_w} < 0$, as green assets become more attractive, reducing the share of dirty assets (x^s). If μ_w increases due to a rise in μ_d, the effect depends on μ_d relative to $\bar{\mu}_d$. If $\bar{\mu}_d < \mu_{d2}$ (variance of the excess return is large)

- For $\mu_d < \bar{\mu}_d$, $\frac{\partial x^s}{\partial \mu_w} > 0$, as dirty assets are still attractive.
- For $\mu_d > \bar{\mu}_d$, $\frac{\partial x^s}{\partial \mu_w} < 0$, as the social cost of pollution dominates the financial incentive.

The changes in emissions (e^s) follow the same pattern, as emissions are directly tied to the share of dirty assets in the portfolio. This can be summarized in the following proposition: Finally, If $\bar{\mu}_d > \mu_{d2}$ (variance of the excess return is small), then $\frac{\partial x^s}{\partial \mu_w} > 0$.

Proposition 2 *(i) At the private optimum, an increase in the total portfolio return driven by higher returns on dirty assets increases the allocation to dirty assets and emissions. While an increase in the total portfolio return driven by higher returns on green assets decreases the allocation to dirty assets and emissions.*
(ii) At the optimal social allocation, if the total portfolio return increases due to higher returns on green assets, the allocation to dirty assets and emissions always decreases, as green assets become more attractive. However, if the total portfolio return increases due to higher returns on dirty assets (μ_d), the result depends on the variance of the excess return. If it is large, social allocation suggests a threshold level for portfolio returns. Below this threshold, an increase in returns raises emissions; however, above this threshold, increases in returns result in reduced emissions. If the variance of excess return is small, then an increase in portfolio return always leads to a higher allocation to dirty assets.

The final part of the proposition is depicted in the figure below when the return on non-clean assets drives the portfolio return.

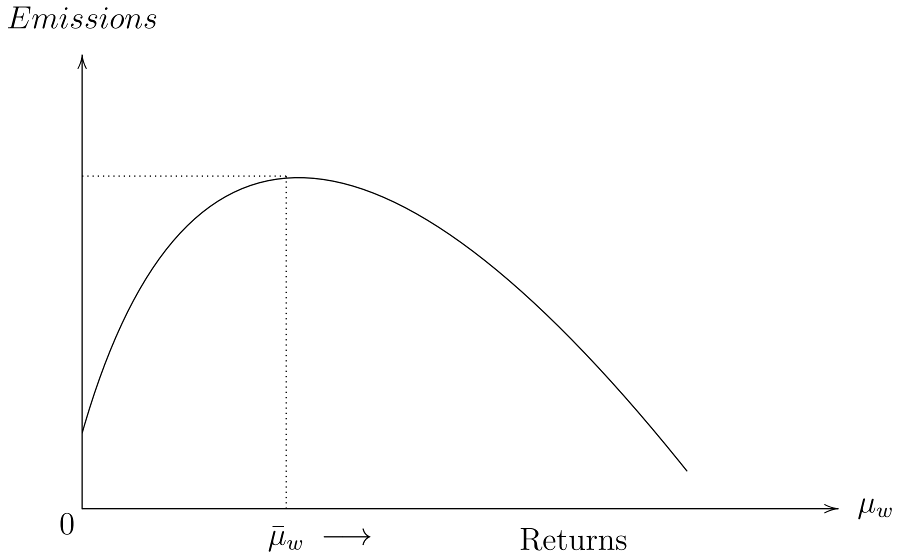

Figure 1: Relationship between efficient emissions level and portfolio returns when the variance of excess return is large

Let's examine the impact of volatility on the portfolio and thus on the level of emission. For simplicity, let's assume that

$$\sigma_d^2 = \sigma_g^2 = \sigma^2$$

. We have that

$$\begin{aligned}
\frac{\partial x^p}{\partial \sigma^2} &= \frac{-(\mu_d - \mu_g)(2A(1-\rho) + a_0)}{\left[2A(1-\rho)\sigma^2 + a_0(\sigma^2 + \mu_d^2)\right]^2} > 0 \\
\frac{\partial x^s}{\partial \sigma^2} &= \frac{a_0 A(1-\rho)\mu_d^2 - (\mu_d - \mu_g)(2A(1-\rho) + a_0)}{\left[2A(1-\rho)\sigma^2 + a_0(\sigma^2 + \mu_d^2)\right]^2}.
\end{aligned}$$

