Asset pricing and impact investing with pro-environmental preferences

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Paris, July 18, 2020.

Qu'est-ce que le bonheur sinon le simple accord entre un être et l'existence qu'il mène ?
— Albert Camus (1939). Noces.

Contents

Introduction

1. Preliminary definitions

Pro-environmental preferences. An investor has pro-environmental preferences when she values, in her utility function, the assets of the least polluting companies more highly than the assets of the most polluting companies. These pro-environmental preferences may be driven by pecuniary or non-pecuniary motives.

Non-pecuniary motives or preferences. An investor has non-pecuniary motives or preferences for some assets when she values them more highly, regardless of their expected returns or variances. In particular, pro-environmental non-pecuniary preferences refer to investors' motives for investing in green assets irrespective of their financial characteristics.

Impact investing. Impact investing refers to an investment technique that seeks to "generate positive, measurable social and environmental impact alongside a financial return" (Global Impact Investing Network). Specifically, environmental impact investing seeks to reduce the environmental footprint of the companies issuing the financial security.

2. Stakes and research questions

The environmental emergency, which involves rethinking the organization of our societies and the functioning of our economies, requires mobilizing considerable financing capacity. For example, the infrastructure needs for the next fifteen years that will enable OECD countries to be consistent with the 2 degrees Celsius trajectory amount to USD 6,900 billion (OECD, 2017a). In addition to public support, private funding is therefore a valuable lever to achieve the mobilization of such amounts.

Concurrently, the interest of financial investors in environmental issues has increased considerably in recent years. Investors referred to as "green investors" adapt their asset allocation by overweighting the assets of the greenest companies and underweighting or even excluding the assets of the most polluting (also referred to as "brown") companies. The adjustment of their asset allocation can be motivated by two main stakes: (i) non-pecuniary preferences for environmental issues and (ii) the internalization of environment-related financial risks. In the first case, investors exclude brown companies for ethical reasons and are willing to forego part of their expected returns for the sake of their environmental convictions. In the second case, investors hedge against environment-related financial risks that are imperfectly priced by the market. These risks may be environmental transition risks (Jakob and Hilaire, 2015), physical risks (Arnell and Gosling, 2016) or litigation risks (Hunter and Salzman, 2007).

Whether for non-pecuniary motives or to internalize environment-related financial risks, the adjustment of green investors' asset allocation has a double impact: (i) it modifies the equilibrium asset prices and returns and, consequently, (ii) it affects firms' practices by shifting their cost of capital. The analysis of the first effect is part of an asset pricing approach, while the analysis of the second effect falls within the emerging field of research that is referred to as "impact investing."

Therefore, three main questions arise:

- How do expected asset returns distort when a group of investors internalizes environmental issues in its asset allocation? [Chapter 1].
- How does the adjustment of the expected return break down between (i) the impact of non-pecuniary preferences and (ii) the impact of the internalization of environment-related financial risks? [Chapter 2].
- Are the most polluting companies, whose cost of capital is affected by green investors' practices, encouraged to reduce their environmental impact? [Chapter 3]

As shown in Figure 1, the three chapters of this thesis focus on answering each of these questions, respectively.

3. Environmental investing

a. Asset pricing approach

i. Asset pricing with pro-environmental preferences

Modern portfolio theory, grounded in the seminal work of Markowitz (1952), and the asset-pricing model, based on the contributions of Sharpe (1964) and Lintner (1965), do not provide the theoretical framework allowing us to explain the effect of investors' pro-environmental preferences on expected returns in equilibrium. Although several risk factors, such as the Fama and French (1993) and Carhart (1997) factors, have been identified as driving the dynamics of asset returns, they also fail to explain the effect of green investing on asset returns.

An extensive empirical literature has sought to highlight the effect of firms' environmental impacts on their returns. Typically, these papers regress realized returns on environmental ratings. However, the results of this literature are mixed:

- Some papers highlight a negative relationship between environmental and financial performances, including Brammer, Brooks, and Pavelin (2006), Renneboog, Ter Horst, and Zhang (2008) and Barber, Morse, and Yasuda (2018). In addition, Sharfman and Fernando (2008), ElGhoul et al. (2011) and Chava (2014)

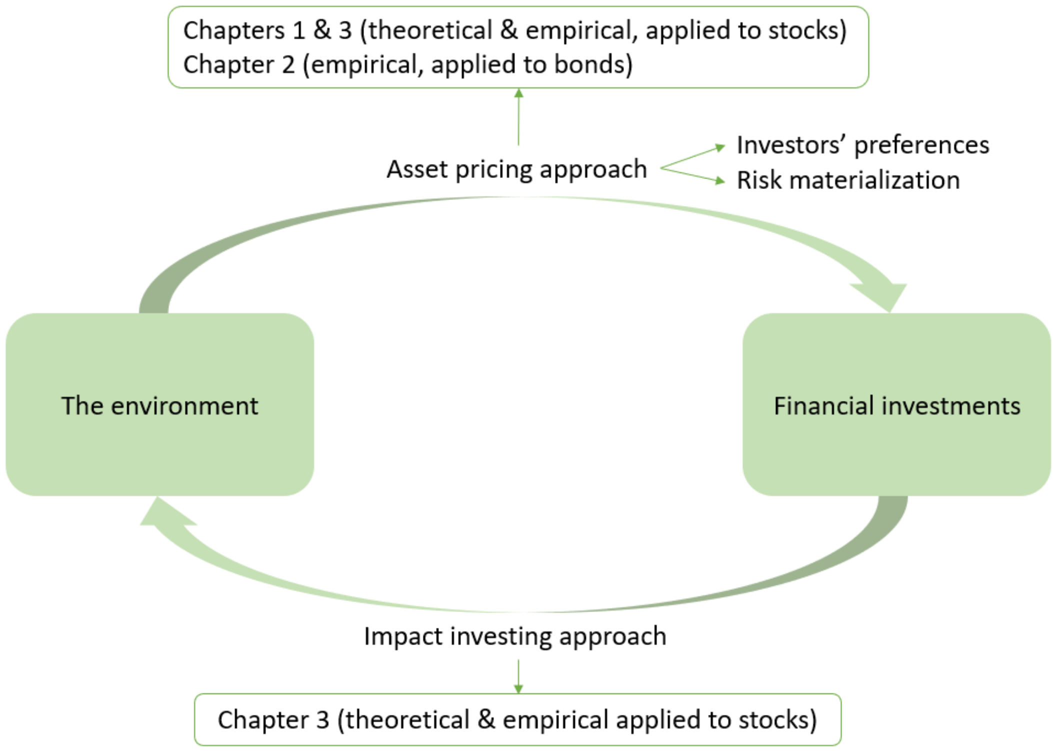

FIGURE 1: **Main research approaches in environmental investment** This figure shows the main research approaches in the field of environmental investment: the asset pricing approach and the impact investing approach.

highlight the same effect on expected returns. Bolton and Kacperczyk (2020), Hsu, Li, and Tsou (2019) and In, Park, and Monk (2019) show that companies that emit the most greenhouse gases have higher returns than companies that emit less.

- Other papers find a positive relationship, including Derwall et al. (2005), Statman and Glushkov (2009), Edmans (2011), Eccles, Ioannou, and Serafeim (2014), Krüger (2015) and Statman and Glushkov (2016). Specifically, Krüger (2015) shows that investors react very negatively to negative news about corporate environmental responsibility.

- Finally, other authors, such as Bauer, Koedijk, and Otten (2005) and Galema, Plantinga, and Scholtens (2008), find no significant relationship between environmental and financial performances.

Based on the literature on heterogeneous preferences and investor disagreement,[1] I shed theoretical and empirical light on the impact of pro-environmental preferences on asset returns in the first chapter of this thesis.

[1]See Harris and Raviv (1993), Biais and Bossaerts (1998), Scheinkman and Xiong (2003), Fama and French (2007b), Jouini and Napp (2007), David (2008), Dumas, Kurshev, and Uppal (2009), Banerjee and Kremer (2010), Banerjee and Kremer (2010), Bhamra and Uppal (2014), Carlin, Longstaff, and Matoba (2014), Baker, Hollifield, and Osambela (2016), Atmaz and Basak (2018) and Banerjee, Davis, and Gondhi (2019).

ii. Non-pecuniary pro-environmental preferences

The analysis of the impact of pro-environmental preferences on bond yields provides more consensual empirical results than the same analysis on equities. Indeed, even if the conclusions are not unanimous, most of the work suggests that companies with a high environmental performance benefit from a lower cost of debt. The authors mainly attribute this cost of capital differential to a financial reality: intangible asset creation (Porter and Linde, 1995; Hart, 1995; Jones, 1995; Ambec and Lanoie, 2008; Flammer, 2015) as well as better risk management and mitigation (Ambec and Lanoie, 2008; Bauer and Hann, 2014), both being imperfectly captured by rating agency models (Ge and Liu, 2015; Oikonomou, Brooks, and Pavelin, 2014). However, the existing literature does not identify how much of this yield differential is attributable to non-pecuniary preferences.

The development of green bonds, as well as the growing liquidity of these assets, offers a favorable framework for identifying the share of the bond yield differential attributable to investors' pro-environmental non-pecuniary preferences. Indeed, the risk of green bonds is that of the issuing company, as is the case for conventional bonds. Thus, comparing green bonds to synthetic counterfactual conventional bonds allows us to eliminate the financial risk differential and isolate the impact of green investors' non-pecuniary preferences on bond yields. This is the approach I take in the second chapter of this thesis.

b. Impact investing approach

Because environmental impact investing affects assets' expected returns in equilibrium, as discussed in Chapters 1 and 2 of this thesis, it changes firms' cost of capital. Therefore, firms may have an incentive to react consequently and mitigate their environmental impact. This is the impact investing mechanism, which has been documented by the seminal works of Oehmke and Opp (2019), Landier and Lovo (2020), and Pastor, Stambaugh, and Taylor (2019).

The first two papers develop a general equilibrium model. Oehmke and Opp (2019) introduce a group of sustainable investors who agree to finance less profitable projects and show that companies reduce their environmental footprint by being forced to internalize their social costs. Landier and Lovo (2020) reach similar findings by introducing a fund that has preferences for environmental, social, and governance (ESG) issues but a financial return objective similar to that of regular investors. Finally, Pastor, Stambaugh, and Taylor (2019) also reach identical conclusions by showing that the most polluting companies have a higher cost of capital.

In the third chapter of this thesis, we approach this problem from the asset pricing perspective through a dynamic model where investors and firms enter into a nonzero-sum game. In particular, we analyze the effect of uncertainty about a firm's future environmental impact on its incentive to reform and mitigate it.

4. Contributions

Chapter 1

In the first chapter of this thesis, I show from a theoretical perspective how the practices of (i) exclusionary screening and (ii) ESG integration by "sustainable investors" affect the expected returns in equilibrium. I empirically validate the model applied (i) to "sin stocks" for the exclusionary screening and (ii) by constructing a proxy for green investors' tastes using green fund holdings for the ESG integration practice.

More precisely, I show that the exclusion and ESG integration practices by sustainable investors induce two "exclusion premia" and two "taste premia," respectively, on expected returns in equilibrium. In this partially segmented market (Errunza and Losq, 1985), I show that these premia have cross-effects between the excluded and non-excluded assets.

The two exclusion premia, induced by the reduction of the investor base, have been independently evidenced by Errunza and Losq (1985) on excluded assets and Jong and Roon (2005) on non-excluded assets in partially segmented markets. I show that these two premia apply simultaneously to all assets. In addition, I show that one of these two premia generalizes the premium on "neglected stocks" characterized by Merton (1987). Although the exclusion effect is indeed positive on average, as highlighted by Hong and Kacperczyk (2009) and Chava (2014), I show that it can be negative for an excluded asset taken individually, especially when it is decorrelated from the other excluded assets. The dynamics of the exclusion effect is strongly related to the correlation between excluded assets; specifically, this effect increased sharply during the 2008 financial crisis and collapsed as markets recovered and the correlation among assets declined. By estimating the model applied to sin stocks, I validate all the theoretical predictions of the model. The annual average exclusion effect is 1.43% between 2007 and 2019, in line with the magnitude of the empirical estimate of Hong and Kacperczyk (2009).

The taste premia are induced by the internalization of ESG externalities by sustainable investors who modify their asset weighting accordingly. Consistent with two independent works by Pastor, Stambaugh, and Taylor (2019) and Pedersen, Fitzgibbons, and Pomorski (2019), the direct taste premium is higher (lower) for brown (green) assets because sustainable investors require a higher return (accept a lower return) to hold them. As a result, the market premium is also adjusted by the direct taste premium in the market. Many papers have tried to explain the impact of ESG ratings on asset returns, resulting in mixed results. Three main reasons explain these mixed results: (i) ESG scores or environmental indicators are imperfect proxies for sustainable investors' aggregated tastes and are generally only available at an annual frequency; (ii) the estimated equations do not take into account the increase in the proportion of sustainable investors; (iii) realized returns are imperfect proxies for expected returns because they do not account for unexpected changes in the preferences of sustainable investors (Pastor, Stambaugh, and Taylor, 2019). I circumvent this threefold hurdle by constructing proxies for (i) the cost of environmental externalities, (ii) the proportion of green investors, and (iii) the unexpected changes in their preferences based on the history of green fund holdings worldwide. By estimating the equilibrium equation applied to the integration of environmental issues, I show that the average taste effect between the least and most polluting industries ranged between -1.12% and 0.14% per year between 2007 and 2019 and increased over time.

Chapter 2

The second chapter of this thesis empirically estimates the share of the return differential between green and non-green assets induced by non-pecuniary preferences. To do so, I focus on the bond market and use green bonds as an instrument to estimate this "green premium."

Using a matching method, I identify the 110 green bonds for which it is possible to construct a synthetic counterfactual conventional bond with the same characteristics (except that it is not a green bond). In particular, I control for the maturity bias and extract the green premium by controlling for the liquidity bias between the green and conventional bonds: the green premium is defined as the unobserved specific effect of a regression of the yield differential between the matched green and conventional bonds on the liquidity differential between these two types of bonds. Estimated between 2013 and 2017, the green premium is worth -2 basis points on average, which means that the yield (price) of green bonds is slightly lower (higher) than that of conventional bonds. This green premium reflects the yield that investors are willing to give up to hold green bonds rather than conventional bonds at equal risk. Although it is statistically significant, this premium is economically very low. It therefore suggests that the difference in yield between the bonds of green and brown companies, widely highlighted in the literature,[2] mainly corresponds to a difference in environment-related financial risk rather than to the effect of green investors' non-pecuniary preferences.

From the practitioners' point of view, this green premium highlights investors' appetite for green bonds and the fact that companies can diversify their bondholder base via this asset class. However, given its very low value, it does not constitute a disincentive for green investors to support the green bond market. Moreover, from the supervisory authorities' point of view, this premium does not reveal a substantial valuation discrepancy between green and brown assets at equal risk.

Finally, I analyze the heterogeneity of this premium among all bonds. I show that this premium is more pronounced for financial and low-rated bonds.

Chapter 3

In the third chapter of this thesis, co-written with Tiziano de Angelis and Peter Tankov, we show how green investing can have an impact on companies' practices,

[2]See, for example, Bauer and Hann (2014), Oikonomou, Brooks, and Pavelin (2014), and Flammer (2015).

especially the most polluting ones, that are spurred on to reduce their environmental impact. We build an equilibrium model in a market populated by (i) a group of regular investors and (ii) a group of green investors who internalize the financial impact of environmental externalities of the assets in which they invest. Investors enter into a nonzero-sum game with companies that choose their carbon footprint trajectory accordingly. In this model, we therefore endogenize the environmental impact of companies and analyze their optimal carbon footprint trajectory.

We show that an increase in the proportion of green investors and their environmental stringency both push companies to reduce their carbon footprint by increasing their cost of capital. This result underlines the importance of public support for the development of green investments—for example, through the definition of rigorous standards for assessing environmental impact, such as the taxonomy on which the European Commission is currently working. From the investors' point of view, this result suggests that they can increase their impact on companies by raising their environmental requirements, for example by restricting their investment scope or by more significantly underweighting the least virtuous companies. Moreover, consistent with the first chapter of this thesis, we show that green investing is financially beneficial when investors favor companies that will effectively lower their environmental impact.

We extend our analysis to the case where green investors internalize future environmental externalities with *uncertainty*. Consistent with the nature of environmental risks, we model this uncertainty as non-Gaussian through a stochastic jump process. We show that heightened uncertainty about future environmental risk pushes green investors to reduce their allocation to risky assets, thereby reducing the pressure they exert on the cost of capital of the most polluting companies. As a result, easing the pressure on companies' cost of capital incentivizes them to increase their carbon footprint compared to the equilibrium without uncertainty. This result underlines the importance of transparency on companies' environmental impact and access to this information by investors: the better the information, the more companies are pushed by green investors to internalize their environmental externalities and reduce their emissions.

We empirically estimate our model applied to companies' carbon intensity by using the history of green fund holdings worldwide. In particular, we show that when the proportion of green investors doubles, the carbon intensity of companies falls by an average of 5% per year.

5. Major implications for the finance industry

The results of this thesis have concrete implications for the financial industry in several respects.

- First, this work shows that investing in a company that is going green is financially profitable. This underlines the importance of "extra-financial" analysis, conducted by financial institutions or rating agencies, so investors can allocate their capital to companies that will be the most virtuous from an environmental perspective.

- Second, this thesis underscores investors' ability to push companies to reform by increasing their environmental requirements. This may result in a downward adjustment of the weighting of the most polluting companies or in restricting the scope of their acceptability.

- Third, this study highlights the importance of transparency regarding companies' environmental information to maximize the internalization by companies of their social and environmental costs, thereby reducing their environmental impact.

- Finally, and more generally, this thesis underlines the importance of public support for the development of green finance, notably through the definition of rigorous norms and standards offering investors a more accurate reading of the environmental impact of the companies in which they may invest.

Chapter 1

A sustainable capital asset pricing model (S-CAPM): Evidence from green investing and sin stock exclusion[1]

[1] This chapter benefited from the valuable comments of Rob Bauer, Milo Bianchi, Claire Bonello, Marco Ceccarelli, Julio Crego, Patricia Crifo, Joost Driessen, Esther Eiling, Caroline Flammer, Olivier Guéant, James Guo, Ulrich Hege, Ying Jiao, Sonia Jimenez Garces, Frank de Jong, Nabil Kazi-Tani, Peter Kondor, Felix Kübler, Augustin Landier, Dong Lou, Valéry Lucas-Leclin, Sophie Moinas, Lionel Melin, Martin Oehmke, Sébastien Pouget, Kevin Ratsimiveh, Christian Robert, Bert Scholtens, Paul Smeets, Dimitri Vayanos, Michela Verardo, Alexander Wagner, workshop participants at the London School of Economics, Tilburg University, University of Zurich–SFI, Toulouse School of Economics, CREST (Ecole Polytechnique - ENSAE), Paris Dauphine University, University of Lille, University of Orléans, I Care, ISFA and the Climate Economics Chair.
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This paper shows how sustainable investing, through the joint practice of Environmental, Social and Governance (ESG) integration and exclusionary screening, affects asset returns. The effect of these two practices translates into two taste premia and two exclusion premia that induce cross-effects between excluded and non-excluded assets. By using the holdings of 453 green funds investing in U.S. stocks between 2007 and 2019 to proxy for sustainable investors' tastes, I estimate the model applied to green investing and sin stock exclusion. The annual taste effect ranges from -1.12% to +0.14% for the different industries and the average exclusion effect is 1.43%.

1.1 Introduction

Sustainable investing now accounts for more than one quarter of the total assets under management (AUM) in the United States (U.S.; US SIF, 2018) and more than half of those in Europe (GSIA, 2016).[2] Primarily motivated by ethical concerns, the two most widely used sustainable investment practices are *exclusionary screening* and *environmental, social, and governance (ESG) integration* (GSIA, 2016). Exclusionary screening involves the exclusion of certain assets from the range of eligible investments, such as the so called *sin stocks*, while ESG integration involves underweighting assets with low ESG ratings and overweighting those with high ESG ratings. Exclusionary screening and ESG integration are often jointly implemented by sustainable investors (GSIA, 2016), and their growing prevalence can create major supply and demand imbalances, thereby distorting market prices. This paper develops a simple theoretical framework to provide an empirical contribution on how these sustainable investing practices—separately and together—affect asset returns.

To reflect the dual practice of exclusion and ESG integration by sustainable investors, I develop a simple asset pricing model with partial segmentation and heterogeneous preferences on the expectation of asset returns. Specifically, I propose a single-period equilibrium model populated by three constant absolute risk aversion (CARA) investor groups: *regular investors* that invest freely in all available assets and have mean-variance preferences; *sustainable investors* practicing exclusionary screening (referred to as *excluders*) that exclude certain assets from their investment scope and have mean-variance preferences; *sustainable investors* practicing ESG integration (referred to as *integrators*) that invest freely in all available assets, but adjust their mean-variance preferences by internalizing a private cost of externalities.[3]

[2]Sustainable investing is also referred to as *socially responsible investing*, *responsible investing* and *ethical investing*. In the European Parliament legislative resolution of 18 April 2019 (COM(2018)0354 – C8-0208/2018 – 2018/0179(COD)), sustainable investments are defined as "investments in economic activities that contribute to environmental or social objectives as well [*sic*] their combination, provided that the invested companies follow good governance practices and the precautionary principle of "do no significant harm" is ensured, i.e. that neither the environmental nor the social objective is significantly harmed." In the U.S., the AUM in sustainable investing amounted to USD 12 trillion in 2018 and increased by 38% between 2016 and 2018 (US SIF, 2018).

[3]Benabou and Tirole (2010b) describe the *delegated philanthropy* mechanism whereby sustainable investors integrate firm externalities into their investment decisions. In the continuation of this theory, Hart and Zingales (2017) and Morgan and Tumlinson (2019) argue that sustainable investors

I propose a unified pricing formula for all assets in the market; namely, the assets excluded by excluders (hereafter, *excluded assets*) and the assets in which they can invest (hereafter, *investable assets*). Two types of premia are induced by sustainable investors: two *taste premia* (*direct* and *indirect* taste premium) and two *exclusion premia* (*exclusion-asset* and *exclusion-market* premium).

The taste premia materialize through three effects. First, consistent with related literature, the *direct taste premium* is induced by integrators' tastes for assets owing to the cost of externalities that they internalize: this premium increases with the cost of externalities and the wealth share of integrators. Second, as a consequence, the market risk premium is also adjusted by the average direct taste premium. Third, a cross-effect arises through the *indirect taste premium* on excluded assets: to hedge their underweighting of investable assets with a high cost of externalities, integrators overweight the excluded assets that are most correlated with these investable assets.

Two exclusion premia affect excluded asset returns. The exclusion premia result from a reduction in the investor base, and are related to Errunza and Losq (1985)'s *super risk premium* and Jong and Roon (2005)'s *local segmentation premium.* I show that one of the two exclusion premia is a generalized form of the premium on neglected stocks characterized by Merton (1987). Both exclusion premia are structured similarly and reflect the dual hedging effect of investors who do not exclude and those who exclude assets: regular investors and integrators, who are compelled to hold the excluded market portfolio, value most highly the assets least correlated with this portfolio; simultaneously, excluders, who seek to replicate the hedging portfolio built from investable assets most closely correlated with excluded assets, value most highly the assets most correlated with this hedging portfolio. The *exclusion effect* is the sum of the two exclusion premia. Although the exclusion effect on asset returns is positive on average, as empirically assessed by Hong and Kacperczyk (2009) and Chava (2014), I show that this effect can be negative for an individual excluded asset, for example, when it is negatively correlated with the other excluded assets. Finally, a cross-effect of one of the two exclusion premia also drives investable asset returns.

I empirically validate the theoretical predictions by estimating the model using the U.S. stocks in the Center for Research in Security Prices (CRSP) database between December 2007 and December 2019. I use sin stocks to constitute the assets excluded by excluders and apply integrators' screening to their tastes for the stocks of *green firms*.[4] I focus on green investing since it is the most popular ESG screening technique among sustainable investors (US SIF, 2018). Focusing on this technique therefore makes it easier to identify the effect of integrators' tastes on asset returns.

Beyond the issue of the econometric specification, there are three main reasons for the mixed results in the empirical literature on the link between environmental

internalize externalities to maximize their welfare instead of solely maximizing market value of their investments. In this paper, the cost of externalities is defined as a deterministic private cost proportional to the weight of the investment made, in the same way as Acharya and Pedersen (2005) model the cost of illiquidity.

[4]A green firm can be defined as a firm with a low environmental impact according to an environmental metric, including, for example, environmental ratings and carbon footprints.

and financial performances. First, identifying the environmental performance of a company through a particular environmental metric weakly proxies for the average tastes of sustainable investors for green firms: the various metrics used to assess the environmental impacts of assets lack a common definition, show low commensurability (Chatterji et al., 2016; Gibson et al., 2019), and are updated with a low frequency, typically on an annual basis. Second, these studies fail to capture the increase in the proportion of green investors over time. Third, by proxying expected returns by realized returns, these papers neglect to control the effect of the unexpected shifts in tastes on realized returns (Pastor, Stambaugh, and Taylor, 2019), which induces a critical omitted variable bias: if the proportion of green investors or their tastes for green companies unexpectedly increase, green assets may outperform brown assets while the former have a lower direct taste premium than the latter.

Therefore, I construct a proxy for the tastes of green investors that allows me to address the three issues raised. First, to circumvent the use of environmental metrics, I construct an agnostic *ex-post* instrument reflecting green investors' private costs of environmental externalities. I identify 453 green funds worldwide with investments in U.S. equities as of December 2019 and use the FactSet data to determine their holding history on a quarterly basis. For a given stock and on a given date, I define this instrument as the relative difference between the weight of the stock in the market portfolio and its weight in the U.S. allocation of the green funds. The higher the proxy is, the more the stock is underweighted by the green funds on that date, and vice versa when the proxy is negative. Second, I approximate the proportion of green investors' wealth as the proportion of assets managed by green funds relative to the market value of the investment universe. Third, I control for the unexpected shifts in green investors' tastes by constructing a proxy defined as the variation of green investors' tastes over time.

For investable stocks, the direct taste premium is significant from 2007 onwards, whether it is estimated by constructing industry-sorted or industry-size double-sorted portfolios. The direct taste premium remains significant after controlling for the unexpected shifts in tastes, as well as for the small-minus-big (SMB), high-minus-low (HML) (Fama and French, 1993), and momentum (MOM) (Carhart, 1997) factors. The taste effect ranges from -1.12% to +0.14% for the different industries evaluated. Specifically, ESG integration significantly contributes toward modifying the expected returns of the industries most impacted by the ecological transition. For example, on average, between 2007 and 2019, green investors induced additional annual returns of 0.50% for the petroleum and natural gas industry when compared to the electrical equipment industry; this taste effect has steadily increased over time. I also find weak evidence supporting the cross-effect effect of sin stock exclusion on investable stock returns.

Regarding sin stocks, I find both exclusion premia and the indirect taste premium to be significant and to remain so when the SMB, HML, and MOM factors are included.[5] The ordinary least squares (OLS) adjusted-R^2 and generalized least squares (GLS) R^2 of the estimated model are substantially higher than those obtained under Carhart (1997)'s four-factor model. The annual average exclusion effect amounts to 1.43% over the period under consideration. Consistent with the theory, the exclusion effect is negative for 10 out of the 52 sin stocks analyzed.

Related literature. The results of this study contribute to two literature strands on asset pricing. First, they clarify the relationship between the environmental and financial performances of assets by building on the disagreement literature.[6] The empirical evidence regarding the effects of ESG integration on asset returns is mixed, as several studies point to the existence of a negative relationship between ESG performance and stock returns,[7] while others argue in favor of a positive effect,[8] or find no significant differentiating effects due to ESG integration.[9] Two independent works by Pedersen, Fitzgibbons, and Pomorski (2019) and Pastor, Stambaugh, and Taylor (2019) provide theoretical contributions on how ESG integration by sustainable investors affects asset returns.[10] Pedersen, Fitzgibbons, and Pomorski (2019) show that when the market is populated by ESG-motivated, ESG-aware, and ESG-unaware investors, the optimal allocation satisfies four-fund separation and is characterized by an ESG-efficient frontier. The authors derive an asset pricing equation in the cases where all investors are ESG-motivated or ESG-unaware. Pastor, Stambaugh, and Taylor (2019) show that green assets have negative alphas and brown assets have positive alphas, and that the alphas of ESG-motivated investors are at their lowest when there is a large dispersion in investors' ESG tastes. Extending the conceptual framework laid out by Fama and French (2007b), I contribute to this literature strand in two ways. First, from a theoretical viewpoint, I show that the taste effect on asset returns is transmitted through a direct and and indirect taste premium, which are adjusted by the taste effect on the market premium. Second and foremost, from an empirical

[5] I am not able to estimate the direct taste premium (induced by green funds) on sin stock returns because of their limited number, but this effect is analyzed for investable assets, which constitute almost the entire investment universe.

[6] A vast literature has examined the effects of disagreement and differences of opinion on asset returns and prices, including Harris and Raviv (1993), Biais and Bossaerts (1998), Scheinkman and Xiong (2003), Fama and French (2007b), Jouini and Napp (2007), David (2008), Dumas, Kurshev, and Uppal (2009), Banerjee and Kremer (2010), Bhamra and Uppal (2014), Carlin, Longstaff, and Matoba (2014), Baker, Hollifield, and Osambela (2016), Atmaz and Basak (2018) and Banerjee, Davis, and Gondhi (2019).

[7] See Brammer, Brooks, and Pavelin (2006), Renneboog, Ter Horst, and Zhang (2008) and Barber, Morse, and Yasuda (2018). Moreover, Sharfman and Fernando (2008), ElGhoul et al. (2011) and Chava (2014) show that the same effect applies to the expected returns. Bolton and Kacperczyk (2020), Hsu, Li, and Tsou (2019) and In, Park, and Monk (2019) show that companies emitting the most greenhouse gases earn higher stock returns than companies emitting the lowest levels.

[8] See Derwall et al. (2005), Statman and Glushkov (2009), Edmans (2011), Eccles, Ioannou, and Serafeim (2014), Krüger (2015) and Statman and Glushkov (2016). Specifically, Krüger (2015) shows that investors react very negatively to negative Corporate Social Responsibility (CSR) news, particularly environmental news, and positively to positive CSR news concerning firms with known controversies.

[9] See Bauer, Koedijk, and Otten (2005) and Galema, Plantinga, and Scholtens (2008).

[10] Both papers focus on ESG integration and do not address exclusionary screening.

viewpoint, this is the first paper in which the asset pricing specification is estimated using a microfounded proxy for sustainable investors' revealed tastes for green companies constructed from green fund holdings. In addition to offering a measure of the aggregate tastes of green investors on a monthly basis, this proxy allows to account for the increase in their proportion and to control for the effect of unexpected shifts in tastes. The significant estimates of the taste premia on investable and excluded stock returns highlight the value of using this *ex-post* monthly measure rather than a yearly environmental rating or a carbon footprint to proxy for sustainable investors' tastes.

The results of this study also contribute to the literature on exclusionary screening by bridging the gap with market segmentation. From a theoretical viewpoint, I show that the exclusion effect results from the sum of two exclusion premia, which are related to the premia identified by Errunza and Losq (1985) in the case of excluded assets and by Jong and Roon (2005) as an indirect effect on investable assets. Moreover, I demonstrate that one of the two exclusion premia is a generalized form of Merton (1987)'s premium on neglected stocks. I also identify the cross-effect of exclusion on investable stock returns. Therefore, this article extends the analysis of Heinkel, Kraus, and Zechner (2001) by characterizing the risk factors associated with exclusionary screening. From an empirical viewpoint, the magnitude of the average annual exclusion effect I estimate for sin stocks is in line with the 2.5% obtained by Hong and Kacperczyk (2009) and is substantially lower than the 16% found by Luo and Balvers (2017). However, I show that this effect is negative for several sin stocks. Compared to Merton (1987), this study emphasizes the importance of considering non-independent returns because the exclusion effect is mostly due to spillovers from other excluded assets. Luo and Balvers (2017) characterize a boycott premium and claim that the exclusion effect is positively related to business cycles. I show that the exclusion effect fluctuates with business cycles because it is driven by conditional covariances, which increase with the multiple correlation among excluded assets.

The remainder of this paper is structured as follows. Section 1 presents the equilibrium equations of the model and characterizes the resulting premia. Section 2 describes the identification method used in the empirical analysis when the model is applied to sin stocks regarded as excluded assets and to green investments for characterizing investors' tastes for investable assets. Sections 3 and 4 present the empirical results on investable and excluded stocks' excess returns, respectively. Section 5 concludes the paper. The Appendix contains the main proofs and the Internet Appendix provides additional proofs and details about the empirical analysis.

1.2 Asset pricing with partial segmentation and disagreement

To reflect the dual practices of sustainable investing based on the exclusion and over- or underweighting of certain assets, I develop a simple asset pricing model with partial segmentation and heterogeneous preferences among investors. I show how the expected excess returns deviate from those predicted by the capital asset pricing model (CAPM) and identify two types of premia that occur in equilibrium: two taste premia and two exclusion premia. I also show that exclusion and taste premia have cross-effects on investable and excluded assets.

1.2.1 Model setup and assumptions

The economy is populated by three investor groups: one group of *regular* investors and two groups of *sustainable* investors—a group practicing exclusionary screening (referred to as *excluders*) and another practicing ESG integration (referred to as *integrators*). This setup does not lose generality compared to a model with several sustainable investors practicing either exclusion, ESG integration or both.[11] The model is based on the following assumptions.

Assumption 1 (Single-period model). *Agents operate in a single-period model from time t to $t+1$. They receive an endowment at time t, have no other source of income, trade at time t, and derive utility from their wealth at time $t+1$.*

Assumption 2 (Partial segmentation). *Regular investors and integrators invest freely in all assets in the market. Excluders restrict their allocation to the sub-market of investable assets, which is composed of assets $I_1, ..., I_{n_I}$, and exclude the sub-market of excluded assets, which is composed of assets $X_1, ..., X_{n_X}$. The proportion of excluded assets' market value is denoted by $q \in [0, 1]$. The wealth shares of excluders, integrators, and regular investors are p_e, p_i, and $1 - p_e - p_i$, respectively.*

Assumption 3 (Heterogeneous preferences). *Integrators have specific tastes for assets. They subtract a deterministic private cost of externalities, c_k, from the expected return on each asset $k \in \{I_1, ..., I_{n_I}, X_1, ...X_{n_X}\}$. $C_I = (c_{I_1}, ..., c_{I_{n_I}})'$ and $C_X = (c_{X_1}, ..., c_{X_{n_X}})'$ are the vectors of stacked costs for investable assets $I_1, ..., I_{n_I}$ and excluded assets $X_1, ..., X_{n_X}$, respectively, where the prime symbol stands for the transposition operator. The cost of externalities of the value-weighted portfolio of investable assets is denoted by c_{m_I} (see Figure 1.1).*

Assumption 4 (Mean-variance preferences). *(i) Investors have an exponential utility and their relative risk aversion is denoted by γ. (ii) The asset returns are assumed to be normally distributed. Since investors maximize the expected utility of their terminal*

[11] In this more general case, the equilibrium equations remain unchanged and the proportions of wealth are adjusted according to the wealth invested utilizing each of the two sustainable investment techniques.

wealth, which is normally distributed, they have mean-variance preferences over their terminal wealth.

Assumption 5 (Perfect market). *The market is perfect and frictionless.*

Assumption 6 (Free lending and borrowing). *Investors can lend and borrow freely, without any constraint, at the same exogenous interest rate.*

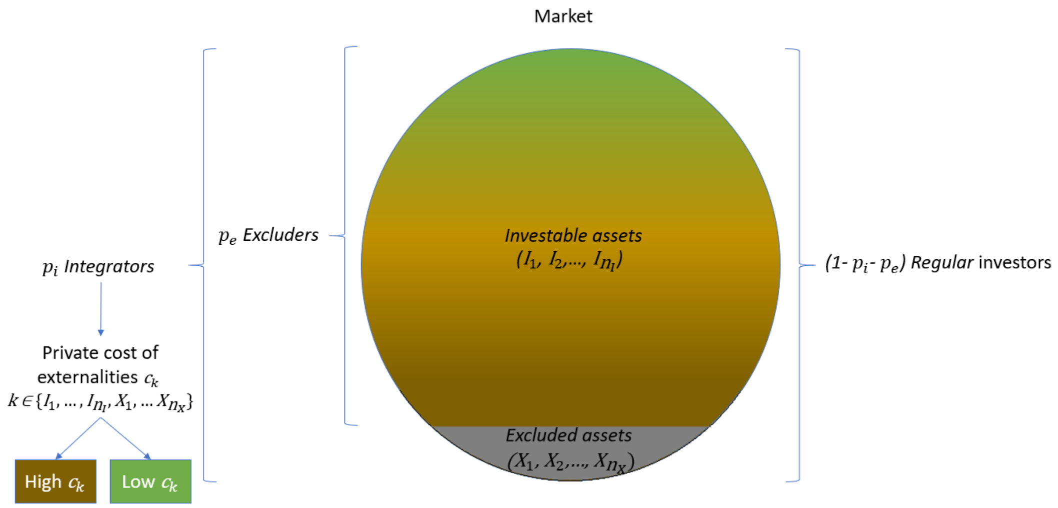


FIGURE 1.1: **Graphical overview of the financial setup.** This graph depicts the three types of investors involved (integrators, excluders and regular investors), their scope of eligible assets and the tastes of integrators through their private cost of externalities c_k.

The specific assumptions adopted in this model are those of a partially segmented market (assumption 2) in which investors have heterogeneous preferences (assumption 3). I do not consider the partial segmentation assumption as a limiting case of the heterogeneous preferences assumption with no-short-sales constraint for two main reasons. First, the absence of no-short-sales constraint makes it possible to obtain a tractable equilibrium equation. Second, the two assumptions are complementary: since short selling is not prohibited, integrators can short an asset with a high externality cost while an excluded asset is not accessible to excluders. The joint analysis of these two mechanisms also makes it possible to study their cross-effects.

By characterizing sustainable investors' practices through both exclusion and ESG integration, the developed model subsumes two types of previous models. On the one hand, when the cost of externalities is zero (i.e., focusing on assumption 2), the present framework is reduced to that of segmentation models, such as the I-CAPM (Errunza and Losq 1985; Jong and Roon 2005),[12] and that used by Luo and Balvers (2017), who analyze the effects of excluding a specific set of assets. The assumptions of the

[12] As shown by Jong and Roon (2005), their model also generalizes Bekaert and Harvey (1995)'s model when investable and non-investable assets have similar characteristics in the absence of cross-country segmentation effects.

present model generalize those of Merton (1987)'s model since I do not impose any particular specification on asset returns, and these are not independent.[13]

On the other hand, when the market is not segmented (i.e., focusing on assumption 3), the present model is reduced to a model of differences of opinion, in which sustainable investors adjust their expected returns on each available asset by internalizing a private cost of externalities.[14] The setup is related to that of Acharya and Pedersen (2005): the cost of illiquidity is replaced here by a deterministic cost of externalities, which is internalized only by a fraction of the investors. Unlike the illiquidity cost, which fluctuates daily, the cost of ESG externalities varies with high inertia and does not necessarily need to be modeled as a stochastic factor.[15] The internalization of the cost of externalities, which is modeled here as a linear adjustment of the expected excess return, is consistent with other theoretical studies on ESG investing (Gollier and Pouget, 2014; Pastor, Stambaugh, and Taylor, 2019; Pedersen, Fitzgibbons, and Pomorski, 2019). It is worth noting that the cost of externalities can have a negative value and reflect the internalization of positive externalities by integrators. This occurs for companies whose assets may benefit from enhanced returns in the future.

1.2.2 Premia induced by sustainable investing

Subscripts I and X are used here as generic indices, standing for the vectors of n_I investable assets and n_X excluded assets, respectively. To simplify the notation, the time subscripts are omitted and all the returns, r, are considered in excess of the risk-free rate. Therefore, the excess return on any asset k in the market is denoted by r_k. The vectors of excess returns on assets, $I = (I_1, ..., I_{n_I})$ and $X = (X_1, ..., X_{n_X})$, are denoted by r_I and r_X, respectively. I refer to the value-weighted portfolios of investable assets and of excluded assets as the *investable market* and *excluded market* portfolios, respectively. The excess returns on the investable market, excluded market, and market are denoted by r_{m_I}, r_{m_X}, and r_m, respectively. I use σ to denote the standard deviation of the excess returns on an asset and ρ for the correlation coefficient (or multiple correlation coefficient) between the excess returns on two assets (or between one asset and a vector of assets, respectively). Let β_{km_I} be the slope coefficient of the regression of the excess returns on asset $k \in \{I_1, ...I_{n_I}, X_1, ..., X_{n_X}\}$ on the excess returns on the investable market m_I, and a constant. Let B_{kI} be the row vector of the slope coefficients in a multiple regression of asset k's excess returns on the excess returns on the investable assets $I_1, ..., I_{n_I}$ and a constant. $\mathbb{C}\text{ov}(r_k, r_{m_X}|r_I)$ and $\mathbb{C}\text{ov}(r_k, r_{m_X}|r_{m_I})$ refer to the conditional covariances between r_k and r_{m_X}, given the vector of returns r_I and return r_{m_I}, respectively.

[13]However, it should be noted that Merton allows each stock to be neglected by a different number of investors, while, in the present model, all excluded stocks are excluded by the same proportion of total wealth p_e.

[14]As in Fama and French (2007b), these tastes may be linked to either non-pecuniary motives (Riedl and Smeets, 2017; Hartzmark and Sussman, 2020) or lower financial risk expectations (Lins, Servaes, and Tamayo, 2017; Krüger, 2015; Battiston et al., 2017; Krüger, Sautner, and Starks, 2020).