The two partial derivatives describe how the allocation to dirty assets changes with respect to the variance under the private optimum and the social planner's optimum, respectively. $\frac{\partial x^p}{\partial \sigma^2} > 0$ means that under the private optimum, a risk-averse investor increases the allocation to dirty assets as σ^2 (volatility) increases, making the dirty asset riskier. This is because safer (less volatile) investments become more attractive when volatility increases. Under the social optimum, the sign of $\frac{\partial x^s}{\partial \sigma^2}$ is ambiguous and depends on two competing effects. First, the environmental cost effect ($a_0 A(1-\rho)\mu_d^2 > 0$), which is positive, meaning that higher volatility increases the perceived risk of environmental damage. Second, the risk aversion effect $(-(\mu_d - \mu_g)(2A(1-\rho) + a_0) < 0)$, which is negative, meaning that higher volatility makes the dirty asset riskier, reducing the allocation to dirty assets. The derivative $\frac{\partial x^s}{\partial \sigma^2}$ can be positive or negative, depending on the relative strength of these effects. For instance, if the excess return $(\mu_d - \mu_g)$ is close to zero, then the environmental cost effect dominates, and thus $\frac{\partial x^s}{\partial \sigma^2} > 0$. Conversely, in the case of higher correlation, the risk aversion effect will dominate, and thus $\frac{\partial x^s}{\partial \sigma^2} < 0$.

Let's turn to the impact of correlation on portfolio allocation.

$$\begin{aligned} \frac{\partial x^p}{\partial \rho} &= \frac{\mu_d - \mu_g}{2A(1-\rho)^2\sigma^2} \\ \frac{\partial x^s}{\partial \rho} &= \frac{A\sigma^2(-a_0\sigma^2 - a_0\mu_d^2 + 2\mu_d - 2\mu_g)}{[2A(1-\rho)\sigma^2 + a_0(\sigma^2 + \mu_d^2)]^2}. \end{aligned}$$

Under the private optimum, an increase in ρ (correlation) leads to an increase in the allocation to dirty assets. This is because higher correlation reduces diversification benefits, making the higher-return dirty asset more attractive. Under the social planner's optimum, the response to ρ depends on the trade-off between financial returns and environmental costs. If the excess return $\mu_d - \mu_g$ is large enough to outweigh the environmental cost a_0, then $\frac{\partial x^s}{\partial \rho} > 0$. Otherwise, $\frac{\partial x^s}{\partial \rho} < 0$.

All of the previous can be summarized in the following proposition.

Proposition 3 *(i) The private investor always reduces allocation to dirty assets (x^p) as volatility increases due to risk aversion, while the social planner may either increase or decrease allocation (x^s) depending on the trade-off between financial returns and environmental costs. (ii) The private investor increases allocation to dirty assets (x^p) as correlation rises, whereas the social planner's response (x^s) depends on whether financial returns or environmental costs dominate. Emissions (e^p and e^s) follow the same patterns as x^p and x^s, reflecting the private investor's focus on risk and returns and the social planner's balance of economic and environmental priorities.*

3.4 Regulatory Mechanism

To ensure that a private investor's actions are aligned with the social optimum, a regulatory tax can be levied on investments in environmentally harmful assets. The tax, denoted as t, is designed so the investor opts for the socially optimal distribution. When a tax of t per unit is applied, the private investor's objective function is transformed into

$$\max_{0\leq x\leq 1} E[U(\tilde{R}_w)) - tx\tilde{R}_d)]$$

By substituting $E[U(\tilde{R}_w)]$ from equation (4) and $\mu_w = E[\tilde{R}_d]$ and applying the first-order condition, we obtain:

$$-\left[A(\sigma_d^2 + \sigma_g^2 - 2\rho\sigma_d\sigma_g) + t(\mu_d - \mu_g)\right] x + \left[\mu_d - \mu_g - t\mu_g - A(\rho\sigma_d\sigma_g - \sigma_g^2)\right] = 0.$$

The optimal tax t induces the investor to produce at the efficient allocation, thus $x = x^s$, after simplification, we get

$$t = a_0 \frac{\sigma_d^2 + \mu_d^2}{x^s\mu_d + (1 - x^s)\mu_g)} = a_0 \left(E[\tilde{R}_d] + \frac{Var[\tilde{R}_d)]}{E[\tilde{R}_d]} \right)$$

The parameter a_0 reflects the cost of environmental damage caused by dirty assets. It determines the magnitude of the tax based on the severity of environmental harm. The numerator $\sigma_d^2 + \mu_d^2$ represents the total risk (variance) and the expected return squared for dirty assets. Both return variability and expected return influence the tax rate. The denominator $x^s\mu_d + (1 - x^s)\mu_g$ accounts for the weighted average return of the portfolio, ensuring that the tax depends on the socially optimal mix of dirty and green assets in the portfolio. The simplified version of the tax, $t = a_0 \left(E[\tilde{R}_d] + \frac{\text{Var}[\tilde{R}_d]}{E[\tilde{R}_d]} \right)$ incorporates two key components. (i) The expected return ($E[\tilde{R}_d]$). The tax increases with higher expected returns on dirty assets, discouraging their overuse by raising their effective cost. (ii) Risk-adjusted cost ($\frac{\text{Var}[\tilde{R}_d]}{E[\tilde{R}_d]}$), the tax penalizes assets with higher return variability, reflecting the environmental risk associated with uncertain outcomes.

This tax ensures that the external costs of pollution are internalized, and the investor chooses an allocation that minimizes the social costs of emissions while still achieving a reasonable return on their portfolio.

4 Empirical Analysis

Building on the theoretical model, we now turn to empirical analysis to examine whether investors incorporate social responsibility or if regulatory mechanisms are already in place to account for the environmental impact of market returns. Specifically, we aim to analyze whether there exists a critical point of returns beyond which an increase in returns leads to a decrease in emissions. This would indicate that social responsibility is being integrated into investment decisions, although it may not necessarily be optimal. By comparing empirical results to the theoretical predictions, we aim to assess the extent to which financial markets internalize environmental externalities and the effectiveness of regulatory or voluntary mechanisms in aligning investment behavior with environmental goals.

4.1 Data and econometric model

The preceding theoretical model indicates a general nonlinear relationship in the form of an inverted U-shape in the financial market - pollution relationship nexus in the presence of environmental regulation in the financial market. We show that without environmental tax, the effect of the return on pollution will be positive. With an environmental tax, there exists a turning point above which this effect of the return on pollution becomes negative.

Then, we specify a non-linear empirical model as follows:

$$GHG_{it} = \alpha + \gamma_1 Return_{it} + \gamma_2 Return_{it}^2 + \gamma_3 Vol_{it} + X_{it}\theta + \mu_i + \lambda_t + \varepsilon_{it}. \tag{10}$$

The indices i and t represent countries and years, respectively. To ensure the relevance of our analysis, we focused on countries that both have well-developed financial markets and are significant polluters (high CO2 emissions) during the period from 1990 to 2021. Thus, our study examines a panel of 43 countries over this period. The dependent variable, GHG_{it}, denotes greenhouse gas emissions. The main explanatory variable is $Return_{it}$, representing returns, while Vol_{it} captures market volatility. The control variables, represented by X_{it}, include the following: economic development level, proxied by GDP; macroeconomic stability, measured through consumer price inflation; demographic factor, reflected in population density; regulatory factor, captured by a carbon tax policy dummy; and other potential determinants of pollution: renewable energy, foreign direct investment net inflow, industry share in the economy, and investment.

The model incorporates country-specific effects μ_i, time-specific effects λ_t, and idiosyncratic shocks ε_{it}.

In this model, if it exists, the turning point for the return is given by :

$$Return^* = \frac{\gamma_1}{-2\gamma_2} \tag{11}$$

where we expect that $\gamma_1 > 0$ and $\gamma_2 < 0$. Below the threshold $Return^*$, an increase in returns leads to higher pollution levels, whereas above this threshold, an increase in returns results in a reduction in pollution.

We construct the return from a financial market performance index, the MSCI (Morgan Stanley Capital International) index. MSCI is an argument financial indicator used to measure stock market performance in various regions, countries or market segments. From this daily index, we obtain the annualized return as follows using the arithmetic aggregation method :

$$Return_{it} = \prod_{j=1}^{n}(1 + r_{jit})^{\frac{1}{n}} - 1 \tag{12}$$

where the daily return $r_{jit} = \frac{MSCI_{jit}}{MSCI_{(j-1)it}} - 1$ for a day j. $MSCI_{jit}$ denotes the MSCI index for day j in country i at year t. Volatility is captured by the standard deviation of the return.