[15]For simplicity, I consider c_k deterministic. Generally, the results are identical when one assumes that $c_{k,t}$ is a random variable of zero variance that is independent of investable asset returns.

Proposition 1 (S-CAPM).

1. The expected excess return on any asset k is

$$\mathbb{E}(r_k) = \beta_{km_I}\left(\mathbb{E}(r_{m_I}) - p_i c_{m_I}\right) + \underbrace{\frac{p_i}{1-p_e} c_k - \frac{p_i p_e}{1-p_e} B_{kI} C_I}_{\textit{Taste premia}} + \underbrace{\gamma \frac{p_e}{1-p_e} q \,\mathbb{C}\mathrm{ov}(r_k, r_{m_X} | r_I) + \gamma q \,\mathbb{C}\mathrm{ov}(r_k, r_{m_X} | r_{m_I})}_{\textit{Exclusion premia}}. \tag{1.1}$$

2. Particularly,

(i) the expected excess return on any investable asset I_k is

$$\mathbb{E}(r_{I_k}) = \beta_{I_k m_I}\left(\mathbb{E}(r_{m_I}) - p_i c_{m_I}\right) + \underbrace{p_i c_{I_k}}_{\textit{Direct taste premium}} + \underbrace{\gamma q \,\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X} | r_{m_I})}_{\textit{Exclusion-market premium}}, \tag{1.2}$$

(ii) the expected excess return on any excluded asset X_k is

$$\mathbb{E}(r_{X_k}) = \beta_{X_k m_I}\left(\mathbb{E}(r_{m_I}) - p_i c_{m_I}\right) + \underbrace{\frac{p_i}{1-p_e} c_{X_k}}_{\textit{Direct taste premium}} - \underbrace{\frac{p_i p_e}{1-p_e} B_{X_k I} C_I}_{\textit{Indirect taste premium}} + \underbrace{\gamma \frac{p_e}{1-p_e} q \,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X} | r_I)}_{\textit{Exclusion-asset premium}} + \underbrace{\gamma q \,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X} | r_{m_I})}_{\textit{Exclusion-market premium}}. \tag{1.3}$$

Proposition 7 shows that sustainable investors' exclusion and integration practices involve two types of additional premia in equilibrium: two exclusion premia[16]—the *exclusion-asset* and *exclusion-market* premia—and two taste premia—the *direct* and *indirect taste* premia. The presence of the exclusion-market premium on investable asset returns and the indirect taste premium on excluded asset returns reflects the cross effects of exclusion and integration practices. Compared to the previous papers on partially segmented markets (Errunza and Losq, 1985; Jong and Roon, 2005), I show that equilibrium returns can be expressed in a unified form for all assets in the market (Equation (1.1)). As in Jong and Roon (2005) and Eiling (2013), the expected excess returns are expressed with respect to those on the investable market, which is the largest investment universe accessible to all investors in a partially segmented market. The expected return on the investable market is lowered by the direct taste premium on this market, $p_i c_{m_I}$.

Three limiting cases can be considered. First, when sustainable investors do not exclude assets but have different tastes for investable assets from regular investors ($p_e = 0$ and $p_i > 0$), the exclusion premia disappear because $q = 0$ and only the direct

[16]The exclusion premia are not random variables but scalars because, for a multivariate normal distribution, the conditional covariance does not depend on the given values (see Lemma 1 in the Appendix).

taste premium remains. In addition, the investable market, m_I, and the market, m, coincide. Denoting the beta of asset k with respect to the market by β_{km} and the average cost of externalities in the market by c_m, the expected excess return on asset k is

$$\mathbb{E}(r_k) = \beta_{km} \left(\mathbb{E}(r_m) - p_i c_m\right) + p_i c_k. \tag{1.4}$$

Specifically, when the economy is only populated by integrators ($p_i = 1$), the equilibrium equation reduces to Acharya and Pedersen (2005)'s liquidity-adjusted CAPM with a deterministic illiquidity cost.

Second, when sustainable investors only practice exclusion and have similar tastes to those of regular investors ($p_e > 0$ and $p_i = 0$), the taste premia vanish ($\forall k \in \{I_1, ..., I_{n_I}, X_1, ..., X_{n_X}\}$, $c_k = 0$) and only the exclusion premia remain. Equation (1.2) reduces to the I-CAPM equilibrium equation for investable assets in Jong and Roon (2005):[17]

$$\mathbb{E}(r_{I_k}) = \beta_{I_k m_I}\, \mathbb{E}(r_{m_I}) + \gamma q\, \mathbb{C}\text{ov}(r_{I_k}, r_{m_X} | r_{m_I}). \tag{1.5}$$

Equation (1.3) is also related to Jong and Roon (2005), who express the equilibrium equation for excluded assets' expected excess returns with respect to the vector of investable assets' expected returns, $\mathbb{E}(r_I)$. I extend their result to express the expected excess returns on excluded assets with respect to those on the investable market, $\mathbb{E}(r_{m_I})$, as

$$\mathbb{E}(r_{X_k}) = \beta_{X_k m_I}\, \mathbb{E}(r_{m_I}) + \gamma \frac{p_e}{1 - p_e} q\, \mathbb{C}\text{ov}(r_{X_k}, r_{m_X} | r_I) + \gamma q\, \mathbb{C}\text{ov}(r_{X_k}, r_{m_X} | r_{m_I}). \tag{1.6}$$

Finally, in the absence of sustainable investors ($p_e = 0$ and $p_i = 0$), there are no longer any excluded assets ($q = 0$, m_I and m coincide), and the model boils down to the CAPM.

Taste premia

Two taste premia induced by integrators' tastes arise in equilibrium: a direct taste premium, $p_i c_{I_k}$ and $\frac{p_i}{1-p_e} c_{X_k}$, for investable asset I_k and excluded asset X_k, respectively; and an indirect taste premium, $-\frac{p_i p_e}{1-p_e} B_{X_k I} C_I$, for excluded asset X_k.

The direct taste premium is proportional to the cost of externalities: the higher the cost of externalities is, the higher will be the premium to incentivize integrators to acquire the asset under consideration, and vice versa when the cost of externalities is low. This finding is in line with the literature on differences of opinion[18] in which the assets' expected returns increase (or decrease) when a group of investors is pessimistic (or optimistic). It is also consistent with Pastor, Stambaugh, and Taylor (2019) who

[17] The *local segmentation* premium in Jong and Roon (2005) can be expressed as a conditional covariance between asset returns (see Lemma 1 in the Appendix).

[18] See, in particular, Jouini and Napp (2007) and Atmaz and Basak (2018).

show that brown and green assets have positive and negative alphas, respectively. The direct taste premium also increases with the proportion of integrators, p_i, as shown by Fama and French (2007b) and Gollier and Pouget (2014). Specifically, for excluded stocks, the direct taste premium also increases with the proportion of excluders, p_e.

The indirect taste premium is a hedging effect induced by integrators: as they underweight investable assets with a high cost of externalities, integrators hedge by overweighting the excluded assets that are most correlated with the investable assets having a high cost of externalities. Therefore, the indirect taste premium is a cross effect of investable assets on excluded asset returns. Here, this cross-effect only arises on excluded asset returns because the expected returns are expressed with respect to the expected returns on the investable market.[19]

Finally, by internalizing externalities on investable assets, integrators simultaneously adjust their total exposure to the investable market and impact the market premium through c_{m_I}. When they internalize a positive global cost of externalities ($c_{m_I} > 0$), they underweight the investable market and the market premium is negatively adjusted. The opposite effect applies when the global cost of externalities is negative. This effect does not arise in Pastor, Stambaugh, and Taylor (2019) because the authors assume that $c_{m_I} = 0$. Therefore, focusing on asset I_k, which has no indirect taste premium, the total *taste effect* caused by integrators' tastes is a relative effect:

$$\text{Taste effect for investable asset } I_k = \underbrace{p_i c_{I_k}}_{\text{Direct taste premium}} - \underbrace{\beta_{I_k m_I} p_i c_{m_I}}_{\text{Market effect}}.$$

Consequently, although the weighted average cost of externalities on the investable market, c_{m_I}, is not necessarily zero, the weighted average taste effect is zero.

Exclusion premia

Two exclusion premia arise in equilibrium on excluded assets' expected excess returns: the exclusion-asset premium, $\gamma \frac{p_e}{1-p_e} q\, \mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X} | r_I)$, and the exclusion-market premium, $\gamma q\, \mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X} | r_{m_I})$. As a cross effect, the exclusion-market premium, $\gamma q\, \mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X} | r_{m_I})$, also arises in equilibrium on investable assets' expected excess returns, while the exclusion-asset premium is zero.

The exclusion-asset premium is the *super risk premium*, as characterized by Errunza and Losq (1985) for excluded assets in partially segmented markets.[20] The

[19]A cross effect of integrators' tastes for excluded assets on investable asset returns also arises in equilibrium when investable asset returns are expressed with respect to the market returns, r_m (see the proof of Proposition 3).

[20]Using different levels of risk aversion, denoting regular investors and integrators' risk aversion by γ_r and the global risk aversion by γ, the exclusion-asset premium is $\left(\frac{\gamma_r}{1-p_e} - \gamma\right) q\, \mathbb{C}\mathrm{ov}(r_k, r_{m_X} | r_I)$. Errunza and Losq (1985) use absolute risk aversions, while relative risk aversions are used in the present model.

exclusion-market premium is the *local segmentation* premium that Jong and Roon (2005) identify for investable asset.[21]

As outlined in Corollary 2, the exclusion premia are induced by the joint hedging effect of regular investors and integrators compelled to hold excluded assets and excluders who cannot hold them.

Corollary 2 (Breakdown of the exclusion premia)**.**
The exclusion premia can be expressed as the difference between a non-excluder effect and an excluder effect:

$$\gamma \frac{p_e}{1-p_e} q\, \mathbb{C}\mathrm{ov}(r_k, r_{m_X} | r_I) = \underbrace{\gamma \tfrac{p_e}{1-p_e} q\, \mathbb{C}\mathrm{ov}(r_k, r_{m_X})}_{\textit{Non-excluder effect}} - \underbrace{\gamma \tfrac{p_e}{1-p_e} q\, \mathbb{C}\mathrm{ov}\left(\mathbb{E}(r_k|r_I), \mathbb{E}(r_{m_X}|r_I)\right)}_{\textit{Excluder effect}}, \tag{1.7}$$

$$\gamma q\, \mathbb{C}\mathrm{ov}(r_k, r_{m_X} | r_{m_I}) = \underbrace{\gamma q\, \mathbb{C}\mathrm{ov}(r_k, r_{m_X})}_{\textit{Non-excluder effect}} - \underbrace{\gamma q\, \mathbb{C}\mathrm{ov}(\mathbb{E}(r_k|r_{m_I}), \mathbb{E}(r_{m_X}|r_{m_I}))}_{\textit{Excluder effect}}. \tag{1.8}$$

The former effect is induced by regular investors' and integrators' need for diversification: since they are compelled to hold the excluded market portfolio, they value most highly the assets that are the least correlated with this portfolio. The latter effect is related to the hedging need of excluders, who cannot hold excluded assets. As the second-best solution, they seek to purchase from regular investors and integrators the hedging portfolios most correlated with the excluded market and built from investable assets, with returns of $\mathbb{E}(r_{m_X}|r_I)$, and from the investable market portfolio, with returns of $\mathbb{E}(r_{m_X}|r_{m_I})$. As a result, excluders value most highly the hedging portfolios of asset k if they are highly correlated with the hedging portfolios of the excluded market.

The exclusion-asset premium is a generalized form of Merton (1987)'s premium on neglected stocks. Proposition 3 characterizes this by expressing the expected excess returns on excluded assets as a function of the market returns, r_m.

Proposition 3 (A generalized form of Merton (1987)'s premium on neglected stocks)**.**

Let $\tilde{\beta}_{X_k m} = \frac{\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_I})}{\mathbb{C}\mathrm{ov}(r_m, r_{m_I})}$. *When the expected excess returns on* X_k *are expressed with respect to those on the market portfolio, the exclusion-asset premium is*

$$\gamma \frac{p_e}{1-p_e} q\, \mathbb{C}\mathrm{ov}(r_{X_k} - \tilde{\beta}_{X_k m} q r_{m_X}, r_{m_X} | r_I), \tag{1.9}$$

and is a generalized form of Merton (1987)'s premium on neglected stocks.

[21] I show that both exclusion premia apply to all assets in the market; indeed, $\gamma \frac{p_e}{1-p_e} q\, \mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_I) = 0$. However, when the expected returns on investable assets, $\mathbb{E}(r_{I_k})$, are expressed with respect to the expected market returns, $\mathbb{E}(r_m)$, the exclusion-asset premium is not zero (see the proof of Proposition 3).

Therefore, the generalized form of Merton (1987)'s premium on neglected stocks is equal to $\gamma \frac{p_e}{1-p_e} q\, \mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_I)$, which is adjusted by factor $-\gamma \frac{p_e}{1-p_e} \tilde{\beta}_{X_k m} q^2\, \mathbb{V}\mathrm{ar}(r_{m_X}|r_I)$ to express the expected excess returns on excluded assets with respect to those on the market.

Hong and Kacperczyk (2009) and Chava (2014) empirically show that sin stocks have higher expected returns than otherwise comparable stocks. Although this finding is true on average, it is not always true for individual stocks (see Proposition 4).

Proposition 4 (Sign of the exclusion premia).
(i) The exclusion premia on an excluded asset are not necessarily positive.
(ii) The exclusion premia on the excluded market portfolio are always positive or zero and equal to

$$\gamma q\, \mathbb{V}\mathrm{ar}(r_{m_X}) \left(\frac{p_e}{1-p_e}(1-\rho_{m_X I}) + (1-\rho_{m_X m_I}) \right). \tag{1.10}$$

When an excluded asset is sufficiently decorrelated from the excluded market, the exclusion premia are likely to be negative.[22] In this case, regular investors and integrators are strongly incentivized to diversify their risk exposure by purchasing the excluded asset. However, although the exclusion effect on individual assets is not necessarily positive, the value-weighted average exclusion effect is always positive or zero.

1.3 Empirical analysis applied to sin stock exclusion and green investing: The identification strategy

I estimate the proposed model, treating sin stocks as excluded assets and applying the ESG integration process through the integrators' tastes for green firms. In this section, I describe the data used, the instrument developed for approximating integrators' tastes, and the identification method.

1.3.1 Data and instrument design

Sin stocks as excluded assets

Although the practice of exclusionary screening has previously targeted other objectives, such as the boycott of the South African state during the apartheid regime (Teoh, Ivo, and Paul, 1999), it is now mainly applied to sin stocks. However, there is no consensus on the scope of the sin industries to be excluded. Luo and Balvers (2017) provide a summary of the sin industries analyzed in the existing literature. The tobacco, alcohol, and gaming industries are always regarded as sin industries. Several authors include the defense industry, but Hong and Kacperczyk (2009) exclude it from U.S. data, noting that not all U.S. investors regard it as a controversial industry.

[22]Precisely, when the correlation of an excluded asset with the excluded market is lower than that of their replicating portfolios using investable assets, the exclusion premia are negative.

Some studies also include the pornography and coal industries as sin stocks. I conduct an analysis on U.S. stocks and follow Hong and Kacperczyk (2009) by focusing on the *triumvirate of sins*, consisting of the tobacco, alcohol, and gaming industries. I check the validity of the results by performing a robustness test including the defense industry.

I start from all the common stocks (share type codes 10 and 11) listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations exchange (NASDAQ; exchange codes 1, 2, and 3) in the CRSP database. I use the Standard Industrial Classification (SIC) to identify 48 different industries. The alcohol (SIC 4), tobacco (SIC 5), and defense (SIC 26) industries are directly identifiable from this classification. Since the classification does not distinguish gaming companies from those in the hotel and entertainment industries, in line with Hong and Kacperczyk (2009), I define a 49th industrial category consisting of gaming based on the North American Industry Classification System (NAICS). Gaming companies have the following NAICS codes: 7132, 71312, 713210, 71329, 713290, 72112, and 721120. Therefore, out of the 49 industries, I focus on the three sin industries of alcohol, tobacco, and gaming, which accounted for 52 stocks between December 31, 2007 and December 31, 2019. Over this period, the number of companies decreased and the market capitalization of all sin companies increased (Table 1.1).

I perform the empirical analysis from December 2007 because the data available on investors' tastes for green firms are too scarce to perform a sufficiently robust analysis before this date (see subsection 1.3.1). However, I carry out a robustness check between December 1999 and December 2019 on the model without heterogeneous preferences, that is, reduced to a single group of sustainable investors practicing exclusion.

TABLE 1.1: **Profile of the sin industries.** This table reports the number of firms and the total market capitalization corresponding to the alcohol, tobacco, gaming and defense industries between December 31, 2007, and December 31, 2019.

	Number of firms				Average Market Capitalization ($ billion)			
	Alcohol	Tobacco	Gaming	Defense	Alcohol	Tobacco	Gaming	Defense
Dec. 2007 - Dec. 2011	15	9	10	21	1.8	26.9	4.7	2.5
Dec. 2011 - Dec. 2015	15	8	8	18	3.3	41.5	7	5.4
Dec. 2015 - Dec. 2019	13	8	10	9	6.4	53.6	13.8	8.1

Integrators' tastes for green firms

I apply integrators' preferences to their taste for the stocks of green firms. Climate change, which is the main selection factor for green investment, is the first ESG criterion considered by asset managers (US SIF, 2018); the assets to which this criterion is applied doubled between 2016 and 2018 in the United States, reaching USD 3 trillion.

Many empirical studies have investigated the effects of a company's environmental performance on its stocks' excess returns. However, the results differ significantly for at least three main reasons. First, this heterogeneity lies in the fact that identifying the environmental performance of a company through a particular environmental metric weakly proxies for sustainable investors' tastes for green firms. Indeed, several dozen environmental impact metrics are offered by various data providers, covering a wide range of themes, methods, and analytical scopes. These metrics lack a common definition and show low commensurability (Chatterji et al., 2016).[23] For instance, Gibson et al. (2019) show that the average correlation between the environmental impact metrics of six major ESG data providers was 42.9% between 2013 and 2017. Each available metric reflects specific information, and the average taste of all sustainable investors for green firms can hardly be captured by a single metric. Moreover, these metrics are generally only available on an annual basis and are liable to have several limitations, such as oversimplifying information (Mattingly and Berman, 2006) and providing low prospective content (Chatterji, Levine, and Toffel, 2009). The second reason for the heterogeneity of the results in the empirical studies is that these papers fail to capture the increase in the proportion of green investors and, thus, the growing impact of their tastes, over time. The third reason is raised by Pastor, Stambaugh, and Taylor (2019): by proxying expected returns by realized returns, these papers omit to control the effect of the unexpected shifts in tastes on realized returns. If the proportion of green investors or their tastes for green companies unexpectedly increase, green assets may outperform brown assets while the former have a lower direct taste premium than the latter.

Therefore, I construct a proxy for the tastes of green investors that allows me to address the three issues raised. I circumvent the first two issues by approximating the shifts in tastes of green investors from a qualitative and quantitative point of view: I approximate both the cost of environmental externalities defined in the model, c_k, and green investors' wealth share, p_i, by using green fund holdings. Such a proxy for the direct taste premium allows me to address the third issue by constructing a proxy for the unexpected shifts in green investors' tastes (see Subsection 1.4.4).

Proxy for the cost of environmental externalities. In Proposition 5, we focus on investable assets and give a first order approximation of the cost of externalities.

Proposition 5 (Proxy for the cost of externalities).
Let us denote integrators' optimal weight of I_k by w^*_{i,I_k} and the market weight of I_k by w_{m,I_k}. Let us assume that (i) integrators do not account for the correlations among

[23] These metrics cover different environmental themes, such as greenhouse gas emissions, air quality, water management, waste treatment, impact on biodiversity, and thematic and global environmental ratings (e.g., KLD ratings). Even for greenhouse gas emissions, various metrics are available: carbon intensity, two-degree alignment, avoided emissions, green share, and emission scores, among others. Additionally, data providers often have their own methods of calculation and analysis scopes. The calculation is further complicated by the inconsistency of the data reported by companies, as well as by the differences in the treatment of data gaps and the benchmarking options chosen by data providers (Kotsantonis and Serafeim, 2019).

assets when internalizing the cost of externalities, (ii) the share of integrators' wealth, p_i, is small, and (iii) the direct taste premium, $p_i c_{I_k}$, is small compared to the expected return, $\mathbb{E}(r_{I_k})$. The cost of environmental externalities, c_{I_k}, is approximated as

$$c_{I_k} \simeq \frac{w_{m,I_k} - w^*_{i,I_k}}{w_{m,I_k}} \mathbb{E}(r_{I_k}). \tag{1.11}$$

First, assuming that integrators account for the correlations between assets in estimating the cost of environmental externalities of a specific asset is pretty strong in practice; therefore, assumption (i) seems fairly plausible. Second, the share of wealth of all sustainable investors in the U.S. reached 25% in 2018; therefore, assumption (ii) focusing only on green investors between 2007 and 2019 is realistic. Finally, assumption (iii) seems also realistic as illustrated by the following example: assuming that the cost of environmental externalities internalized by green investors accounts for 10% of the expected return and that the share of green investors' wealth is 10%, $p_i c_{I_k}$ is 100 times lower than $\mathbb{E}(r_{I_k})$.

Therefore, I exclude the expected return, $\mathbb{E}(r_{I_k})$, in the approximation of Proposition 5 to avoid endogeneity bias, and I define the proxy for the cost of externalities of asset I_k, $\tilde{c}_{I_k}$, as

$$\tilde{c}_{I_k} = \frac{w_{m,I_k} - w^*_{i,I_k}}{w_{m,I_k}}. \tag{1.12}$$

The more integrators underweight I_k with respect to market weights, the higher $\tilde{c}_{I_k}$ is, and vice versa when they overweight I_k.

I compute the microfounded proxy, $\tilde{c}_{I_k}$, by using the holding history of all the listed green funds investing in U.S. equities. Specifically, among all funds listed by Bloomberg on December 2019, I select the 453 funds whose asset management mandate includes environmental guidelines ("environmentally friendly," "climate change," and "clean energy"), of which the investment asset classes are defined as "equity," "mixed allocation," and "alternative,"[24] with the geographical investment scope including the United States.[25] I retrieve the entire asset holding history of each of these funds on a quarterly basis (March, June, September, and December) via the data provider FactSet. The number of green funds exceeded 100 in 2010 and reached 200 in 2018. I aggregate the holdings of all green funds on a quarterly basis and focus on the U.S. stock investment universe in CRSP (referred to as the *US allocation*). Given the large number of stocks and the high sensitivity of $\tilde{c}_{I_k}$ when w_{m,I_k} is close to zero, I perform the analysis on industry-sorted portfolios. The investable market consists of 46 industries corresponding to the 49 industries from which the three sin industries have been removed. For every quarter t, I calculate the weight of each industry I_k in the U.S. allocation of the aggregated green fund to estimate w^*_{i,I_k} at date t. I estimate w_{m,I_k} as the weight of industry I_k in the investment universe. I construct instrument

[24] The last two categories include diversified funds that also invest in equities.

[25] The geographical areas selected are "Global," "International," "Multi," "North American Region," "Organisation for Economic Co-operation and Development countries," and "the U.S." (see the Internet Appendix).

$\tilde{c}_{I_k}$ by substituting the estimates of w^*_{i,I_k} and w_{m,I_k} in equation (1.12). I then extend the value of the instrument over the next two months of the year in which no holding data are available. However, I do not approximate the cost of environmental externalities of the 52 sin stocks, c_{X_k}, because of the low number of sin stocks held by the 453 green funds.

This agnostic instrument proxies the revealed tastes of *green investors* by comparing green funds' asset allocations with the asset weights in the investment universe. It offers the dual advantage of covering a large share of the assets in the market (46% of the stocks at the end of 2019) and being constructed from a minimal fraction of the AUM (green funds' AUM accounted for only 0.12% of the market capitalization of the investment universe at the end of 2019).[26] Therefore, by using instrument $\tilde{c}_{I_k}$, I implicitly assume that all green investors have fairly similar tastes to those revealed by the aggregated 453 green funds, and I test this assumption by estimating the asset pricing model.[27]

In line with the gradual development of green investing during the 2000s and concomitantly with the enforcement of the U.S. Securities and Exchange Commission's (SEC's) February 2004 amendment requiring U.S. funds to disclose their holdings on a quarterly basis, the number of green funds reporting their holdings exceeded 50 as of 2007. Therefore, to construct sufficiently robust proxies for the taste premia, I start the analysis from December 2007. Table 1.2 summarizes the proxy for the cost of environmental externalities and the excess returns for the various investable industries in descending order of average cost, $\tilde{c}_{I_k}$, between December 2007 and December 2019.

This ranking shows that the industries least held by green funds include fossil energies (coal, petroleum, and natural gas), highly polluting manufacturing industries (defense, and printing and publishing), polluting transportation (aircraft and shipping containers), and mining (non-metallic and industrial mining and precious metals). However, to be able to overweight the least polluting companies, green investors not only underweight the most polluting companies, but also some of the largest market capitalizations. Particularly, they substantially underweight the largest companies in the investment universe, which belong to the entertainment (e.g., Time Warner and Walt Disney), retail (e.g., Walmart), communication (e.g., Verizon and CBS), banking (e.g., JP Morgan, Wells Fargo, and Citigroup), and insurance (e.g., Berkshire Hathaway, United Health, and AIG) industries. This is the reason these specific industries are at the top of the ranking in Table 1.2.

[26] The AUMs of the 453 green funds account for only 0.12% of the total market capitalization of the investment universe for two main reasons: most green investments are made through the proprietary funds of institutional investors (pension funds, life insurers, etc.) rather than via open-ended funds; not all green funds worldwide are necessarily listed in Bloomberg and FactSet.

[27] Given that the list of green funds is not historically available, I acknowledge that the proposed instrument may introduce survivorship bias. However, given the massive and steady increase in green investments, the net creation of green funds can be assumed to be positive over the period. As a result, the number of closed green funds should be limited compared to the number of green funds still in operation. Additionally, it can be assumed that the average tastes of the closed funds do not differ significantly from the average tastes of the funds still in operation.

TABLE 1.2: **Descriptive statistics on the investable industries.** This table reports the descriptive statistics for the proxy for the cost of environmental externalities $\tilde{c}$ and the monthly returns in excess of the 1-month T-Bill between December 31, 2007, and December 31, 2019, in each of the 46 investable industries (i.e., the 49 SIC industries from which the alcohol, tobacco and gaming industries have been excluded). The construction of the proxy for the cost of environmental externalities is described in section 1.3.1. In this table, the industries are ranked in descending order of the average proxy $\tilde{c}$.

	Environmnetal cost proxy					Returns				
Industry Name	Mean	Median	St dev.	Min.	Max.	Mean	Median	St dev.	Min.	Max.
Defense	0.87	0.83	0.08	0.72	0.96	0.021	0.018	0.011	-0.001	0.039
Aircraft	0.69	0.72	0.09	0.47	0.80	0.018	0.018	0.004	0.004	0.028
Precious metals	0.66	0.61	0.08	0.52	0.75	0.008	0.015	0.018	-0.026	0.043
Printing and publishing	0.58	0.58	0.05	0.43	0.66	0.017	0.017	0.009	0.000	0.039
Non-metallic and industrial metal mining	0.54	0.63	0.18	0.17	0.86	0.013	0.012	0.009	-0.007	0.038
Coal	0.52	0.53	0.25	0.32	0.99	-0.002	-0.006	0.018	-0.041	0.039
Agriculture	0.50	0.40	0.61	-1.58	1.00	0.017	0.018	0.011	-0.006	0.036
Entertainment	0.41	0.38	0.18	0.15	0.64	0.025	0.024	0.006	0.010	0.035
Personal services	0.38	0.38	0.04	0.29	0.46	0.016	0.017	0.005	0.004	0.025
Petroleum and natural gas	0.36	0.33	0.08	0.27	0.58	0.008	0.008	0.006	-0.005	0.023
Cand & Soda	0.36	0.32	0.10	0.28	0.57	0.010	0.010	0.003	0.005	0.018
Communication	0.32	0.27	0.09	0.24	0.49	0.014	0.013	0.005	0.005	0.025
Trading	0.32	0.30	0.09	0.22	0.50	0.014	0.014	0.005	0.002	0.026
Retail	0.29	0.28	0.11	0.15	0.47	0.015	0.015	0.005	0.006	0.024
Banking	0.27	0.27	0.07	0.19	0.44	0.012	0.012	0.005	-0.002	0.026
Pharmaceutical products	0.23	0.22	0.03	0.19	0.29	0.017	0.017	0.006	0.007	0.029
Insurance	0.22	0.18	0.20	0.04	0.57	0.015	0.014	0.004	0.005	0.025
Meals	0.19	0.18	0.09	0.10	0.41	0.017	0.016	0.004	0.010	0.032
Shipbuilding & Railroad equipment	0.19	0.10	1.12	-2.28	0.92	0.014	0.014	0.007	0.000	0.032
Chemicals	0.16	0.21	0.12	-0.26	0.25	0.015	0.015	0.005	0.007	0.033
Real estate	0.14	0.11	0.22	-0.13	0.50	0.017	0.017	0.009	0.003	0.044
Clothes apparel	0.13	0.24	0.21	-0.10	0.50	0.018	0.020	0.008	0.004	0.038
Transportation	0.11	0.15	0.17	-0.18	0.43	0.016	0.016	0.004	0.010	0.029
Recreation	0.10	0.09	0.18	-0.11	0.57	0.014	0.014	0.006	0.003	0.031
Steel works	0.08	0.06	0.49	-0.54	0.74	0.012	0.011	0.004	0.005	0.028
Business services	0.05	0.05	0.07	-0.01	0.23	0.019	0.019	0.003	0.011	0.029
Computers	0.02	0.05	0.14	-0.25	0.17	0.018	0.016	0.005	0.010	0.035
Automobiles and trucks	-0.05	-0.02	0.07	-0.16	0.05	0.016	0.013	0.010	0.003	0.050
Shipping containers	-0.08	0.30	0.52	-1.13	0.64	0.013	0.013	0.004	0.005	0.026
Consumer Goods	-0.10	-0.02	0.14	-0.38	0.09	0.010	0.009	0.004	0.003	0.021
Rubber and plastic products	-0.18	-0.12	0.54	-1.61	0.39	0.018	0.018	0.008	0.004	0.046
Healthcare	-0.22	-0.19	0.14	-0.39	0.04	0.014	0.015	0.006	0.002	0.026
Food products	-0.23	-0.21	0.10	-0.41	-0.05	0.014	0.015	0.005	0.003	0.021
Medical equipment	-0.26	-0.27	0.09	-0.46	-0.15	0.017	0.018	0.004	0.006	0.026
Fabricated products	-0.33	0.11	1.05	-3.44	0.66	0.014	0.016	0.010	-0.005	0.034
Chips	-0.40	-0.40	0.14	-0.73	-0.22	0.017	0.017	0.004	0.008	0.027
Textiles	-0.54	-0.69	0.64	-1.88	0.61	0.021	0.021	0.007	0.010	0.046
Wholesale	-0.57	-0.59	0.13	-0.71	-0.25	0.016	0.016	0.005	0.008	0.029
Utilities	-0.59	-0.50	0.28	-1.12	-0.27	0.010	0.010	0.003	0.001	0.018
Business supplies	-0.77	-0.62	0.42	-1.44	0.16	0.015	0.015	0.006	0.005	0.037
Machinery	-0.83	-0.77	0.37	-1.81	-0.40	0.012	0.010	0.006	0.002	0.036
Construction materials	-2.17	-1.97	0.63	-3.54	-1.45	0.018	0.017	0.005	0.008	0.038
Construction	-2.33	-2.95	1.44	-4.36	-0.44	0.016	0.015	0.005	0.005	0.027
Electrical equipment	-2.58	-2.43	0.43	-3.51	-2.06	0.013	0.013	0.005	0.003	0.030
Measuring and control equipment	-2.63	-2.57	0.28	-3.85	-2.29	0.019	0.018	0.004	0.012	0.031
Other	-6.62	-6.56	2.40	-11.93	-3.48	0.012	0.012	0.002	0.005	0.018
Investable market portfolio m_I	-0.02	-0.02	0.00	-0.02	-0.01	0.015	0.015	0.003	0.009	0.027
Excluded market portfolio m_X						0.017	0.016	0.007	0.002	0.038

Some of the green funds under consideration may also implement social (S) and governance (G) screens. Therefore, it should be noted that the estimates $\tilde{c}$ and $\tilde{p}_i$ potentially include a limited bias towards S and G factors. However, this does not hamper the present analysis as the objective is to identify the impact of integrators' tastes on asset returns.

Proxy for the proportion of integrators' wealth. To capture the shifts in tastes from a quantitative point of view, I construct a proxy for the proportion of integrators' wealth, p_i. I estimate the proportion of assets managed following environmental guidelines as the market value of the 453 green funds divided by the market value of the investment universe at each considered date. The instrument is denoted by $\tilde{p}_i$ and defined as:

$$\tilde{p}_{i,t} = \frac{\text{Market value of green funds in } t}{\text{Total market capitalization in } t}. \tag{1.13}$$

Between December 2007 and December 2019, $\tilde{p}_i$ increased from 0.02% to 0.12% (see the Internet Appendix).

1.3.2 Empirical method

I conduct the estimations based on the equations in Proposition 7 being applied to sin stocks for excluded assets and green investors' tastes—through $\tilde{c}_{I_k}$ and $\tilde{p}_i$—to reflect integrators' preferences. I assume that the cost of externalities is proportional to its proxy: $c_{I_k} = \kappa_c \tilde{c}_{I_k}$ and $C = \kappa_c \tilde{C}$ ($\kappa_c \in \mathbb{R}_+$) for investable stock I_k and the vector of investable stocks, I, respectively. Similarly, I assume that the share of integrators' wealth is proportional to its proxy: $p_i = \kappa_p \tilde{p}_i$ ($\kappa_p \in \mathbb{R}_+$).

Investable asset specification. For each investable asset I_k ($k \in \{1, ..., n_I\}$), equation (1.2) is written as:

$$\mathbb{E}(r_{I_k}) = (\mathbb{E}(r_{m_I}) - p_i c_{m_I})\beta_{I_k m_I} + \kappa_p \kappa_c \tilde{p}_i \tilde{c}_{I_k} + \gamma q \operatorname{\mathbb{C}ov}(r_{I_k}, r_{m_X} | r_{m_I}). \tag{1.14}$$

The three independent variables are the beta coefficient, $\beta_{I_k m_I}$, the proxy for the *direct taste factor*, $\tilde{p}_i \tilde{c}_{I_k}$, and the *exclusion-market factor*, $q \operatorname{\mathbb{C}ov}(r_{I_k}, r_{m_X} | r_{m_I})$. As shown in the correlation matrix reported in the Internet Appendix, the correlations between all factors are low.

Excluded asset specification. For each excluded asset X_k ($k \in \{1, ..., n_X\}$), equation (1.3) is written as:

$$\begin{aligned}\mathbb{E}(r_{X_k}) = (\mathbb{E}(r_{m_I}) - p_i c_{m_I})\, \beta_{X_k m_I} &- \frac{p_e}{1-p_e} \kappa_p \kappa_c \tilde{p}_i B_{X_k I} \tilde{C}_I \\ &+ \gamma \frac{p_e}{1-p_e} q \operatorname{\mathbb{C}ov}(r_{X_k}, r_{m_X} | r_I) + \gamma q \operatorname{\mathbb{C}ov}(r_{X_k}, r_{m_X} | r_{m_I}).\end{aligned} \tag{1.15}$$

The four independent variables of the estimation are the beta coefficient, $\beta_{X_k m_I}$, the proxy for the *indirect taste factor*, $\tilde{p}_i B_{X_k I} \tilde{C}_I$, the *exclusion-asset factor*, $q\,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X} | r_I)$, and the *exclusion-market factor*,[28] $q\,\mathbb{C}\mathrm{ov}(r_{X_i}, r_{m_X} | r_{m_I})$. It is worth noting two points regarding this specification. First, I do not proxy the proportion of excluders' wealth, p_e, because the funds that exclude sin stocks are not directly identifiable; furthermore, unlike green investment, sin stock exclusion is one of the oldest sustainable investment practices and is therefore likely to have grown at a moderate pace over the period studied. However, I perform a robustness check by using $\tilde{p}_i$ as a proxy for p_e. Second, I do not include the direct taste factor, c_{X_k}, because its proxy cannot be estimated for a sufficiently large number of stocks. In addition, the significance of the direct taste premium is already tested for investable assets, which constitute 99% of the investment universe. In the above specification, the correlations between all factors are low.

Estimation method. I estimate specifications (1.14) and (1.15) by performing a two-stage cross-sectional regression (Fama and MacBeth, 1973). To account for conditional heteroskedasticity and serial correlation, the standard errors are adjusted in line with Newey and West (1987). Investable assets account for 5,660 stocks, and there are 52 sin stocks between December 2007 and December 2019. The estimates on the former are conducted on industry portfolios, while those on the latter are conducted on individual stocks. For investable assets, I take the value-weighted returns on the industry portfolios. All returns are in excess of the 1-month Treasury Bill (T-bill) rate. In the first pass, I compute the dependent and independent variables over a 3-year rolling period at monthly intervals, which yields a time series of 109 dates for each variable per stock (or portfolio).[29] Robustness tests are performed by repeating the analysis over a 5-year rolling period. In the second pass, I run the 109 cross-sectional regressions of the n_I and n_X dependent variables for portfolios I and stocks X, respectively, on a constant and the independent variables. The estimated loadings are equal to the average over the 109 dates. To evaluate and compare the models, I report the OLS adjusted-R^2 of the cross-sectional regressions. As suggested by Kandel and Stambaugh (1995) and Lewellen, Nagel, and Jay (2010), I also report the GLS R^2 as an alternative measure of model fit because it is determined by the factor's proximity to the minimum-variance boundary.

To check for the robustness of the estimated effects and to benchmark the model, I also include the betas of the SMB, HML (Fama and French, 1992), and MOM (Carhart, 1997) factors with respect to the investable market in the estimations. The

[28] The exclusion-asset and exclusion-market factors expressed as conditional covariances are easily computable from stacked excess returns as Schur complements in vector form (see Lemma 1 in the Appendix). I estimate the inverse of the investable asset covariance matrix by assuming that returns follow a one-factor model (Ledoit and Wolf, 2003).

[29] The betas are estimated as univariate betas.

three factors are downloaded from Kenneth French's website.[30] Table 1.3 presents descriptive statistics on the dependent and independent variables.

TABLE 1.3: **Summary statistics on the dependent and independent variables.** This table provides the summary statistics on the dependent and independent variables in the estimations of the S-CAPM in the case of investable industry portfolios and excluded stocks between December 2007 and December 2019. The investable market corresponds to the 49 SIC industries from which the alcohol, tobacco and gaming industries have been excluded. The excluded market corresponds to the 52 stocks issued by the alcohol, tobacco and gaming industries. The statistics relate to the exclusion-market factors for investable industry portfolios ($q\,\mathbb{C}\mathrm{ov}(r_I, r_{m_X}|r_{m_I})$) and excluded stocks ($q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_{m_I})$), respectively; the exclusion-asset factor for excluded stocks ($q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_I)$); the proxy for the direct taste factor for investable assets ($\tilde{p}_i\tilde{C}_I$); the proxy for the indirect taste factor in the case of excluded stocks ($\tilde{p}_i B_{XI}\tilde{C}_I$); the betas of the investable industry portfolios and excluded stocks with the Fama and French (1993) size and value factors ($\beta_{I.SMB}$, $\beta_{I.HML}$, $\beta_{X.SMB}$, $\beta_{X.HML}$) and the Carhart (1997) momentum factor ($\beta_{I.MOM}$, $\beta_{X.MOM}$), respectively. The statistics presented are the means, medians, standard deviations, minima, maxima and first-order autocorrelations (ρ_1) of the variables of interest based on monthly excess returns on the NYSE, AMEX and NASDAQ common stocks between December 31, 2007, and December 31, 2019.

	Mean	Median	Stdev	Min	Max	ρ_1
r_I	0.015	0.015	0.008	-0.041	0.05	0.347
β_{Im_I}	1.07	1.106	0.364	-0.338	2.296	0.271
$\tilde{p}_i\tilde{C}_I$	-2×10^{-4}	10^{-4}	10^{-3}	-7×10^{-3}	10^{-3}	0.018
$q\,\mathbb{C}\mathrm{ov}(r_I, r_{m_X}\|r_{m_I})$	-2×10^{-7}	-3×10^{-7}	7×10^{-6}	-6×10^{-5}	3×10^{-5}	0.291
$\beta_{I.SMB}$	-0.11	-0.005	3.866	-39.247	16.100	0.441
$\beta_{I.MOM}$	-0.485	-1.351	6.064	-15.853	59.577	0.481
$\beta_{I.MOM}$	1.383	2.253	7.778	-57.340	30.540	0.504
r_X	0.014	0.017	0.035	-0.440	0.197	0.017
β_{Xm_I}	0.822	0.615	0.926	-4.120	5.943	0.201
$\tilde{p}_i B_{XI}\tilde{C}_I$	6×10^{-5}	-6×10^{-5}	6×10^{-3}	-4×10^{-2}	3×10^{-2}	-0.033
$q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}\|r_I)$	-5×10^{-6}	-10^{-6}	8×10^{-5}	-6×10^{-4}	9×10^{-4}	0.08
$q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}\|r_{m_I})$	10^{-5}	9×10^{-6}	5×10^{-5}	6×10^{-4}	10^{-3}	0.117
$\beta_{X.SMB}$	-1.151	-0.796	8.282	-50.964	56.431	0.004
$\beta_{X.HML}$	-2.458	-2.511	9.790	-88.123	55.329	0.014
$\beta_{X.MOM}$	0.297	0.021	14.101	-76.370	114.336	0.080

The mean of the proxy for the direct taste factor, $\tilde{p}_i\tilde{C}_I$, is -2×10^{-4} and its median is 10^{-5}. The instrument reaches a maximum of 10^{-3} and the minimum is -7×10^{-3}. The exclusion factors are evenly distributed around a mean close to zero.

1.4 Stock returns with tastes for green firms

In this section, I empirically assess the effect of sustainable investors' tastes for green firms and that of their exclusion of sin stocks on investable stock excess returns. The direct taste premium significantly impacts excess returns. I find weak evidence supporting the effect of sin stock exclusion on investable stock returns.

[30]The website address is `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

1.4.1 Main estimation

I estimate the following three models. (i) The *S-CAPM* corresponds to equation (1.14):

$$\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{taste}\tilde{p}_i\tilde{c}_{I_k} + \delta_{ex.mkt} q\,\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_{m_I}); \tag{1.16}$$

(ii) the *four-factor S-CAPM* (denoted as *4F S-CAPM*) corresponds to the S-CAPM specification to which the SMB, HML, and MOM betas are added; and (iii) for benchmarking purposes, the *four-factor model* (denoted as *4F model*) corresponds to the CAPM specification with respect to the investable market returns to which the SMB, HML, and MOM betas are added.

Table 1.4 reports the estimates of the three specifications using industry-sorted portfolios between December 31, 2007 and December 31, 2019. Consistent with the model predictions, the direct taste premium is significant (t-statistic of 2.07) and its loading is positive ($\hat{\delta}_{taste} = 0.17$). When the SMB, HML, and MOM factors are included, this premium becomes highly significant (t-statistic of 5.55) and the loading increases to 0.49. The *annual* average market effect is $-\hat{\delta}_{taste}\tilde{p}_i\tilde{c}_{m_I} = 0.25$ basis point (bp).[31] Therefore, the market effect is negligible, and the taste effect is almost exclusively driven by the direct taste premium.

Although the exclusion-market premium—related to the indirect effect of the 52 excluded sin stocks on the 5,660 investable stocks—is positive and significant when considered individually, it is not significant in the S-CAPM specification.

For each industry, Table 1.5 provides the average annual taste effect estimates using the main model. Compared to the industry ranking in Table 1.2 that only takes into account proxy $\tilde{c}_{I_k}$, Table 1.5 provides a ranking according to the taste effect, $\widehat{\delta}_{taste}\tilde{p}_i\tilde{c}_{I_k} + \widehat{\delta}_{taste}\tilde{p}_i\tilde{c}_{m_I}\beta_{I_k m_I}$, that includes the market effect, $\widehat{\delta}_{taste}\tilde{p}_i\tilde{c}_{m_I}\beta_{I_k m_I}$. The rankings differ because $\beta_{I_k m_I}$ is not perfectly correlated with $\tilde{c}_{I_k}$.

The taste effect ranges from -1.12% to +0.14% for the different industries. Specifically, the return differential between industries differently impacted by the ecological transition is substantial. For example, green investors induce additional annual returns of 0.50% for the petroleum and natural gas industry compared to the electrical equipment industry.

1.4.2 Alternative estimations

I conduct alternative estimations, the results of which are available in the Internet Appendix. First, the estimate of the direct taste premium is robust to a first-pass regression using a 5-year rolling window, and its significance increases. Second, when using equally weighted returns, the direct taste premium is not significant, but the exclusion-market premium becomes significant and positive as predicted by the model. Third, I repeat the estimation using a set of 230 (= 46 × 5) industry-size portfolios

[31] The proxies for the value-weighted average cost of externalities and the taste factor of the investable market, $\tilde{c}_{m_I}$ and $\tilde{p}_i\tilde{c}_{m_I}$, are -55 bps and -0.12 bps, respectively, over the period.

double-sorted by industries and market capitalization quintiles. The direct taste premium is significant and consistent with the estimation using industry portfolios.

1.4.3 Reverse causality bias

The first concern is the risk of reverse causality bias through instrument $\tilde{c}$. In other words, is δ_{taste} significant because the return on industry I_k affects the relative weight differential between the market and integrators' asset allocation in this industry, $\frac{w_{m,I_k}-w^*_{i,I_k}}{w_{m,I_k}}$? I address this issue from theorical and empirical viewpoints. From a

TABLE 1.4: **Cross-sectional regressions for investable stock industry-sorted portfolios with tastes for green firms.** This table presents the estimates of the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for 46 investable stock industry-sorted portfolios between December 31, 2007, and December 31, 2019. The specification of the S-CAPM is written as follows: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{taste}\tilde{p}_i\tilde{c}_{I_k} + \delta_{ex.mkt}q\,\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$, where r_{I_k} is the value-weighted excess return on portfolio k ($k = 1, ..., n_I$), $\beta_{I_k m_I}$ is the slope of an OLS regression of r_{I_k} on r_{m_I}; $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; $\tilde{c}_{I_k}$ is the proxy for the cost of environmental externalities of stock I_k; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$ is the covariance of the excess return on portfolio I_k with that of the excluded market, the excess returns on the investable market being given. This specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added, and (ii) the 4F model is the CAPM with respect to the investable market returns to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{SMB}\beta_{I_k SMB} + \delta_{HML}\beta_{I_k HML} + \delta_{MOM}\beta_{I_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated portfolio-by-portfolio in a 3-year rolling window at monthly intervals. In the second pass, a cross-sectional regression is performed month-by-month on all the portfolios. The estimated parameter is the average value of the estimates obtained on the 109 months during the period. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0143	0.0004						0.05 [0.03,0.07]
t-value	(13)	(0.44)						0.07 [0.05,0.09]
Estimate	0.0149		0.174					-0.02 [-0.02,-0.01]
t-value	(24.16)		(2.2)					0.01 [0,0.01]
Estimate	0.0149			119.2				0.06 [0.04,0.08]
t-value	(26.22)			(2.15)				0.08 [0.06,0.1]
Estimate	0.0144	0.0004	0.1922					0.03 [0.02,0.05]
t-value	(12.95)	(0.44)	(2.55)					0.08 [0.06,0.1]
Estimate	0.0137	0.0012	0.1737	56.1				0.08 [0.06,0.11]
t-value	(10.51)	(1.13)	(2.07)	(0.77)				0.14 [0.12,0.17]
Estimate	0.0148	0.0024	0.491	-105.7	0.0001	0.0005	0.000	0.22 [0.19,0.26]
t-value	(14.54)	(2.71)	(4.55)	(-1.94)	(0.36)	(2.26)	(0.09)	0.33 [0.3,0.36]
Estimate	0.0139	0.0028			0.000	0.0004	0.000	0.23 [0.19,0.27]
t-value	(14.81)	(3.14)			(0.14)	(2.14)	(0.15)	0.3 [0.26,0.33]

TABLE 1.5: **Annual environmental taste effect estimates by industry.** For all 46 investable SIC industries, this table reports the estimates of the annual taste effect $\widehat{\delta}_{taste}\tilde{p}_i\tilde{c}_{I_k} + \widehat{\delta}_{taste}\tilde{p}_i\tilde{c}_{m_I}\beta_{I_k m_I}$, which is the sum of the direct taste premium and the market effect. The market effect, $\widehat{\delta}_{taste}\tilde{p}_i\tilde{c}_{m_I}\beta_{I_k m_I}$, accounts for only 0.25 basis points in the total taste effect. The industries are ranked in descending order of their taste effect.

Industry name	Annual taste premium (in %)
Defense	0.14
Aircraft	0.12
Coal	0.12
Printing and publishing	0.1
Precious metals	0.1
Non-metallic and industrial metal mining	0.09
Agriculture	0.07
Entertainment	0.07
Personal services	0.07
Cand & Soda	0.06
Petroleum and natural gas	0.06
Communication	0.06
Trading	0.06
Retail	0.05
Banking	0.05
Pharmaceutical products	0.04
Meals	0.04
Insurance	0.04
Clothes apparel	0.03
Chemicals	0.03
Steel works	0.03
Real estate	0.03
Recreation	0.02
Transportation	0.02
Business services	0.01
Computers	0.01
Automobiles and trucks	0
Shipping containers	0
Consumer Goods	-0.02
Fabricated products	-0.02
Healthcare	-0.03
Food products	-0.04
Medical equipment	-0.04
Rubber and plastic products	-0.05
Textiles	-0.05
Chips	-0.06
Shipbuilding & Railroad equipment	-0.07
Wholesale	-0.09
Utilities	-0.1
Business supplies	-0.1
Machinery	-0.13
Construction materials	-0.37
Construction	-0.37
Measuring and control equipment	-0.43
Electrical equipment	-0.44
Other	-1.12

theoretical viewpoint, according to the model, investors rebalance their allocation at each period to adjust their asset weights to the optimal level. Therefore, the micro-founded instrument should not depend on the current and past returns. However, it is likely that the effective asset weights do not necessarily correspond to the optimal weights predicted by the theory. Consequently, since the industry weights of green investors and those of the market vary slowly over time, I repeat the regression using proxy $\tilde{c}$ delayed by 3 years to ensure that the returns estimated in the first pass of the Fama MacBeth regression do not affect the instrument retroactively. The direct taste premium is highly significant (t-statistics of 3.09) and positive ($\hat{\delta}_{taste} = 0.47$). The estimate is robust to the inclusion of the SMB, HML, and MOM factors. Although the loading is higher than that of the main model, this estimation supports the significant effect of the direct taste premium on investable asset returns. The results are reported in the Internet Appendix.

1.4.4 Unexpected shifts in tastes

As pointed out by Pastor, Stambaugh, and Taylor (2019), proxying the expected returns by the realized returns induces a critical omitted variable bias: the unexpected shifts in tastes between $t-1$ and t also affect the realized returns in t. As a consequence, when the tastes for green companies increase over a period, a green asset can have a negative direct taste premium and yet outperform brown assets. This effect can arise from both a shift in green investors' tastes (qualitative effect) and an increase in the share of their wealth (quantitative effect). The lack of consideration of the unexpected (qualitative and quantitative) shifts in tastes may partly explain why the results of the empirical analyses on the link between ESG and financial performance are mixed. Pastor, Stambaugh, and Taylor (2019) suggest using the in- and out-flows of ESG-tilted funds to proxy for this effect. The analysis of green fund holdings thus offers a dual advantage: (i) constructing a proxy for the unexpected shifts in green investors' tastes at a monthly frequency that is (ii) homogeneous with the proxy for the direct taste premium. Therefore, I define the proxy for the unexpected shifts in green investors' tastes for asset I_k between $t-1$ and t as the variation of the direct taste factor between these two dates:

$$\Delta\tilde{p}_{i,t}\tilde{c}_{I_k,t} = \tilde{p}_{i,t}\tilde{c}_{I_k,t} - \tilde{p}_{i,t-1}\tilde{c}_{I_k,t-1}, \tag{1.17}$$

and I perform a robustness check on the following augmented specification:

$$\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{taste}\tilde{p}_i\tilde{c}_{I_k} + \delta_u\Delta\tilde{p}_i\tilde{c}_{I_k} + \delta_{ex.mkt}q\,\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_{m_I}). \tag{1.18}$$

Table 1.6, Panel A, reports the estimates for all industries. Although the direct taste premium is not significant in the augmented S-CAPM, it becomes significant when controlling for the SMB, HML and MOM factors (referred to as the *augmented*

4F S-CAPM hereinafter). Its loading is in line with that estimated in the main specification. However, two industries have experienced massive divestments by green investors since 2012: the relative weights of the coal and construction industries in the portfolios of green investors relative to the market weights, $\tilde{c}$, have dropped from -48% to -93% and from +330% to +43%, respectively, between December 2012 and December 2019. Therefore, I repeat the estimation by removing these outliers. Panel B presents the estimates for all industries except coal. The direct taste premium is significant in the absence of the exclusion-market premium and remains significant for the augmented 4F S-CAPM. The estimates are in line with those of the main estimation. Panel C presents the estimates for all industries except coal and construction. The direct taste premium is highly significant for the augmented S-CAPM and the augmented 4F S-CAPM. The loading is twice as high for the augmented S-CAPM than for the S-CAPM but is similar for the augmented 4F S-CAPM and the 4F S-CAPM. In addition, the premium for the unexpected shifts in tastes becomes significant and, as expected, its effect is negative: an increase in the taste factor (e.g., the cost of environmental externalities increases) leads to a drop in the short-term returns. Finally, under the augmented S-CAPM, when the coal or the coal and construction industries are removed, the exclusion-market premium is weakly significant and positive as predicted by the model.

1.4.5 Taste effect over time

I analyze the dynamics of the direct taste premium by repeating the estimation over several sub-periods. Given the violent effect induced by the divestment from the coal industry between 2012 and 2019 and the short periods over which theses estimations are carried out, the latter are performed on all industries except coal in this subsection.

First, I repeat the estimation over three consecutive sub-periods between 2007 and 2019 (Table 1.14 in the Appendix). The significance of the direct taste premium increases over time to reach a t-statistic of 7.27 between 2013 and 2019.[32] In addition, although the average direct taste premium is constant over time, the difference in direct taste premium between the brown and green industries increases over time; this spread between the petroleum and natural gas industry and the electrical equipment industry increased from 50 bps between 2007 and 2013 to 1.23% between 2013 and 2019 (Table 1.7).[33]

Second, I repeat the estimation over 3-year rolling periods for the second pass. The dynamics depicted in Figure 1.2 show the steady increase in the taste effect spread between the petroleum and natural gas and electrical equipment industries.

[32] Over this 6-year period, the first pass is carried out during the first 3 years and the second pass during the last 3 years.

[33] The taste effect is higher when the coal industry is removed compared to the entire period in the main estimation.

TABLE 1.6: **Cross-sectional regressions for investable stock industry-sorted portfolios with tastes for green firms and unexpected shifts in tastes.** This table presents the estimates of the *augmented S-CAPM* with unexpected shifts in tastes on the value-weighted monthly returns in excess of the 1-month T-Bill for 46 investable stock industry-sorted portfolios between December 31, 2007, and December 31, 2019. Panel A, B, and C, present the estimates on all industries, all industries without the coal industry, and all industries without the coal and construction industries, respectively. The specification of the augmented S-CAPM is written as follows: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{taste}\tilde{p}_i\tilde{c}_{I_k} + \delta_u\Delta\tilde{p}_i\tilde{c}_{I_k} + \delta_{ex.mkt}q\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$, where r_{I_k} is the value-weighted excess return on portfolio k ($k = 1, ..., n_I$), $\beta_{I_k m_I}$ is the slope of an OLS regression of r_{I_k} on r_{m_I}; $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; $\tilde{c}_{I_k}$ is the proxy for the cost of environmental externalities of stock I_k; $\Delta\tilde{p}_i\tilde{c}_{I_k}$ is the proxy for the unexpected shifts in tastes; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$ is the covariance of the excess return on portfolio I_k with that of the excluded market, the excess returns on the investable market being given. This specification is compared with the *augmented 4F S-CAPM*, which is the augmented S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated portfolio-by-portfolio in a 3-year rolling window at monthly intervals. In the second pass, a cross-sectional regression is performed month-by-month on all the portfolios. The estimated parameter is the average value of the estimates obtained on the 109 months during the period. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	δ_u	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
				Panel A: All industries					
Estimate	0.0144	0.0004	0.1922						0.03 [0.02,0.05]
t-value	(12.95)	(0.44)	(2.55)						0.08 [0.06,0.1]
Estimate	0.0145	0.0003		-8.9					0.04 [0.03,0.06]
t-value	(12.98)	(0.31)		(-1.33)					0.09 [0.07,0.11]
Estimate	0.0145	0.0003	-0.1562	-18.5					0.03 [0.01,0.05]
t-value	(12.94)	(0.31)	(-1.05)	(-2.22)					0.1 [0.08,0.11]
Estimate	0.014	0.001	-0.1977	-14.9	46.3				0.08 [0.06,0.11]
t-value	(10.67)	(0.96)	(-1.44)	(-1.78)	(0.62)				0.16 [0.14,0.18]
Estimate	0.015	0.0022	0.2496	-9.3	-113.6	0.0001	0.0004	0.000	0.22 [0.18,0.26]
t-value	(14.91)	(2.43)	(1.69)	(-1.27)	(-2.01)	(0.39)	(2.1)	(-0.17)	0.34 [0.31,0.37]
				Panel B: All industries without the coal industry (SIC 29)					
Estimate	0.0135	0.0016	0.3931						0.03 [0.01,0.05]
t-value	(16.54)	(1.94)	(9.25)						0.08 [0.05,0.1]
Estimate	0.0135	0.0016		-2.3					0.04 [0.02,0.06]
t-value	(16.67)	(1.88)		(-0.42)					0.08 [0.06,0.1]
Estimate	0.0136	0.0015	0.1879	-8.8					0.02 [0,0.05]
t-value	(16.68)	(1.84)	(1.66)	(-1.32)					0.09 [0.07,0.11]
Estimate	0.0132	0.0021	0.0983	-8.3	82.1				0.03 [0.01,0.06]
t-value	(18.39)	(2.53)	(0.89)	(-1.19)	(1.57)				0.12 [0.1,0.14]
Estimate	0.014	0.002	0.2704	-8.7	15.9	0.0002	0.0001	0.0002	0.13 [0.09,0.16]
t-value	(19.46)	(2.13)	(1.87)	(-1.27)	(0.3)	(1.96)	(0.62)	(2.09)	0.27 [0.24,0.29]
				Panel C: All industries without the coal (SIC 29) and construction (SIC 18) industries					
Estimate	0.0135	0.0015	0.4527						0.03 [0.01,0.05]
t-value	(15.98)	(1.81)	(7.44)						0.08 [0.06,0.1]
Estimate	0.0136	0.0015		-6.6					0.04 [0.02,0.06]
t-value	(16.44)	(1.78)		(-1.13)					0.09 [0.07,0.11]
Estimate	0.0137	0.0014	0.3642	-13.2					0.03 [0,0.05]
t-value	(16.35)	(1.68)	(3.08)	(-1.94)					0.09 [0.07,0.11]
Estimate	0.0132	0.002	0.2947	-12.7	80.4				0.03 [0.01,0.06]
t-value	(17.64)	(2.42)	(2.39)	(-1.77)	(1.54)				0.12 [0.1,0.15]
Estimate	0.0141	0.0019	0.546	-12.7	9.8	0.0003	0.0001	0.0002	0.13 [0.1,0.16]
t-value	(18.83)	(1.9)	(3.06)	(-1.68)	(0.19)	(2.08)	(0.61)	(2.13)	0.27 [0.24,0.3]

TABLE 1.7: **Average taste premium over time.** This table presents the average direct taste premium for the investable market ($\hat{\delta}_{taste}\tilde{p}_i\tilde{c}_{m_I}$), the petroleum and natural gas industry ($\hat{\delta}_{taste}\tilde{p}_i\tilde{c}_{\text{P.\&N.G.}}$), and the electrical equipment industry ($\hat{\delta}_{taste}\tilde{p}_i\tilde{c}_{\text{Elec}}$) estimated without the coal industry over three consecutive periods between 2007 (2010 for the second pass) and 2019. The former industry is underweighted by integration investors ($\tilde{c}_{\text{P.\&N.G.}} = 0.49$ between Dec. 2007 and Dec. 2019) while the latter industry is overweighted by integration investors ($\tilde{c}_{\text{Elec.}} = -0.63$ between Dec. 2007 and Dec. 2019). Finally, the spread between the average direct taste premia of the two industries under consideration is presented.

First pass First and second pass	2010-2013 2007-2013	2013-2016 2010-2016	2016-2019 2013-2019
Average direct taste premium (%)	-0.07	-0.10	-0.09
Petrol. and Nat. Gas average direct taste premium (%) (a)	0.08	0.11	0.12
Elec. Equip. average direct taste premium (%) (b)	-0.42	-0.87	-1.11
Taste spread (%) (a-b)	0.50	0.98	1.23

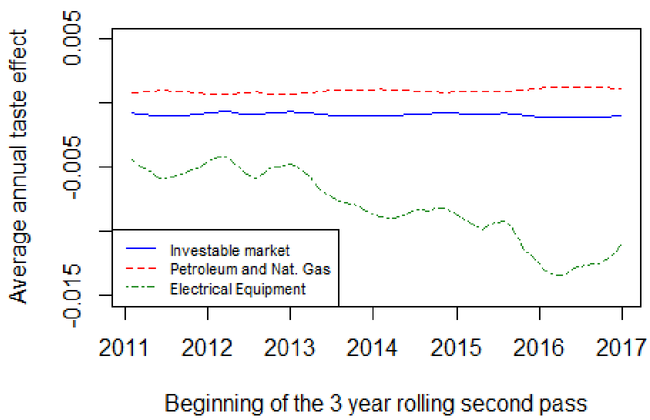


FIGURE 1.2: **Evolution of the taste effect** This figure shows the evolution of the taste effect for the investable market, the petroleum and natural gas industry, and the electrical equipment industry between December 2007 and December 2019. The first and second pass are both estimated over 3-year rolling periods.

1.4.6 Measurement error bias

A measurement error in the proxy for the cost of environmental externalities reduces the estimate (because it is positive) as well as the t-statistics. Therefore, if the proxy is poor, the taste effect may appear weaker and less significant than it actually is. Consequently, to address the risk of measurement error, I compare the significance of the estimate to that where the cost of environmental externalities is approximated by the carbon intensity of the issuer, which is the environmental metric most used by green investors in their screening process (Krüger, Sautner, and Starks, 2020). To do so, I consider two approaches, the results of which are available in the Internet Appendix.

First, I estimate the S-CAPM with industry portfolios using the carbon intensity of asset I_k as a proxy for c_{I_k}. Since this metric is reported annually, I consider it from the month following the month of the company's financial close and extend it over the following 12 months. Although the direct taste premium is negative and significant for the S-CAPM without controls, it is no longer significant once the SMB, HML and MOM betas are added. In the second approach, I analyze the alpha of the S-CAPM without taste premium by considering industry portfolios consisting of long brown assets and short green assets. Specifically, I build portfolios that are long for the 20% most carbon-intensive assets and short for the 20% least carbon-intensive assets within each of the 46 industries. With or without the SMB, HML, and MOM betas, the alpha of the estimate is positive, but not significant.

Therefore, the use of carbon intensity does not allow us to identify a significant direct taste premium on 5,660 U.S. stocks between 2007 and 2019. These results suggest that the instrument constructed in this study using green fund holdings mitigates the measurement error compared to the metric most used by green investors in their environmental screening process.

1.5 Sin stock returns

I perform an empirical analysis to assess the effect of sustainable investors' exclusion of sin stocks and that of their tastes for green firms on sin stocks' excess returns. The exclusion premia significantly impact the excess returns. I also find evidence supporting the cross-effect of green tastes on sin stock returns via the indirect taste premium. Focusing on the exclusion effect, I analyze its dynamics and the spillover effects that contribute to it.

1.5.1 Main estimation

I estimate the following three models. (i) The *S-CAPM* corresponds to equation (1.15):

$$\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{taste}\tilde{p}_i B_{X_k I}\tilde{C}_I + \delta_{ex.asset} q \,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_I) + \delta_{ex.mkt} q \,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_{m_I}); \tag{1.19}$$

(ii) the *four-factor S-CAPM* (denoted as *4F S-CAPM*) corresponds to the S-CAPM specification to which the SMB, HML, and MOM betas are added; and (iii) for benchmarking purposes, the *four-factor model* (denoted as *4F model*) corresponds to the CAPM with respect to the investable market returns to which the SMB, HML, and MOM betas are added.

I work with 52 sin stocks during the period of interest, for an annual mean number of 40 stocks.[34] Given the substantial noise that occurs when performing regressions on a small number of individual stocks, especially when several of them have extreme return variations, I winsorize the data by removing the lowest and highest excess returns in each cross-sectional regression.

Table 1.8 reports the estimates of the three specifications for sin stocks using industry-sorted portfolios of investable assets. The OLS adjusted-R^2 of 24% and GLS R^2 of 30% are much higher under the S-CAPM than under the 4F model (10% and 16%, respectively).

The estimation of the exclusion premia supports the model predictions. First, the loadings of the exclusion-asset and exclusion-market factors are positive ($\widehat{\delta}_{ex.asset} = 49$ and $\widehat{\delta}_{ex.index} = 196.9$, respectively) and significant (t-statistics of 2.32 and 3.88, respectively). Second, the indirect taste premium is negative ($\widehat{\delta}_{taste} = -0.41$) and significant (t-statistics of -2.14). The estimates are robust to the inclusion of the SMB, HML, and MOM factors.

The exclusion effect, which is the sum of the exclusion-asset and exclusion-market premia, is estimated at 1.43% per year for the 2007–2019 period. This effect is of a similar magnitude as the one estimated on U.S. sin stocks by Hong and Kacperczyk (2009) between 1965 and 2006 (2.5%). However, it is substantially lower than the annual 16% effect estimated by Luo and Balvers (2017) between 1999 and 2012 and based on the same modeling framework (in the absence of tastes for green firms). Additionally, consistent with Proposition 4, I find that the exclusion effect is positive on average, but it is negative for 10 out of 52 sin stocks (Figure 1.3). The indirect effect of green investors' taste on sin stock returns is limited to 3 bps per year between 2007 and 2019.

Using $\widehat{\gamma\frac{p_e}{1-p_e}} = \widehat{\delta}_{ex.asset}$ and $\widehat{\gamma} = \widehat{\delta}_{ex.mkt}$, the proportion of AUM practicing sin stock exclusion between 2007 and 2019 is estimated at $\hat{p}_e = 20\%$. This estimate

[34] In the robustness check that includes the defense industry, I work with 67 sin stocks, giving an annual mean number of 50 stocks.

TABLE 1.8: **Cross-sectional regressions on sin stocks' excess returns.** This table provides the estimates obtained with the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for 52 sin stocks between December 31, 2007, and December 31, 2019. The specification is written as follows: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{taste}\tilde{p}_i B_{X_k I}\tilde{C}_I + \delta_{ex.asset} q\,\mathbb{C}\text{ov}(r_{X_i}, r_{m_X}|r_I) + \delta_{ex.mkt} q\,\mathbb{C}\text{ov}(r_{X_i}, r_{m_X}|r_{m_I})$, where r_{X_k} is the value-weighted excess return on stock k ($k = 1, ..., n_X$), and $\beta_{X_k m_I}$ is the slope of an OLS regression of r_{X_k} on r_{m_I}; $\tilde{p}_i B_{X_k I}\tilde{C}_I$ is the proxy for the indirect taste factor and $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_I)$ (and $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_{m_I})$) are the covariances of the excess returns on stock X_k with those on the excluded market, the excess returns on the investable market (and the vector of investable assets, respectively) being given. The investable assets are analyzed using 46 industry-sorted portfolios. The S-CAPM specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added, and (ii) the 4F model is the CAPM with respect to the investable market to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{SMB}\beta_{X_k SMB} + \delta_{HML}\beta_{X_k HML} + \delta_{MOM}\beta_{X_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated, stock-by-stock, in a 3-year rolling window, at monthly intervals. In the second pass, a cross-sectional regression is performed on a monthly basis on all the stocks. The data are winsorized: the two stocks giving the highest and lowest excess returns every month are removed from the second pass. The estimated parameter is the average value of the estimates obtained on all months during the period of interest. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.asset}$	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0114	0.0041							0.03 [0.02,0.05]
t-value	(10.18)	(4.35)							0.05 [0.04,0.07]
Estimate	0.0153		-0.4434						0.07 [0.05,0.09]
t-value	(16.54)		(-1.99)						0.07 [0.05,0.08]
Estimate	0.0152			-12.5					0.08 [0.06,0.11]
t-value	(19.13)			(-0.49)					0.08 [0.06,0.1]
Estimate	0.0134				162.3				0.18 [0.15,0.21]
t-value	(14.93)				(2.79)				0.14 [0.11,0.17]
Estimate	0.0136			50.2	211.7				0.2 [0.17,0.23]
t-value	(14.58)			(2.7)	(3.95)				0.21 [0.18,0.24]
Estimate	0.0116	0.0015		56	230.3				0.21 [0.18,0.25]
t-value	(8.4)	(1.3)		(2.74)	(4.17)				0.25 [0.22,0.28]
Estimate	0.0124	0.0005	-0.4093	49	196.9				0.24 [0.21,0.28]
t-value	(9.14)	(0.42)	(-2.14)	(2.32)	(3.88)				0.3 [0.27,0.33]
Estimate	0.0115	0.0014	-0.8344	42.3	219.3	0.0001	-0.0003	0.0002	0.31 [0.27,0.35]
t-value	(8.25)	(0.97)	(-2.59)	(1.92)	(3.97)	(0.58)	(-2.68)	(1.67)	0.42 [0.39,0.44]
Estimate	0.0115	0.0039				0.0000	0.0000	0.0001	0.1 [0.08,0.13]
t-value	(9.93)	(3.24)				(0.04)	(-0.29)	(0.72)	0.16 [0.14,0.18]

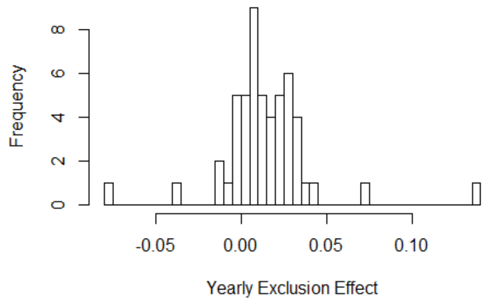


FIGURE 1.3: **Distribution of the annual exclusion effect.** This figure shows the distribution of the annual exclusion effect, $\widehat{\delta}_{ex.asset} q\,\mathbb{C}\mathrm{ov}_t(r_X, r_{m_X}|r_I) + \widehat{\delta}_{ex.mkt} q\,\mathbb{C}\mathrm{ov}_t(r_X, r_{m_X}|r_{m_I})$, over all sin stocks estimated between December 31, 2007, and December 31, 2019.

should be regarded with caution as it is based on the assumptions of this model, but it gives an order of magnitude that is consistent with the proportion of sustainably managed assets in the U.S. in 2018 (US SIF, 2018).

1.5.2 Alternative estimations

I perform additional analyses presented in this subsection and detailed in the Internet Appendix. In all robustness tests, the S-CAPM has a higher OLS adjusted-R^2 and GLS R^2 than those of the 4F model. I repeat the estimation in three alternative cases: (i) using a 5-year rolling window for the first pass, (ii) using equally weighted returns, and (iii) including the defense industry among sin industries. In all three cases, the estimates are of a similar magnitude to those in the main estimation but only the exclusion-market premium is significant. The exclusion-asset premium is weak or not significant.

1.5.3 Exclusion effect over time

I repeat the estimation over three consecutive periods between 2007 and 2019.[35] In each period, at least one of the two exclusion factors is significant. The indirect taste premium becomes negative and significant from 2013 onwards.

I extend the analysis to assess the exclusion effect over a longer time period. I perform this estimation between 1999 and 2019 removing the indirect taste factor, which cannot be estimated with sufficient robustness before 2007. The loadings of the exclusion-asset and exclusion-market factors are still positive ($\widehat{\delta}_{ex.asset} = 92$ and $\widehat{\delta}_{ex.index} = 131.2$, respectively) and significant (t-statistics of 3.99 and 3.49, respectively). The average exclusion effect is 1.16% and 20 out of 77 sin stocks have a negative exclusion effect.

[35]The second pass starts in 2010 because the variables are computed using a 3-year rolling window in the first pass.

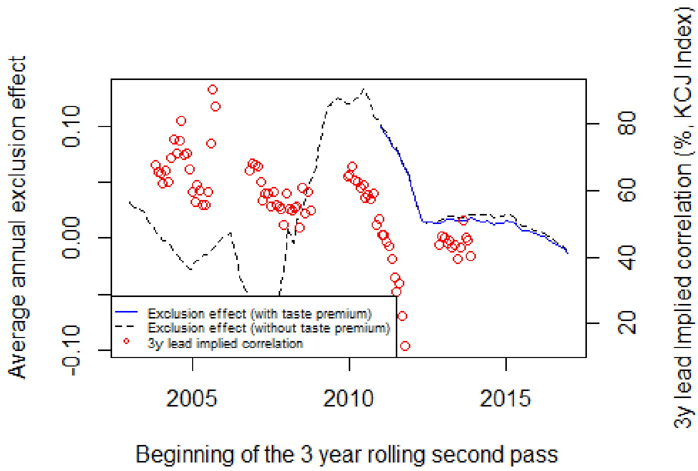


FIGURE 1.4: **Evolution of the exclusion effect.** This figure shows the evolution of the exclusion effect, $\widehat{\delta}_{ex.asset} q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_I) + \widehat{\delta}_{ex.mkt} q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_{m_I})$, between December 2007 and December 2019. The first and second pass are both estimated over 3-year rolling periods. This rolling estimation is based on winsorized data, where the lowest and highest excess returns in each cross-sectional regression have been removed. The 3-year lead S&P 500 implied correlation (KCJ Index) is also plotted.

To highlight the dynamics of the exclusion effect, I repeat the second-pass estimation using a 3-year rolling window (i) between 2007 and 2019 based on the S-CAPM (blue line on Figure 1.4) and (ii) between 1999 and 2019 based on the S-CAPM without the indirect taste factor (dashed black line on Figure 1.4). The exclusion effect increased sharply during and after the 2008 financial crisis and collapsed by 2010. This effect is not due to a change in the strategy of sustainable investors (e.g., a shift from exclusionary screening to ESG integration) but is related to the multiple correlation in the excluded market as the exclusion premia are conditional covariances between the excluded assets and the excluded market. This can be observed by comparing the dynamics of the exclusion effect with the dynamics of the implied correlation of the S&P500 (see Figure 1.4). Therefore, the higher the correlation between the sin stocks is, the greater will be the conditional covariances and the exclusion effect.

1.5.4 Dynamics of excluders' wealth

In contrast to the taste factors that take into account the proportion of green investors' wealth, the exclusion-asset factor does not incorporate an approximation of the wealth share of excluders, p_e, in $\frac{p_e}{1-p_e}$. Although the wealth dynamics of investors excluding sin stocks and that of green investors are presumably different, I repeat the estimation by assuming that the proportion of excluders' wealth grows at a pace proportional to that of green investors: $p_e = \kappa_i p_i$. Since the proportion of excluders is small enough, I linearly approximate $\frac{p_e}{1-p_e}$ by assuming that $\frac{p_e}{1-p_e} = \kappa_e p_e$ ($\kappa_e \in \mathbb{R}_+$). Therefore, the new specification has the following form:

$$\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{taste}\tilde{p}_i^2 B_{X_k I}\tilde{C}_I + \delta_{ex.asset}\tilde{p}_i q\,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_I) + \delta_{ex.mkt} q\,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_{m_I}). \tag{1.20}$$

The indirect taste factor is quadratic in $\tilde{p}_i$ and the exclusion-asset factor is linear in $\tilde{p}_i$.

Under the S-CAPM, the estimates are in line with those of the main specification: the loadings of the exclusion factors are significant and positive, and the loading of the indirect taste factor is significant and negative (see the Internet Appendix). Consistent with the main estimation, the total exclusion effect is 1.49% between 2007 and 2019.

1.5.5 Spillover effects

In the first section, I broke down the exclusion premia into a non-excluder effect and an excluder effect. Here, I present another form of decomposition of the exclusion premia to highlight the spillover effects of all excluded assets (through r_{m_X}) into the expected excess returns on each excluded asset. These effects underline the point of relaxing the assumption of independence between returns made by Merton (1987).

Corollary 6 (Spillover effects).
Let q_{X_k} be the proportion of the market value of X_k in the market.
(i) The spillover effect of asset X_j on the expected excess returns on asset X_k is

$$\gamma\frac{p}{1-p} q_{X_j}\,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_I) + \gamma q_{X_j}\,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_{m_I}). \tag{1.21}$$

(ii) The spillover effects of assets $(X_j)_{j\in\{1,...,n_X\}\setminus\{k\}}$ on the expected excess returns on asset X_k are additive, and the exclusion premia can be broken down into an own effect and a spillover effect:

$$\gamma\frac{p}{1-p} q\,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_I) + \gamma q\,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_{m_I}) =$$
$$\underbrace{q_{X_k}\left(\gamma\frac{p_e}{1-p_e}\mathbb{V}\mathrm{ar}(r_{X_k}|r_I) + \gamma\,\mathbb{V}\mathrm{ar}(r_{X_k}|r_{m_I})\right)}_{Own\ effect} + \underbrace{\sum_{j=1,j\neq k}^{n_X} q_{X_j}\left(\gamma\frac{p_e}{1-p_e}\mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_I) + \gamma\,\mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_{m_I})\right)}_{Spillover\ effect}. \tag{1.22}$$

The spillover effect of each excluded stock is induced by its conditional covariances with the other excluded stocks. The following question arises: what is the share of the spillover effect in the total exclusion effect? To address this issue, I define the share of the spillover effect in the exclusion premia as the ratio of the sum of the absolute values of the spillover effect to the sum of the absolute values of the own and spillover effects:

$$\frac{\sum_{j=1,j\neq k}^{n_X} |q_{X_j} \left(\gamma \frac{p_e}{1-p_e} \mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_I) + \gamma \, \mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_{m_I})\right)|}{\sum_{j=1}^{n_X} |q_{X_j} \left(\gamma \frac{p_e}{1-p_e} \mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_I) + \gamma \, \mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_{m_I})\right)|}.$$

To estimate this effect, I use the estimates of $\gamma \frac{p_e}{1-p_e}$ and γ from the previous subsection. On average, among the 52 sin stocks of interest, the spillover effect accounts for 92.5% of the exclusion effect. The heatmap in the Internet Appendix offers a graphical depiction of the spillover effects.

1.6 Conclusion

In this paper, I develop an asset pricing model with partial segmentation and heterogeneous preferences to describe the effects of exclusionary screening and ESG integration practices by sustainable investors on expected asset returns. By estimating this model for green investing and sin stock exclusion, I show that the taste and exclusion premia significantly affect asset returns. I also find evidence for the cross effects of tastes and exclusion between investable and excluded stocks.

Whether through exclusionary screening or ESG integration, sustainable investing contributes toward the cost of capital increase of the least ethical or most environmentally risky companies. Both practices are thus effective means of pressure available to sustainable investors to encourage companies to reform. This study provides a comparison between the effects of green investing and sin stock exclusionary screening. The integration of environmental criteria by green investors impacts the different industries with an annual premium ranging from -1.12% for the most overweighted to +14bps for the most underweighted industries, while the average annual exclusion effect of sin stocks is 1.43%.

The Internet Appendix presents the derivation of the expected excess returns on investable assets in the case of several sustainable investors with different tastes and exclusion scopes. The result shows that the conclusions for the three groups of investors remain valid in a more general case. Future research may consider extending this model to a multiperiod framework by endogenizing companies' ESG profiles in response to regular and sustainable investors' optimal asset allocations. Therefore, by internalizing the responses of companies to their investments, sustainable investors can engage in ESG integration and exclusionary screening to have an impact on companies' practices.[36] However, the asset pricing equation may not remain tractable in this more refined modeling framework. This study can also be extended in the case where sustainable investors internalize a stochastic and non-Gaussian environment-related financial risk.

[36] Oehmke and Opp (2019), Landier and Lovo (2020), and Pastor, Stambaugh, and Taylor (2019) show that ESG investors push companies to partially internalize their social costs.

1.7 Appendix A: Proofs

Problem setup

We model regular investors, integrators and excluders on an aggregate basis: one generic regular investor (referred to using subscript r), one generic integrator (referred to using subscript i), and one generic excluder (referred to using subscript e).

Heterogeneous preferences. The three groups of investors maximize at time t the expected utility of their terminal wealth at time $t+1$. We denote by γ_j^a the absolute risk aversion of investors j ($j \in \{r, i, e\}$) and by $W_{j,t}$ and $W_{j,t+1}$ their wealth on t and $t+1$, respectively.

However, investors have heterogeneous preferences. On the one hand, regular investors and excluders $j \in \{r, e\}$ have an exponential utility. They select the optimal vector of weights of *risky assets*, w_j, corresponding to the solution of the following optimization problem:

$$\max_{w_j} \mathbb{E}\left(U_j(W_{j,t+1})\right) = \max_{w_j} \mathbb{E}\left(1 - e^{-\gamma_j^a W_{j,t+1}}\right).$$

On the other hand, integrators have specific tastes for assets; they adjust their exponential utility by internalizing a deterministic private cost of externalities as in Pastor, Stambaugh, and Taylor (2019). We denote by C^W the vector of private costs of externalities that integrators internalize in their utility function; C^W has the same unit as a wealth. Integrators' utility decreases when the cost of externalities increases; they select the optimal vector of weights of *risky assets*, w_i, corresponding to the solution of the following optimization problem:

$$\max_{w_i} \mathbb{E}\left(U_i(W_{i,t+1})\right) = \max_{w_i} \mathbb{E}\left(1 - e^{-\gamma_i^a W_{i,t+1} + w_i' C^W}\right)$$

In Pastor, Stambaugh, and Taylor (2019), investors internalize nonpecuniary benefits, which positively impact their utility. In the present paper, integrators internalize costs of externalities, which negatively impact their utility.

Partially segmented market. Investors can invest in a risk-free asset, the return on which is denoted by r_f, and in risky assets. Excluders can only invest in *investable* risky assets, the returns on which are denoted by the $n_I \times 1$ vector R_I, while integrators and regular investors can invest in *investable* and *excluded* risky assets, the returns on which are denoted by the $(n_I + n_X) \times 1$ vector $R = \begin{pmatrix} R_I & R_X \end{pmatrix}'$. We assume that risky asset returns are normally distributed.