Table 1 presents the variables included in our model.

Table 1: Variables description

Variable	Definition	Unit
GHG	Greenhouse gases emission	Mt CO2e
Return	Return of MSCI index	-
Vol	Volatility of MSCI index	-
GDP	Gross Domestic Product	dollar US
dPOP	Population density	people per sq. km of land area
INFL	Inflation, consumer prices	annual %
Tax	Carbon tax policy dummy	-
Renew	Renewable energy (% final energy consumption)	%
FDI	Foreign direct investment, net inflow	% GDP
Industry	Industry Value Added Share	% GDP
Investment	Investment	% GDP

Source: MSCI is collected from https://www.msci.com/ and all others variables collected from the World Development Indicators (WDI) database of the World Bank.

4.2 Descriptive analysis

Our initial descriptive analysis focuses on examining the performance trends of the financial market, as reflected in the returns and volatility of the MSCI index. Figure 2 shows the evolution of the return and volatility of the MSCI index for the various countries in my database over the period from 1990 to 2021. Generally speaking, there is no clear trend towards an increase or decrease in these two indicators. Rather, there are significant fluctuations over the period studied. More specifically, there are volatility peaks, notably around 1998 and 2008, which correspond to periods of global financial crisis. For example, 1998 was marked by the Russian economic crisis, which led to a devaluation of the ruble, followed in 2008 by the subprime crisis. Volatility spikes are generally associated with very low or negative returns. This result is consistent with the expected behavior of financial markets, since increased uncertainty, i.e. high volatility, tends to reduce returns. The graph also shows that periods of relatively stable, positive returns are accompanied by moderate volatility. Taken together, these results show that periods of crisis highlight the vulnerability of returns to global economic and financial shocks, while periods of relative stability offer the prospect of steady gains. These two indicators can therefore be used to account for the performance of financial markets.

Figure 3 shows the overall trend in greenhouse gas (GHG) and CO2 emissions from 1990 to 2018. The general trend indicates a continuous increase in emissions, reflecting the intensity of economic activities. CO2 emissions, a type of greenhouse gas (GHG), are considered among the most significant due to their persistence in the atmosphere after being emitted. They exhibit a trend similar to that of overall GHG emissions. From 1990 to 2018, GHG emissions (for the 43 countries in the sample) increased by 50.8% over the entire period, with an average annual growth rate of 1.5%. As for CO2 emissions, they rose by 59.8% over the same period, with an average annual increase of 1.7%.

We present in Figure 4 the distribution of greenhouse gas emissions by income group. High-income countries exhibit significant emissions compared to other groups. This can be

Figure 2: Trend of return and volatility of MSCI index over time - mean across countries