Mean-Variance problems. Without loss of generality, we assume that investors have the same relative risk aversion, $\gamma = W_{j,t}\gamma_j^a$ ($j \in \{r, i, e\}$). We denote by $C = \frac{1}{\gamma} C^W$ the vector of private costs of environmental externalities per unit of relative risk aversion; C has the same unit as a return. We now work with vector C and refer to its entries as the *private costs of environmental externalities* (without referring to the normalization by the risk aversion). C is a $(n_I + n_X) \times 1$ vector that is broken down as $C = \begin{pmatrix} C_I & C_X \end{pmatrix}'$, where C_I and C_X are the $n_I \times 1$ and $n_X \times 1$ vectors of costs for investable and excluded assets, respectively. We denote by $r = R - r_f \mathbb{1}_{n_I+n_X}$, $r_I = R_I - r_f \mathbb{1}_{n_I}$, and $r_X = R_X - r_f \mathbb{1}_{n_X}$ the vectors of excess returns on all assets, investable assets, and excluded assets, respectively, where $\mathbb{1}_n$ is the vector of ones of length $n \in \mathbb{N}^*$.

All weights add up to one, including the weight of the risk-free asset. Since the wealth in $t+1$ is normally distributed and C^W is determinisitic, integrators' expected utility writes

$$\begin{aligned}\mathbb{E}(U_i(W_{i,t+1})) &= 1 - \mathbb{E}\left(e^{-\gamma_i^a W_{i,t}\left(1+w_i'R+\left(1-w_i'\mathbb{1}_{n_I+n_X}\right)r_f\right)+w_i'C^W}\right) \\ &= 1 - e^{-\gamma\left(1+r_f\right)} e^{-\gamma w_i'(\mathbb{E}(r)-C)+\frac{\gamma^2}{2}w_i' \mathbb{V}\mathrm{ar}(r) w_i}.\end{aligned}$$

Similarly, regular investors' expected utility is

$$\mathbb{E}(U_r(W_{r,t+1})) = 1 - e^{-\gamma\left(1+r_f\right)} e^{-\gamma w_r' \mathbb{E}(r)+\frac{\gamma^2}{2}w_r' \mathbb{V}\mathrm{ar}(r) w_r},$$

and the expected utility of excluders, who can only invest in investable assets, writes

$$\mathbb{E}(U_e(W_{e,t+1})) = 1 - e^{-\gamma\left(1+r_f\right)} e^{-\gamma w_{e,I}' \mathbb{E}(r_I)+\frac{\gamma^2}{2}w_{e,I}' \mathbb{V}\mathrm{ar}(r_I) w_{e,I}}.$$

Let us also denote the vectors $\mu_I = \mathbb{E}_t(r_I)$, $\mu_X = \mathbb{E}_t(r_X)$, and the matrices $\Sigma_{XX} = \mathbb{V}\mathrm{ar}_t(r_X)$, $\Sigma_{II} = \mathbb{V}\mathrm{ar}_t(r_I)$, $\Sigma_{XI} = \mathbb{C}\mathrm{ov}_t(r_X, r_I)$, $\Sigma_{IX} = \mathbb{C}\mathrm{ov}_t(r_I, r_X)$. Therefore:

- Regular investors choose their optimal asset allocation by solving the following problem:

$$\max_{\left(w_{r,I}, w_{r,X}\right)} \begin{pmatrix} w_{r,I} \\ w_{r,X} \end{pmatrix}' \begin{pmatrix} \mu_I \\ \mu_X \end{pmatrix} - \frac{\gamma}{2} \begin{pmatrix} w_{r,I} \\ w_{r,X} \end{pmatrix}' \begin{pmatrix} \Sigma_{II} & \Sigma_{IX} \\ \Sigma_{XI} & \Sigma_{XX} \end{pmatrix} \begin{pmatrix} w_{r,I} \\ w_{r,X} \end{pmatrix}. \tag{1.23}$$

- Integrators choose their optimal asset allocation by solving the following problem:

$$\max_{\left(w_{i,I}, w_{i,X}\right)} \begin{pmatrix} w_{i,I} \\ w_{i,X} \end{pmatrix}' \begin{pmatrix} \mu_I - C_I \\ \mu_X - C_X \end{pmatrix} - \frac{\gamma}{2} \begin{pmatrix} w_{i,I} \\ w_{i,X} \end{pmatrix}' \begin{pmatrix} \Sigma_{II} & \Sigma_{IX} \\ \Sigma_{XI} & \Sigma_{XX} \end{pmatrix} \begin{pmatrix} w_{i,I} \\ w_{i,X} \end{pmatrix}. \tag{1.24}$$

- Excluders choose their optimal asset allocation by solving the following problem:

$$\max_{w_{e,I}} \quad w_{e,I}'\mu_I - \frac{\gamma}{2} w_{e,I}' \Sigma_{II} w_{e,I}. \tag{1.25}$$

Notice that this single-period model where investors have heterogeneous preferences through C^W is equivalent to a single-period model where investors disagree about the expected returns through C (see Problem (1.24) compared to Problem (1.23)) because the private costs are deterministic.

First-order conditions. Denoting the inverse of the risk aversion by $\lambda = \frac{1}{\gamma}$, regular investors, integrators and excluders therefore solve the following first-order conditions:

$$\begin{cases} \lambda \begin{pmatrix} \mu_I \\ \mu_X \end{pmatrix} = \begin{pmatrix} \Sigma_{II} & \Sigma_{IX} \\ \Sigma_{XI} & \Sigma_{XX} \end{pmatrix} \begin{pmatrix} w_{r,I} \\ w_{r,X} \end{pmatrix}, \\ \\ \lambda \begin{pmatrix} \mu_I - C_I \\ \mu_X - C_X \end{pmatrix} = \begin{pmatrix} \Sigma_{II} & \Sigma_{IX} \\ \Sigma_{XI} & \Sigma_{XX} \end{pmatrix} \begin{pmatrix} w_{i,I} \\ w_{i,X} \end{pmatrix}, \\ \\ \lambda \mu_I = \Sigma_{II} w_{e,I}. \end{cases} \tag{1.26}$$

Proof of Proposition 7: S-CAPM

Lemma 1. ***Preliminary results.***
The covariance column vector between the vector of excess returns on investable assets, r_I, and the excess returns on the investable market, r_{m_I}, is denoted by σ_{Im_I}; $\sigma_{m_I I}$ refers to the covariance line vector between r_{m_I} and r_I. σ_{Xm_I} and $\sigma_{m_I X}$ are defined similarly.
Assuming that the returns are normally distributed, σ_{m_I} is non-null and Σ_{II} is non-singular, we have the following equalities:
1. (i) $\Sigma_{XX} - \frac{1}{\sigma^2_{m_I}} \sigma_{Xm_I} \sigma_{m_I X} = \mathbb{V}\mathrm{ar}_t(r_X | r_{m_I})$,
(ii) $\Sigma_{IX} - \frac{1}{\sigma^2_{m_I}} \sigma_{Im_I} \sigma_{m_I X} = \mathbb{C}\mathrm{ov}_t(r_I, r_X | r_{m_I})$,
(iii) $\Sigma_{XX} - \Sigma_{XI} \Sigma_{II}^{-1} \Sigma_{IX} = \mathbb{V}\mathrm{ar}_t(r_X | r_I)$,
(iv) $\sigma_{Xm_X} - \Sigma_{XI} \Sigma_{II}^{-1} \Sigma_{Im_X} = \mathbb{C}\mathrm{ov}_t(r_X, r_{m_X} | r_I)$.
2. $\mathbb{C}\mathrm{ov}_t(r_I, r_X | r_{m_I}) q_X = q\, \mathbb{C}\mathrm{ov}_t(r_I, r_{m_X} | r_{m_I})$.

Proof. See the Internet Appendix. □

From here on, the time subscripts will be omitted to simplify the notations.

Derivation of the expected excess returns on I

Multiplying the first, third and fifth rows of System (1.26) by the wealth of investors r, i, and e, respectively, we have

$$\lambda (W_r + W_i + W_e) \mu_I - \lambda W_i C_I = \Sigma_{II} (W_r w_{r,I} + W_i w_{i,I} + W_e w_{e,I}) + \Sigma_{IX} (W_r w_{r,X} + W_i w_{i,X}). \tag{1.27}$$

Dividing by the total wealth W, and noting that $\frac{W_i}{W} = p_i$, we obtain

$$\lambda \mu_I = \Sigma_{II} \left(\frac{W_r w_{r,I} + W_i w_{i,I} + W_e w_{e,I}}{W} \right) + \Sigma_{IX} \left(\frac{W_r w_{r,X} + W_i w_{i,X}}{W} \right) + \lambda p_i C_I. \tag{1.28}$$

Denoting by D_I and D_X the column vectors equal to the total demand for stocks I and X, respectively, we have $W_r w_{r,I} + W_i w_{i,I} + W_e w_{e,I} = D_I$ and $W_r w_{r,X} + W_i w_{i,X} = D_X$. Consequently,

$$\lambda \mu_I = \Sigma_{II} \frac{D_I}{W} + \Sigma_{IX} \frac{D_X}{W} + \lambda p_i C_I. \tag{1.29}$$

In equilibrium, the total demand of assets is equal to the total supply in the entire market (S). The same holds for the markets of investable (S_I) and excluded (S_X) assets: $W = S$, $D_I = S_I$ and $D_X = S_X$. The $(n_X \times 1)$ weight vectors of the excluded assets' values as a fraction of the market value is denoted by $q_X = \frac{S_X}{S}$. Therefore,

$$\lambda \mu_I = \Sigma_{II} \frac{S_I}{S} + \Sigma_{IX} q_X + \lambda p_i C_I. \tag{1.30}$$

We denote by q the proportion of the excluded assets' market value in the market. The proportion of the investable market is $1 - q$. Let us denote by w_I the vector of market values of stocks $(I_k)_{k \in \{1,\dots,n_I\}}$ in the investable market. Therefore, we have $\frac{S_I}{S} = (1-q) w_I$, and equation (1.30) rewrites

$$\lambda \mu_I = (1-q)\, \Sigma_{II} w_I + \Sigma_{IX} q_X + \lambda p_i C_I. \tag{1.31}$$

Multiplying by $w_I{}'$, we obtain

$$\lambda w_I{}' \mu_I = (1-q)\, w_I{}' \Sigma_{II} w_I + w_I{}' \Sigma_{IX} q_X + \lambda p_i w_I{}' C_I \tag{1.32}$$

Since $w_I{}' \mu_I = \mu_{m_I}$ is the expected excess return on the investable market, and denoting $c_{m_I} = w_I{}' C_I$ and the row vector of covariances $\sigma_{m_I X} = w_I{}' \Sigma_{IX}$,

$$\lambda \mu_{m_I} = (1-q)\, \sigma^2_{m_I} + \sigma_{m_I X} q_X + \lambda p_i c_{m_I}. \tag{1.33}$$

Therefore, assuming $\sigma^2_{m_I} \neq 0$,

$$(1-q) = \frac{1}{\sigma^2_{m_I}} \left(\lambda \mu_{m_I} - \sigma_{m_I X} q_X - \lambda p_i c_{m_I} \right). \tag{1.34}$$

Substituting (1.34) into (1.31) and the column vector of covariances $\sigma_{I m_I} = \Sigma_{II} w_I$, we obtain

$$\mu_I = \left(\mu_{m_I} - p_i c_{m_I} \right) \frac{1}{\sigma^2_{m_I}} \sigma_{I m_I} + p_i C_I + \gamma \left(\Sigma_{IX} - \frac{1}{\sigma^2_{m_I}} \sigma_{I m_I} \sigma_{m_I X} \right) q_X. \tag{1.35}$$

Denoting by $\beta_{I m_I} = \frac{1}{\sigma^2_{m_I}} \sigma_{I m_I}$ the vector of slope of the regression of the excess returns on the investable assets r_I on the excess returns on the investable market r_{m_I} and a constant, and from Lemma 1, we rewrite the above equation as follows using vector notations:

$$\mathbb{E}(r_I) = \left(\mathbb{E}(r_{m_I}) - p_i c_{m_I} \right) \beta_{I m_I} + p_i C_I + \gamma q\, \mathbb{C}\text{ov}(r_I, r_{m_X} | r_{m_I}). \tag{1.36}$$

Derivation of the expected excess returns on X

Multiplying the second and fourth rows of System (1.26) by the wealth of investors r and i, respectively, we have

$$\lambda\left(W_r+W_i\right)\mu_X-\lambda W_i C_X=\Sigma_{XI}\left(W_r w_{r,I}+W_i w_{i,I}\right)+\Sigma_{XX}\left(W_r w_{r,X}+W_i w_{i,X}\right) \tag{1.37}$$

But, assuming that Σ_{II} is nonsingular, the first and third rows of System (1.26) yield

$$\begin{cases} w_{r,I}=\Sigma_{II}^{-1}\left(\lambda\mu_I-\Sigma_{IX}w_{r,X}\right) \\ w_{i,I}=\Sigma_{II}^{-1}\left(\lambda\left(\mu_I-C_I\right)-\Sigma_{IX}w_{i,X}\right) \end{cases} \tag{1.38}$$

Therefore, substituting $w_{r,I}$ and $w_{i,I}$ into Equation (1.37), and denoting $B_{XI}=\Sigma_{XI}\Sigma_{II}^{-1}$, we obtain

$$\begin{aligned}\lambda\left(W_r+W_i\right)\mu_X-\lambda W_i C_X=&\ \lambda B_{XI}\left(W_r+W_i\right)\mu_I-\lambda W_i B_{XI}C_I \\ &+\left(\Sigma_{XX}-\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}\right)\left(W_r w_{r,X}+W_i w_{i,X}\right).\end{aligned} \tag{1.39}$$

Dividing the previous equation by W, knowing that $\frac{W_i}{W}=p_i$, $\frac{W_r+W_i}{W}=1-p_e$, and since that $\frac{\left(W_r w_{r,X}+W_i w_{i,X}\right)}{W}=\frac{S_X}{S}=q_X$ in equilibrium, we get

$$\mu_X=B_{XI}\mu_I+\frac{p_i}{1-p_e}\left(C_X-B_{XI}C_I\right)+\frac{\gamma}{1-p_e}\left(\Sigma_{XX}-\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}\right)q_X. \tag{1.40}$$

Substituting μ_I (Equation (1.35)) into the previous equation, and since $\sigma_{Im_I}=\Sigma_{II}w_I$ and $p_iB_{XI}C_I-\frac{p_i}{1-p_e}B_{XI}C_I=-\frac{p_ip_e}{1-p_e}B_{XI}C_I$,

$$\begin{aligned}\mu_X=&\left(\mu_{m_I}-p_ic_{m_I}\right)\frac{1}{\sigma_{m_I}^2}\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{II}w_I+\frac{p_i}{1-p_e}C_X-\frac{p_ip_e}{1-p_e}B_{XI}C_I \\ &+\gamma\left(\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}-\frac{1}{\sigma_{m_I}^2}\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{II}w_I\sigma_{m_IX}\right)q_X+\frac{\gamma}{1-p_e}\left(\Sigma_{XX}-\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}\right)q_X.\end{aligned} \tag{1.41}$$

By adding and subtracting $\gamma\Sigma_{XX}q_X$ to the previous equation,

$$\begin{aligned}\mu_X=&\left(\mu_{m_I}-p_ic_{m_I}\right)\frac{1}{\sigma_{m_I}^2}\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{II}w_I+\frac{p_i}{1-p_e}C_X-\frac{p_ip_e}{1-p_e}B_{XI}C_I \\ &+\gamma\left(\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}-\Sigma_{XX}\right)q_X+\gamma\left(\Sigma_{XX}-\frac{1}{\sigma_{m_I}^2}\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{II}w_I\sigma_{m_IX}\right)q_X \\ &+\frac{\gamma}{1-p_e}\left(\Sigma_{XX}-\Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}\right)q_X.\end{aligned} \tag{1.42}$$

We denote $\beta_{Xm_I} = \frac{1}{\sigma^2_{m_I}}\Sigma_{XI}w_I$; we notice that $\frac{\gamma}{1-p_e} - \gamma = \gamma\frac{p_e}{1-p_e}$; from Lemma 1, the previous equation is simplified as follows using vector notations:

$$\begin{aligned}\mathbb{E}(r_X) = (\mathbb{E}(r_{m_I}) - p_i c_{m_I})\,\beta_{Xm_I} + \frac{p_i}{1-p_e}C_X - \frac{p_i p_e}{1-p_e}B_{XI}C_I \\ + \gamma\frac{p_e}{1-p_e}q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_I) + \gamma q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_{m_I}).\end{aligned} \tag{1.43}$$

Derivation of the general pricing formula

For any investable asset I_k,

$$\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_I) = \sigma_{I_k m_X} - \sigma_{I_k I}\Sigma_{II}^{-1}\sigma_{I m_X} = \sigma_{I_k m_X} - \sigma_{I_k m_X} = 0, \tag{1.44}$$

and

$$\frac{p_i}{1-p_e}c_{I_k} - \frac{p_i p_e}{1-p_e}B_{I_k I}C_I = \frac{p_i}{1-p_e}c_{I_k} - \frac{p_i p_e}{1-p_e}c_{I_k} = p_i c_{I_k} \tag{1.45}$$

Therefore, for any asset k,

$$\begin{aligned}\mathbb{E}(r_k) = \beta_{km_I}\,(\mathbb{E}(r_{m_I}) - p_i c_{m_I}) + \frac{p_i}{1-p_e}c_k - \frac{p_i p_e}{1-p_e}B_{kI}C_I \\ + \gamma\frac{p_e}{1-p_e}q\,\mathbb{C}\mathrm{ov}(r_k, r_{m_X}|r_I) + \gamma q\,\mathbb{C}\mathrm{ov}(r_k, r_{m_X}|r_{m_I}).\end{aligned} \tag{1.46}$$

Proof of Corollary 2: Expression of the exclusion premia as the difference between a regular investor effect and a sustainable investor effect

(i) From the law of total covariance, we express the expectation of the conditional covariance as a difference between two covariances:

$$\mathbb{E}(\mathbb{C}\mathrm{ov}(r_k, r_{m_X}|r_I)) = \mathbb{C}\mathrm{ov}(r_k, r_{m_X}) - \mathbb{C}\mathrm{ov}(\mathbb{E}(r_k|r_I), \mathbb{E}(r_{m_X}|r_I)). \tag{1.47}$$

Since the conditional covariance of multivariate normal distributions is independent of the conditioning variable (see Lemma 1), $\mathbb{E}(\mathbb{C}\mathrm{ov}(r_k, r_{m_X}|r_I)) = \mathbb{C}\mathrm{ov}(r_k, r_{m_X}|r_I)$. By multiplying the previous equation by $\gamma\frac{p_e}{1-p_e}q$, we obtain the expected result.

(ii) The proof is analogous for the exclusion-market premium.

Proof of Proposition 3: A generalized form of Merton (1987)'s premium on neglected stocks

Derivation of the expected excess returns on I with respect to those on the market

Denoting by q_I and q_X the weight vectors of the market values of the investable and excluded assets in the total market, respectively, we have

$$\mu_m = q_I' \mu_I + q_X' \mu_X. \tag{1.48}$$

Substituting the expressions for the expected excess returns on I and X with respect to m_I (Proposition 7) in the above equation, and noting that $-\frac{p_i p_e}{1-p_e} B_{XI} C_I = (p_i - \frac{p_i}{1-p_e}) B_{XI} C_I$, we obtain

$$\begin{aligned}\mu_m =& q_I' \left((\mu_{m_I} - p_i c_{m_I}) \beta_{I m_I} + p_i C_I + \gamma q \,\mathbb{C}\mathrm{ov}(r_I, r_{m_X} | r_{m_I}) \right) \\ &+ q_X' \Bigg((\mu_{m_I} - p_i c_{m_I}) \beta_{X m_I} + p_i B_{XI} C_I + \frac{p_i}{1-p_e} (C_X - B_{XI} C_I) \\ &+ \gamma \frac{p_e}{1-p_e} q \,\mathbb{C}\mathrm{ov}(r_X, r_{m_X} | r_I) + \gamma q \,\mathbb{C}\mathrm{ov}(r_X, r_{m_X} | r_{m_I}) \Bigg).\end{aligned} \tag{1.49}$$

By grouping together the terms representing the same effect, the equation yields

$$\begin{aligned}\mu_m =& (\mu_{m_I} - p_i c_{m_I}) \left(q_I' \beta_{I m_I} + q_X' \beta_{X m_I} \right) + p_i \left(q_I' + q_X' B_{XI} \right) C_I + \frac{p_i}{1-p_e} q_X' \left(C_X - B_{XI} C_I \right) \\ &+ \gamma \frac{p_e}{1-p_e} q q_X' \,\mathbb{C}\mathrm{ov}(r_X, r_{m_X} | r_I) + \gamma q \left(q_I' \,\mathbb{C}\mathrm{ov}(r_I, r_{m_X} | r_{m_I}) + q_X' \,\mathbb{C}\mathrm{ov}(r_X, r_{m_X} | r_{m_I}) \right).\end{aligned} \tag{1.50}$$

However,

$$q_I' \beta_{I m_I} + q_X' \beta_{X m_I} = (1-q) w_I' \frac{\sigma_{I m_I}}{\sigma_{m_I}^2} + q w_X' \frac{\sigma_{X m_I}}{\sigma_{m_I}^2} = (1-q) \frac{\sigma_{m_I}^2}{\sigma_{m_I}^2} + q \frac{\sigma_{m_X m_I}}{\sigma_{m_I}^2} = \beta_{m m_I}, \tag{1.51}$$

and

$$\left(q_I' + q_X' B_{XI} \right) = \left(q_I' \Sigma_{II} \Sigma_{II}^{-1} + q_X' \Sigma_{XI} \Sigma_{II}^{-1} \right) = \left(q_I' \Sigma_{II} + q_X' \Sigma_{XI} \right) \Sigma_{II}^{-1} = \sigma_{mI} \Sigma_{II}^{-1} = B_{mI}, \tag{1.52}$$

and

$$q_X' \left(C_X - B_{XI} C_I \right) = q \left(w_X' C_X - w_X' \Sigma_{XI} \Sigma_{II}^{-1} C_I \right) = q \left(c_{m_X} - B_{m_X I} C_I \right). \tag{1.53}$$

where B_{mI} and $B_{m_X I}$ are the row vectors of slope coefficients of the regression of r_m and r_{m_X}, respectively, on the excess returns on the investable assets $(r_I)_{k \in \{1, \ldots n_I\}}$ and a constant, and $c_{m_X} = w_X' C_X$ is the cost of externalities of the excluded market.

Therefore, using Lemma 1, Equation (1.50) rewrites as follows:

$$\begin{aligned}\mu_m =&(\mu_{m_I} - p_i c_{m_I})\beta_{mm_I} + p_i B_{mI} C_I + \frac{p_i}{1-p_e} q\,(c_{m_X} - B_{m_X I} C_I)\\ &+\gamma \frac{p_e}{1-p_e} q^2\,\mathbb{V}\mathrm{ar}(r_{m_X}|r_I) + \gamma q\left((1-q)\,\mathbb{C}\mathrm{ov}(r_{m_I}, r_{m_X}|r_{m_I}) + q\,\mathbb{C}\mathrm{ov}(r_{m_X}, r_{m_X}|r_{m_I})\right).\end{aligned} \tag{1.54}$$

This equation is simplified as follows:

$$\begin{aligned}\mu_m =&(\mu_{m_I} - p_i c_{m_I})\beta_{mm_I} + p_i B_{mI} C_I + \frac{p_i}{1-p_e} q\,(c_{m_X} - B_{m_X I} C_I)\\ &+\gamma \frac{p_e}{1-p_e} q^2\,\mathbb{V}\mathrm{ar}(r_{m_X}|r_I) + +\gamma q\,\mathbb{C}\mathrm{ov}(r_m, r_{m_X}|r_{m_I}).\end{aligned} \tag{1.55}$$

Consequently, the expected excess returns on the investable market are

$$\begin{aligned}\mu_{m_I} =& \frac{1}{\beta_{mm_I}}\Bigg(\mu_m + p_i \beta_{mm_I} c_{m_I} - p_i B_{mI} C_I - \frac{p_i}{1-p_e} q\,(c_{m_X} - B_{m_X I} C_I)\\ &-\gamma \frac{p_e}{1-p_e} q^2\,\mathbb{V}\mathrm{ar}(r_{m_X}|r_I) - \gamma q\,\mathbb{C}\mathrm{ov}(r_m, r_{m_X}|r_{m_I})\Bigg).\end{aligned} \tag{1.56}$$

Substituting μ_{m_I} into the expression for the excess returns on I (Proposition 7), we obtain

$$\begin{aligned}\mu_I =& \Bigg(\frac{1}{\beta_{mm_I}}\Bigg(\mu_m + p_i \beta_{mm_I} c_{m_I} - p_i B_{mI} C_I - \frac{p_i}{1-p_e} q\,(c_{m_X} - B_{m_X I} C_I)\\ &-\gamma \frac{p_e}{1-p_e} q^2\,\mathbb{V}\mathrm{ar}(r_{m_X}|r_I) - \gamma q\,\mathbb{C}\mathrm{ov}(r_m, r_{m_X}|r_{m_I})\Bigg) - p_i c_{m_I}\Bigg)\beta_{Im_I} + p_i C_I + \gamma q\,\mathbb{C}\mathrm{ov}(r_I, r_{m_X}|r_{m_I}).\end{aligned} \tag{1.57}$$

Denoting $\frac{1}{\beta_{mm_I}}\beta_{Im_I} = \frac{1}{\mathbb{C}\mathrm{ov}(r_m, r_{m_I})}\,\mathbb{C}\mathrm{ov}(r_I, r_{m_I}) = \tilde{\beta}_{Im}$, and by grouping the terms related to the same effect, we obtain the expected expression using vector notations:

$$\begin{aligned}\mathbb{E}(r_I) =& \Bigg(\mathbb{E}(r_m) - p_i\Bigg(B_{mI} C_I + \frac{q}{1-p_e}\,(c_{m_X} - B_{m_X I} C_I)\Bigg)\Bigg)\tilde{\beta}_{Im} + p_i C_I\\ &-\gamma \frac{p_e}{1-p_e} q^2\,\mathbb{V}\mathrm{ar}(r_{m_X}|r_I)\tilde{\beta}_{Im} + \gamma q\,\mathbb{C}\mathrm{ov}(r_I - r_m \tilde{\beta}_{Im}, r_{m_X}|r_{m_I}).\end{aligned} \tag{1.58}$$

Derivation of the expected excess returns on X with respect to those on the market

Substituting μ_{m_I} from Equation (1.56) into the expression for the excess returns on X (Proposition 7), we obtain

$$\begin{aligned}\mu_X = &\left(\frac{1}{\beta_{mm_I}}\left(\mu_m + p_i\beta_{mm_I}c_{m_I} - p_i B_{mI}C_I - \frac{p_i}{1-p_e}q\left(c_{m_X} - B_{m_X I}C_I\right) - \gamma\frac{p_e}{1-p_e}q^2\,\mathbb{V}\mathrm{ar}(r_{m_X}|r_I)\right.\right.\\ &\left.\left. - \gamma q\,\mathbb{C}\mathrm{ov}(r_m, r_{m_X}|r_{m_I})\right) - p_i c_{m_I}\right)\beta_{Xm_I} + \frac{p_i}{1-p_e}C_X - \frac{p_i p_e}{1-p_e}B_{XI}C_I\\ &+ \gamma\frac{p_e}{1-p_e}q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_I) + \gamma q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_{m_I}).\end{aligned} \tag{1.59}$$

Denoting $\frac{1}{\beta_{mm_I}}\beta_{Xm_I} = \frac{1}{\mathbb{C}\mathrm{ov}(r_m, r_{m_I})}\mathbb{C}\mathrm{ov}(r_X, r_{m_I}) = \tilde{\beta}_{Xm}$, and by grouping the terms related to the same effect, we obtain the expected expression using vector notations:

$$\begin{aligned}\mathbb{E}(r_X) = &\left(\mathbb{E}(r_m) - p_i\left(B_{mI}C_I + \frac{q}{1-p_e}\left(c_{m_X} - B_{m_X I}C_I\right)\right)\right)\tilde{\beta}_{Xm} + \frac{p_i}{1-p_e}C_X - \frac{p_i p_e}{1-p_e}B_{XI}C_I\\ &+ \gamma\frac{p_e}{1-p_e}q\,\mathbb{C}\mathrm{ov}(r_X - q r_{m_X}\tilde{\beta}_{Xm}, r_{m_X}|r_I) + \gamma q\,\mathbb{C}\mathrm{ov}(r_X - r_m\tilde{\beta}_{Xm}, r_{m_X}|r_{m_I}).\end{aligned} \tag{1.60}$$

Derivation of the general pricing formula with respect to the market expected excess returns

This subsection is not necessary to the proof but provides a general result.

For any investable asset I_k,

$$\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_I) = \sigma_{I_k m_X} - \sigma_{I_k I}\Sigma_{II}^{-1}\sigma_{I m_X} = \sigma_{I_k m_X} - \sigma_{I_k m_X} = 0, \tag{1.61}$$

and

$$\frac{p_i}{1-p_e}c_{I_k} - \frac{p_i p_e}{1-p_e}B_{I_k I}C_I = \frac{p_i}{1-p_e}c_{I_k} - \frac{p_i p_e}{1-p_e}c_{I_k} = p_i c_{I_k} \tag{1.62}$$

Therefore, for any asset k,

$$\begin{aligned}\mathbb{E}(r_k) = &\tilde{\beta}_{km}\left(\mathbb{E}(r_m) - p_i\left(B_{mI}C_I + \frac{q}{1-p_e}\left(c_{m_X} - B_{m_X I}C_I\right)\right)\right) + \frac{p_i}{1-p_e}c_k - \frac{p_i p_e}{1-p_e}B_{kI}C_I\\ &+ \gamma\frac{p_e}{1-p_e}q\,\mathbb{C}\mathrm{ov}(r_k - \tilde{\beta}_{km}q r_{m_X}, r_{m_X}|r_I) + \gamma q\,\mathbb{C}\mathrm{ov}(r_k - \tilde{\beta}_{km}r_m, r_{m_X}|r_{m_I}).\end{aligned} \tag{1.63}$$

A generalized form of Merton (1987)'s premium on neglected stocks

a) On the one hand, *using Merton (1987)'s notation* and combining equations (26), (19) and (15) in his paper, the premium on the neglected stock k that the author finds is equal to

$$\alpha_k = \delta \frac{1-q_k}{q_k} \sigma_k^2 x_k - \delta \beta_k \sum_{j=1}^{n} \frac{1-q_j}{q_j} \sigma_j^2 x_j^2. \tag{1.64}$$

In Merton (1987), q_k accounts for the "fraction of all investors who know about security k", i.e., the fraction of investors that can invest in security k. In the present framework, this fraction is the share of regular and integration investors' wealth $1 - p_e$, which is the same for all excluded assets. Thus, taking $q_k = q$, Merton (1987)'s premium on neglected stocks is equal to

$$\alpha_k = \delta \frac{1-q}{q} \left(\sigma_k^2 x_k - \beta_k \sum_{j=1}^{n} \sigma_j^2 x_j^2 \right). \tag{1.65}$$

Let us now reconcile Merton (1987)'s notation with those of this paper. Let us denote by $Q = (q_k)_{k \in \{1,\ldots,n_I+n_X\}} = (q_{I_1}, \ldots, q_{I_{n_I}}, q_{X_1}, \ldots, q_{X_{n_X}})'$ the $(n_I + n_X, 1)$ vector of weights of the assets $I_1, \ldots, I_{n_I}, X_1, \ldots, X_{n_X}$ as a fraction of the market value and $r = (r_k)_{k \in \{1,\ldots,n_I+n_X\}} = (r_{I_1}, \ldots, r_{I_{n_I}}, r_{X_1}, \ldots, r_{X_{n_X}})'$ the $(n_I + n_X, 1)$ vector of excess returns on assets $I_1, \ldots, I_{n_I}, X_1, \ldots, X_{n_X}$.

In Merton (1987), σ_k^2 is the variance of the idiosyncratic risk's (IR) excess returns that is denoted by $\mathbb{V}\mathrm{ar}_{id}(r_{X_k})$ in this paper, δ is the risk aversion (γ in this paper), x_k is the proportion of the market portfolio invested in asset k (q_k in this paper), q is the proportion of regular and integration investors ($1 - p_e$ in this paper), β_k is the beta of asset k with respect to the market portfolio m ($\tilde{\beta}_{X_k m}$ in this paper) and n is the number of assets in the market ($n_I + n_X$ in this paper). Rewritten with the notations of this paper, Merton (1987)'s premium on neglected stock X_k is

$$\alpha_k = \gamma \frac{p_e}{1-p_e} \left(\mathbb{V}\mathrm{ar}_{id}(r_{X_k}) q_{X_k} - \beta_{X_k m} \sum_{j=1}^{n_I+n_X} \mathbb{V}\mathrm{ar}_{id}(r_j) q_j^2 \right). \tag{1.66}$$

b) On the other hand, when the cost of environmental externalities is zero as in Merton (1987)'s framework, equation (1.60) for stock X_k is expressed as follows:

$$\begin{aligned} \mathbb{E}(r_{X_k}) =& \tilde{\beta}_{X_k m} \mathbb{E}(r_m) + \underbrace{\gamma \frac{p_e}{1-p_e} q \, \mathbb{C}\mathrm{ov}(r_{X_k} - \tilde{\beta}_{X_k m} q r_{m_X}, r_{m_X} | r_I)}_{\text{Exclusion-asset premium}} \\ &+ \underbrace{\gamma q \, \mathbb{C}\mathrm{ov}(r_{X_k} - \tilde{\beta}_{X_k m} r_m, r_{m_X} | r_{m_I})}_{\text{Exclusion-market premium}}. \end{aligned} \tag{1.67}$$

The exclusion-asset premium of excluded asset X_k is equal to

$$\alpha_k = \gamma \frac{p_e}{1-p} \left(q \, \mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X} | r_I) - \tilde{\beta}_{X_k m} q^2 \, \mathbb{V}\mathrm{ar}(r_{m_X} | r_I) \right). \tag{1.68}$$

However, from Lemma 1, 2.(i),

$$q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_I) = \mathbb{V}\mathrm{ar}(r_X|r_I)q_X, \tag{1.69}$$

and

$$q^2\,\mathbb{V}\mathrm{ar}(r_{m_X}|r_I) = q_X'\,\mathbb{V}\mathrm{ar}(r_X|r_I)q_X. \tag{1.70}$$

Therefore, denoting by $[\mathbb{V}\mathrm{ar}(r_X|r_I)]_{k,.}$ the kth row of matrix $\mathbb{V}\mathrm{ar}(r_X|r_I)$,

$$\alpha_k = \gamma\frac{p_e}{1-p_e}\left([\mathbb{V}\mathrm{ar}(r_X|r_I)]_{k,.}q_X - \tilde{\beta}_{X_k m}q_X'\,\mathbb{V}\mathrm{ar}(r_X|r_I)q_X\right). \tag{1.71}$$

Since $\mathbb{V}\mathrm{ar}(r_I|r_I) = \mathbb{0}_{n_I,n_I}$ and $\mathbb{C}\mathrm{ov}(r_X, r_I|r_I) = \mathbb{0}_{n_X,n_I}$ (see Lemma 1),

$$q_X'\,\mathbb{V}\mathrm{ar}(r_X|r_I)q_X = Q'\,\mathbb{V}\mathrm{ar}(r|r_I)Q. \tag{1.72}$$

Consequently,

$$\alpha_k = \gamma\frac{p_e}{1-p_e}\left([\mathbb{V}\mathrm{ar}(r_X|r_I)]_{k,.}q_X - \tilde{\beta}_{X_k m}Q'\,\mathbb{V}\mathrm{ar}(r|r_I)Q\right). \tag{1.73}$$

is a *generalized form* of Merton (1987)'s premium on neglected stocks.

Nevertheless, it should be noted that taking Merton's stated assumptions, this premium does not boil down to the author's result for two reasons: 1) the beta is different $\tilde{\beta}_{X_k m} = \beta_{X_k m}\frac{\rho_{X_k,m_I}}{\rho_{X_k,m}\rho_{m,m_I}} \neq \beta_{X_k m}$, consistent with a segmented market, and 2) $[\mathbb{V}\mathrm{ar}(r_X|r_I)]_{k,.}$ is not necessarily equal to $(\mathbb{V}\mathrm{ar}_{id}(r_{X_k}), 0, ...0)$.

Let us take a simple example with three assets X_k, X_j, I to prove that $[\mathbb{V}\mathrm{ar}(r_X|r_I)]_{k,.}$ can differ from $(\mathbb{V}\mathrm{ar}_{id}(r_{X_k}), 0, ...0)$. For each asset $i \in \{X_k, X_j, I\}$, we express the excess return as in Merton's paper as a sum of a common factor and an IR: $r_k = \mathbb{E}(R_k) + b_k Y + \sigma_k\epsilon_k - r_f$, where $\mathbb{E}(Y) = 0$, $\mathbb{E}(Y^2) = 1$, $\mathbb{E}(\epsilon_k|\epsilon_{-k}, Y) = 0$ and $\mathbb{V}\mathrm{ar}(\epsilon_k) = 1$.[37] Therefore,

$$[\mathbb{V}\mathrm{ar}(r_X|r_I)]_{k,.} = \left(\mathbb{V}\mathrm{ar}(r_{X_k}|r_I), \mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_I)\right) = \left(\sigma^2_{X_k}, b_{X_k}b_{X_j} - \frac{b_I^2}{b_I^2+\sigma_I^2}b_{X_k}b_{X_j}\right). \tag{1.74}$$

Consequently, $(\mathbb{V}\mathrm{ar}(r_{X_k}|r_I), \mathbb{C}\mathrm{ov}(r_{X_k}, r_{X_j}|r_I)) = (\mathbb{V}\mathrm{ar}_{id}(r_{X_k}), 0)$ only if one assumes that the IR of the investable asset—in Merton's framework, the asset that is not neglected by any investor—is zero: $\sigma_I = 0$. However, this type of assumption is not stated in Merton (1987). That is the reason why I refer to a *generalized form* and not to a generalization of Merton's result.

Proof of Proposition 4: Sign of the exclusion premia

(i) Let us focus on the exclusion-asset premium. Since $\gamma, q \geq 0$, and $p_e \in [0,1]$, $\gamma\frac{p_e}{1-p_e}q$ is positive.

[37] This last assumption is not explicitely specified by Merton but is used in his calculations.

As shown in Lemma 1, the conditional covariance is equal to:

$$q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_I) = \left(\Sigma_{XX} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}\right) q_X. \tag{1.75}$$

When there is at least one excluded asset, i.e., $q > 0$ and $q_X \neq \mathbb{0}_{n_X}$, denoting by $w_X = \frac{1}{q} q_X > 0$ the weights of assets X in the excluded market, we express the covariance matrix as the product of a Schur complement by a strictly positive vector of weights:

$$\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_I) = \left(\Sigma_{XX} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}\right) \frac{1}{q} q_X = \left(\Sigma_{XX} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}\right) w_X. \tag{1.76}$$

However, Σ_{II} is positive-definite (because it is nonsingular positive semidefinite) and with $\begin{pmatrix} \Sigma_{II} & \Sigma_{IX} \\ \Sigma_{XI} & \Sigma_{XX} \end{pmatrix}$ being positive semidefinite, Schur complement $\left(\Sigma_{XX} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}\right)$ is positive semidefinite. Therefore, the exclusion-asset effects for assets X are the elements of the vector being the product of a semidefinite positive matrix by a strictly positive vector of weights. Consequently, not all elements of this vector are necessarily positive.

The same applies to the exclusion-market premium.

(ii) The expected excess return of the excluded market $\mathbb{E}(r_{m_X})$ is obtained by multiplying the vector of excluded assets' expected excess returns $\mathbb{E}(r_X)$ by their weight in the excluded market w'_X:

$$\begin{aligned}\mathbb{E}(r_{m_X}) =& (\mathbb{E}(r_{m_I}) - p_i c_{m_I}) w'_X \beta_{X m_I} + \frac{p_i}{1-p_e} w'_X C_X - \frac{p_i p_e}{1-p_e} w'_X B_{XI} C_I \\ &+ \gamma \frac{p_e}{1-p_e} q w'_X \,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_I) + \gamma q w'_X \,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}|r_{m_I})\end{aligned} \tag{1.77}$$

Since the covariance and the conditional covariance are bilinear, we have

$$\begin{aligned}\mathbb{E}(r_{m_X}) =& \beta_{m_X m_I}(\mathbb{E}(r_{m_I}) - p_i c_{m_I}) + \frac{p_i}{1-p_e} c_{m_X} - \frac{p_i p_e}{1-p_e} B_{m_X I} C_I \\ &+ \gamma \frac{p_e}{1-p_e} q \,\mathbb{V}\mathrm{ar}(r_{m_X}|r_I) + \gamma q \,\mathbb{V}\mathrm{ar}(r_{m_X}|r_{m_I}),\end{aligned} \tag{1.78}$$

where c_{m_X} is the cost of externalities of the excluded market, $B_{m_X I}$ is the row vector of regression coefficients in a regression of the excluded market excess returns on the investable assets' excess returns and a constant, and $\beta_{m_X m_I}$ is the slope of the regression of the excluded market excess returns on the investable market excess returns and a constant. Let $\rho_{m_X m_I}$ be the correlation coefficient between the excess returns on the excluded market, m_X, and those on the investable market, m_I, and $\rho_{m_X I}$ be the multiple correlation coefficient between the excess returns on the excluded market, m_X, and those on the vector of investable assets' excess returns, I. Since $\mathbb{V}\mathrm{ar}(r_{m_X}|r_I) = \mathbb{V}\mathrm{ar}(r_{m_X})\,(1 - \rho_{m_X I})$ and $\mathbb{V}\mathrm{ar}(r_{m_X}|r_{m_I}) = \mathbb{V}\mathrm{ar}(r_{m_X})\,(1 - \rho_{m_X m_I})$ (see Dhrymes, 1974, Theorem 2 (iv) p.24), the exclusion premia on the excluded market are equal to $\gamma q \,\mathbb{V}\mathrm{ar}(r_{m_X}) \left(\frac{p_e}{1-p_e}(1 - \rho_{m_X I}) + (1 - \rho_{m_X m_I})\right)$, and are always positive or zero. Indeed, since the Schur complement is a positive semidefinite matrix, we have $w_X' \left(\Sigma_{XX} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}\right) w_X \geq 0$ and $w_X' \left(\Sigma_{XX} - \frac{1}{\sigma_{m_I}^2}\sigma_{Xm_I}\sigma_{m_IX}\right) w_X \geq 0$.

Proof of Proposition 5: Cost of externalities

Let $w_{r,I}^*$ and $w_{r,X}^*$ be regular investors' optimal weight vectors of investable and excluded assets, respectively. The optimal weights of integrators, $w_{i,I}^*$ and $w_{i,X}^*$, are defined similarly. By substituting the first-order condition of integrators into the first-order condition of regular investors via risk aversion $\gamma = \frac{1}{\lambda}$ (using System of equations (1.26)), the cost of externalities of asset $k \in \{I_1, ..., I_{n_I}, X_1, ..., X_{n_X}\}$ is

$$c_k = \frac{\mathbb{C}\mathrm{ov}(r_k, r_I')(w_{r,I}^* - w_{i,I}^*) + \mathbb{C}\mathrm{ov}(r_k, r_X')(w_{r,X}^* - w_{i,X}^*)}{\mathbb{C}\mathrm{ov}(r_k, r_I')w_{r,I}^* + \mathbb{C}\mathrm{ov}(r_k, r_X')w_{r,X}^*}\mathbb{E}(r_k). \tag{1.79}$$

Let us focus on asset I_k. Assuming that the asset returns are independent (assumption (i)), using the first, third and fifth rows of system (1.26) yields:

$$w_{r,I_k}^* = \lambda\frac{\mathbb{E}(r_{I_k})}{\mathbb{V}\mathrm{ar}(r_{I_k})}, \quad w_{i,I_k}^* = \lambda\frac{\mathbb{E}(r_{I_k}) - c_{I_k}}{\mathbb{V}\mathrm{ar}(r_{I_k})}, \quad w_{e,I_k}^* = \lambda\frac{\mathbb{E}(r_{I_k})}{\mathbb{V}\mathrm{ar}(r_{I_k})}. \tag{1.80}$$

But,

$$w_{m,I_k} = (1-p_i-p_e)\lambda\frac{\mathbb{E}(r_{I_k})}{\mathbb{V}\mathrm{ar}(r_{I_k})} + p_i\lambda\frac{\mathbb{E}(r_{I_k}) - c_{I_k}}{\mathbb{V}\mathrm{ar}(r_{I_k})} + p_e\lambda\frac{\mathbb{E}(r_{I_k})}{\mathbb{V}\mathrm{ar}(r_{I_k})} = \lambda\frac{\mathbb{E}(r_{I_k})}{\mathbb{V}\mathrm{ar}(r_{I_k})} - p_i\lambda\frac{c_{I_k}}{\mathbb{V}\mathrm{ar}(r_{I_k})}.$$

Therefore,

$$\frac{w_{m,I_k} - w_{i,I_k}^*}{w_{m,I_k}}\mathbb{E}(r_{I_k}) = \frac{\lambda\frac{\mathbb{E}(r_{I_k})}{\mathbb{V}\mathrm{ar}(r_{I_k})} - p_i\lambda\frac{c_{I_k}}{\mathbb{V}\mathrm{ar}(r_{I_k})} - \lambda\frac{\mathbb{E}(r_{I_k})-c_{I_k}}{\mathbb{V}\mathrm{ar}(r_{I_k})}}{\lambda\frac{\mathbb{E}(r_{I_k})}{\mathbb{V}\mathrm{ar}(r_{I_k})} - p_i\lambda\frac{c_{I_k}}{\mathbb{V}\mathrm{ar}(r_{I_k})}}\mathbb{E}(r_{I_k}) \tag{1.81}$$

Simplifying the above expression,

$$\frac{w_{m,I_k} - w_{i,I_k}^*}{w_{m,I_k}}\mathbb{E}(r_{I_k}) = \frac{c_{I_k} - p_i c_{I_k}}{1 - \frac{p_i c_{I_k}}{\mathbb{E}(r_{I_k})}}. \tag{1.82}$$

Using the first order expansion of $\frac{1}{1-\frac{p_i c_{I_k}}{\mathbb{E}(r_{I_k})}}$ when $\frac{p_i c_{I_k}}{\mathbb{E}(r_{I_k})}$ is small (assumption (iii)),

$$\frac{w_{m,I_k} - w_{i,I_k}^*}{w_{m,I_k}}\mathbb{E}(r_{I_k}) \simeq \left(1 - p_i\left(1 - \frac{(1-p_i)c_{I_k}}{\mathbb{E}(r_{I_k})}\right)\right)c_{I_k}. \tag{1.83}$$

When p_i is small (assumption (ii)),

$$\frac{w_{m,I_k} - w_{i,I_k}^*}{w_{m,I_k}}\mathbb{E}(r_{I_k}) \simeq c_{I_k}. \tag{1.84}$$

Let us consider an illustrative example where $\mathbb{E}(r_{I_k}) = 1\%$, $c_{I_k} = 0.10\%$, and $p_i = 10\%$. The approximation is verified: $\left(1 - p_i\left(1 - \frac{(1-p_i)c_{I_k}}{\mathbb{E}(r_{I_k})}\right)\right)c_{I_k} = 0.09\% \simeq c_{I_k}$.

Proof of Corollary 6: Spillover effects

Denoting by w_X the vector of weights of assets X in the excluded market, we write the exclusion-asset premium as:

$$\gamma\frac{p_e}{1-p_e}q\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{m_X}|r_I)=\gamma\frac{p_e}{1-p_e}q\,\mathbb{C}\mathrm{ov}(r_{X_k},r_X|r_I)w_X. \tag{1.85}$$

Since $qw_X = q_X$,

$$\gamma\frac{p_e}{1-p_e}q\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{m_X}|r_I)=\gamma\frac{p_e}{1-p_e}\sum_{j=1}^{n_X}q_{X_j}\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{X_j}|r_I). \tag{1.86}$$

The breakdown is done in the same way for the exclusion-market premium, and thus

$$\begin{aligned}\gamma\frac{p_e}{1-p_e}q\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{m_X}|r_I)+\gamma q\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{m_X}|r_{m_I})=\sum_{j=1}^{n_X}q_{X_j}\Bigg(&\gamma\frac{p_e}{1-p_e}\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{X_j}|r_I)\\&+\gamma\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{X_j}|r_{m_I})\Bigg).\end{aligned} \tag{1.87}$$

1.8 Appendix B: Internet Appendix

Geometric interpretation of the exclusion premia

The exclusion premia can be interpreted from a geometric perspective. By assimilating the standard deviation to the norm of a vector and the correlation coefficient to the cosine of the angle between two vectors, the conditional covariance of the exclusion-asset premium can be associated with the following difference between two scalar products:

$$\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_I) \sim ||X_k||\;||m_X||\;cos(\alpha) - ||\,\mathbb{E}(X_k|I)||\;||\,\mathbb{E}(m_X|I)||\;cos(\alpha'),$$

where $\alpha = \widehat{X_k, m_X}$ and $\alpha' = \widehat{\mathbb{E}(X_k|I), \mathbb{E}(m_X|I)}$. The same applies to the exclusion-market premium. This effect is presented graphically in Figure 1.5: the better the hedge for sustainable investors is (i.e., the closer the vectors X_k and m_X are to space $(I_1, ..., I_{n_I})$), the lower the exclusion-asset premium will be.

SEC's February 2004 amendment

The proxy is built as detailed in section 1.3.1 of the paper. Given the low reporting frequency of many funds until 2007 (the funds mainly reported their holdings in June and December), the proxy becomes robust from 2007 onwards. This period is notably subsequent to the entry into force of the SEC's February 2004 amendment requiring U.S. funds to disclose their holdings on a quarterly basis (Figure 1.6).

Proof of Lemma 1

To lighten the writing in this proof, I remove notation r referring to the returns.

- Let us prove 1.(iii): $\Sigma_{XX} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX} = \mathbb{V}\text{ar}(X|I)$.
  Let $\begin{pmatrix} X \\ I \end{pmatrix}$ follow a multivariate normal distribution with mean $\begin{pmatrix} \mu_X \\ \mu_I \end{pmatrix}$ and covariance matrix $\begin{pmatrix} \Sigma_{XX} & \Sigma_{XI} \\ \Sigma_{IX} & \Sigma_{II} \end{pmatrix}$.
  Assuming that all the random variables (I_k) are not perfectly correlated, Σ_{II} is invertible and the conditional distribution of X given I is multivariate normal with mean vector $\mu_X + \Sigma_{XI}\Sigma_{II}^{-1}(I - \mu_I)$ and covariance matrix $\Sigma_{XX} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}$.
  Indeed, the joint distribution $\begin{pmatrix} X - \Sigma_{XI}\Sigma_{II}^{-1}I \\ I \end{pmatrix}$ is multivariate normal with mean $\begin{pmatrix} \mu_X - \Sigma_{XI}\Sigma_{II}^{-1}\mu_I \\ \mu_I \end{pmatrix}$ and covariance matrix $\begin{pmatrix} \Sigma_{XX} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX} & 0 \\ 0 & \Sigma_{II} \end{pmatrix}$.
  Therefore, $X - \Sigma_{XI}\Sigma_{II}^{-1}I$ is independent of I, and hence its conditional distribution given I is equal to its unconditional distribution. Consequently, the covariance matrix of X given I is equal to $\Sigma_{XX} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX}$, and it does not

depend on the value of I.

- Let us prove 1.(iv): $\sigma_{Xm_X} - \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{Im_X} = \mathbb{C}\mathrm{ov}(X, m_X|I)$.
  Since 1.(iii) is true for any vector X, we can define $\bar{X} = \begin{pmatrix} X \\ m_X \end{pmatrix}$, and $\mathbb{V}\mathrm{ar}(\bar{X}|I) = \begin{pmatrix} \mathbb{V}\mathrm{ar}(X|I) & \mathbb{C}\mathrm{ov}(X, m_X|I) \\ \mathbb{C}\mathrm{ov}(m_X, X|I) & \mathbb{V}\mathrm{ar}(m_X|I) \end{pmatrix}$. We are looking for the upper-right corner of this matrix.
  Let us define $\Sigma_{\bar{X}\bar{X}} = \begin{pmatrix} \Sigma_{X,X} & \sigma_{X,m_X} \\ \sigma_{m_X,X} & \sigma^2_{m_X} \end{pmatrix}$, $\Sigma_{\bar{X}I} = \begin{pmatrix} \Sigma_{X,I} \\ \sigma_{m_X,I} \end{pmatrix}$, and $\Sigma_{I\bar{X}} = \begin{pmatrix} \Sigma_{X,I} & \sigma_{m_X,I} \end{pmatrix}$.
  Substituting these into the first equation yields:

$$\begin{aligned}\mathbb{V}\mathrm{ar}(\bar{X}|I) &= \begin{pmatrix} \Sigma_{X,X} & \sigma_{X,m_X} \\ \sigma_{m_X,X} & \sigma^2_{m_X} \end{pmatrix} - \begin{pmatrix} \Sigma_{X,I} \\ \sigma_{m_X,I} \end{pmatrix} \Sigma_{II}^{-1} \begin{pmatrix} \Sigma_{X,I} & \sigma_{m_X,I} \end{pmatrix} \\ &= \begin{pmatrix} \Sigma_{X,X} & \sigma_{X,m_X} \\ \sigma_{m_X,X} & \sigma^2_{m_X} \end{pmatrix} - \begin{pmatrix} \Sigma_{XI}\Sigma_{II}^{-1}\Sigma_{IX} & \Sigma_{XI}\Sigma_{II}^{-1}\sigma_{Im_X} \\ \sigma_{m_XI}\Sigma_{II}^{-1}\Sigma_{IX} & \sigma_{m_XI}\Sigma_{II}^{-1}\sigma_{Im_X} \end{pmatrix}\end{aligned} \tag{1.88}$$

  The upper-right corner is $\sigma_{X,m_X} - \Sigma_{XI}\Sigma_{II}^{-1}\sigma_{Im_X}$.

- Equations 1.(i) and 1.(ii) are proved similarly when one conditions by a random variable m_I instead of a random vector I.

- Let us prove 2. We know from 1.(ii) that $\mathbb{C}\mathrm{ov}(I, X|m_I) = \Sigma_{IX} - \frac{\sigma_{Im_I}}{\sigma^2_{m_I}}\sigma_{m_IX}$.
  Let w_X be the weight vector of assets $(X_k)_k$ in the excluded market. Noting that $q_X = qw_X$, we have

$$\begin{aligned}\mathbb{C}\mathrm{ov}(I, X|m_I)q_X =& q\left(\Sigma_{IX} - \frac{\sigma_{Im_I}}{\sigma^2_{m_I}}\sigma_{m_IX}\right) w_X \\ & q\left(\sigma_{Im_X} - \frac{\sigma_{Im_I}}{\sigma^2_{m_I}}\sigma_{m_Im_X}\right).\end{aligned} \tag{1.89}$$

  Consequently, from 1.(ii), we obtain

$$\mathbb{C}\mathrm{ov}(I, X|m_I)q_X = q\,\mathbb{C}\mathrm{ov}(I, m_X|m_I). \tag{1.90}$$

  Similarly, we can also prove that

$$\mathbb{C}\mathrm{ov}(X, X|I)q_X = q\,\mathbb{C}\mathrm{ov}(X, m_X|I). \tag{1.91}$$

Generalization of the S-CAPM for investable assets with $N+1$ types of sustainable investors and N types of excluded assets

This section derives the pricing formula for investable assets in the presence of $N+1$ sustainable investors with different exclusion scopes and different levels of disagreement regarding the assets in which they invest.

Let us consider a group of $N+1$ sustainable investors $(s_0, s_1, s_2, ..., s_N)$. The group of investors s_0 can only invest in assets I and penalizes these assets via the vector of cost of externalities $C_{0.0}$. The group of sustainable investors s_1 can only invest in assets I and X_1 and penalizes assets I and X_1 via the vectors of cost of externalities $C_{1.0}$ and $C_{1.1}$, respectively. This is the case up to N, and the group of sustainable investors s_N invests in assets $I, X_1, ..., X_N$ and penalizes these assets via the vectors of cost of externalities $C_{N,0}, C_{N,1}, ..., C_{N,N}$, respectively. Finally, the group of regular investors can invest in all assets (like investors s_N) but does not charge any environmental externality costs.

Sustainable and regular investors maximize their wealth. They solve the following first-order conditions:

$$\begin{cases} \lambda(\mu_I - C_{00}) = \Sigma_{II} w_{s_0 I} \\ \\ \lambda \begin{pmatrix} \mu_I - C_{10} \\ \mu_{X_1} - C_{11} \end{pmatrix} = \begin{pmatrix} \Sigma_{II} & \Sigma_{IX_1} \\ \Sigma_{X_1 I} & \Sigma_{X_1 X_1} \end{pmatrix} \begin{pmatrix} w_{s_1 I} \\ w_{s_1 X_1} \end{pmatrix} \\ \vdots \\ \\ \lambda \begin{pmatrix} \mu_I - C_{N0} \\ \mu_{X_1} - C_{N1} \\ \vdots \\ \mu_{X_N} - C_{NN} \end{pmatrix} = \begin{pmatrix} \Sigma_{II} & \Sigma_{IX_1} & ... & \Sigma_{IX_N} \\ \Sigma_{X_1 I} & \Sigma_{X_1 X_1} & ... & \Sigma_{X_1 X_N} \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{X_N I} & \Sigma_{X_N X_1} & ... & \Sigma_{X_N X_N} \end{pmatrix} \begin{pmatrix} w_{s_N I} \\ w_{s_N X_1} \\ \vdots \\ w_{s_N X_N} \end{pmatrix} \\ \lambda \begin{pmatrix} \mu_I \\ \mu_{X_1} \\ \vdots \\ \mu_{X_N} \end{pmatrix} = \begin{pmatrix} \Sigma_{II} & \Sigma_{IX_1} & ... & \Sigma_{IX_N} \\ \Sigma_{X_1 I} & \Sigma_{X_1 X_1} & ... & \Sigma_{X_1 X_N} \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{X_N I} & \Sigma_{X_N X_1} & ... & \Sigma_{X_N X_N} \end{pmatrix} \begin{pmatrix} w_{rI} \\ w_{rX_1} \\ \vdots \\ w_{rX_N} \end{pmatrix}. \end{cases} \tag{1.92}$$

Multiplying the first row of each first-order condition by $\frac{W_{s_0}}{W}, \frac{W_{s_1}}{W}, ..., \frac{W_{s_N}}{W}, \frac{W_r}{W}$, respectively, and summing up the terms, we have

$$\begin{aligned}
& \lambda\left(\frac{W_{s_0}}{W}+...+\frac{W_{s_N}}{W}+\frac{W_r}{W}\right)\mu_I-\lambda\left(\frac{W_{s_0}}{W}C_{00}+...+\frac{W_{s_N}}{W}C_{N0}\right) \\
= \quad & \frac{W_{s_0}}{W}\Sigma_{II}w_{s_0I} \\
& +\frac{W_{s_1}}{W}\Sigma_{II}w_{s_1I}+\frac{W_{s_1}}{W}\Sigma_{IX_1}w_{s_1X_1} \\
& +... \\
& +\frac{W_{s_N}}{W}\Sigma_{II}w_{s_NI}+\frac{W_{s_N}}{W}\Sigma_{IX_1}w_{s_NX_1}+...+\frac{W_{s_N}}{W}\Sigma_{IX_N}w_{s_NX_N} \\
& +\frac{W_r}{W}\Sigma_{II}w_{rI}+\frac{W_r}{W}\Sigma_{IX_1}w_{rX_1}+...+\frac{W_r}{W}\Sigma_{IX_N}w_{rX_N}.
\end{aligned} \tag{1.93}$$

Denoting $p=\frac{W_{s_0}}{W}+...+\frac{W_{s_N}}{W}$, and the intermediate value theorem, there exists C such that

$$\frac{W_{s_0}}{W}C_{00}+...+\frac{W_{s_N}}{W}C_{N0}=pC, \tag{1.94}$$

Therefore, rearranging equation (1.93),

$$\begin{aligned}
\lambda\mu_I = & \Sigma_{II}\left(\frac{W_{s_0}}{W}w_{s_0I}+\frac{W_{s_1}}{W}w_{s_1I}+...+\frac{W_{s_N}}{W}w_{s_NI}+\frac{W_r}{W}w_{rI}\right) \\
& +\Sigma_{IX_1}\left(\frac{W_{s_1}}{W}w_{s_1X_1}+...+\frac{W_{s_N}}{W}w_{s_NX_1}+\frac{W_r}{W}w_{rX_1}\right) \\
& +... \\
& +\Sigma_{IX_N}\left(\frac{W_{s_N}}{W}w_{s_NX_N}+\frac{W_r}{W}w_{rX_N}\right) \\
& +\lambda pC.
\end{aligned} \tag{1.95}$$

In equilbibrium the demand of assets is equal to the supply of assets on all the markets. Denoting by $q_I, q_{X_1}, ..., q_{X_N}$ the vectors of weights of assets $I, X_1, ..., X_N$ in the market, respectively, we obtain

$$\lambda\mu_I=\Sigma_{II}q_I+\Sigma_{IX_1}q_{X_1}+...+\Sigma_{IX_N}q_{X_N}+\lambda pC. \tag{1.96}$$

Let us denote by w_I the vector of weights of assets I held by all investors $s_0, ..., s_N, r$, and for each asset X_k, $q_{X_k}=(q_{k1}, ..., q_{kn_i})'$. Therefore,

$$q_I=\left(1-\sum_{i=1}^{N}\sum_{j=1}^{n_i}q_{ij}\right)w_I. \tag{1.97}$$

Consequently, equation (1.96) is rewritten as

$$\lambda\mu_I=\left(1-\sum_{i=1}^{N}\sum_{j=1}^{n_i}q_{ij}\right)\Sigma_{II}w_I+\Sigma_{IX_1}q_{X_1}+...+\Sigma_{IX_N}q_{X_N}+\lambda pC. \tag{1.98}$$

Multiplying by ${w_I}'$, we obtain

$$\lambda {w_I}' \mu_I = \left(1 - \sum_{i=1}^{N}\sum_{j=1}^{n_i} q_{ij}\right) {w_I}'\Sigma_{II} w_I + \sum_{i=1}^{N} {w_I}'\Sigma_{IX_k} q_{X_k} + p\lambda \underbrace{{w_I}'C}_{c_{m_I}}, \tag{1.99}$$

$$\lambda \mu_{m_I} = \left(1 - \sum_{i=1}^{N}\sum_{j=1}^{n_i} q_{ij}\right) \sigma^2_{m_I} + \sum_{i=1}^{N} \sigma_{m_I X_k} q_{X_k} + p\lambda c_{m_I}. \tag{1.100}$$

Substituting $\left(1 - \sum_{i=1}^{N}\sum_{j=1}^{n_i} q_{ij}\right)$ in (1.98), we obtain

$$\lambda \mu_I = \frac{1}{\sigma^2_{m_I}} \left(\lambda \mu_{m_I} - \sum_{i=1}^{N} \sigma_{m_I X_k} q_{X_k} - p\lambda c_{m_I}\right) \Sigma_{II} w_I + \Sigma_{IX_1} q_{X_1} + ... + \Sigma_{IX_N} q_{X_N} + \lambda p C. \tag{1.101}$$

Denoting by $\beta_{Im_I} = \frac{1}{\sigma^2_{m_I}} \sigma_{Im_I}$ the vector of betas of investable assets with respect to the investable market, and by $q_{\Omega_{X_k}}$ the weight of the excluded market of assets X_k in the total market, we can rewrite the previous equation as

$$\begin{aligned} \mu_I &= (\mu_{m_I} - p c_{m_I})\, \beta_{Im_I} + \gamma \sum_{i=1}^{N} (\Sigma_{IX_k} - \beta_{Im_I} \sigma_{m_I X_k})\, q_{X_k} + pC \\ &= (\mu_{m_I} - p c_{m_I})\, \beta_{Im_I} + \gamma \sum_{i=1}^{N} q_{\Omega_{X_k}}\, \mathbb{C}\text{ov}(r_I, r_{m_{X_k}} | r_{m_I}) + pC. \end{aligned} \tag{1.102}$$

Therefore, we can write the above equation as follows:

$$\mathbb{E}(r_I) = (\mathbb{E}(r_{m_I}) - p c_{m_I})\, \beta_{Im_I} + \gamma \sum_{j=1}^{N} q_{\Omega_{X_j}}\, \mathbb{C}\text{ov}(r_I, r_{m_{X_j}} | r_{m_I}) + pC, \tag{1.103}$$

which yields for each asset I_k ($k \in \{1, ..., n_I\}$):

$$\mathbb{E}(r_{I_k}) = \beta_{I_k m_I} (\mathbb{E}(r_{m_I}) - p c_{m_I}) + \gamma \sum_{j=1}^{N} q_{\Omega_{X_j}}\, \mathbb{C}\text{ov}(r_{I_k}, r_{m_{X_j}} | r_{m_I}) + p c_{I_k}. \tag{1.104}$$

Green and conventional funds used to construct instruments $\tilde{C}_I$ and $\tilde{p}_i$

To construct the proxy for the cost of environmental externalities $\tilde{C}_I$, I consider the 453 green funds identified in Bloomberg as of December 2019 whose mandate includes environmental guidelines (flagged as "Environmentally friendly", "Climate change" or "Clean Energy"), and of which the geographical investment scope includes the United States (flagged as "Global", "International", "Multi", "North American Region", "OECD countries", and "U.S.", see Table 1.9). As shown in Figure 1.7a, the number of funds has grown steadily from over 50 funds in 2007 to 100 funds in 2010, reaching 200 funds in 2018. The number of stocks held by these green funds has naturally increased, from approximately 2000 in 2007 to over 6000 in 2019 (Figure 1.7b). Figure 1.8 shows the dynamics of $\tilde{C}_I$ for the two industries—coal and construction—that experienced the strongest divestment by green funds between 2012 and 2019.

I also construct a proxy capturing the proportion of integrators, $\tilde{p}_i$, by using green fund holdings, as detailed in Section 1.3.1 of the paper. Figure 1.9 depicts the dynamics of $\tilde{p}_i$.

Factor correlation matrix

Table 1.10 shows the correlation matrix between the regression factors for both investable and excluded assets.

Robustness tests for investable assets

I perform several alternative regressions to test the robustness of the pricing formula for investable assets. Two premia are analyzed: the direct taste premium, which carries the effect related to integrators' preferences for green firms, and the exclusion-market premium, which reflects the effect of market partial segmentation on the return on investable assets.

In addition to the main case detailed in the paper, the direct taste premium remains significant:

- using industry-size portfolios (Table 1.11);
- when the proxy for the direct taste premium is lagged by three years (Table 1.12);
- when using a 5-year window in the first pass of the Fama and MacBeth (1973) regression (Table 1.13);
- over three consecutive periods between December 2007 and December 2019 (Table 1.14)

The exclusion-market premium is significant when considering equally weighted returns of industry-sorted portfolios (Table 1.15).

Finally, when using the carbon intensity as a proxy for green investors' tastes, the taste effect is not significant (Table 1.16).

Empirical analysis for sin stocks as excluded assets

Robustness tests

I perform alternative regressions to test the robustness of the pricing formula for excluded assets applied to sin stocks. Three factors are analyzed: the exclusion-asset factor and the exclusion-market factor, which carry the effect related to excluders' practice; the indirect taste factor, which reflects the effect of integrators' tastes for green firms on sin stocks.

The two exclusion premia are significant:

- From December 1999 to December 2019 (Table 1.17);
- Using $\tilde{p}_i$ as a proxy for p_e (Table 1.22).

At least one of the two exclusion premia is significant:

- when using equally weighted excess returns (Table 1.18);
- when using a 5-year rolling window in the first-pass regression (Table 1.19);
- when adding the defense industry to the gaming, alcohol and tobacco industries (Table 1.20);
- during the sub-periods between December 2007 and December 2019 (Table 1.21).

The indirect taste premium is significant:

- when using equally weighted excess returns (Table 1.18);
- when adding the defense industry to the gaming, alcohol and tobacco industries (Table 1.20);
- Using $\tilde{p}_i$ as a proxy for p_e (Table 1.22).

Spillovers

Figure 1.10 shows the distribution of the share of the spillover effect in the exclusion premia. This metric is defined in subsection 1.5.5 of the paper. For a given stock, on average, 92.5% of the exclusion premia is induced by the interaction with other sin stocks. The share of spillovers in the exclusion premia is most often between 90% and 100%.

The heatmap presented in Figure 1.11 offers a graphical depiction of the spillover effects of every sin stock (in columns) on each sin stock of interest (in rows) and illustrates two findings. First, although most of the spillover effects are positive, some can be negative (in green on the graph). Second, some stocks exert strong spillover effects on all the sin stocks under consideration (red columns).

Tables and Figures

TABLE 1.9: **Geographical distribution of green funds.** This table reports the geographical distribution of the green funds that are allowed to invest in the United States as of December 2019. These areas are: Global, International, U.S., Multi, OECD countries, North American Region.

Geographical zone	Number of funds
Global	313
International	63
U.S.	48
OECD Countries	14
Multi	12
North American Region	3
Total	453

TABLE 1.10: **Correlation matrix.** This table reports the correlation matrix between the factors involved in the S-CAPM and the 4F S-CAPM pricing models. $\beta_{I.SMB}$, $\beta_{I.HML}$ and $\beta_{I.MOM}$ are the slopes of the regression of the excess returns on the industry-sorted investable portfolios on the SMB, HML (Fama and French, 1993) and MOM (Carhart, 1997) factors, respectively. $\beta_{X.SMB}$, $\beta_{X.HML}$ and $\beta_{X.MOM}$ are the slopes of the regression of the excluded stocks' excess returns on the SMB, HML, and MOM factors, respectively. $\tilde{p}_i\tilde{C}_I$ is the direct taste factor for investable assets and $\tilde{p}_i B_{XI}\tilde{C}_I$ is the indirect taste factor for excluded assets. $q\,\mathbb{C}\mathrm{ov}_t(r_I, r_{m_X}|r_{m_I})$ and $q\,\mathbb{C}\mathrm{ov}_t(r_X, r_{m_X}|r_{m_I})$ are the exclusion-market factors for portfolios I and stocks X, respectively. $q\,\mathbb{C}\mathrm{ov}_t(r_X, r_{m_X}|r_I)$ is the exclusion-asset factor for stocks X. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% levels, respectively.

	$\tilde{p}_i\tilde{C}_I$		$q\,\mathbb{C}\mathrm{ov}(r_I, r_{m_X}\|r_{m_I})$	$\beta_{I.SMB}$	$\beta_{I.HML}$
$q\,\mathbb{C}\mathrm{ov}(r_I, r_{m_X}\|r_{m_I})$	-0.01				
$\beta_{I.SMB}$	-0.14***		-0.19***		
$\beta_{I.HML}$	0.08***		-0.34***	0.04***	
$\beta_{I.MOM}$	0.01		-0.17***	0.28***	-0.58***
	$\tilde{p}_i B_{XI}\tilde{C}_I$	$q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}\|r_I)$	$q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}\|r_{m_I})$	$\beta_{X.SMB}$	$\beta_{X.HML}$
$q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}\|r_I)$	0.09***				
$q\,\mathbb{C}\mathrm{ov}(r_X, r_{m_X}\|r_{m_I})$	-0.15***	-0.16***			
$\beta_{X.SMB}$	0.09***	0.26***	-0.22***		
$\beta_{X.HML}$	-0.07***	0.10***	-0.1***	0.14***	
$\beta_{X.MOM}$	0.31***	0.35***	-0.3***	0.2***	-0.35***

TABLE 1.11: **Cross-sectional regressions for investable stock portfolios with tastes for green firms using industry-size portfolios.** This table presents the estimates of the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for industry-size portfolios between December 31, 2007, and December 31, 2019. The specification of the S-CAPM is written as follows: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{taste}\tilde{p}_i\tilde{c}_{I_k} + \delta_{ex.mkt} q\,\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$, where r_{I_k} is the value-weighted excess return on portfolio k ($k = 1, ..., n_I$), $\beta_{I_k m_I}$ is the slope of an OLS regression of r_{I_k} on r_{m_I}; $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; $\tilde{c}_{I_k}$ is the proxy for the cost of environmental externalities of industry I_k; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$ is the covariance of the excess return on portfolio I_k with that of the excluded market, the excess returns on the investable market being given. This specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added, and (ii) the 4F model is the CAPM with respect to the investable market returns to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{SMB}\beta_{I_k SMB} + \delta_{HML}\beta_{I_k HML} + \delta_{MOM}\beta_{I_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated portfolio-by-portfolio in a 3-year rolling window at monthly intervals. In the second pass, a cross-sectional regression is performed month-by-month on all the portfolios. The estimated parameter is the average value of the estimates obtained on all months during the period. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0133	0.003						0.06 [0.04,0.08]
t-value	(11.96)	(2.55)						0.06 [0.04,0.08]
Estimate	0.0173		0.4165					0 [0,0]
t-value	(16.97)		(5.01)					0.01 [0.01,0.01]
Estimate	0.0169			38				0.03 [0.02,0.05]
t-value	(17.54)			(0.62)				0.04 [0.03,0.05]
Estimate	0.0135	0.0029	0.324					0.06 [0.04,0.08]
t-value	(12.39)	(2.52)	(5.57)					0.06 [0.04,0.08]
Estimate	0.0133	0.0032	0.2369	28.2				0.08 [0.06,0.1]
t-value	(13.78)	(2.86)	(2.9)	(0.48)				0.09 [0.07,0.11]
Estimate	0.0129	0.0044	0.3127	-66.4	0.0001	-0.0002	-0.0005	0.16 [0.14,0.18]
t-value	(13.8)	(3.65)	(3.66)	(-0.88)	(0.64)	(-1.81)	(-5.69)	0.18 [0.16,0.2]
Estimate	0.0127	0.0046			0.0001	0.000	-0.0004	0.13 [0.11,0.15]
t-value	(12.41)	(3.99)			(0.47)	(-0.17)	(-5.91)	0.14 [0.12,0.17]

TABLE 1.12: **Cross-sectional regressions for investable stock industry-sorted portfolios with tastes for green firms where proxy $\tilde{p}_i\tilde{c}$ is lagged by 3 years.** This table presents the estimates of the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for 46 investable stock industry-sorted portfolios between December 31, 2007, and December 31, 2019. The proxy for the direct taste premium, $\tilde{p}_i\tilde{c}$, is lagged by 3 years. The specification of the S-CAPM is written as follows: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{taste}\tilde{p}_i\tilde{c}_{I_k} + \delta_{ex.mkt} q\,\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_{m_I})$, where r_{I_k} is the value-weighted excess return on portfolio k ($k = 1, ..., n_I$), $\beta_{I_k m_I}$ is the slope of an OLS regression of r_{I_k} on r_{m_I}; $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; $\tilde{c}_{I_k}$ is the proxy for the cost of environmental externalities of stock I_k; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_{m_I})$ is the covariance of the excess return on portfolio I_k with that of the excluded market, the excess returns on the investable market being given. This specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added, and (ii) the 4F model is the CAPM with respect to the investable market returns to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{SMB}\beta_{I_k SMB} + \delta_{HML}\beta_{I_k HML} + \delta_{MOM}\beta_{I_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated portfolio-by-portfolio in a 3-year rolling window at monthly intervals. In the second pass, a cross-sectional regression is performed month-by-month on all the portfolios. The estimated parameter is the average value of the estimates obtained on all months during the period. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0159	-0.0018						0.03 [0.02,0.05]
t-value	(14.25)	(-1.83)						0.05 [0.04,0.07]
Estimate	0.0138		0.0893					-0.02 [-0.02,-0.02]
t-value	(24.83)		(0.95)					0 [0,0.01]
Estimate	0.0134			-95.8				0.03 [0.02,0.04]
t-value	(27.73)			(-1.49)				0.05 [0.04,0.07]
Estimate	0.016	-0.0018	0.1526					0.02 [0,0.03]
t-value	(13.95)	(-1.86)	(1.53)					0.06 [0.05,0.07]
Estimate	0.0188	-0.005	0.4652	-308.9				0.1 [0.08,0.12]
t-value	(11.54)	(-3.28)	(3.09)	(-2.63)				0.16 [0.14,0.18]
Estimate	0.0179	-0.0028	0.4921	-483.6	-0.0008	0.0004	-0.0007	0.27 [0.24,0.3]
t-value	(13.36)	(-2.13)	(1.93)	(-5.94)	(-3.65)	(2.22)	(-4.17)	0.37 [0.34,0.39]
Estimate	0.0148	-0.0005			-0.0008	0.0003	-0.0006	0.21 [0.18,0.24]
t-value	(13.43)	(-0.42)			(-3.2)	(1.97)	(-4.48)	0.28 [0.25,0.3]

TABLE 1.13: **Cross-sectional regressions for 46 industry-sorted portfolios of investable stocks with tastes for green firms, using a 5-year rolling window for the first-pass estimates.** This table presents the estimates of the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for 46 investable stock industry-sorted portfolios between December 31, 2007, and December 31, 2019. The specification of the S-CAPM is written as follows: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{taste}\tilde{p}_i\tilde{c}_{I_k} + \delta_{ex.mkt}q\,\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_{m_I})$, where r_{I_k} is the value-weighted excess return on portfolio k ($k = 1, ..., n_I$), $\beta_{I_k m_I}$ is the slope of an OLS regression of r_{I_k} on r_{m_I}; $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; $\tilde{c}_{I_k}$ is the proxy for the cost of environmental externalities of stock I_k; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_{m_I})$ is the covariance of the excess return on portfolio I_k with that of the excluded market, the excess returns on the investable market being given. This specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added, and (ii) the 4F model is the CAPM with respect to the investable market returns to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{SMB}\beta_{I_k SMB} + \delta_{HML}\beta_{I_k HML} + \delta_{MOM}\beta_{I_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated portfolio-by-portfolio in a 5-year rolling window at monthly intervals. In the second pass, a cross-sectional regression is performed month-by-month on all the portfolios. The estimated parameter is the average value of the estimates obtained on all months during the period. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0133	0.0003						0.03 [0.02,0.04]
t-value	(14.18)	(0.36)						0.05 [0.04,0.06]
Estimate	0.0137		0.1812					-0.02 [-0.02,-0.02]
t-value	(21.12)		(3.27)					0 [0,0.01]
Estimate	0.0137			117.9				0.04 [0.03,0.05]
t-value	(22.49)			(2.93)				0.06 [0.05,0.07]
Estimate	0.0134	0.0002	0.173					0.01 [0,0.02]
t-value	(14.38)	(0.28)	(3.78)					0.05 [0.04,0.07]
Estimate	0.0119	0.0018	0.1938	78.5				0.07 [0.05,0.09]
t-value	(10.07)	(1.87)	(3.68)	(1.36)				0.13 [0.11,0.15]
Estimate	0.0129	0.0001	0.4156	-124.2	-0.0001	-0.0003	-0.0001	0.31 [0.27,0.35]
t-value	(14.07)	(0.12)	(10.31)	(-3.29)	(-2.35)	(-1.51)	(-0.98)	0.4 [0.36,0.43]
Estimate	0.0116	0.0012			-0.0001	-0.0003	-0.0001	0.31 [0.27,0.35]
t-value	(14.55)	(1.56)			(-2.65)	(-1.63)	(-0.83)	0.38 [0.34,0.41]

TABLE 1.14: **Cross-sectional regressions for investable stock industry-sorted portfolios with tastes for green firms over three consecutive periods between December 2007 and December 2019.** This table presents the estimates of the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for 46 investable stock industry-sorted portfolios between December 31, 2007, and December 31, 2019. The specification of the S-CAPM is written as follows: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{taste}\tilde{p}_i\tilde{c}_{I_k} + \delta_{ex.mkt}q\,\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$, where r_{I_k} is the value-weighted excess return on portfolio k ($k = 1, ..., n_I$), $\beta_{I_k m_I}$ is the slope of an OLS regression of r_{I_k} on r_{m_I}; $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; $\tilde{c}_{I_k}$ is the proxy for the cost of environmental externalities of stock I_k; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$ is the covariance of the excess return on portfolio I_k with that of the excluded market, the excess returns on the investable market being given. This specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added, and (ii) the 4F model is the CAPM with respect to the investable market returns to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{SMB}\beta_{I_k SMB} + \delta_{HML}\beta_{I_k HML} + \delta_{MOM}\beta_{I_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated portfolio-by-portfolio in a 3-year rolling window at monthly intervals. In the second pass, a cross-sectional regression is performed month-by-month on all the portfolios. The estimated parameter is the average value of the estimates obtained on the 109 months during the period. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.mkt}$	Adj. OLS/GLS R^2
Panel A: Dec. 2010 - Dec. 2013 (second pass) / Dec. 2007 - Dec. 2013 (first pass and second pass)					
Estimate	0.0123	0.0044	0.2306	117.8	0.1 [0.03,0.16]
t-value	(8.28)	(3.73)	(2.19)	(2.49)	0.16 [0.1,0.22]
Panel B: Dec. 2013 - Dec. 2016 (second pass) / Dec. 2009 - Dec. 2013 (first pass and second pass)					
Estimate	0.0144	0.0013	0.4036	231.5	0.02 [-0.01,0.04]
t-value	(10.07)	(0.74)	(4.54)	(2.22)	0.08 [0.06,0.11]
Panel C: Dec. 2016 - Dec. 2019 (second pass) / Dec. 2013 - Dec. 2019 (first pass and second pass)					
Estimate	0.0125	0.0006	0.2988	-82.5	0 [-0.01,0.02]
t-value	(34.38)	(1.48)	(7.27)	(-1.39)	0.07 [0.06,0.08]

TABLE 1.15: **Cross-sectional regressions for 46 industry-sorted portfolios of investable stocks with tastes for green firms, using equally weighted returns.** This table presents the estimates of the S-CAPM on the equally weighted monthly returns in excess of the 1-month T-Bill for 46 investable stock industry-sorted portfolios between December 31, 2007, and December 31, 2019. The specification of the S-CAPM is written as follows: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{taste}\tilde{p}_i\tilde{c}_{I_k} + \delta_{ex.mkt} q\,\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$, where r_{I_k} is the value-weighted excess return on portfolio k ($k = 1, ..., n_I$), $\beta_{I_k m_I}$ is the slope of an OLS regression of r_{I_k} on r_{m_I}; $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; $\tilde{c}_{I_k}$ is the proxy for the cost of environmental externalities of stock I_k; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\text{ov}(r_{I_k}, r_{m_X}|r_{m_I})$ is the covariance of the excess return on portfolio I_k with that of the excluded market, the excess returns on the investable market being given. This specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added, and (ii) the 4F model is the CAPM with respect to the investable market returns to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{SMB}\beta_{I_k SMB} + \delta_{HML}\beta_{I_k HML} + \delta_{MOM}\beta_{I_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated portfolio-by-portfolio in a 3-year rolling window at monthly intervals. In the second pass, a cross-sectional regression is performed month-by-month on all the portfolios. The estimated parameter is the average value of the estimates obtained on all months during the period. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0185	-0.0075						0.18 [0.15,0.21]
t-value	(8.91)	(-3.46)						0.2 [0.17,0.22]
Estimate	0.0108		-0.4386					0 [0,0]
t-value	(10.29)		(-2.55)					0.02 [0.02,0.03]
Estimate	0.0109			412.4				0.18 [0.14,0.21]
t-value	(10.71)			(5.43)				0.19 [0.16,0.23]
Estimate	0.0184	-0.0076	-0.2301					0.17 [0.15,0.2]
t-value	(8.91)	(-3.51)	(-1.74)					0.21 [0.18,0.24]
Estimate	0.0156	-0.0047	-0.1776	290.9				0.26 [0.22,0.3]
t-value	(8.71)	(-2.63)	(-1.25)	(4.41)				0.31 [0.27,0.34]
Estimate	0.0136	-0.0017	-0.0911	256.8	0.0002	-0.0001	-0.0009	0.34 [0.3,0.38]
t-value	(9.43)	(-1.35)	(-0.54)	(3.48)	(0.85)	(-0.2)	(-5.34)	0.43 [0.39,0.47]
Estimate	0.015	-0.0028			0.0004	0.0003	-0.0006	0.3 [0.26,0.35]
t-value	(8.37)	(-1.82)			(1.86)	(0.88)	(-4.78)	0.37 [0.33,0.41]