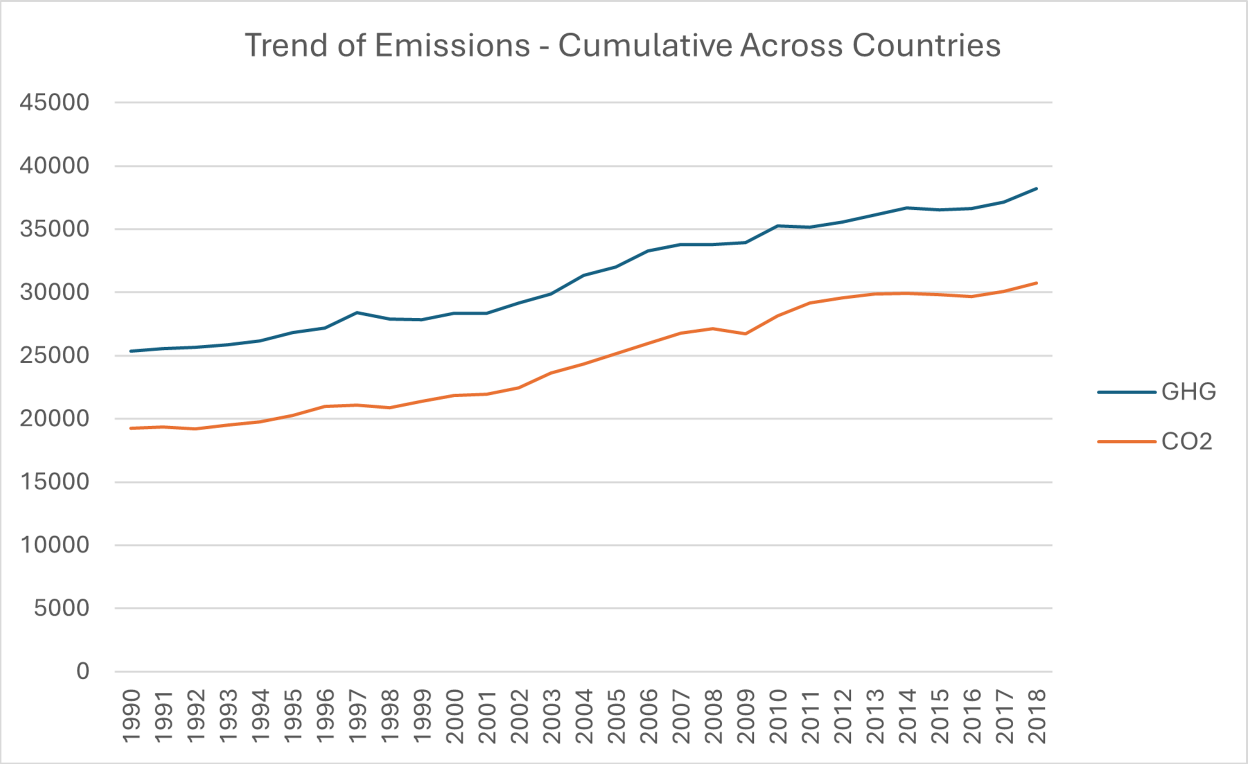

Figure 3: Total GHG Emissions Over Time (43 Countries Included)

explained by their level of development, particularly advanced industrialization and high consumption levels. Due to their intense economic activities, they are considered ”major polluters.” Similarly, upper-middle-income countries show substantial emissions, although lower than those of high-income countries. These emerging economies, often undergoing rapid industrialization and urbanization, contribute considerably to emissions. Lastly, lower-middle-income countries have low emissions, reflecting their lower level of economic activity. Considering these characteristics could prove essential for analyzing heterogeneity in the subsequent stages of our analysis.

4.3 Results and discussions

This section provides the results and discussion of our analysis. We begin with a presentation of the summary statistics for the key variables, followed by the detailed findings from our estimations.

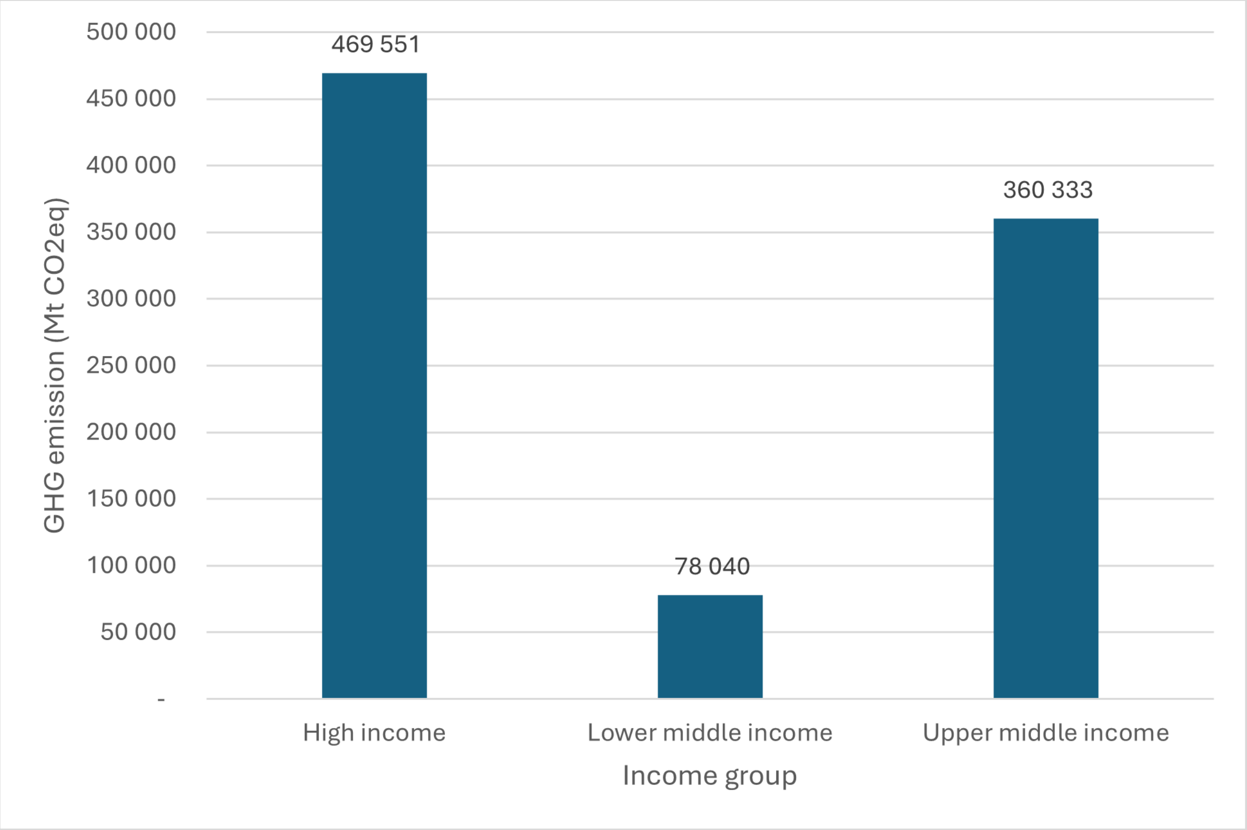

Figure 4: Cumulative GHG Emissions by Income Group (1990-2018)

Table 2 summarizes the main statistics for the different variables in our study. The average return is 0.104. This means that, over the entire study period, the financial assets analyzed generated an average positive return of 10.4%. However, this return remains highly volatile, as the standard deviation is quite substantial at 0.407. Also, the distribution of returns is highly skewed to the right (Skew = 5.42), implying that there is an occurrence, albeit rare, of extreme returns relative to the mean. Kurtosis also indicates that the distribution of returns is leptokurtic, i.e. the tails of the distribution are thicker than those of the normal distribution. This shows that there are more extreme returns (positive and negative) than would be observed in a normal distribution. For greenhouse gas emissions, we observe a significant amount of emissions between 1990 and 2021, with an average of 752.8 MtCO2e. The standard deviation shows that there is considerable variability in GHG emissions among the countries studied. This variability could be linked to the size of the economy, environmental policies, or the energy dependence of each country. As with yields, the distribution of emissions is asymmetrical to the right, reinforcing the idea of extreme emissions. The tails of the distribution are also thicker than those of the normal distribution, indicating that some emissions are well above average.

Table 3 presents the estimation results. Column (1) displays the model estimated for the entire panel, column (2) focuses on high-income countries, column (3) shows the estimations for middle-income countries, column (4) provides results for G20 countries, and the final column (5) presents estimations for OECD countries.

The global model indicates a significant nonlinear relationship between financial returns and pollution. Specifically, for returns below an estimated threshold of 23.8%, an increase in financial returns, given the level of volatility and other factors, leads to a rise in pollution. Conversely, beyond this threshold, higher financial returns result in reduced pollution levels.

The estimations based on income levels reveal that the turning point for financial returns is 20.5% for high-income countries and 21.0% for middle-income countries. For G20 countries, the threshold at which financial returns begin to reduce pollution is estimated at 32.5%,

Table 2: Summary statistics of the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
GHG	1218	752.828	1563.889	6.930	12791.580
Return	1247	0.104	0.407	-0.832	7.451
Volatility	1247	0.244	0.116	0.066	1.137
GDP (billions of dollars)	1247	2040	3560	109	28800
Infl	1247	6.07	28,20	-4.45	874.25
dPOP	1247	443.785	1384.893	2.296	7965.878
Tax	1247	0.201	0.401	0	1
Renew	1247	0.115	0.261	0.000	4.555
FDI	1247	44.646	152.808	0.475	1567.975
Industry	1247	594.857	1451.519	26.097	12717.660
Investment	1247	10.178	5.666	1.690	28.746

which is higher than the threshold obtained for the entire panel. On the other hand, the estimation for OECD countries shows no significant relationship between financial market performance and pollution.