TABLE 1.16: **Cross-sectional regressions for investable stock industry-sorted portfolios with carbon intensity as a proxy for green investors' tastes.** Panel A presents the estimates of the S-CAPM using the carbon intensity as a proxy for green investors' tastes and based on the value-weighted monthly returns in excess of the 1-month T-Bill for 46 investable stock industry-sorted portfolios between December 31, 2007, and December 31, 2019. The specification estimated is written as follows: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{carbon.intensity}CARB_{I_k} + \delta_{ex.mkt}q\,\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_{m_I})$. Panel B presents the estimates of the S-CAPM without taste factor based on the value-weighted monthly returns in excess of the 1-month T-Bill for 46 investable stock long-short industry-sorted portfolios between December 31, 2007, and December 31, 2019. The industry portfolios are long the 20% assets that have the highest carbon intensity and short the 20% assets that have the lowest carbon intensity. The specification estimated is written as follows: $\mathbb{E}(r_{I_k}) = \alpha + \delta_{mkt}\beta_{I_k m_I} + \delta_{ex.mkt}q\,\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_{m_I})$. In the specifications, r_{I_k} is the value-weighted excess return on portfolio k ($k = 1, ..., n_I$), $\beta_{I_k m_I}$ is the slope of an OLS regression of r_{I_k} on r_{m_I}; $CARB_{I_k}$ is the carbon intensity of stock I_k; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\mathrm{ov}(r_{I_k}, r_{m_X}|r_{m_I})$ is the covariance of the excess return on portfolio I_k with that of the excluded market, the excess returns on the investable market being given. To these specifications, the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor are added for robustness analysis. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated portfolio-by-portfolio in a 3-year rolling window at monthly intervals. In the second pass, a cross-sectional regression is performed month-by-month on all the portfolios. The estimated parameter is the average value of the estimates obtained on the 109 months during the period. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	$\delta_{carbon.intensity}$	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
			Panel A: Industry portfolios					
Estimate	0.0143	0.0004						0.05 [0.03,0.07]
t-value	-13	(0.44)						0.07 [0.05,0.09]
Estimate	0.0153		0.000					-0.01 [-0.03,0.02]
t-value	(24.76)		(-5.13)					n.a.
Estimate	0.0149			119.2				0.06 [0.04,0.08]
t-value	(26.22)			(2.15)				0.08 [0.06,0.1]
Estimate	0.0153	0.000	0.000					0.04 [0,0.08]
t-value	(17.13)	(-0.02)	(-5.04)					n.a.
Estimate	0.0125	0.0026	0.000	225.8				0.06 [0.02,0.11]
t-value	(10.6)	(1.84)	(-5.06)	(2.7)				n.a.
Estimate	0.0176	0.0036	0.000	-349.2	0.0008	0.0007	0.0003	0.15 [0.02,0.28]
t-value	(8.25)	(1.88)	(-1.62)	(-1.6)	(1.04)	(1.5)	(1.32)	n.a.
		Panel B: Long high carbon-intensity and Short low carbon-intensity industry portfolios						
Estimate	0.0002	-0.0015						-0.01 [-0.01,-0.01]
t-value	(0.1)	(-0.06)						0 [0,0]
Estimate	0.0002	0.012		-27.1				0.18 [0.12,0.24]
t-value	(0.14)	(0.46)		(-1.59)				0.2 [0.14,0.25]
Estimate	0.001	0.0187		7	0.0004	0.0001	0.0001	0.46 [0.39,0.53]
t-value	(0.55)	(0.99)		(0.32)	(1.06)	(0.96)	(0.83)	0.49 [0.42,0.56]

TABLE 1.17: **Cross-sectional regressions on sin stocks' excess returns between December 1999 and December 2019.** This table provides the estimates obtained with the S-CAPM without ESG integration on the value-weighted monthly returns in excess of the 1-month T-Bill for 52 sin stocks between December 31, 1999, and December 31, 2019. The specification is written as follows: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{taste}\tilde{p}_i B_{X_k I}\tilde{C}_I + \delta_{ex.asset} q\,\mathbb{C}\text{ov}(r_{X_i}, r_{m_X}|r_I) + \delta_{ex.mkt} q\,\mathbb{C}\text{ov}(r_{X_i}, r_{m_X}|r_{m_I})$, where r_{X_k} is the value-weighted excess return on stock k ($k = 1, ..., n_X$), and $\beta_{X_k m_I}$ is the slope of an OLS regression of r_{X_k} on r_{m_I}; $\tilde{p}_i B_{X_k I}\tilde{C}$ is the proxy for the indirect taste factor and $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_I)$ (and $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_{m_I})$) are the covariances of the excess returns on stock X_k with those on the excluded market, the excess returns on the investable market (and the vector of investable assets, respectively) being given. The investable assets are analyzed using 46 industry-sorted portfolios. The S-CAPM specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added, and (ii) the 4F model is the CAPM with respect to the investable market to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{SMB}\beta_{X_k SMB} + \delta_{HML}\beta_{X_k HML} + \delta_{MOM}\beta_{X_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated, stock-by-stock, in a 3-year rolling window, at monthly intervals. In the second pass, a cross-sectional regression is performed on a monthly basis on all the stocks. The data are winsorized: the two stocks giving the highest and lowest excess returns every month are removed from the second pass. The estimated parameter is the average value of the estimates obtained on all months during the period of interest. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	$\delta_{ex.asset}$	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0104	0.0034						0.03 [0.02,0.04]
t-value	(8.23)	(3.73)						0.04 [0.03,0.05]
Estimate	0.0127		17.3					0.05 [0.04,0.06]
t-value	(9.05)		(0.96)					0.06 [0.05,0.07]
Estimate	0.0112			121.4				0.1 [0.08,0.12]
t-value	(8.43)			(3.74)				0.09 [0.08,0.11]
Estimate	0.0114		70.1	124.2				0.12 [0.1,0.14]
t-value	(8.25)		(3.54)	(3.62)				0.15 [0.13,0.17]
Estimate	0.0104	0.001	92	131.2				0.14 [0.11,0.16]
t-value	(7.52)	(0.76)	(3.99)	(3.49)				0.19 [0.16,0.21]
Estimate	0.0107	0.0017	99.3	120.1	-0.0001	-0.0002	0.0005	0.22 [0.19,0.25]
t-value	(7.96)	(1.26)	(3.88)	(2.93)	(-0.64)	(-1.02)	(2.43)	0.33 [0.31,0.35]
Estimate	0.0107	0.0034			-0.0002	-0.0001	0.0004	0.11 [0.09,0.13]
t-value	(8.76)	(3.27)			(-1.26)	(-0.9)	(2.19)	0.19 [0.17,0.21]

TABLE 1.18: **Cross-sectional regressions for sin stocks with equally weighted returns.** This table provides the estimates obtained with the S-CAPM on the equally weighted monthly returns in excess of the 1-month T-Bill for 52 sin stocks between December 31, 2007, and December 31, 2019. The specification is written as follows: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{taste}\tilde{p}_i B_{X_k I}\tilde{C}_I + \delta_{ex.asset} q\,\mathbb{C}\mathrm{ov}(r_{X_i}, r_{m_X}|r_I) + \delta_{ex.mkt} q\,\mathbb{C}\mathrm{ov}(r_{X_i}, r_{m_X}|r_{m_I})$, where r_{X_k} is the value-weighted excess return on stock k ($k = 1, ..., n_X$), and $\beta_{X_k m_I}$ is the slope of an OLS regression of r_{X_k} on r_{m_I}; $\tilde{p}_i B_{X_k I}\tilde{C}$ is the proxy for the indirect taste factor and $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_I)$ (and $\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_{m_I})$) are the covariances of the excess returns on stock X_k with those on the excluded market, the excess returns on the investable market (and the vector of investable assets, respectively) being given. The investable assets are analyzed using 46 industry-sorted portfolios. The S-CAPM specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added, and (ii) the 4F model is the CAPM with respect to the investable market to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{SMB}\beta_{X_k SMB} + \delta_{HML}\beta_{X_k HML} + \delta_{MOM}\beta_{X_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated, stock-by-stock, in a 3-year rolling window, at monthly intervals. In the second pass, a cross-sectional regression is performed on a monthly basis on all the stocks. The data are winsorized: the two stocks giving the highest and lowest excess returns every month are removed from the second pass. The estimated parameter is the average value of the estimates obtained on all months during the period of interest. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.asset}$	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0131	0.0007							0.03 [0.01,0.04]
t-value	(12.83)	(0.44)							0.04 [0.03,0.05]
Estimate	0.014		0.0067						0.03 [0.02,0.05]
t-value	(15.69)		(0.03)						0.05 [0.04,0.07]
Estimate	0.0147			-63.8					0.03 [0.02,0.05]
t-value	(17.66)			(-2.85)					0.09 [0.07,0.11]
Estimate	0.0137				135.6				0.17 [0.14,0.19]
t-value	(15.5)				(2.56)				0.14 [0.12,0.17]
Estimate	0.0136			-8	130.9				0.17 [0.14,0.2]
t-value	(15.26)			(-0.42)	(2.47)				0.2 [0.17,0.23]
Estimate	0.0126	-0.001		-6.4	139.5				0.2 [0.17,0.23]
t-value	(9.37)	(-0.51)		(-0.33)	(2.55)				0.24 [0.21,0.26]
Estimate	0.0117	-0.0011	-0.3533	15.2	148.8				0.22 [0.18,0.25]
t-value	(9.88)	(-0.56)	(-1.77)	(0.64)	(2.74)				0.27 [0.24,0.29]
Estimate	0.0117	-0.0018	-0.5973	-36.2	152.4	0.0006	-0.0004	0.0002	0.3 [0.26,0.34]
t-value	(8.7)	(-0.68)	(-2.56)	(-1.02)	(2.49)	(2.33)	(-1.72)	(1.15)	0.39 [0.36,0.41]
Estimate	0.0128	0.0018				0.0001	0.0000	0.0002	0.1 [0.07,0.13]
t-value	(11.51)	(0.87)				(0.23)	(0.06)	(1.07)	0.15 [0.13,0.17]

TABLE 1.19: **Cross-sectional regressions on sin stocks' excess returns, using a 5-year rolling window for the first pass.** This table provides the estimates obtained with the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for 52 sin stocks between December 31, 2007, and December 31, 2019. The specification is written as follows: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{taste}\tilde{p}_i B_{X_k I}\tilde{C}_I + \delta_{ex.asset} q\,\mathbb{C}\text{ov}(r_{X_i}, r_{m_X}|r_I) + \delta_{ex.mkt} q\,\mathbb{C}\text{ov}(r_{X_i}, r_{m_X}|r_{m_I})$, where r_{X_k} is the value-weighted excess return on stock k ($k = 1, ..., n_X$), and $\beta_{X_k m_I}$ is the slope of an OLS regression of r_{X_k} on r_{m_I}; $\tilde{p}_i B_{X_k I}\tilde{C}_I$ is the proxy for the indirect taste factor and $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_I)$ (and $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_{m_I})$) are the covariances of the excess returns on stock X_k with those on the excluded market, the excess returns on the investable market (and the vector of investable assets, respectively) being given. The investable assets are analyzed using 46 industry-sorted portfolios. The S-CAPM specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added, and (ii) the 4F model is the CAPM with respect to the investable market to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{SMB}\beta_{X_k SMB} + \delta_{HML}\beta_{X_k HML} + \delta_{MOM}\beta_{X_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated, stock-by-stock, in a 5-year rolling window, at monthly intervals. In the second pass, a cross-sectional regression is performed on a monthly basis on all the stocks. The data are winsorized: the two stocks giving the highest and lowest excess returns every month are removed from the second pass. The estimated parameter is the average value of the estimates obtained on all months during the period of interest. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.asset}$	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.009	0.0035							0.02 [0.01,0.03]
t-value	(7.09)	(4.34)							0.03 [0.03,0.04]
Estimate	0.0119		-0.6269						0.09 [0.07,0.11]
t-value	(9.27)		(-1.83)						0.08 [0.07,0.09]
Estimate	0.0118			0.1041					0.01 [0,0.02]
t-value	(9.8)			(0.01)					0.05 [0.04,0.06]
Estimate	0.0096				222.6				0.13 [0.1,0.16]
t-value	(7.47)				(8.77)				0.13 [0.11,0.15]
Estimate	0.0099			13.1	220.8				0.15 [0.11,0.18]
t-value	(7.56)			(0.64)	(7.5)				0.16 [0.14,0.18]
Estimate	0.0103	-0.001		10.2	237.3				0.16 [0.12,0.19]
t-value	(7.65)	(-1.01)		(0.45)	(7.27)				0.18 [0.16,0.21]
Estimate	0.0109	-0.0015	-0.3364	9.7	203.1				0.2 [0.16,0.24]
t-value	(8.35)	(-1.33)	(-1.26)	(0.36)	(7.08)				0.24 [0.22,0.27]
Estimate	0.0104	-0.0006	-0.1025	-12.3	204.9	-0.0005	0.0000	0.0003	0.24 [0.2,0.28]
t-value	(7.31)	(-0.35)	(-0.41)	(-0.41)	(6.8)	(-4.82)	(0.24)	(2.45)	0.31 [0.28,0.33]
Estimate	0.0092	0.0037				-0.0007	0.0002	0.0000	0.1 [0.08,0.13]
t-value	(6.58)	(2.45)				(-7.1)	(1.29)	(-0.18)	0.13 [0.11,0.14]

TABLE 1.20: **Cross-sectional regressions for sin stocks including the stocks of the defense industry.** This table provides the estimates obtained with the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for 67 sin stocks, including the stocks in the defense industry (i.e., all the stocks in the tobacco, alcohol, gaming and defense industries) between December 31, 2007, and December 31, 2019. The specification is written as follows: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{taste}\tilde{p}_i B_{X_k I}\tilde{C}_I + \delta_{ex.asset} q\,\mathbb{C}\text{ov}(r_{X_i}, r_{m_X}|r_I) + \delta_{ex.mkt} q\,\mathbb{C}\text{ov}(r_{X_i}, r_{m_X}|r_{m_I})$, where r_{X_k} is the value-weighted excess return on stock k ($k = 1, ..., n_X$), and $\beta_{X_k m_I}$ is the slope of an OLS regression of r_{X_k} on r_{m_I}; $\tilde{p}_i B_{X_k I}\tilde{C}_I$ is the proxy for the indirect taste factor and $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_I)$ (and $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_{m_I})$) are the covariances of the excess returns on stock X_k with those on the excluded market, the excess returns on the investable market (and the vector of investable assets, respectively) being given. The investable assets are analyzed using 46 industry-sorted portfolios. The S-CAPM specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added, and (ii) the 4F model is the CAPM with respect to the investable market to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{SMB}\beta_{X_k SMB} + \delta_{HML}\beta_{X_k HML} + \delta_{MOM}\beta_{X_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated, stock-by-stock, in a 3-year rolling window, at monthly intervals. In the second pass, a cross-sectional regression is performed on a monthly basis on all the stocks. The data are winsorized: the two stocks giving the highest and lowest excess returns every month are removed from the second pass. The estimated parameter is the average value of the estimates obtained on all months during the period of interest. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.asset}$	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0114	0.0044							0.03 [0.01,0.04]
t-value	(8.76)	(5.19)							0.04 [0.03,0.05]
Estimate	0.0152		-0.3536						0.05 [0.04,0.07]
t-value	(13.28)		(-1.78)						0.06 [0.04,0.07]
Estimate	0.0153			-36.3					0.05 [0.04,0.07]
t-value	(14.53)			(-1.63)					0.06 [0.05,0.08]
Estimate	0.0136				162.4				0.11 [0.09,0.13]
t-value	(13.36)				(4.11)				0.12 [0.09,0.14]
Estimate	0.0142			16.5	193.5				0.14 [0.12,0.17]
t-value	(14.36)			(0.73)	(5.28)				0.17 [0.15,0.2]
Estimate	0.0119	0.0025		19	195.4				0.15 [0.12,0.18]
t-value	(8.42)	(2.34)		(0.77)	(5.22)				0.21 [0.18,0.24]
Estimate	0.0124	0.0019	-0.2493	28.9	180.7				0.17 [0.15,0.2]
t-value	(8.9)	(1.88)	(-1.61)	(1.13)	(4.95)				0.24 [0.21,0.27]
Estimate	0.0116	0.0014	-0.6497	31	190.5	-0.0001	-0.0003	0.0001	0.21 [0.18,0.23]
t-value	(8.55)	(1.15)	(-2.67)	(1.2)	(5.1)	(-0.78)	(-2.66)	(1.94)	0.33 [0.3,0.36]
Estimate	0.0114	0.0039				-0.0001	-0.0001	0.0000	0.06 [0.04,0.08]
t-value	(8.75)	(3.36)				(-1.03)	(-0.95)	(0.06)	0.11 [0.1,0.13]

TABLE 1.21: **Cross-sectional regressions for sin stocks over three consecutive periods between December 2007 and December 2019.** This table provides the estimates obtained with the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for 52 sin stocks between December 31, 2007, and December 31, 2019 over three consecutive periods. The specification is written as follows: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{taste}\tilde{p}_i B_{X_k I}\tilde{C}_I + \delta_{ex.asset} q\,\mathbb{C}\mathrm{ov}(r_{X_i}, r_{m_X}|r_I) + \delta_{ex.mkt} q\,\mathbb{C}\mathrm{ov}(r_{X_i}, r_{m_X}|r_{m_I})$, where r_{X_k} is the value-weighted excess return on stock k ($k = 1, ..., n_X$), and $\beta_{X_k m_I}$ is the slope of an OLS regression of r_{X_k} on r_{m_I}; $\tilde{p}_i B_{X_k I}\tilde{C}_I$ is the proxy for the indirect taste factor and $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_I)$ (and $\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_{m_I})$) are the covariances of the excess returns on stock X_k with those on the excluded market, the excess returns on the investable market (and the vector of investable assets, respectively) being given. The investable assets are analyzed using 46 industry-sorted portfolios. This specification is estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated, stock-by-stock, in a 3-year rolling window, at monthly intervals. In the second pass, a cross-sectional regression is performed on a monthly basis on all the stocks. The data are winsorized: the two stocks giving the highest and lowest excess returns every month are removed from the second pass. The estimated parameter is the average value of the estimates obtained on all months during the period of interest. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

Panel A: Dec. 2010 - Dec. 2013 (second pass) / Dec. 2007 - Dec. 2013 (first pass and second pass)						
	α	δ_{mkt}	δ_{taste}	$\delta_{ex.asset}$	$\delta_{ex.mkt}$	Adj. OLS/GLS R^2
Estimate	0.0046	0.0063	0.4618	11.9	311.4	0.26 [0.2,0.31]
t-value	(2.37)	(3.49)	(3.21)	(0.5)	(6.7)	0.36 [0.32,0.4]
Panel B: Dec. 2013 - Dec. 2016 (second pass) / Dec. 2009 - Dec. 2013 (first pass and second pass)						
	α	δ_{mkt}	δ_{taste}	$\delta_{ex.asset}$	$\delta_{ex.mkt}$	Adj. OLS/GLS R^2
Estimate	0.0162	-0.0014	-1.2	4.9	278.7	0.16 [0.1,0.21]
t-value	(16.23)	(-1.03)	(-4.26)	(0.23)	(5.18)	0.23 [0.18,0.27]
Panel C: Dec. 2016 - Dec. 2019 (second pass) / Dec. 2013 - Dec. 2019 (first pass and second pass)						
	α	δ_{mkt}	δ_{taste}	$\delta_{ex.asset}$	$\delta_{ex.mkt}$	Adj. OLS/GLS R^2
Estimate	0.0166	-0.0034	-0.4444	132.7	-4.5	0.33 [0.27,0.38]
t-value	(14.33)	(-1.96)	(-1.76)	(3.27)	(-0.04)	0.32 [0.26,0.38]

TABLE 1.22: **Cross-sectional regressions on sin stocks' excess returns where p_i is a proxy for p_e.** This table provides the estimates obtained with the S-CAPM on the value-weighted monthly returns in excess of the 1-month T-Bill for 52 sin stocks between December 31, 2007, and December 31, 2019. In the exclusion-asset and the indirect taste factors, p_i is used as a proxy for p_e. The specification is written as follows: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{taste}\tilde{p}_i^2 B_{X_k I}\tilde{C}_I + \delta_{ex.asset}\tilde{p}q\,\mathbb{C}\mathrm{ov}(r_{X_i}, r_{m_X}|r_I) + \delta_{ex.mkt}q\,\mathbb{C}\mathrm{ov}(r_{X_i}, r_{m_X}|r_{m_I})$, where r_{X_k} is the value-weighted excess return on stock k ($k = 1, ..., n_X$), and $\beta_{X_k m_I}$ is the slope of an OLS regression of r_{X_k} on r_{m_I}; $\tilde{p}_i B_{X_k I}\tilde{C}_I$ is the proxy for the indirect taste factor and $\tilde{p}_i$ is the proxy for the proportion of integration investors' wealth; q is the proportion of the excluded assets' market value in the market, and $\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_I)$ (and $\mathbb{C}\mathrm{ov}(r_{X_k}, r_{m_X}|r_{m_I})$) are the covariances of the excess returns on stock X_k with those on the excluded market, the excess returns on the investable market (and the vector of investable assets, respectively) being given. The investable assets are analyzed using 46 industry-sorted portfolios. The S-CAPM specification is compared with two other specifications: (i) the 4F S-CAPM is the S-CAPM to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added, and (ii) the 4F model is the CAPM with respect to the investable market to which the betas of the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor have been added: $\mathbb{E}(r_{X_k}) = \alpha + \delta_{mkt}\beta_{X_k m_I} + \delta_{SMB}\beta_{X_k SMB} + \delta_{HML}\beta_{X_k HML} + \delta_{MOM}\beta_{X_k MOM}$. These specifications are estimated using the Fama and MacBeth (1973) procedure. First, the variables are estimated, stock-by-stock, in a 3-year rolling window, at monthly intervals. In the second pass, a cross-sectional regression is performed on a monthly basis on all the stocks. The data are winsorized: the two stocks giving the highest and lowest excess returns every month are removed from the second pass. The estimated parameter is the average value of the estimates obtained on all months during the period of interest. t-values, estimated following Newey and West (1987) with three lags, are reported between parentheses. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in brackets.

	α	δ_{mkt}	δ_{taste}	$\delta_{ex.asset}$	$\delta_{ex.mkt}$	δ_{SMB}	δ_{HML}	δ_{MOM}	Adj. OLS/GLS R^2
Estimate	0.0114	0.0041							0.03 [0.02,0.05]
t-value	(10.18)	(4.35)							0.05 [0.04,0.07]
Estimate	0.0153		-474.7						0.07 [0.05,0.09]
t-value	(16.54)		(-1.62)						0.07 [0.05,0.08]
Estimate	0.0152			-33487.3					0.08 [0.06,0.11]
t-value	(19.13)			(-1.19)					0.08 [0.06,0.1]
Estimate	0.0134				162.3				0.18 [0.15,0.21]
t-value	(14.93)				(2.79)				0.14 [0.11,0.17]
Estimate	0.0136			51849.7	211.7				0.2 [0.17,0.23]
t-value	(14.58)			(2.52)	(3.95)				0.21 [0.18,0.24]
Estimate	0.0116	0.0015		60221	230.3				0.21 [0.18,0.25]
t-value	(8.4)	(1.3)		(2.62)	(4.17)				0.25 [0.22,0.28]
Estimate	0.0124	0.0005	-465.2	49515.9	196.9				0.24 [0.21,0.28]
t-value	(9.14)	(0.42)	(-1.81)	(2.1)	(3.88)				0.3 [0.27,0.33]
Estimate	0.0115	0.0014	-1028.8	40277.1	219.3	0.0001	-0.0003	0.0002	0.31 [0.27,0.35]
t-value	(8.25)	(0.97)	(-2.3)	(1.52)	(3.97)	(0.58)	(-2.68)	(1.67)	0.42 [0.39,0.44]
Estimate	0.0115	0.0039				0.0000	0.0000	0.0001	0.1 [0.08,0.13]
t-value	(9.93)	(3.24)				(0.04)	(-0.29)	(0.72)	0.16 [0.14,0.18]

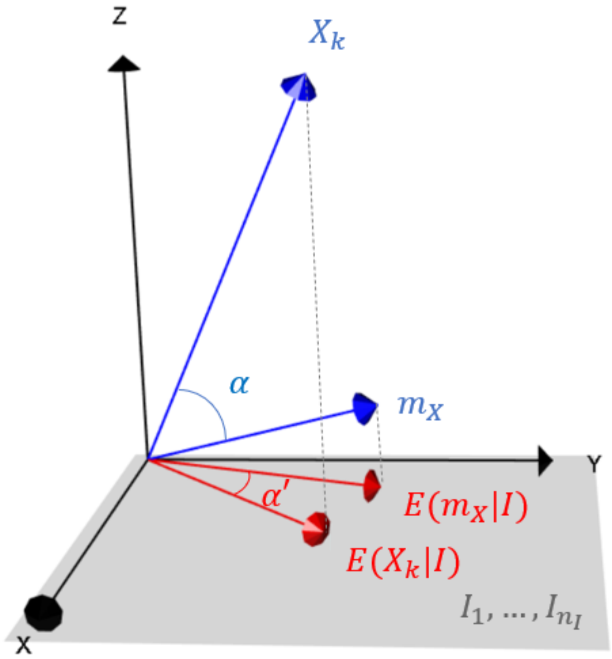


FIGURE 1.5: **Geometric representation of the exclusion-asset premium.** This figure provides a geometric picture of the conditional covariance $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_I)$, which, after being multiplied by factor $\gamma\frac{p_e}{1-p_e}q$, forms the exclusion-asset premium on asset X_k. In the graph, the standard deviation of the excess returns on an asset is depicted by the norm of the associated vector, and the correlation coefficient between the excess returns on two assets is depicted by the cosine of the angle between the two vectors. The total market is depicted by the space $\mathbb{R}^3$, and the assets in the investable market $(I_1, ..., I_{n_I})$ is depicted by plane (X, Y). Asset X_k and the excluded market, m_X, projected onto the space of investable assets offer a graphic depiction of the conditional expectations, $\mathbb{E}(X_k|I)$ and $\mathbb{E}(m_X|I)$, respectively. $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_I)$ is therefore depicted geometrically as the difference between the cosines of the two angles α and α', both of which are normalized by the norms of vectors generating them: $\mathbb{C}\text{ov}(r_{X_k}, r_{m_X}|r_I) \sim ||X_k||\ ||m_X||\ cos(\alpha) - ||\,\mathbb{E}(X_k|I)||\ ||\,\mathbb{E}(m_X|I)||\ cos(\alpha')$.

Home > News & Statements > Press Releases

SEC Adopts Enhanced Mutual Fund Expense and Portfolio Disclosure; Proposes Improved Disclosure of Board Approval of Investment Advisory Contracts and Prohibition on the Use of Brokerage Commissions to Finance Distribution

FOR IMMEDIATE RELEASE
2004-16

Washington, D.C. Feb. 11, 2004 -- The Securities and Exchange Commission took the following actions today at its open meeting:

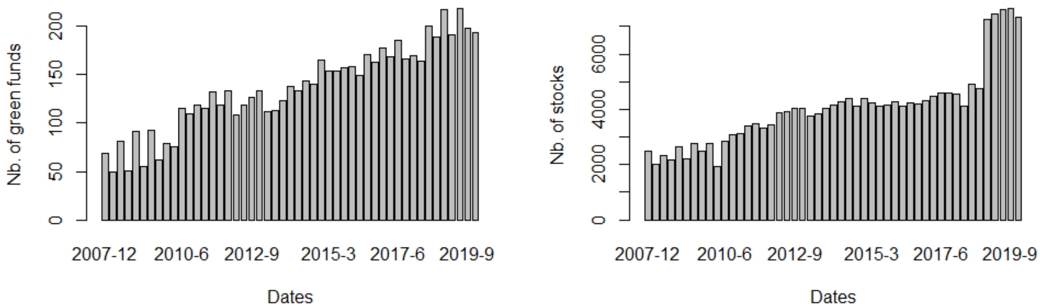
Shareholder Reports and Quarterly Portfolio Disclosure by Funds

The Commission adopted several amendments to its rules and forms that are intended to improve significantly the periodic disclosure that mutual funds and other registered management investment companies provide to their shareholders about their costs, portfolio investments, and performance.

The amendments include the following:

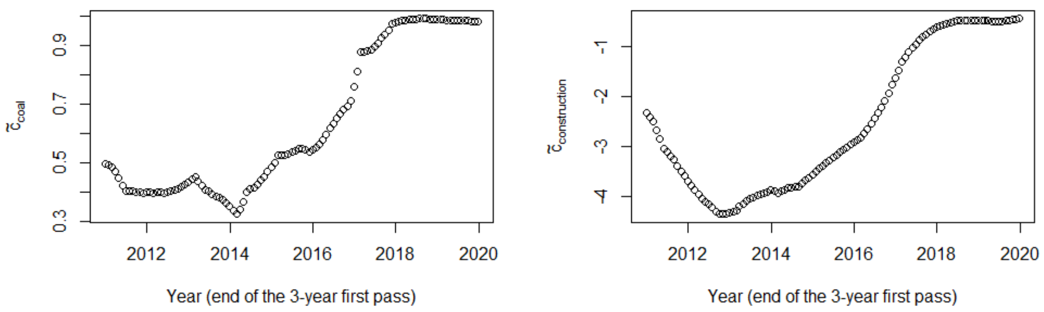
- **Enhanced Mutual Fund Expense Disclosure in Shareholder Reports.** The amendments will require open-end management investment companies (mutual funds) to disclose fund expenses borne by shareholders during the reporting period in their shareholder reports. Shareholder reports will be required to include: (i) the cost in dollars associated with an investment of $1,000, based on the fund's actual expenses for the period; and (ii) the cost in dollars, associated with an investment of $1,000, based on the fund's actual expense ratio for the period and an assumed return of 5 percent per year. The first figure is intended to permit investors to estimate the actual costs, in dollars, that they bore over the reporting period. The second figure is intended to provide investors with a basis for comparing the level of current period expenses of different funds. The expense disclosure will also be required to include the fund's expense ratio and the account values as of the end of the period for an initial investment of $1,000.
- **Quarterly Disclosure of Fund Portfolio Holdings.** The amendments will require a registered management investment company (fund) to file its complete portfolio holdings schedule with the Commission on a quarterly basis. These filings will be publicly available through the Commission's Electronic Data Gathering, Analysis, and Retrieval System (EDGAR). This amendment is intended to enable interested investors, through more frequent access to portfolio information, to monitor whether, and how, a fund is complying with its stated investment objective.

FIGURE 1.6: **U.S. funds holdings disclosure.** This figure shows the text of the SEC's February 2004 amendment requiring U.S. funds to disclose their holdings on a quarterly basis.



(A) Number of green funds (B) Number of stocks in the green funds

FIGURE 1.7: **Green funds' holdings.** This figure shows, quarter-by-quarter, the number of green funds for which the composition has been retrieved in FactSet (a), and the number of stocks held by all these green funds (b).



(A) Coal industry

(B) Construction industry

FIGURE 1.8: This figure depicts the dynamics of the proxy for the cost of environmental externalities, $\tilde{c}$, for the coal (Figure (a)) and the construction (Figure (b)) industries. For industry I_k, $\tilde{c}_{I_k} = \frac{w_{m,I_k} - w^*_{i,I_k}}{w_{m,I_k}}$, where w_{m,I_k} is the market weight of industry I_k and w^*_{i,I_k} is the proxy for the weight of industry I_k in green investors portfolios.

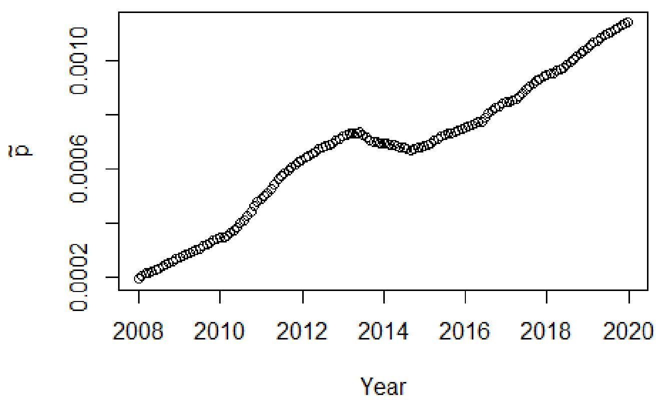


FIGURE 1.9: **Dynamics of proxy $\tilde{p}_i$.** This figure depicts the dynamics of the proxy for the proportion of integration investors, $\tilde{p}_i = \frac{\text{Market value of green funds in } t}{\text{Total market capitalization in } t}$, between December 31, 2007 and December 31, 2019.

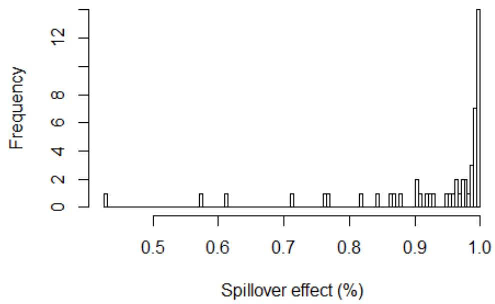


FIGURE 1.10: **Distribution of the share of the spillover effect.** This figure shows the distribution of the share of the spillover effect in the exclusion effect, $\left(\frac{\sum_{j=1,j\neq k}^{n_X} |q_{X_j}\left(\widehat{\delta}_{ex.asset}\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{X_j}|r_I)+\widehat{\delta}_{ex.mkt}\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{X_j}|r_{m_I})\right)|}{\sum_{k=1}^{n_X} |q_{X_j}\left(\widehat{\delta}_{ex.asset}\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{X_j}|r_I)+\widehat{\delta}_{ex.mkt}\,\mathbb{C}\mathrm{ov}(r_{X_k},r_{X_j}|r_{m_I})\right)|}\right)_k$, over all sin stocks estimated between December 31, 2007, and December 31, 2019.

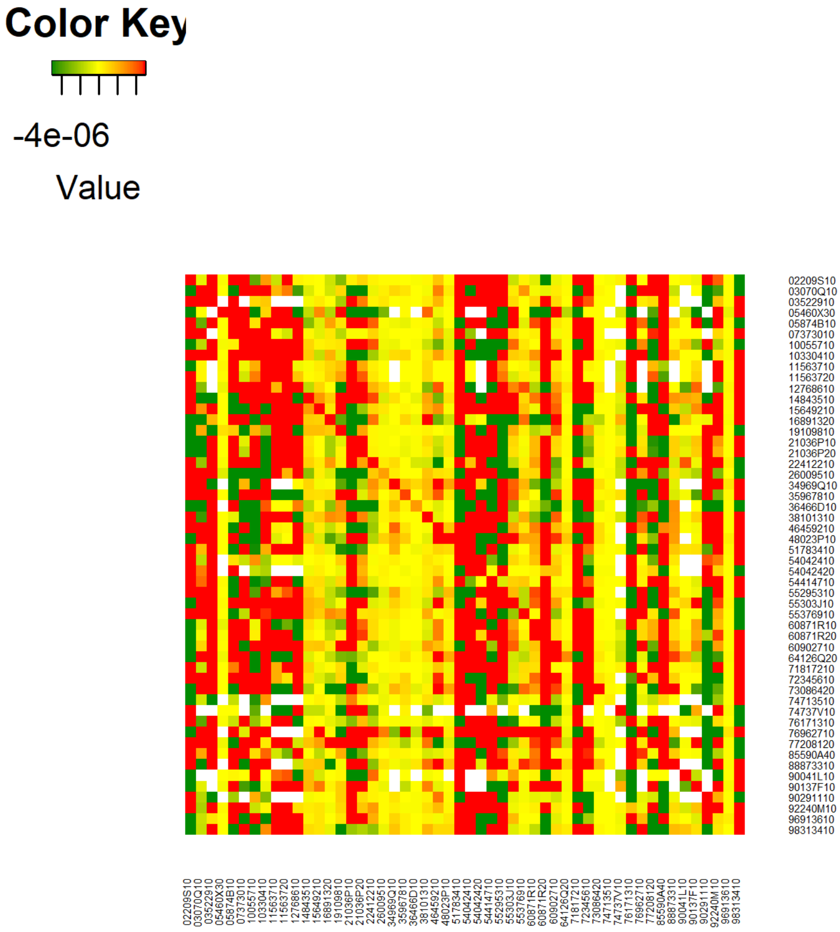


FIGURE 1.11: **Heatmap of the spillover effects.** This figure shows, for each sin stock X_k (presented in rows), the estimated spillover effects of the other sin stocks $(X_j)_{j\in\{1,\dots,n_X\}}$ (presented in columns), estimated as $\widehat{\delta}_{ex.asset} q_{X_j} \operatorname{\mathbb{C}ov}(r_{X_k}, r_{X_j}|r_I) + \widehat{\delta}_{ex.mkt} q_{X_j} \operatorname{\mathbb{C}ov}(r_{X_k}, r_{X_j}|r_{m_I})$. The positive effects are shown in red, and the negative effects are shown in green. The first diagonal gives the own effects, which all have a positive or zero estimated value.

Chapter 2

The effect of pro-environmental preferences on bond prices: Evidence from green bonds[1]

[1]This chapter was published in the *Journal of Banking and Finance*, 2019, 98:39-60. It was awarded the Best Paper Award at International Conference on Energy, Finance and the Macroeconomy (2017), the Best Paper Award at the International Conference on Finance (2018), and the SUERF/UniCredit Foundation & Universities Research Prize (2018).
It benefited from the valuable comments of Hansjoerg Albrecher, Claire Bonello, Jean-François Boulier, Marc Boubal, Ian Cochran, Joost Driessen, Damir Filipovic, Christian Francq, Christian Gouriéroux, Olivier Guéant, Nabil Kazi-Tani, Morgane Nicol, Joël Petey, Xavier Pieri, Sébastien Pouget, Bacem Rezgui, Christian Robert, Igor Shishlov, Paul Smeets, participants in the 32nd Annual Congress of the European Economic Association - 70th European Meeting of the Econometric Society, the 2017 Central Banking and Green Finance workshop (CEP-DNB), the 26th European Financial Management Associaton Conference, the 23rd European Association of Environmental and Resource Economists Annual Conference, the 1st Global Research Alliance for Sustainable Finance and Investment Conference, the 2017 Green Finance Research Advances Conference, the 2018 International Conference on Finance, the 1st International Conference on Energy, Finance and the Macroeconomy, the 34th International Conference of the French Finance Association, the 5th International Symposium on Environment and Energy Finance Issues, as well as seminar participants at CREST, ISFA, Paris School of Economics, Paris-Dauphine and the Climate Economics Chair.

In this chapter, I use green bonds as an instrument to identify the effect of non-pecuniary motives, specifically pro-environmental preferences, on bond market prices. I perform a matching method, followed by a two-step regression procedure, to estimate the yield differential between a green bond and a counterfactual conventional bond from July 2013 to December 2017. The results suggest a small negative premium: the yield of a green bond is lower than that of a conventional bond. On average, the premium is -2 basis points for the entire sample and for euro and USD bonds separately. I show that this negative premium is more pronounced for financial and low-rated bonds. The results emphasize the low impact of investors' pro-environmental preferences on bond prices, which does not represent, at this stage, a disincentive for investors to support the expansion of the green bond market.

2.1 Introduction

In response to environmental crises, financial investors have recently taken up the challenge and become key actors in the energy and environmental transition. This pivotal role is notably due to their ability to mobilize a considerable amount of funds: the global stock of manageable assets[2], which amounted to USD 160 trillion in 2016 (Financial Stability Board, 2018), can be compared to the infrastructure investment needs of 6.9 trillion over the next 15 years to be consistent with the 2 degrees Celsius threshold (OECD, 2017a). Several initiatives have been launched to redirect assets toward green investments. For example, by signing the Montreal Carbon Pledge,[3] more than 120 investors with assets under management worth more than USD 10 trillion have committed to supporting the development of the green bond market and to measuring and publishing the carbon footprint of their investments.

The drivers to invest in assets with a low environmental impact (*green assets* hereafter) can be related to financial motives, such as the expectation of better financial performance (Nilsson, 2008; Bauer and Smeets, 2015; Hartzmark and Sussman, 2018) or a lower risk (Krüger, 2015). These drivers can also be attributable to non-pecuniary motives. Preferences linked to pro-social and pro-environmental[4] norms and attitudes lead investors to increase their investments in the assets of companies behaving more ethically (Hong and Kacperczyk, 2009; Riedl and Smeets, 2017; Hartzmark and Sussman, 2018). The incentive is not necessarily a proprietary choice of the asset manager: it can be delegated by the asset owner through the *delegated philanthropy* mechanism described by Benabou and Tirole (2010a).

The price impact of investors' preferences for green assets has been broadly documented in the literature. Although there is no unanimity on the subject, most of the

[2] This amount corresponds to the *Monitoring Universe of Non-bank Financial Intermediation*, including all non-bank financial intermediation: insurance corporations, pension funds, other financial intermediaries and financial auxiliaries.

[3] http://montrealpledge.org/

[4] Pro-social and pro-environmental motives refer to investors' interest in social and environmental issues per se in their investment decisions.

works focusing on the bond market suggest that companies with high environmental performance benefit from a lower cost of capital (see Section 2.2 for an extensive literature review). Authors mainly attribute this negative yield differential to a financial reality: intangible asset creation (Porter and Linde, 1995; Hart, 1995; Jones, 1995; Ambec and Lanoie, 2008; Flammer, 2015) as well as better risk management and mitigation (Ambec and Lanoie, 2008; Bauer and Hann, 2014), both being imperfectly captured by rating agencies' models (Ge and Liu, 2015; Oikonomou, Brooks, and Pavelin, 2014). However, the existing literature does not identify whether, and by how much, this yield differential is driven by non-pecunary motives.

By integrating into the utility function of a group of investors an appetite for certain types of assets in addition to their expectations regarding return and risk, Fama and French (2007a) show that investors' *tastes* modify equilibrium prices. Nevertheless, few studies have empirically isolated the impact of non-pecuniary motives on market prices. Focusing on sin stocks and controlling for a battery of financial indicators, Hong and Kacperczyk (2009) show that social norms lead to a 2.5% higher return for sin stocks than non-sin stocks. However, the analysis of non-pecuniary motives on the stock market implies comparing the financial securities of different companies and thus makes it very difficult to identify the effect.

In this paper, I exploit the bond market to clearly identify the impact of pro-environmental preferences on prices. To do so, I use green bonds as an instrument: I compare each green bond with an otherwise identical counterfactual conventional bond. Unlike two bonds issued by companies with different environmental performances, green and conventional bonds of the same company are subject to the same financial risk once all their differences have been controlled. Comparing the yield of a green bond and that of a conventional counterfactual thus makes it possible to isolate the impact of pro-environmental preferences on bond prices.

Therefore, this paper aims to provide answers to the following two questions:

- Research question 1: Do pro-environmental preferences translate into bond market prices?
- Research question 2: If so, do they apply uniformly across the entire bond market?

The study of the green bond market is made possible by the recent accelerated development of this asset class, which has been supported by the definition of the Green Bond Principles[5] providing issuers with guidance and investors with reliable information about environmental impacts. The labeled green bond market reached USD 301 billion outstanding in December 2017. Green bond issuances rose to USD 163 billion in 2017, up 68% from the previous year. Government-related bonds, including government, national and supranational agencies, account for 30% of the total, while 32% are financial bonds and 21% are bonds issued by energy companies. Among the 44% of the bonds rated by S&P, Moody's or Fitch in the entire database, 90% are

[5]The 2017 voluntary process guidelines for issuing green bonds are summarized in https://www.icmagroup.org/assets/documents/Regulatory/Green-Bonds/GreenBondsBrochure-JUNE2017.pdf.

investment-grade bonds, and 10% are high-yield bonds. The main currencies involved are the USD and the euro (EUR), each of which accounts for one-third of the total outstanding green bond debt.

We identify the effect of pro-environmental preferences through a *green bond premium*, which is defined as the yield differential between a green bond and an otherwise identical conventional bond. I perform an analysis on 110 green bonds on the secondary market between July 2013 and December 2017. This sample accounts for 10% of the number and 17% of the amount of green bonds issued worldwide at the end of 2017. I first use a matching method to estimate the yield of an equivalent synthetic conventional bond for each live green bond issued in the global universe on December 31, 2017. To do so, I build a counterfactual conventional bond from the same issuer, having the same maturity, currency, rating, bond structure, seniority, collateral and coupon type, as well as a limited difference in issue date and size. In the second stage, I control for the residual difference in liquidity between each green bond and its counterfactual to extract a green premium by performing a fixed-effects panel regression: the green premium is the unobserved specific effect of the regression of the yield differential on the bonds' liquidity differential. By performing a panel regression on matched pairs of bonds for which the characteristics are identical except for the green feature of one of the two, we circumvent two biases inherent in a cross-sectional regression of yields on bonds' characteristics: an omitted variables bias and a bias related to overweighting assets with the longest price history. Finally, to identify the factors affecting the costliness of a green bond, I explain these green premia according to the specific characteristics of the bonds through a cross-sectional regression.

We show that there exists a small, albeit significant, negative green bond premium of -2 basis points (bps) in our sample. The sector and the rating are significant drivers of the premium: the negative premium is greater[6] for financial bonds and low-rated bonds. Through several robustness tests, I verify that the premium is neither a risk premium nor a market premium, that the matching method is sufficiently stringent, and that the average and median premia remained negative on a monthly basis from May 2016 onward. I also show that the estimated premium in our sample has a reasonable chance of reflecting a similar phenomenon across the total sample of green bonds.

Our contribution to the literature is threefold. First, I contribute to the literature on non-pecuniary motives in ethical investing. I use green bonds as an instrument to cleanly identify the effect of pro-environmental preferences on the bond market. Although social and environmental preferences can have a substantial positive impact on investment inflows in ethical funds and assets, the 2-bps negative yield premium on green bonds shows that the impact of pro-environmental motives on bond prices is still limited. I also contribute to the literature linking the cost of debt and the company's environmental performance. The low negative green bond premium, which is related

[6]When the premium is negative, we use the terms *greater negative premium* and *lower premium* interchangeably to mean that the negative premium has a higher absolute value.

to the price impact of pro-environmental preferences, suggests that the lower cost of debt for companies with good environmental performances should be more related to a lower level of risk than to non-pecuniary motives. Third, this study on the valuation of green bonds complying with the Green Bonds Principles is the most extensive in terms of geographical scope, number of bonds studied as well as price history. The methodology developed–which, more generally, can be used to estimate the valuation of other types of bonds of which the proceeds are directed to a specific use, such as *social bonds*[7]–includes strict liquidity control and is supplemented by numerous robustness tests.

The negative yield premium of 2 bps has distinct implications for the various market players; it does not represent a notable disincentive for investors who should not substitute their purchase of green bonds with conventional bonds. Moreover, although low, this premium demonstrates investors' appetite for green bond issues and supports the hypothesis that this instrument offers issuers the opportunity to broaden their debtholder base. Finally, from the supervisory authority perspective, while this negative premium underlines a certain buying pressure on green bonds, it does not yet reveal any substantial valuation discrepancy between green and conventional bonds.

This paper is organized as follows. In the second section, the literature on the topic of interest is reviewed. The method used to build the data on which this study is based is described in the third section. Our empirical approach is described in the fourth section, and the results obtained using the empirical model are presented in section five. The robustness checks run are described in the sixth section, and the results are discussed in section seven. The conclusions of our findings are summarized in section eight.

2.2 Literature review

Numerous authors have addressed the effects of corporate social performance (CSP)[8], especially the effects related to good environmental performance[9], on companies' stock returns (Konar and Cohen, 2001; Derwall et al., 2005; Kempf and Osthoff, 2007; Semenova and Hassel, 2008; Statman and Glushkov, 2009; Dixon, 2010). Although no consensus has been reached, most of the articles published have suggested that

[7]The ICMA recently published voluntary guidelines for issuing *social bonds*, which are a nascent asset class: https://www.icmagroup.org/assets/documents/Regulatory/Green-Bonds/June-2018/Social-Bond-Principles—June-2018-140618-WEB.pdf

[8]Luo and Bhattacharya (2009) clarify the difference between corporate social responsibility (CSR) and CSP: CSP (i) refers to stakeholders' assessment of the quality of CSR investments, (ii) can be a proxy for a firm's cumulative involvement in CSR and (iii) is a notion relative to the competition in the industry.

[9]According to the Forum for Sustainable and Responsible Investment, "Sustainable, responsible and impact investing (SRI) is an investment discipline that considers environmental, social and corporate governance (ESG) criteria to generate long-term competitive financial returns and positive societal impact." (https://www.ussif.org/sribasics, answer to the question "What is sustainable, responsible and impact investing?"). Investments with a positive environmental impact (or *good environmental performance*) are therefore a form of sustainable investment for which the expected benefits specifically concern the environment.

CSP has a positive impact on companies' financial performance. Moreover, CSP has been found to have similar effects on the cost of equity capital: firms with better CSP (ElGhoul et al., 2011; Dhaliwal et al., 2011[10]) or a low environmental impact (Heinkel, Kraus, and Zechner, 2001; Sharfman and Fernando, 2008; Chava, 2014) benefit from a lower cost of equity capital. However, these findings are not necessarily transferable to the debt market for at least two reasons. First, the payoff profile of a debtholder differs from that of a stockholder (Oikonomou, Brooks, and Pavelin, 2014 and Ge and Liu, 2015): Merton (1973) specifies that a bond payoff can be replicated by the purchase of a stock and the sale of a call option on the same asset. Since bondholders have little upside available, it is crucial for them to analyze and assess all the downside risks, including environmental hazards. This need for insurance against a market downturn is all the more relevant for socially responsible investing, as CSP leads to better credit ratings (Jiraporn et al., 2014) and has a strong effect on a company's default risk reduction (Sun and Cui, 2014). Second, as previously suggested by Oikonomou, Brooks, and Pavelin (2014), firms are more sensitive to the pressure exerted by bond market investors because firms refinance via the debt market more frequently than they increase their capital. This pressure can be all the more easily exerted because debt instruments are frequently held by institutional investors with advanced risk analysis capacities.

Although several studies have focused on the effects of CSP on corporate bond yields, no unequivocal conclusions have yet been reached on this topic. Magnanelli and Izzo (2017), using a database of 332 companies worldwide with 1641 observations from 2005 to 2009, are among the few authors showing that CSP increases the cost of debt. In line with the shareholder theory, their results support the assertion that CSR is considered "a waste of resources that can negatively affect the performance of the firm." Conversely, Menz (2010) focuses on the European corporate bond market and observes that socially responsible firms suffer more from a greater credit spread than do non-socially responsible companies, although this finding is weakly significant. Likewise, Stellner, Klein, and Zwergel (2015) obtain relatively weak evidence that good CSP systematically reduces credit risks. Other authors, however, report a significant negative relationship between CSP and the cost of debt. Oikonomou, Brooks, and Pavelin (2014) show that for U.S. corporate debt, good CSR performance is rewarded by lower bond yields and CSR irresponsibility is positively correlated with financial risk. Based on information provided by a cross-industrial sample of U.S. public corporations, Bauer and Hann (2014) establish that environmental strengths are associated with lower bond yields. Other authors, such as Klock, Mansi, and Maxwell (2005), using U.S. data, and Ghouma, Ben-Nasr, and Yan (2018), using Canadian data, report that bond spreads decline with the quality of corporate governance. Klock, Mansi, and Maxwell (2005) notably show that compared to firms with the strongest shareholder

[10]Dhaliwal et al. (2011) focus on the initiation of a voluntary disclosure of CSR activities and show that it leads to a reduction in a firm's cost of capital.

rights (proxied by weak antitakeover provisions), firms with the strongest management rights (strongest antitakeover provisions) benefited from a 34 bps reduction in the cost of debt for the period 1990-2000. Ge and Liu (2015) focus on the effects of CSP disclosure on the spreads of new corporate bonds issued in the U.S. primary market and establish that firms reporting favorable CSPs enjoy lower bond spreads. Hasan, Hoi, and Zhang (2017) also examine the primary market of U.S. firms from 1990 to 2012 and find that firms headquartered in U.S. counties with higher levels of social capital benefit from lower at-issue bond spreads. Finally, although the financing of private loans and public bonds must be analyzed differently mainly because banks have access to more information than bondholders, Goss and Roberts (2011) reach similar conclusions after examining the impact of the CSR scores of 3996 U.S. companies on the cost of the companies' bank loans. They also establish that firms with the lowest CSR scores pay between 7 and 18 bps more than the most responsible firms.

However, few articles have been published on the specific cost of green bonds. Table 2.1 summarizes the results of and differences between these studies.

In contrast to the analyses in the papers presented above, the analysis of the green bond yield is not based on the CSP of the issuing company because the green bond label is associated with the funded projects and not with the issuer type. Thus, we can compare a green bond yield with the yield of a similar conventional bond from the same issuer.

HSBC (2016) and Climate Bonds Initiative (2017) study the difference in yield at issuance between a green bond and a conventional bond by calculating the difference between the two yields for samples of 30 and 14 bonds, respectively. These two works do not find any significant differences on the primary market, which confirms the analyses conducted in OECD (2017) and I4CE (2016) showing that investors are not willing to pay a premium to acquire a green bond at issuance ("flat pricing"). Barclays (2015) and Bloomberg (2017) focus on the yield differential on the secondary market. Through an OLS regression of the credit spread on several market risk factors, Barclays (2015) points to a negative premium of 17 bps between March 2014 and August 2015. By analyzing 12 bonds between March 2014 and December 2016, Bloomberg (2017) highlights a negative 25 bps premium on EUR-denominated government-related bonds but does not identify any premium on USD-denominated and corporate bonds.

Subsequent works have built on the first version of this paper (Ehlers and Packer, 2017; Karpf and Mandel, 2018; Hachenberg and Schiereck, 2018 and Baker et al., 2018). Ehlers and Packer (2017) and Hachenberg and Schiereck (2018) study samples of 21 and 63 green bonds aligned with the Green Bond Principles, respectively. Ehlers and Packer (2017) focus on the primary market between 2014 and 2017, whereas Hachenberg and Schiereck (2018) analyze the secondary market over 6 months between 2015 and 2016 using a matching procedure and a panel regression based on the methodology of our paper. Both papers find a negative premium but of very different magnitudes: -18 bps for the former and -1 bp for the latter. Karpf and Mandel (2018)

TABLE 2.1: **Research methods and findings on green bond pricing.** This table summarizes the research methods and empirical findings of studies on the relative pricing of green bonds in relation to conventional bonds.

	Barclays (2015)	HSBC (2016)	Bloomberg (2017)	Climate Bonds Initiative (2017)
Green bonds (Alignment with the GBP)	Yes	Yes	Yes	Yes
Scope	Global	Euro and US	European Investment Bank, Nordic Investment Bank and International Bank for Reconstruction and Development	EUR- and USD-denominated Govt.-related and corporate bonds
Primary / Secondary market	Secondary	Primary / Secondary	Secondary	Primary
Number of bonds	N.A.	30 / 4	12	14
Time period	Mar. 2014 - Aug. 2015	Nov. 2015 - Sep. 2016	Mar. 2014 - Dec. 2016	Jan. 2016 - Mar. 2017
Method	OLS regression	Comparison	Comparison	Comparison
Liquidity control	Date of issuance	No	No	No
Strict maturity control	No	No	No	No
Yield premium	-17bps	No	EUR-denominated Govt.-related bonds: -25ps USD-denominated and corporate bonds: No	No

(A) Literature prior to this paper.

	Ehlers and Packer (2017)	Karpf and Mandel (2018)	Baker et al. (2018)	Hachenberg and Schiereck (2018)
Green bonds (Alignment with the GBP)	Yes	No	No	Yes
Scope	Euro and US	US Municpal bonds with a Bloomberg green flag	US Corporate and Municpal bonds with a Bloomberg green flag	Global
Primary / Secondary market	Primary	Secondary	Primary	Secondary
Number of bonds	21	1880	2083	63
Time period	2014-2017	2010-2016	2010-2016	Oct. 2015 - March. 2016
Method	Comparison	Oaxaca-Blinder decomposition	OLS regression	Matching + panel regression based on our paper's method
Liquidity control	No	Number of transactions within the past 30 days	Issue amount	Issue amount
Strict maturity control	Yes	Yes	Yes	Yes
Yield premium	-18 bps	+7.8 bps	-7 bps	-1 bp

(B) Literature subsequent to and building on this paper.

and Baker et al. (2018) study a less restrictive framework than that of green bonds aligned with the Green Bond Principles: U.S. bonds with a Bloomberg green flag. Karpf and Mandel (2018) focus on municipal bonds on the secondary market, and Baker et al. (2018) analyze municipal and corporate bonds on the primary market. By controlling bonds' liquidity through the number of transactions within the past 30 days, Karpf and Mandel (2018) find a positive premium of 7.8 bps. In contrast, using the issue amount as a proxy of the liquidity, Baker et al. (2018) find evidence of a 7 bps negative premium.

Existing works on the relative valuation of green bonds aligned with the Green Bond Principles therefore suffer from both a limited scope of analysis as well as imperfect control of the liquidity premium, leading to mixed results. This paper aims to estimate the fair yield of green bonds compared to that of conventional bonds over an extensive scope, ensuring that all the discrepancies between the two types of bonds are duly controlled.

2.3 Data description and matching method

The empirical method primarily used in the CSR literature to analyze bond spreads consists in performing an appropriate regression on a suitable specification. This step requires determining the financial and extra-financial independent variables likely to explain the intrinsic value of the bond spread as exhaustively as possible while ensuring the robustness of the specification. Analyzing the yield of a green bond allows us to forgo this method because we can match two similar bonds from the same issuer, for which most of the factors explaining the yield are identical. I therefore use a matching method, also known as a model-free approach or a direct approach, which is a useful technique for analyzing the intrinsic value of a specialized financial instrument. This method consists of matching a pair of securities with the same properties except for the one property whose effects we are interested in. This method has been used to assess the additional return of ethical funds in comparison with identical conventional funds or indices (Kreander et al., 2005; Renneboog, Ter Horst, and Zhang, 2008; Bauer, Koedijk, and Otten, 2005) as well as the cost of liquidity by matching and comparing pairs of bonds issued by the same firm (Helwege, Huang, and Wang, 2014).

We set up this database to evaluate the yield spread between a green bond and an equivalent synthetic conventional bond. For this purpose, I take matched pairs consisting of a green and a conventional bond with identical characteristics except for their liquidity. The variable construction procedure used here is closely related to that used by Helwege, Huang, and Wang (2014) to assess the effects of liquidity on corporate bond spreads. However, while building on the latter study, we add a new parameter–the greenness of a bond: determining the impact of this parameter on the bond yield is the goal of our assessment. The difference between the green bond yield and the equivalent synthetic conventional bond yield is therefore precisely the cumulative effect of the liquidity differential and the green bond premium.

We examine the entire sample of 1065 green bonds complying with the Green Bond Principles indexed by Bloomberg on December 31, 2017. This set includes bonds of various kinds: supranational, sub-sovereign and agency (SSA), municipal, corporate, financial and covered bonds. To build this synthetic conventional bond, for each green bond, I first search for the two conventional bonds with the closest maturity from the same issuer and having exactly the same characteristics: they all have the same currency, rating,[11] bond structure, seniority, collateral and coupon type. Since the maturities cannot be equal, I collect conventional bonds with a maturity that is neither two years shorter nor two years longer than the green bond's maturity. The difference in maturity is limited in this way to estimate more accurately the equivalent synthetic conventional bond yield in the next stage. The other difference between the two categories of bonds is their liquidity, which can be assessed from either their issue amount or their issue date (see Bao, Pan, and Wang (2011) and Houweling, Mentink, and Vorst (2005)). A substantial difference in liquidity can have a notable effect on the yield level and must therefore be limited.[12] Here again, to ensure a fair approximation in this first stage, I combine a double constraint on the difference in liquidity: I restrict the eligible conventional bonds to those (i) with an issue amount of less than four times the green bond's issue amount and greater than one-quarter of this amount (Table 2.10) and (ii) with an issue date that is, at most, six years earlier or six years later than the green bond's issue date[13] (see Figure 2.1). This double restriction in the matching method allows us to better control for any residual liquidity bias in the estimation step of the green bond premium (see Section 2.4.1). Any green bonds for which fewer than two of the corresponding conventional bonds comply with these requirements is excluded from the database.

In a second stage, the maturity bias is eliminated by building a panel composed of pairs of bonds: an equivalent synthetic conventional bond with the same maturity is assigned to each green bond. The ask yields of each triplet of bonds (the green bond and the two corresponding conventional bonds) are retrieved from the issue date of the green bond up to December 31, 2017. The source used for this purpose is Bloomberg BGN[14], which provides end-of-day market prices and yields based on multiple contributors' market prices as well as all the characteristics of the bonds. As green bonds are not all listed in TRACE, we cannot take advantage here of the

[11]Since an institution can issue various bonds of different kinds or seniority levels and, thus, with different ratings, we make sure that the rating is the same.

[12]It is widely agreed that bond credit spreads incorporate a positive illiquidity premium (see for example Chen, Lesmond, and Wei (2007), Beber, Brandt, and Kavajecz (2009), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhütter, and Lando (2012), Jong and Driessen (2012)).

[13]Authors controlling for the difference in liquidity solely through the date of issuance suggest different levels, from 1 year (Elton et al., 2004) to 2 years (Alexander, Edwards, and Ferri, 2000; Houweling, Mentink, and Vorst, 2005). In this paper, we combine three different liquidity controls (two in the matching method and one in the estimation process), with less stringent restrictions for the first two controls, to enable a closer maturity matching and a wider sample. I verify in the robustness checks (Section 2.6) that these liquidity controls are acceptable. Furthermore, Wulandari et al. (2018) find that the impact of illiquidity on green bonds' yield spread has become negligible in most recent years.

[14]We voluntarily exclude Bloomberg BVAL prices that combine market data with model pricing.

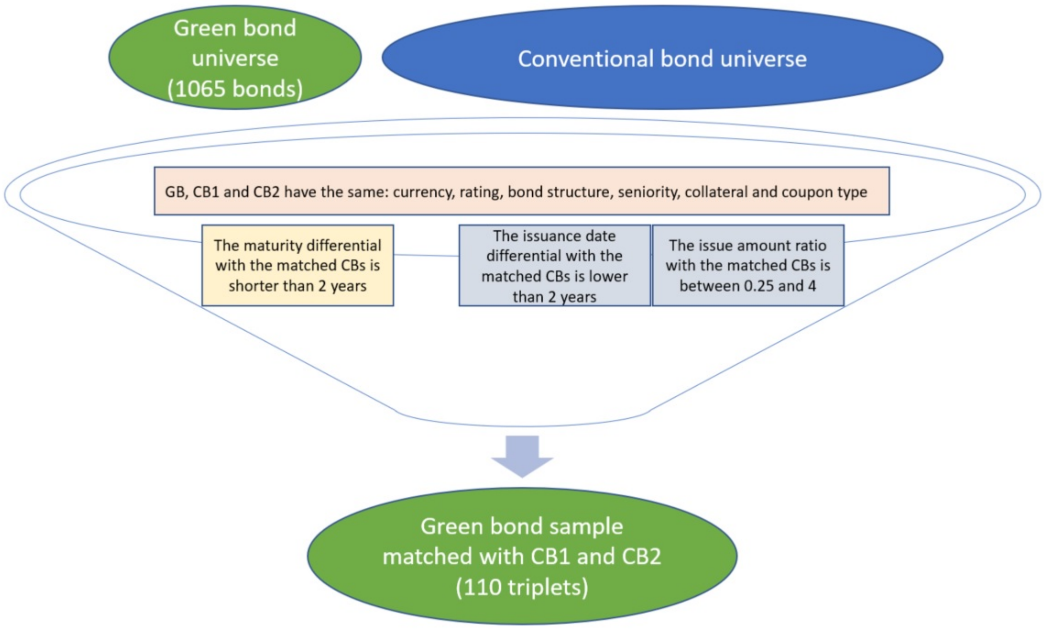


FIGURE 2.1: **Matching process**. This figure illustrates the matching process. We match each green bond (GB) of the universe on December 31, 2017, with two conventional bonds (CB1 and CB2). Green and conventional bonds are required to have the same currency, rating, bond structure, seniority, collateral and coupon type. Moreover, the maturity of the conventional bond is neither two years shorter nor two years longer than that of the green bond. Also, we select the conventional bonds (i) with an issue amount of less than four times the green bond's issue amount and greater than one-quarter of this amount. We therefore collect 110 triplets of (GB, CB1, CB2).

richness of this source, especially with respect to the volumes traded. Since this study focuses on the investors' demand and the issuers' supply of green bonds, we focus on the ask yields of each triplet for a more precise analysis. If, on a specific day, at least one of the three ask yields is not available, I remove the line from our panel. I then interpolate (or extrapolate) the two conventional bonds' yields linearly at the green bond maturity date to obtain a synthetic conventional bond yield, which thus shows the same properties as the green bond except for the difference in liquidity. Practically, for each triplet, with a^* the slope and b^* the intercept of the affine function passing through (Maturity_{CB1}, y^{CB1}) and (Maturity_{CB2}, y^{CB2}), the yield of the synthetic conventional bond is $\tilde{y}^{CB} = a^*\text{Maturity}_{GB} + b^*$ (see Figure 2.4). Because of the linear interpolation (or extrapolation), this method differs slightly from that used in Helwege, Huang, and Wang (2014), in which the closest bond is selected, which gives rise to a tiny maturity bias. The constitution of the database is finalized by defining the yield spread between the green bond and the equivalent synthetic conventional bond. Let $y^{GB}_{i,t}$ and $\tilde{y}^{CB}_{i,t}$ be the green bond and the conventional bond i's ask yields, respectively, on day t. We take $\Delta\tilde{y}_{i,t} = y^{GB}_{i,t} - \tilde{y}^{CB}_{i,t}$.

This approach enables us to remove all the unobservable factors common to both bonds in the matched pairs and to significantly reduce the liquidity bias. The process leaves us with 110 matched green bonds accounting for 10% of the global green bond universe and 17% of the total outstanding green bond debt. All of the bonds in our sample are senior, bullet, fixed-coupon bonds. Except for one BB and 12 non-rated, all of them are investment-grade bonds. Significant variations are observed in the yield levels, notably between the various issue currencies, i.e., across the corresponding rate and credit curves (see Table 2.2). For example, while the average AAA government-related green bond yield in Turkish lira is 10.28%, it only amounts to 0.26% in the same market segment for the bond labeled in EUR.

The sample comprises a 37,503-line unbalanced bond-day panel in which the earliest information dates back to July 18, 2013, and the latest is dated December 29, 2017. For the sample, the statistics of the green and conventional bonds' yields, maturities and issue amounts are presented in Table 2.3.

Upon focusing on the time average difference in yield ($\Delta\tilde{y}_i$), the distribution across bonds is found to be skewed to the left: There are 63% negative values, giving an average of -2 bps[15] and a median value of -1 bp. In the next section, I will therefore study $\Delta\tilde{y}_{i,t}$ to determine whether there is a premium attributable to the greenness of a bond.

2.4 Empirical methodology

2.4.1 Step 1: Estimation of the green bond premium

The first step of the empirical methodology aims at controlling for the residual difference in liquidity between both bonds of each pair and estimating the green bond premium. I therefore design a variable, $\Delta\text{Liquidity}_{i,t}$, capturing the difference in liquidity and defined as the difference between a green bond and a conventional bond's liquidity indicator:

$$\Delta\text{Liquidity}_{i,t} = \text{Liquidity}_{i,t}^{GB} - \text{Liquidity}_{i,t}^{CB} \tag{2.1}$$

The green bond premium p_i is therefore defined as the unobserved effect in the fixed-effects panel regression of $\Delta\tilde{y}_{i,t}$ on $\Delta\text{Liquidity}_{i,t}$:

$$\Delta\tilde{y}_{i,t} = p_i + \beta\Delta\text{Liquidity}_{i,t} + \epsilon_{i,t}, \text{ with } \epsilon_{i,t} \text{ being the error term} \tag{2.2}$$

Given the data sources and the type of regression, the liquidity proxies that can be used here are subject to three constraints. Firstly, since we cannot use intraday data to calculate intraday liquidity indicators, such as the Amihud measure (Amihud, 2002), Range measure (Han and Zhou, 2016) or intraday Roll and Gamma measure (Roll, 1984; Bao, Pan, and Wang, 2011), for example, we focus on low-frequency data. Secondly, in constrast to what can be done with the TRACE database, we do not have any information about the daily trading volumes that might have been used

[15] Note that one cannot infer the -2-bps average yield difference with y^{GB} and $\tilde{y}^{CB}$ because the average in i of the average in t of the yield differences is not equal to the yield difference on the average in i of the average in t of the green bonds' yields and the conventional bonds' yields. The same applies to the medians and quartiles.

TABLE 2.2: **Description of the sample of 110 green bonds**. This table shows the average yield and maturity of the sample of 110 green bonds, broken down by sector, rating, and currency.

		AUD	**CAD**	**CHF**	**CNY**	**EUR**	**GBP**	**INR**	**JPY**	**RUB**	**SEK**	**TRY**	**USD**	**Total**
Basic Materials														
NR	Average yield (%)										0.96			0.96
	Average maturity (years)										4.74			4.74
	Nb. of GB										1			1
Consumer, Non-cyclical														
BBB	Average yield (%)					0.78								0.78
	Average maturity (years)					5.51								5.51
	Nb. of GB					1								1
Financial														
AAA	Average yield (%)	2.43				0.07	0.79				0.10		1.98	0.83
	Average maturity (years)	2.50				4.94	2.43				2.96		3.52	4.13
	Nb. of GB	1				10	1				1		6	19
AA	Average yield (%)	3.00				0.28							2.10	1.11
	Average maturity (years)	3.37				5.68							2.70	4.86
	Nb. of GB	3				8							1	12
A	Average yield (%)				3.70	0.36					0.77		2.17	1.34
	Average maturity (years)				0.53	4.25					4.13		1.98	3.09
	Nb. of GB				1	8					2		8	19
BBB	Average yield (%)					0.61							3.65	2.13
	Average maturity (years)					4.49							2.92	3.70
	Nb. of GB					1							1	2
BB	Average yield (%)												5.23	5.23
	Average maturity (years)												3.38	3.38
	Nb. of GB												1	1
NR	Average yield (%)										0.66			0.66
	Average maturity (years)										2.77			2.77
	Nb. of GB										11			11
Government														
AAA	Average yield (%)	2.41	1.57	0.03		0.26	0.59	5.70		6.65	0.49	10.28	1.73	1.92
	Average maturity (years)	1.33	2.85	7.10		5.54	2.18	3.15		1.57	4.75	1.24	3.15	3.50
	Nb. of GB	1	2	1		3	1	1		1	4	1	15	30
AA	Average yield (%)			0.31									2.16	1.23
	Average maturity (years)			11.92									1.64	6.78
	Nb. of GB			2									2	4
A	Average yield (%)								0.39					0.39
	Average maturity (years)								14.79					14.79
	Nb. of GB								3					3
BBB	Average yield (%)												2.68	2.68
	Average maturity (years)												2.25	2.25
	Nb. of GB												1	1
Industrial														
BBB	Average yield (%)					0.83								0.83
	Average maturity (years)					5.94								5.94
	Nb. of GB					1								1
Utilities														
A	Average yield (%)					0.49								0.49
	Average maturity (years)					2.85								2.85
	Nb. of GB					2								2
BBB	Average yield (%)					0.94								0.94
	Average maturity (years)					6.41								6.41
	Nb. of GB					3								3
	Average yield	2.77	1.57	0.22	3.70	0.34	0.69	5.70	0.39	6.65	0.62	10.28	2.09	1.31

TABLE 2.3: **Descriptive statistics of the bonds in the sample.** This table gives the distribution of several variables of interest in all 110 triplets of bonds in our sample. The number of days per bond is the length of the time series per pair of bonds since their inception. The distribution of the ask yield is presented for green bonds (y^{GB}), the two closest conventional bonds (y^{CB_1} and y^{CB_2}) and the interpolated (or extrapolated) conventional bonds ($\tilde{y}^{CB}$). The difference in yield ($\Delta\tilde{y}_{i,t}$) is the difference between the green bonds' ask yield and the interpolated (or extrapolated) conventional bonds' ask yield. To compare the accuracy of the interpolations (or extrapolations), this table also shows the distribution of maturities and the issue amounts of the green bonds and the two closest conventional bonds.

	Sample					
	Min.	1st Quart.	Median	Mean	3rd Quart.	Max
Number of days per bond	12	99	306	341	518	1 150
Ask yield of the GB (y^{GB})	- 0.35	0.26	0.92	1.31	1.90	10.28
Ask yield of the interp. CB ($\tilde{y}^{CB}$)	- 0.43	0.27	0.94	1.33	1.92	10.19
Ask yield of the CB1 (y^{CB1})	- 0.34	0.22	0.88	1.29	1.98	10.17
Ask yield of the CB2 (y^{CB2})	- 0.33	0.24	0.81	1.25	1.95	10.28
Yield difference % ($\Delta\tilde{y}_{i,t}$)	- 0.46	- 0.03	- 0.01	- 0.02	0.01	0.10
Green bond maturity on Dec. 30, 2017 (years)	0.14	2.20	3.45	4.15	4.87	29.74
Conventional bond 1 maturity	0.07	1.86	3.29	4.03	4.72	28.99
Conventional bond 2 maturity	0.26	1.82	3.11	3.79	4.93	28.23
Green bond issue amount (USD bn)	0.01	0.30	0.50	0.65	0.80	3.60
Conventional bond 1 issue amount	0.01	0.32	1.00	1.34	1.48	7.20
Conventional bond 2 issue amount	0.01	0.28	0.90	1.24	1.24	7.48

as liquidity proxies (Beber, Brandt, and Kavajecz, 2009; Dick-Nielsen, Feldhütter, and Lando, 2012). Thirdly, to ensure the full rank condition of a *within* regression, any variable that does not change over time with a given bond is not suitable. Proxies such as the issue amount, the issue date or off-the-run versus on-the-run indicators (Bao, Pan, and Wang, 2011; Houweling, Mentink, and Vorst, 2005) therefore cannot be used.

We take the closing percent quoted bid-ask spread as a proxy of the liquidity, consistent with Fong, Holden, and Trzcinka (2017), who show, through an extensive analysis of the quality of high- and low-frequency liquidity proxies, that it is the best low-frequency liquidity proxy. Indeed, bid-ask spread has been widely used as a major measure of the degree of illiquidity of a bond (see Beber, Brandt, and Kavajecz (2009), Dick-Nielsen, Feldhütter, and Lando (2012), Chen, Lesmond, and Wei (2007)).

Since the synthetic conventional bonds are based on the two closest conventional bonds, the conventional bond's bid-ask spread is defined as the distance-weighted average of CB1's and CB2's bid-ask spreads. In practical terms, let $d_1 = |\text{Green Bond maturity - CB1 maturity}|$ and $d_2 = |\text{Green Bond maturity - CB2 maturity}|$. The synthetic conventional bond's bid-ask spread is therefore as follows:

$$\mathrm{BA}_{i,t}^{CB} = \frac{d_2}{d_1 + d_2}\mathrm{BA}_{i,t}^{CB1} + \frac{d_1}{d_1 + d_2}\mathrm{BA}_{i,t}^{CB2} \tag{2.3}$$

$\Delta \mathrm{BA}_{i,t} = \mathrm{BA}^{GB}_{i,t} - \mathrm{BA}^{CB}_{i,t}$ is consequently the independent variable used in equation 2.2 to estimate the fixed-effects linear panel.

Table 2.4 show that ΔBA is concentrated around zero and has a low standard deviation. This condition indicates that the first liquidity controls on the issue amount and the date of issuance in the matching method yielded acceptable results.

TABLE 2.4: **Descriptive statistics of the liquidity proxy ΔBA.** This table summarizes the distribution of the liquidity control: ΔBA is the difference between the green bonds' bid-ask spread and the conventional bonds' distance-weighted average bid-ask spread, in a specific pair of bonds, during the period under consideration.

	Min.	1st Quart.	Median	Mean	3rd Quart.	Max	Std. Dev.
ΔBA	-0.436%	-0.021%	0.000%	0.006%	0.032%	0.758%	0.11%

We use a *within* regression to estimate the fixed effects p_i in equation 2.2 for various reasons. Firstly, we want to bring out the bond-specific time-invariant unobserved effect without imposing any distribution or using any information about the other bonds. Secondly, these data do not hold for a broader category but, rather, give the characteristics of a specific bond. From the technical point of view, strict exogeneity holds and ensures unbiasedness and consistency of the estimator. Finally, the fact that we do not require the difference in liquidity proxy to be uncorrelated with the unobserved specific effects provides for a wide range of potential control parameters.

Several individual effect tests and a Hausman test are performed to check the efficiency of the fixed-effects estimator. Moreover, controlling the difference in yield by the difference in liquidity prevents the occurrence of any simultaneity effects: the difference between two yields does not have any retroactive effect on the liquidity of the bonds. Lastly, various robustness tests are performed and, to address the loss of efficiency due to heteroscedasticity and serial correlation, I use the Newey-West and Beck-Katz robust estimations of the standard errors.[16]

2.4.2 Step 2: The determinants of the green premium

In the first step, we isolated the yield premium of a green bond linked to the specific nature of the debt security. The second step highlights the determinants of the green bond premium since it may not be stable across bonds. We therefore consider the characteristics through which bonds differ to determine where, and to what extent, the premium applies. The variables considered are the rating, the sector, the currency, the maturity and the issue amount of the green bond. Table 2.5 provides details on the variables and their construction.

After performing robustness tests, I estimate several cross-sectional specifications, including the main specification described in the following equation, through an OLS

[16]The results are robust to performing a Fixed Effects Generalized Least Squares regression: the estimated premia are equal to those estimated with a Fixed Effects Ordinary Least Squares (*within*) regression by a factor of 0.1 bps. Since the number of bonds studied is lower than the average number of days and for the sake of simplicity, I present here the results of the Fixed Effect OLS regression with robust estimation of the standard errors.

Table 2.5: **Description of the independent variables of the step 2 regression.** This table provides details about the independent variables used in the step 2 regression, namely, their type, unit and description.

Variable	Type	Unit	Description
Rating	Qualitative		The rating of the bond can be AAA, AA, A, BBB, BB or Non-rated (NR) in our sample. The reference value is AAA. To attribute a single rating to the bond, the following procedure is used. The issuer ratings of the three agencies S&P, Moody's and Fitch are rounded off by removing the potential + or −. We then take the majority rating among those available. If there are only two different ratings available, we take the highest one.
Sector	Qualitative		We use the level 1 Bloomberg classification (BICS level 1) for the issuer-type breakdown procedure, which leaves us, in the case of the present sample, with six categories: (i) *Basic Materials*; (ii) *Consumer, Non-cyclical*; (iii) *Financials*, which encompasses non-public banks and financial services; (iv) *Government*, also referred to as *Government-related*, which includes public institutions, municipalities, regional and sovereign agencies, and national, supranational and development banks; (v) *Industrial*; and (vi) *Utilities*. The reference value is *Government*.
Currency	Qualitative		The currency of the bond issuance. In our sample, the referenced currencies are as follows: AUD, CHF, EUR, JPY, SEK, USD, CAD, RUB, GBP, TRY, CNY and INR. The reference level is the USD. See the online appendix for the meaning of each acronym.
Maturity	Quantitative	Years	The maturity of the bond on December 31, 2017.
Issue Amount	Quantitative	bn USD	The issue amount of the green bond considered December 31, 2017.

regression with robust estimation of the standard errors. Taking η_i to denote the error term, we set the following:

$$
\begin{aligned}
\widehat{p_i} =& \alpha_0 + \sum_{j=1}^{N_{rating}-1} \alpha_{1,rating_j} 1_{rating_j} + \sum_{j=1}^{N_{sector}-1} \alpha_{2,sector_j} 1_{sector_j} \\
&+ \sum_{j=1}^{N_{currency}-1} \alpha_{3,currency_j} 1_{currency_j} + \alpha_4 \text{Maturity} + \alpha_5 log(\text{Issue Amount}) + \eta_i
\end{aligned}
\tag{2.4}
$$

We take the logarithm of the issue amount to linearize the values of the variable that can be interpolated by an exponential function. Moreover, as an alternative to having the variables represent rating and sector, we also consider the dummy variables that capture rating $\times$ sector cross effects because descriptive statistics indicate that this segmentation may promote the variation of the premium.

2.5 The green bond premium

2.5.1 A small, albeit significant, negative green bond premium

The first step in the analysis aims to estimate the green bond premium, including its significance, sign and magnitude. I confirm the presence of an unobserved heterogeneous effect via an F-test, a Wooldridge test, a Breusch-Pagan test and a Honda test.[17] I also conduct a Hausman test that indicates that the fixed-effects within estimator is more robust than the random-effect estimator. The within estimator is unbiased and consistent: although it is intuitive that the idiosyncratic error term may not be correlated with either the previous or future differences in liquidity (neither feedback effect nor financial periodicity), I confirm the strict exogeneity hypothesis through Su, Zhang, and Wei (2016)'s test.[18] This estimation is all the more satisfactory as the average number of days is higher than the number of bonds (see Goldstein (2003)) and $\Delta\text{BA}_{i,t}$ varies substantially with time.

Moreover, I run Breusch-Godfrey, Durbin Watson, and Wooldridge tests, all of which indicate the existence of serial correlation. In addition, a Breusch-Pagan test shows the presence of heteroscedasticity. To account for heteroscedasticity and serial correlation, I complement the regression with Newey-West and Beck-Katz[19] robust estimations of the standard errors.

Although the regression evidences a weak R^2 equal to 1%, the bid-ask spread differential used to control for the difference in liquidity proves to be highly significant for the three different estimators of the standard errors (Table 2.6). Although small in the present case, the residual liquidity differential has significant explanatory power

[17] See the online appendix for the details of the tests performed.

[18] We test strict exogeneity for a two-day lag and lead period. The P-value is equal to 73.1%.

[19] Beck and Katz (1995) prove that their robust estimator performs well in small panels.

TABLE 2.6: **Results of the step 1 regression.** This table gives the results of the step 1 regression: $\Delta\tilde{y}_{i,t} = p_i + \beta\Delta\text{BA}_{i,t} + \epsilon_{i,t}$. In addition to a classical within regression, Newey-West and Beck-Katz robust standard error tests are performed.