Table 3: Estimations results (fixed effect)

	(1)	(2)	(3)	(4)	(5)
	Whole Sample	High Income	Middle Income	G20	OECD
Return	34.324**	20.797**	55.589*	52.614*	3.371
	(13.093)	(10.185)	(31.768)	(29.781)	(6.821)
Return square	-72.256**	-50.781*	-132.279	-81.041	-0.370
	(35.700)	(29.735)	(80.352)	(76.635)	(21.936)
Volatility	23.564	-1.991	53.557	47.078	3.328
	(29.536)	(25.210)	(65.727)	(67.560)	(15.076)
GDP	$2x10^{-11} * **$	$1.9x10^{-11} * **$	$-4.6x10^{-11}$	$4x10^{-12}$	$2.3x10^{-11} * **$
	$(3, 3x10^{-12})$	$(2, 2x10^{-12})$	$(6, 1x10^{-11})$	$(6, 5x10^{-12})$	$(1, 9x10^{-12})$
Inflation	0.535***	0.536***	-0.064	0.605***	0.723***
	(0.089)	(0.055)	(0.603)	(0.134)	(0.186)
Density of population	0.009	0.804***	0.014	2.977***	0.045
	(0.016)	(0.124)	(0.025)	(0.532)	(0.090)
Carbon tax	-4.256	-13.448*	28.862	-14.995	-0.351
	(9.938)	(7.319)	(28.135)	(21.542)	(4.023)
Renew consumption	82.994***	53.823**	130.828**	137.254**	-1.845
	(22.212)	(17.269)	(53.957)	(44.297)	(16.153)
FDI net entry (% GDP)	-0.595**	-0.560***	3.567**	0.773*	1.554***
	(0.236)	(0.162)	(1.811)	(0.447)	(0.292)
Industry share	0.988***	0.981***	0.624	0.842***	0.842***
	(0.029)	(0.020)	(0.439)	(0.056)	(0.016)
Investement (% GDP)	1.770	3.316**	18.843	4.445	6.104***
	(2.090)	(1.369)	(13.901)	(6.636)	(0.917)
Constante	101.618***	-87.200***	169.657**	-118.929	-21.695
	(24.289)	(26.354)	(84.148)	(87.810)	(19.487)
___Turning point estimated___	___0.238**___	___0.205**___	___0.210**___	___0.325**___	___4.555___
N	1191	803	388	479	802
p	0.000	0.000	0.000	0.000	0.000

5 Conclusion and Policy Implications

This dissertation investigates the intricate relationship between financial market performance and pollution, focusing on the dual role financial markets can play in influencing environmental outcomes. By integrating theoretical modeling with empirical analysis, we provide a comprehensive examination of how investment decisions in "dirty" and "green" assets impact environmental sustainability.

The theoretical framework presented in this study highlights the divergence between private and social optima in asset allocation. At the private optimum, investors prioritize expected returns and risks without considering the external costs of pollution, leading to higher investments in dirty assets. In contrast, the social optimum internalizes these external costs, either through regulatory mechanisms or by incorporating social responsibility into investment decisions, resulting in lower investments in dirty assets.

The analysis reveals that at the private optimum, an increase in total portfolio returns driven by higher returns on dirty assets leads to increased allocation to dirty assets and higher emissions. Conversely, higher returns on green assets decrease the allocation to dirty assets and emissions. At the social optimum, higher returns on green assets consistently reduce the allocation to dirty assets and emissions. However, if higher returns on dirty assets drive the total portfolio return, there exists a threshold level for portfolio returns. Below this threshold, increased returns raise emissions; above it, increased returns reduce emissions due to the rising environmental damage costs necessitating a shift towards green assets.

The introduction of a tax incentive mechanism, which adjusts based on expected returns and risk-adjusted costs of dirty assets, ensures that the external costs of pollution are internalized. This mechanism encourages investors to minimize social costs while achieving reasonable portfolio returns.

The empirical analysis aims to validate the theoretical predictions by examining realworld data to determine if investors incorporate social responsibility or if regulatory frameworks effectively mitigate the environmental impact of investments. The analysis focuses on identifying a critical point of returns beyond which increased returns lead to decreased emissions, indicating the integration of social responsibility into investment decisions.

The results reveal a significant nonlinear relationship between financial returns and pollution. For returns below an estimated threshold of 23.8%, increased financial returns lead to higher pollution. Beyond this threshold, higher returns result in reduced pollution levels. This finding supports the theoretical prediction of a critical threshold influencing the environmental impact of financial returns.

The disaggregated analysis reveals key insights: high-income countries have a lower threshold for reducing pollution, showing their advanced capabilities in integrating green technologies. Middle-income countries need more efforts to decouple financial growth from environmental degradation due to a higher threshold. G20 countries' higher threshold highlights their significant influence on global environmental trends. OECD countries show no significant relationship between financial performance and pollution, raising questions about the effectiveness of their policies.

Our findings underscore the importance of aligning financial systems with sustainability goals. Policy interventions such as promoting green investments, strengthening environmental regulations, and incorporating climate risks into financial decision-making are essential to leveraging financial markets as a tool for environmental sustainability. These measures can help internalize the external costs of pollution and encourage investments that align with long-term environmental objectives.

This study contributes to the growing literature on the intersection of financial economics and environmental sustainability by combining theoretical modeling with empirical validation. The insights provided offer actionable recommendations for policymakers and financial stakeholders to enhance the role of financial markets in promoting environmental sustainability.

6 Appendix

Static comparative

These following partial derivatives indicate how the investment in dirty assets changes with respect to changes in the expected return of the green asset, μ_g

$$\begin{aligned}\frac{\partial x^p}{\partial \mu_g} &= \frac{-1}{A(\sigma_d^2+\sigma_g^2-2\rho\sigma_d\sigma_g)} < 0\\ \frac{\partial x^s}{\partial \mu_g} &= \frac{-1}{A(\sigma_d^2+\sigma_g^2-2\rho\sigma_d\sigma_g)+a_0(\sigma_d^2+\mu_d^2)} < 0\\ \frac{\partial x^p}{\partial \mu_d} &= \frac{1}{A(\sigma_d^2+\sigma_g^2-2\rho\sigma_d\sigma_g)} > 0\end{aligned}$$

Let us determine how the efficient allocation x^s changes with respect to μ_d. The partial derivative of x^s with respect to μ_d is given by:

$$\frac{\partial x^s}{\partial \mu_d} = \frac{-a_0\mu_d^2 + 2a_0\mu_d(\mu_g + A(\rho\sigma_d\sigma_g - \sigma_g^2)) + A(\sigma_d^2+\sigma_g^2-2\rho\sigma_d\sigma_g) + a_0\sigma_d^2}{\left[A(\sigma_d^2+\sigma_g^2-2\rho\sigma_d\sigma_g)+a_0(\sigma_d^2+\mu_d^2)\right]^2}.$$

Let $K = A(\sigma_d^2+\sigma_g^2-2\rho\sigma_d\sigma_g)+a_0\sigma_d^2 > 0$, and define $\mu_{d1} = \mu_g + A(\rho\sigma_d\sigma_g - \sigma_g^2)$. The sign of $\frac{\partial x^s}{\partial \mu_d}$ is determined by the sign of the quadratic equation:

$$f(\mu_d) = -a_0\mu_d^2 + 2a_0\mu_d^1\mu_d + K = 0.$$

The reduced discriminant of this equation is:

$$\triangle = a_0^2(\mu_{d1})^2 + a_0 K > 0.$$

Since the discriminant is positive, Equation (1) has two solutions of opposite signs. The relevant solution is the positive one:

$$\bar{\mu}_d = \mu_d^1 + \sqrt{(\mu_d^1)^2 + \frac{K}{a_0}}.$$

We must ensure that $\bar{\mu}_d$ satisfies the condition $\mu_d^1 < \bar{\mu}_d < \mu_d^2$, where $\mu_d^2 = \mu_g + A(\sigma_d^2 - \rho\sigma_d\sigma_g)$. It is clear that $\bar{\mu}_d > \mu_d^1$, as $\sqrt{(\mu_{d1})^2 + \frac{K}{a_0}} > 0$. However, whether $\bar{\mu}_d < \mu_{d2}$ depends on the specific parameter values.

If $\bar{\mu}_d < \mu_{d2}$

$$\bar{\mu}_d - \mu_g < A(\sigma_d^2 - \rho\sigma_d\sigma_g).$$

In this case: - $\frac{\partial x^s}{\partial \mu_d} > 0$ for $\mu_d < \bar{\mu}_d$. - $\frac{\partial x^s}{\partial \mu_d} < 0$ for $\mu_d > \bar{\mu}_d$.

If $\bar{\mu}_d > \mu_{d2}$, this implies:

$$\bar{\mu}_d - \mu_g > A(\sigma_d^2 - \rho\sigma_d\sigma_g).$$

In this case: - $\frac{\partial x^s}{\partial \mu_d} > 0$ for all μ_d.

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