	Dependent variable: $\Delta\tilde{y}_{i,t}$		
	Within	Newey-West robust std. err.	Beck-Katz robust std. err.
ΔBA	-9.881^{***}	-9.881^{***}	-9.881^{***}
	(0.440)	(2.774)	(3.334)
Observations		37,504	
R^2		0.013	
Adjusted R^2		0.010	
F Statistic		504.125^{***} (df = 1; 37393)	
Note:			*p<0.1; **p<0.05; ***p<0.01

and the step used for its control should not be discarded, *a fortiori* in situations in which the matching constraints are less stringent and because it is useful for developing a general method. Thus, a 1-bp increase in the percentage price bid-ask spread differential induces a 9.88-bps decrease in $\Delta\tilde{y}_{i,t}$.

The value of the 110 fixed-effects p_i constituting each of the green bonds' premia is more important for the present purposes. The distribution ranges from -38 bps to +10 bps with a mean and a median value of -1.76 bps and -1.04 bps, respectively (Table 2.7). A total of 63% of the premia are negative, and the amplitudes are greater on the downside than on the upside (Figure 2.2). It is worth noting that the extreme values of $\widehat{p_i}$ appear for currencies presenting a high yield (such as INR, RUB or TRY).

TABLE 2.7: **Distribution of the estimated green bond premia**. This table summarizes the distribution of the estimated green bond premia in our full green bond sample, i.e., the fixed effect of the following regression: $\Delta\tilde{y}_{i,t} = p_i + \beta\Delta\text{Liquidity}_{i,t} + \epsilon_{i,t}$.

$\hat{p}_i$ (%)					
Min.	1st Quart.	Median	Mean	3rd Quart.	Max
- 0.381	- 0.029	- 0.01	- 0.018	0.008	0.100

Lastly, I break down the sample in several subsamples by the main characteristics of the bond: its rating, sector and currency. I calculate the average premium by subsample and test whether it is significantly different from zero for subsamples with at least ten bonds. Through a Shapiro-Wilk normality test, we reject the normality hypothesis for all subsamples except AA bonds and SEK-denominated bonds. I therefore use the non-parametric Wilcoxon signed-rank test, which is applied to our specific

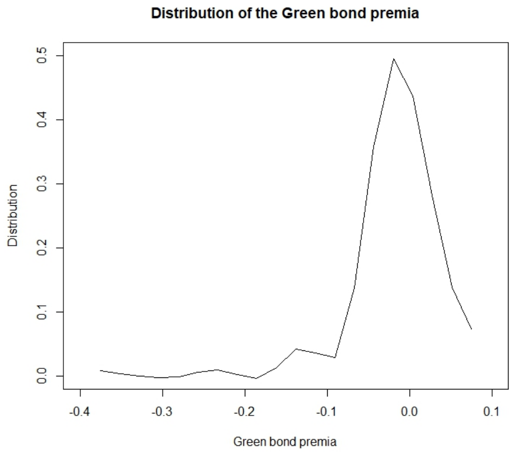


FIGURE 2.2: **Green bond premia distribution.** This figure gives the distribution of the green bond premia $\widehat{p_i}$ across all bonds included in this study.

framework,[20] to assess the significance of the premia per subsample. The results are robust to a test under the hypothesis of normality for A and SEK-denominated bonds.

Table 2.8 shows the average and median premia per subsample. The -1.8-bp average premium on the entire sample is significantly different from zero at a 99% level of confidence. Financial green bonds carry a -2.3-bps average premium with the same degree of significance. EUR-denominated and USD-denominated green bonds also have a significant negative premium of -1.7 bp and -2.3 bps, respectively. Lastly, AA green bonds show a -2.9-bps premium. Although the average and median premia of the other categories are not significantly different from zero, most of them are negative.

The literature analyzing the liquidity of off-the-run vs. on-the-run bonds highlights a significant liquidity premium of approximately 1.5 bp on U.S. Treasury bonds with the same characteristics except for their issue date. The comparison can be of interest because this premium affects bonds from the same issuer that have the same characteristics except for their issue date and, therefore, their degree of liquidity. By matching 55 pairs of bonds between 1994 and 2000, Goldreich, Hanke, and Nath (2005) show a yield differential of 1.5 bp between off-the-run and on-the-run US Treasury bonds. Pasquariello and Vega (2009) also find a yield difference of 1.6 bp on 5-year U.S. Treasury bonds by matching 86 bonds over the period 1992-2000.

We therefore provide evidence that investors in the secondary market pay a small

[20]For a subsample of n premia, the test is built as follows. We rank the n premia in ascending order of their absolute value and assign them a rank, R, from 1 to n. Let sgn represent the sign of the premium; we consider the following statistic:

$$W = \sum_{i=1}^{n} sgn(\widehat{p_i}) R_i$$

Under the null hypothesis H_0: $\widehat{p} = 0$, with $\sigma_w = \sqrt{\frac{n(n+1)(2n+1)}{6}}$, $\frac{W \pm 0.5}{\sigma_w}$ converges to a normal distribution. We add (subtract, resp.) 0.5 if $W < 0$ ($W > 0$, resp.) as a *continuity correction* since we compare discrete data to a continuous probability function.

Table 2.8: **Green bond premia in several market segments**. This table shows the mean and median green bond premia in several market segments, the level of significance at which we rejected $H_0 : \widehat{p_i} = 0$, and the number of green bonds in each of the subsamples. We use a Wilcoxon signed-rank test with continuity correction.

		Mean($\widehat{p_i}$)	Median($\widehat{p_i}$)	$\widehat{p_i} \neq 0$	# GB
	Total	-0.018	-0.010	***	110
Sector	Basic Materials	-0.016	-0.016		1
	Consumer, NC	-0.011	-0.011		1
	Financial	-0.025	-0.013	***	64
	Government	-0.009	0.000		38
	Industrial	0.005	0.005		1
	Utilities	0.002	-0.003		5
Currency	AUD	-0.031	-0.019		5
	CAD	-0.010	-0.010		2
	CHF	0.000	0.001		3
	CNY	0.024	0.024		1
	EUR	-0.017	-0.011	**	37
	GBP	-0.001	-0.001		2
	INR	0.055	0.055		1
	JPY	0.033	0.051		3
	RUB	-0.381	-0.381		1
	SEK	-0.009	-0.007		19
	TRY	0.079	0.079		1
	USD	-0.023	-0.019	***	35
Rating	AAA	-0.010	-0.003		49
	AA	-0.029	-0.024	***	16
	A	-0.018	-0.011		24
	BBB	-0.021	-0.009		8
	BB	-0.206	-0.206		1
	NR	-0.012	-0.007		12

Note: *p<0.1; **p<0.05; ***p<0.01

negative yield premium inherent to green bonds, which is of a magnitude comparable to that of the on-the-run liquidity premium on U.S. Treasury bonds.

2.5.2 The determinants of the green bond premium

To determine and evaluate the determinants of a green bond premium, a linear regression of $\widehat{p_i}$ is performed on the characteristics of the green bonds. Table 2.9 shows the four regression specifications considered: (a) represents the most general specification, based on equation 2.4; (b) excludes the variables *Maturity* and *log(Issue Amount)*; (c) further excludes the currency dummies and the independent variables; and (d) represents solely the Rating $\times$ Sector cross effects. To avoid artificially high R^2s, the four regressions are performed on samples in which each of the dummy variables captures more than three observations. The R^2s therefore range from 11.3% (d) to 14.1% (a). The regression on the entire sample, of which the results are in line with that on restricted samples, is shown in Appendix (Table 2.11) and has an R^2 equal to 60.6%. Since the results of the Breusch-Pagan test evidence the presence of heteroscedasticity for the first three specifications[21], I estimate White robust standard errors. Besides, the VIF calculation does not lead to a suspicion of multicollinearity.

Specifications (a) and (b) show that neither the maturity, the issue amount, nor the currency has a significant impact on the level of the premia in the considered subsample. The first two conclusions hold for the regression on the entire sample (Table 2.11); however, although the number of observations is limited, we suspect that the currency involved may have an impact in less mature financial markets. Specifications (a), (b), and (c) show that the rating significantly affects the premium: the lower the rating of the green bond is, the lower the green premium. The effect is particularly significant for AA and A bonds, with both values -2.3 bps with respect to AAA bonds (specification (b)). The study of Rating $\times$ Sector cross effects (specification (d)) shows that the level of premia varies between government-related bonds and financial bonds: while the negative impact of a lower rating is maintained in both sectors, the premia on financial bonds (-2.7 bps and -2.5 bps for AA and A, respectively) are lower than those on government-related bonds (-1.7 bps for AA).

These findings can be linked with the literature on the liquidity premium. Similar to the liquidity premium, the green bond premium fades with the increase of the credit quality (Longstaff, Mithal, and Neis, 2005; Chen, Lesmond, and Wei, 2007; Bao, Pan, and Wang, 2011; Dick-Nielsen, Feldhütter, and Lando, 2012; Huang and Huang, 2012; Abudy and A., 2016). In addition, the absolute value of the negative green bond premium is greater for financial bonds, similar to the situation regarding the liquidity premium (Longstaff, Mithal, and Neis, 2005). However, contrary to the liquidity premium, which increases for low issue amounts (Longstaff, Mithal, and Neis, 2005), the green bond premium does not seem to be affected by low issue amounts. Moreover, Driessen, Nijman, and Simon (2016) find liquidity segmentation between long- and short-dated bonds, and Ejsing, Grother, and Grothe (2012) and Schuster

[21] See the online appendix for the details of the tests performed.

TABLE 2.9: **Results of step 2 regressions.** This table gives the results of step 2 regressions in which the green bond premium is explained by the characteristics of the bonds through specifications (a),(b), (c), and (d). The premium is expressed as a percentage. The rating is a qualitative variable, the four modalities of which are AAA (reference modality), AA, A, and BBB. Maturity is the maturity of the bond expressed in years on December 31, 2017. The issue amount is the amount of green bonds issued expressed in USD billions. Sector is a qualitative variable, of which the three modalities are Government (reference modality), Financials and Utilities. We also consider Rating × Sector cross effects. Currency is a qualitative variable, of which the four modalities are USD (reference modality), AUD, EUR, and SEK.

	Dependent variable: $\widehat{p_i}$			
	Cross-sectional regressions with White robust standard errors			
	(a)	(b)	(c)	(d)
Constant	−0.003	−0.004	−0.002	−0.007
	(0.015)	(0.010)	(0.009)	(0.009)
Rating AA	−0.025**	−0.023**	−0.024**	
	(0.010)	(0.010)	(0.010)	
Rating A	−0.026*	−0.023*	−0.022*	
	(0.014)	(0.013)	(0.013)	
Rating BBB	−0.043	−0.040	−0.041	
	(0.043)	(0.041)	(0.040)	
Non-rated	−0.018	−0.009	−0.001	
	(0.020)	(0.018)	(0.014)	
Sector Financial	−0.008	−0.009	−0.008	
	(0.012)	(0.012)	(0.012)	
Sector Utilities	0.039	0.035	0.037	
	(0.034)	(0.032)	(0.031)	
AA × Government				−0.017*
				(0.009)
AAA × Financial				0.004
				(0.011)
AA × Financial				−0.027**
				(0.013)
A × Financial				−0.025*
				(0.013)
NR × Financial				−0.005
				(0.015)
Currency AUD	−0.009	−0.006		
	(0.014)	(0.013)		
Currency EUR	0.009	0.004		
	(0.010)	(0.010)		
Currency SEK	0.004	0.010		
	(0.016)	(0.011)		
Maturity	−0.001			
	(0.002)			
log(Issue Amount) (bn USD)	−0.006			
	(0.009)			
Observations	92	92	92	84
R^2	0.141	0.134	0.127	0.113
Adjusted R^2	0.023	0.039	0.066	0.056
Residual Std. Error	0.041 (df = 80)	0.041 (df = 82)	0.040 (df = 85)	0.038 (df = 78)
F Statistic	1.195 (df = 11; 80)	1.411 (df = 9; 82)	2.064* (df = 6; 85)	1.987* (df = 5; 78)
Note:				*p<0.1; **p<0.05; ***p<0.01

and Uhrig-Hombourg (2012) show that the liquidity premium is greater in the short term. The green bond premium, in contrast, does not appear to be significantly impacted by the maturity of the bond.

Focusing on specification (b), we can express the green bond premia in absolute terms: they increase as the rating improves and are lower for financial bonds. For example, the yield of an AAA, AA, A and BBB EUR financial green bond is lower than that of an equivalent conventional bond by 0.9 bps, 3.2 bps, 3.2 bps and 4.9 bps, respectively. However, the yields of green and conventional AAA government-related bonds are in line (0 bp for EUR and -0.4bp for USD). As for the EUR (USD, resp.) utilities, although not significantly different from zero, the average premium is +1.2 bps (+0.8 bps, resp.) for A-green bonds and -0.5 bps (-0.9 bps, resp.) for BBB-green bonds.

These findings nuance several previous works that addressed this issue. I show that the yield differential between green and conventional bonds is negative for financial bonds–which are the most active corporate issuers–as suspected by Barclays (2015) and Ehlers and Packer (2017). Nevertheless, I substantially qualify the premium amount, of which the magnitude for A and AA bonds is closer to -3 bps than to -17 bps (Barclays, 2015) or -18 bps (Ehlers and Packer, 2017). Similar to HSBC (2016) and Climate Bonds Initiative (2017), I find evidence that this premium may be close to zero in several market segments, such as AAA government-related bonds or utilities. Lastly, I do not find evidence of a positive premium on USD-denominated bonds, as estimated by Karpf and Mandel (2018) (+7.8 bps).

In the final step, as a result of step 2, a green bond curve can be obtained from a conventional bond curve by applying the estimated green bond premium to the latter. This exercise is useful for investors as well as for issuers since few green bond benchmarks have been issued to date. Figure 2.5 presents the reconstituted green bond curve obtained by performing specification (b) as well as the conventional bond curve for eight different issuers. The quality of the fit achieved on the entire sample is satisfactory. However, the green bond curve does not always exactly intersect with the green bond market yields for three main reasons. Firstly, the green bond premia we calculate and explain here are long-term green premia, which reflect the average distortion since their inception. To obtain a closer fit, a short-term analysis would be more appropriate (see Section 2.6). Secondly, the low liquidity of several green bonds results in a yield that does not always reflect the actual yield on the reference date. Lastly, the greater the number of data available for estimating the green bond premium is, the closer the fit will be.

2.6 Robustness checks

In the first step of our robustness checks, we examine whether a negative premium may reflect the fact that the level of risk involved in a green bond is lower than in a conventional bond. I calculate the 10-day, 20-day and 30-day rolling annualized volatility during the period of interest in the case of both green and synthetic conventional bonds, following equation 2.3 applied to the volatility, and take the difference between the members of each pair. I then estimate a step 1 regression adding the difference in volatility as an additional independent variable (Table 2.12). Using a robust standard errors estimation, I find no evidence that a difference in volatility is embedded in the yield differential between green and conventional bonds. This result indicates that the green bond premium should differ from a risk premium.

Another main issue is the question as to whether or not a green bond premium remains stable with time. We add a time fixed effect in the panel regression procedure. The estimated bid-ask spread parameter is found to be significant and almost equal to the parameter estimated above. Nevertheless, the individual time effect is significant during 24% of the 1162 days considered, which means that there might not be a durable daily time effect involved in the green bond premium.

However, upon applying the same regression procedure to the whole range of data on a monthly basis from January 2016 onward, I find the green bond premium to be variable,[22] although the mean and the median premia have become and remained negative since May 2016 (Figure 2.3), similar to what Karpf and Mandel (2018) reported. Moreover, interestingly, Delis, Grieff, and Ongena (2018) find a similar result on bank loans: they show that, before 2015, bank did not price climate risk and, after 2015, a 2-bps average premium is charged to fossil fuel firms compared to non-fossil fuel firms.[23] I carry out the same analysis on each rating, sector (*Government* and *Financials*) and currency (EUR and USD) subgroups and find the same pattern for most of them with different amplitude ranges (Figure 2.6). It is worth noting that the robustness checks on a monthly basis are performed on rather small samples, and fewer bonds than in the main regression are therefore included. Thus, the information involved is somewhat different from that in the entire data history, which largely explains the discrepancies observed between the results.

A further potential concern is whether the green bond premium reflects a market risk premium over time. I therefore compare the daily returns of the time effects with three market indices' returns. Based on the S&P 500, the Eurostoxx 50 and the MSCI World indices, I first establish that the correlations between the index daily returns and the green bonds' time effects daily returns are low (10.9%, 7.8%, and 10.6%, respectively). In addition, to address the heteroscedasticity issue, I perform an OLS regression, with White robust standard errors,[24] to explain the daily returns of the green bond's time effects by the index daily returns (Table 2.13). Neither the S&P 500, the Eurostoxx 50, nor the MSCI World shows a significant effect. This analysis indicates that the time effect is not explained by a market risk premium and, hence, that the green bond premium does not reflect any market risk premium.

[22] As a comparison, Longstaff, Mithal, and Neis (2005), Favero, Pagano, and Thadden (2010), and Huang and Huang (2012) show that the liquidity premium also varies over time.

[23] More precisely, Delis, Grieff, and Ongena (2018) show that a one standard deviation increase in their measure of climate policy exposure induces a 2-bps increase of the loan rate.

[24] None of the Durbin Watson tests performed on the three specifications indicate any evidence of autocorrelation in the residuals. However, the hypothesis of heteroscedasticity is rejected.

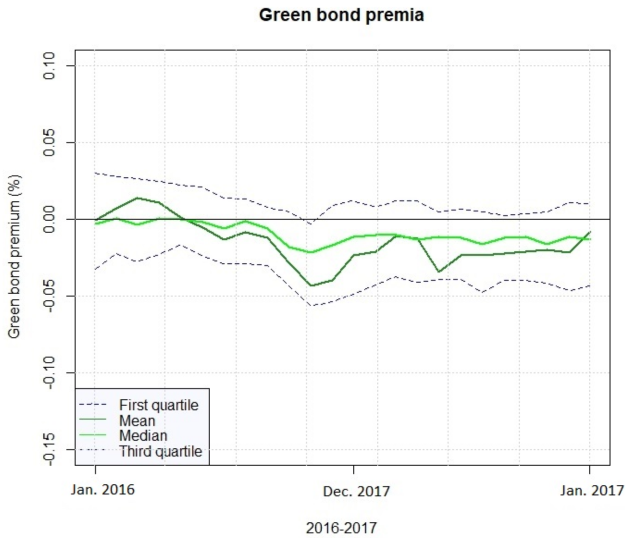


FIGURE 2.3: **Green bond premium dynamics.** This figure shows the evolution over time of the mean (light green solid line), the median (dark green solid line) and the quartiles (dashed blue lines) of the green bond premium during the years 2016 and 2017 based on the step 1 regression for the entire sample of green bonds.

The quality of the matching method, as well as the interpolation or the extrapolation performed to obtain the synthetic conventional bond yield, must also be addressed. If CB1 and CB2 have significantly different levels of liquidity from that of the green bond, the first-step regression might not completely control for the residual liquidity. Furthermore, if the maturities of CB1 and CB2 differ greatly from that of the green bond, the yield of the synthetic conventional bond is liable to be over- or under-estimated. I therefore reproduce the matching method with more stringent liquidity constraints: I restrict the eligible conventional bonds to those (i) with an issue amount of less than twice the green bond's issue amount and greater than one-half of this amount and (ii) with an issue date that is, at most, two years earlier or two years later than the green bond's issue date. I also restrict the difference in maturity between CB1 and the green bond to a maximum of one year.[25] Comparing the estimated premia[26] of this sample to that of the same sample stemming from the matching constraints used in the general method, I find the descriptive statistics to be almost equal (Table 2.14). Moreover, after performing the step 2 regression, the estimated premia per subsample are very close for each of the two methods (Table 2.15). The minor difference is generally due to a poorer maturity matching with the second liquidity matching constraints. Therefore, in addition to restraining the obtained sample, requiring very stringent matching constraints can degrade the quality of the estimation.

Furthermore, I carry out a linear regression with White robust standard errors

[25]Requiring the same restriction on CB2 leads to a total sample of only 30 matched pairs of bonds and, thus, to very small subsamples.

[26]The independent variable in step 1, ΔBA, is no longer significant with the second matching method, demonstrating that there is almost no more residual liquidity to be controlled.

on the matched bond-day panel to explain the yield differential between GB and CB by the independent variables of specifications (a), (b), (c), (d), adding the liquidity differential control ΔBA.[27] For the sake of the comparison, we focus on the samples of 92 bonds ((a), (b) and (c)) and 84 bonds ((d)) used in the step 2 regression. The results (Table 2.16) confirm the necessity of controlling for the residual liquidity, although the effect is weakly significant for specifications (c) and (d). Moreover, the estimated effects are very close to that of the general method with less than 1 bp difference. However, the findings are slightly biased by overweighting the effect of bonds with the longest history. Furthermore, all of the estimated paramaters are significant, which makes it difficult to discriminate between groups on the basis of the significance of their impact on the premium. Moreover, the R^2, approximately 5%, is less satisfactory than that of the second step in our general method.

It may also be interesting to contextualize our results with those of an OLS regression with White robust standard errors of the yield of green and conventional bonds on their characteristics. I apply specifications (a) and (b) on the sample consisting of the green and the closest conventional bonds (CB1),[28] using BA (instead of ΔBA) as a control for liquidity and adding a firm fixed effect as well as a dummy variable controlling for green bonds. Likewise, I find a significant negative premium that ranges from -0.6 bp to -0.9 bp (Table 2.17). However, as in the previous case, this method overweights premia for which a long price history is available.

Finally, the representativeness of the green premium estimated in our sample is addressed. Figure 2.7 compares the distribution of bonds in our sample with that of the global sample by rating and sector, which are the two factors that significantly influence the green premium. To assess goodness of fit, I perform a Chi-squared test on the distributions of investment-grade bonds and on three of the four most represented sectors (*Government*, *Financials*, and *Utilities*) which account for 78% of the total sample of green bonds. With P-values of 21.3% and 19.9%, respectively, I find that our green premium estimate should be reasonably representative of the overall sample for investment-grade bonds in the considered sectors. Moreover, to estimate a premium over a broader scope, I use a matching method between each green bond and one conventional bond with less restrictive criteria requiring the same issuer, currency and coupon type; I also impose a maximum maturity difference of four years and an issue amount ratio between one-quarter and four. I therefore perform a cross-sectional regression on the 179 matched pairs, accounting for 40% of the global amount of green bonds issued, controlling for all the different characteristics of the bonds. The amount of the estimated negative premium (Table 2.18) is found to be of a similar magnitude to that which we find with our main method. Finally, we test the robustness of the result by restricting our estimate to subsamples. By carrying out 10,000 draws with and without replacement of 40, 60 and 80 pairs among the 110

[27] It is worth noting that, as in our two-step regression, the better the matching, the more accurate the estimations.

[28] The same method could be applied to non-matched bonds, but the results would be much less accurate and would not be comparable with those of the main method presented in this paper.

studied, we observe that more than 99% of the estimated premia are negative in the six different cases.

2.7 Discussion

The -2-bps average green bond yield premium (1.5% of the average yield in the sample) indicates the yield that investors are willing to give up to fund green investments rather than conventional investments with strictly equal risk. I find evidence of a low impact of investors' pro-environmental motives on bond prices. This statistically significant effect is consistent with existing theoretical works. Fama and French (2007a) demonstrate that when a group of investors has a *taste* for a certain type of assets, equilibrium prices shift and the capital asset pricing model (CAPM) fails to explain asset returns. Focusing on equity, Heinkel, Kraus, and Zechner (2001) show that, by excluding polluting assets from their portfolio, *green investors* drive up the cost of capital of polluting companies. We also relate our result to the empirical finding that investors' pro-social and pro-environmental inclinations increase inflows to socially responsible investments (Hong and Kacperczyk, 2009; Riedl and Smeets, 2017; Hartzmark and Sussman, 2018), of which the psychological origin can be altruism (Brodback, Guenster, and Mezger, 2018) or social pressure (DellaVigna, List, and Malmendier, 2012). However, I show that, in contrast to the effects on the volume of financial flows, the impact on prices is very limited. In this respect, our findings suggest that the lower cost of debt for companies with good environmental performance should be predominantly related to a lower level of financial risk, through intangible asset creation[29] (Porter and Linde, 1995; Hart, 1995; Jones, 1995; Ambec and Lanoie, 2008; Flammer, 2015) and better risk management and mitigation (Ambec and Lanoie, 2008; Bauer and Hann, 2014), rather than investors' non-pecuniary preferences.

A negative yield differential of 2 bps for green bonds has several implications for the different types of market participants. Regarding investors, the amount of this premium should not constitute a sufficient differential likely to discourage them from investing in green bonds. Becker and Ivashina (2015) study the arbitrage of insurers between investment-grade U.S. corporate bonds with the same rating but different yields, controlling for duration and liquidity, between 2004 and 2010. In particular, they show that a positive differential of 100 bps leads to a reallocation of between 3.6% and 7.4% of insurance companies' holdings on the primary market and 0% to 2.5% on the secondary market. Given the amounts highlighted by this article in a similar framework, a -2-bps premium should therefore not constitute a disincentive to invest in green bonds. Moreover, although this premium is low, it demonstrates investors' appetite for green bond issues and thus highlights the opportunity for issuers to broaden their bondholder base by issuing green bonds, as suggested by I4CE (2016).

[29] Intangible assets may refer to an improvement in the company's reputation, the attraction of new customers or a greater loyalty of employees towards the company.

This premium is also consistent with the results of Flammer (2018), who finds that green bond issuances induce an increase in ownership by long-term and green investors. Finally, from the supervisory authority perspective, this result addresses the concern about the appearance of a bubble on green assets raised by the Dutch Central Bank (De Nederlandsche Bank, 2017): while the amount of this premium indicates investors' preference for green bonds, it does not yet reveal any substantial pricing discrepancy between green and conventional bonds.

The opportunity to increase the issuance of green bonds, which still accounted for 1.3% of the outstanding global debt in 2017,[30] is not only supported by the results of this paper but also consistent with political ambitions and the recommendations of financial players. Policymakers can play a crucial role by providing green project developers and investors with a clearer legal framework to unlock the full potential of the green bond market. Indeed, as recommended by the EU High-Level Group on Sustainable Finance (European Union High Level Expert Group on Sustainable Finance, 2018), the European Commission set a roadmap on March 8, 2018, to establish a common taxonomy (*EU Classification System*) for sustainable finance and to create EU labels for green financial products based on this classification (European Commission, 2018). These actions will notably help establish a precisely defined framework for green bond requirements and should streamline the approval process to increase the flow of low-carbon projects.[31]

2.8 Conclusion

In this paper, I use green bonds as an instrument to identify the effect of non-pecuniary motives, specifically pro-environmental preferences, on bond market prices. I analyze the yield of green bonds compared to that of equivalent synthetic non-green bonds through a matching method for bonds issued from July 2013 to December 2017. I identify the effect of pro-environmental preferences through a *green bond premium*, which is defined as the yield differential between a green bond and its counterfactual conventional bond after controlling for their difference in liquidity. I evidence a significant, albeit low, premium related to investors' pro-environmental preferences in the bond market. This result highlights the opportunity for issuers to benefit from an expansion of their bondholder base through this asset class, especially for low-rated and financial bonds. However, at this stage, the premium is still low enough not to demonstrate any substantial valuation discrepancy between green and conventional bonds or to dissuade investors from supporting the development of the green bond market.

[30] According to the Bank for International Settlements, the total outstanding debt worldwide amounted to USD 23,580 billion in the third quarter of 2017: https://www.bis.org/statistics/c1.pdf

[31] In 2016, green bonds accounted for only 17% of the USD 694 billion climate-aligned bonds universe (Climate Bonds Initiative, 2016) that gathers numerous potential candidates for a green bond label.

The main limitation of this study arises from the quality of the data. Since bonds–and *a fortiori* corporate bonds–are not frequently traded, a bond yield does not accurately reflect the fair value of the bond in some cases. Further research along these lines could focus on pursuing the following two main objectives. An empirical study could be performed to assess whether the use of proceeds has a differentiating impact on the premium. This study could also be extended to social impact bonds, once this market is sufficiently mature, to analyze the impact of pro-social preferences on bond prices.

2.9 Appendix A: Additional tables and figures

TABLE 2.10: **Average issue amount broken down per type of bond and currency**. This table gives the average amount of green bonds, CB1 and CB2 issued in each currency.

	Average issue amount (bn USD)		
	Green bonds	Conventional bonds 1	Conventional bonds 2
AUD	0.45	0.63	0.64
CAD	0.40	1.11	0.95
CHF	0.33	0.29	0.35
CNY	0.23	0.15	0.08
EUR	1.05	1.95	1.98
GBP	1.89	6.84	2.47
INR	0.08	0.30	0.22
JPY	0.09	0.15	0.17
RUB	0.01	0.10	0.01
SEK	0.11	0.13	0.13
TRY	0.07	0.03	0.10
USD	0.65	1.50	1.38
Average	0.65	1.34	1.24
Median	0.28	0.29	0.28

TABLE 2.11: **Results of the step 2 regression on the entire sample.** This table gives the result of the step 2 regression in which the green bond premium is explained by the characteristics of the bonds through specification (a) on the entire sample of 110 bonds.

	Dependent variable: $\widehat{p_i}$
	Linear regression with White robust standard errors
Constant	−0.005
	(0.011)
Rating AA	−0.022**
	(0.010)
Rating A	−0.023*
	(0.014)
Rating BBB	−0.040
	(0.044)
Rating BB	−0.194***
	(0.010)
Non-rated	−0.011
	(0.018)
Sector Basic Materials	−0.011
	(0.018)
Sector Consumer, Non-cyclical	0.031
	(0.046)
Sector Financial	−0.007
	(0.012)
Sector Industrial	0.047
	(0.046)
Sector Utilities	0.037
	(0.034)
Currency AUD	−0.007
	(0.014)
Currency CAD	−0.005
	(0.013)
Currency CHF	0.020
	(0.015)
Currency CNY	0.059***
	(0.012)
Currency EUR	0.003
	(0.011)
Currency GBP	0.007
	(0.020)
Currency INR	0.060***
	(0.011)
Currency JPY	0.062**
	(0.024)
Currency RUB	−0.376***
	(0.011)
Currency SEK	0.011
	(0.011)
Currency TRY	0.084***
	(0.011)
Observations	110
R^2	0.606
Adjusted R^2	0.513
Residual Std. Error	0.040 (df = 88)
F Statistic	6.459*** (df = 21; 88)
Note:	*p<0.1; **p<0.05; ***p<0.01

TABLE 2.12: **Results of the step 1 regression with a control of the difference in volatility.** This table gives the results of the step 1 regression to which the difference in volatility between green and conventional bonds is added as an independent variable: $\Delta\tilde{y}_{i,t} = p_i + \beta\Delta\text{BA}_{i,t} + \Delta\text{Vol}_{i,t} + \epsilon_{i,t}$. Newey-West and Beck-Katz robust standard error tests are performed.

	Dependent variable: $\Delta\tilde{y}_{i,t}$					
	Newey-West	Beck-Katz	Newey-West	Beck-Katz	Newey-West	Beck-Katz
ΔBA	−11.778***	−11.778***	−12.316***	−12.316***	−12.484***	−12.484***
	(3.178)	(3.861)	(3.330)	(3.989)	(3.459)	(4.129)
Δ 10-day volatility	−0.020	−0.020				
	(0.040)	(0.049)				
Δ 20-day volatility			0.037	0.037		
			(0.055)	(0.086)		
Δ 30-day volatility					0.017	0.017
					(0.060)	(0.119)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 2.13: **Green premium and market returns**. This table shows the regression of the daily returns of the time effects in the step 1 regression on the daily returns of several market indices.

	Dependent variable: Time effects' returns		
	White robust std. err. estimation		
Constant	−0.818**	−0.764**	−0.802**
	(0.416)	(0.380)	(0.402)
S&P 500 returns	184.449		
	(133.206)		
Eurostoxx 50 returns		85.116	
		(60.130)	
MSCI World returns			203.006
			(135.363)
Note:			*p<0.1; **p<0.05; ***p<0.01

TABLE 2.14: **Descriptive statistics of more stringent matching criteria**. This table gives the descriptive statistics of the estimated green bond premia through a step 1 regression on two different samples: a) the sample stemming from the matching criteria #2 and b) the sample stemming from the matching criteria #1 restricted to bonds in sample a). Matching criteria #1 require the conventional bonds to have (i) a maturity that is neither two years shorter nor two years longer than the green bond's maturity, (ii) an issue amount of less than four times the green bond's issue amount and greater than one-quarter of this amount, and (iii) an issue date that is at most six years earlier or six years later than the green bond's issue date. Matching criteria #2 require the conventional bonds to have (i) a maturity that is neither one (resp. two) year(s) lower nor one (resp. two) year(s) greater than the green bond's maturity for CB1 (resp. CB2), (ii) an issue amount of less than twice the green bond's issue amount and greater than one-half of this amount, and (iii) an issue date that is, at most, two years earlier or two years later than the green bond's issue date.

	Green bond premia	
	Matching 2	Matching 1 on M2's sample
Min.	- 0.130	- 0.127
1st Quartile	- 0.034	- 0.039
Mean	- 0.020	- 0.018
Median	- 0.012	- 0.011
1st Quartile	0.003	0.001
Max.	0.079	0.079

TABLE 2.15: **Estimated premia using more stringent matching criteria, broken down by rating and sector.** This table gives the estimated average EUR and USD premia through a step 2 (b) regression using bonds stemming from matching criteria #1 and matching criteria #2, both restricted to the same largest common sample. The premia are broken down by ratings and sector. Matching criteria #1 require the conventional bonds to have (i) a maturity that is neither two years shorter nor two years longer than the green bond's maturity, (ii) an issue amount of less than four times the green bond's issue amount and greater than one-quarter of this amount, and (iii) an issue date that is at most six years earlier or six years later than the green bond's issue date. Matching criteria #2 require the conventional bonds to have (i) a maturity that is neither one (resp. two) year(s) shorter nor one (resp. two) year(s) longer than the green bond's maturity for CB1 (resp. CB2), (ii) an issue amount of less than twice the green bond's issue amount and greater than one-half of this amount, and (iii) an issue date that is at most two years earlier or two years later than the green bond's issue date.

Matching criteria		EUR		USD	
		Govt	Financials	Govt	Financials
1	AAA	- 0.00	- 0.02	- 0.02	- 0.04
2		- 0.02	- 0.03	- 0.03	- 0.04
1	AA		- 0.02		- 0.04
2			- 0.01		- 0.01
1	A		- 0.02		- 0.04
2			- 0.03		- 0.04
1	BBB		- 0.02		- 0.04
2			- 0.03		- 0.04

TABLE 2.16: **Results of a step 2 regression performed on the difference in the yield while controlling for the difference in liquidity.** This table gives the results of step 2 regressions performed on the bond-day sample in which we explain the yield differential by a proxy of the difference in liquidity ΔBA and the bonds' characteristics of specifications (a),(b), (c), and (d). The yield differential and ΔBA are expressed as percentages. The rating is a qualitative variable, of which the four modalities are AAA (reference modality), AA, A and BBB. Maturity is the maturity of the bond expressed in years on December 31, 2017. The issue amount is the amount of green bonds issued expressed in USD billions. Sector is a qualitative variable, of which the three modalities are Government (reference modality), Financials and Utilities. We also consider Rating × Sector cross effects. Currency is a qualitative variable, of which the four modalities are USD (reference modality), AUD, EUR, and SEK.

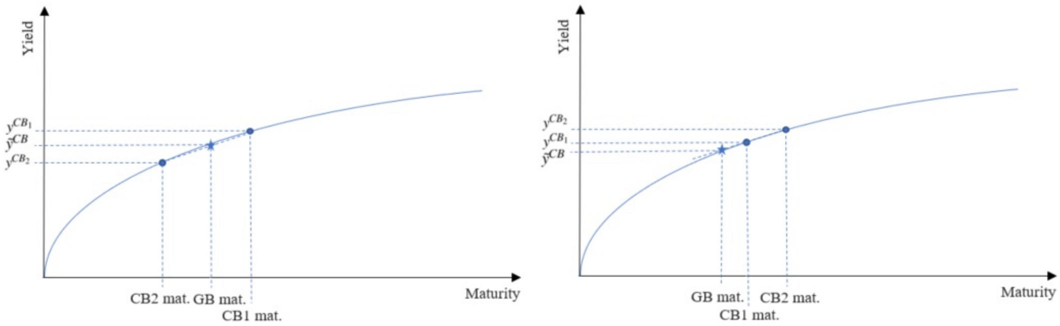
	Dependent variable: $\Delta\tilde{y}_{i,t}$			
	Linear regressions with White robust standard errors			
	(a)	(b)	(c)	(d)
Constant	0.001 (0.001)	-0.006^{***} (0.001)	-0.002^{***} (0.001)	-0.009^{***} (0.001)
ΔBA	-1.378^{***} (0.533)	-1.399^{***} (0.521)	-0.939^{*} (0.500)	0.578 (0.460)
Rating AA	-0.014^{***} (0.001)	-0.019^{***} (0.001)	-0.021^{***} (0.001)	
Rating A	-0.028^{***} (0.001)	-0.030^{***} (0.001)	-0.031^{***} (0.001)	
Rating BBB	-0.026^{***} (0.003)	-0.035^{***} (0.003)	-0.038^{***} (0.003)	
Non-rated	-0.006^{***} (0.001)	-0.009^{***} (0.001)	-0.002^{**} (0.001)	
Sector Financial	-0.010^{***} (0.001)	-0.009^{***} (0.001)	-0.006^{***} (0.001)	
Sector Utilities	0.027^{***} (0.002)	0.034^{***} (0.002)	0.041^{***} (0.002)	
AA × Government				-0.014^{***} (0.002)
AAA × Financial				0.006^{***} (0.001)
AA × Financial				-0.019^{***} (0.001)
A × Financial				-0.033^{***} (0.001)
NR × Financial				-0.002^{**} (0.001)
Currency AUD	0.003^{***} (0.001)	-0.0003 (0.001)		
Currency EUR	0.012^{***} (0.001)	0.009^{***} (0.001)		
Currency SEK	0.028^{***} (0.002)	0.014^{***} (0.001)		
Maturity	-0.002^{***} (0.0002)			
log(Issue Amount) (bn USD)	0.007^{***} (0.001)			
Observations	33,127	33,127	33,127	28,682
R^2	0.059	0.053	0.049	0.046
Adjusted R^2	0.059	0.052	0.049	0.045
Residual Std. Error	0.071 (df = 33114)	0.071 (df = 33116)	0.071 (df = 33119)	0.071 (df = 28675)
F Statistic	173.178^{***} (df = 12; 33114)	183.831^{***} (df = 10; 33116)	243.608^{***} (df = 7; 33119)	228.418^{***} (df = 6; 28675)
Note:				*p<0.1; **p<0.05; ***p<0.01

TABLE 2.17: **Results of an OLS regression of the yields on the characteristics of green and conventional bonds.** This table provides the results of an OLS regression with White standard errors performed on the yields of the green and the closest conventional bonds (CB1). Following specifications (a) and (b), the yields are explained by the characteristics of the bonds (rating, sector, currency, maturity) and a control for liquidity (bid-ask spread, BA), to which a dummy variable for green bonds and a firm fixed effect are added. The issue amount is not included in this regression since the bid-ask spread is used to control for bonds' liquidity.

	Dependent variable: Bonds' yields	
	(a)	(b)
Constant	1.633***	1.748***
	(0.010)	(0.015)
Green	−0.006**	−0.009***
	(0.002)	(0.003)
BA	80.880***	134.779***
	(4.009)	(5.169)
Maturity	0.082***	
	(0.001)	
Rating control	Yes	Yes
Sector control	Yes	Yes
Currency control	Yes	Yes
Firm control	Yes	Yes
Observations	66,254	66,254
R^2	0.905	0.890
Adjusted R^2	0.905	0.890
Residual Std. Error	0.312 (df = 66198)	0.336 (df = 66199)
F Statistic	11,515.150*** (df = 55; 66198)	9,928.532*** (df = 54; 66199)
Note:		*p<0.1; **p<0.05; ***p<0.01

TABLE 2.18: **Results of an OLS regression of the yields on the characteristics of green and conventional bonds matched with less stringent criteria.** This table provides the results of an OLS regression with White standard errors performed on the yields of the green and the matched conventional bonds with less stringent criteria than the main matching method. We require that both bonds have the same issuer, currency, coupon type, a maximum maturity difference of four years and an issue amount ratio of between one-quarter and four. The yields are explained by the characteristics of the bonds (rating, sector, currency, maturity, collateral, coupon type, bullet/callable structure) and the price percentage bid-ask spread as control for liquidity, to which a dummy variable for green bonds is added. The 179 bond pairs are studied over the same time period as the main regression: from July 18, 2013 to December 31, 2017.

	Dependent variable: Bonds' yields
Constant	3.284***
	(0.049)
Green	−0.042***
	(0.003)
Maturity	0.099***
	(0.001)
Bid-Ask	21.952***
	(0.560)
Rating control	OK
Sector control	OK
Currency control	OK
Collateral control	OK
Coupon type control	OK
Bullet/Callable control	OK
Observations	138,272
R^2	0.901
Adjusted R^2	0.901
Residual Std. Error	0.649 (df = 138226)
F Statistic	27,975.340*** (df = 45; 138226)
Note:	*p<0.1; **p<0.05; ***p<0.01



(A) Interpolation (B) Extrapolation

FIGURE 2.4: **Interpolation and extrapolation of the synthetic conventional bond yield.** This figure shows how we calculate the yield of the synthetic conventional bond through (a) a linear interpolation or (b) a linear extrapolation of the yields of CB1 and CB2 at the maturity date of the green bond.

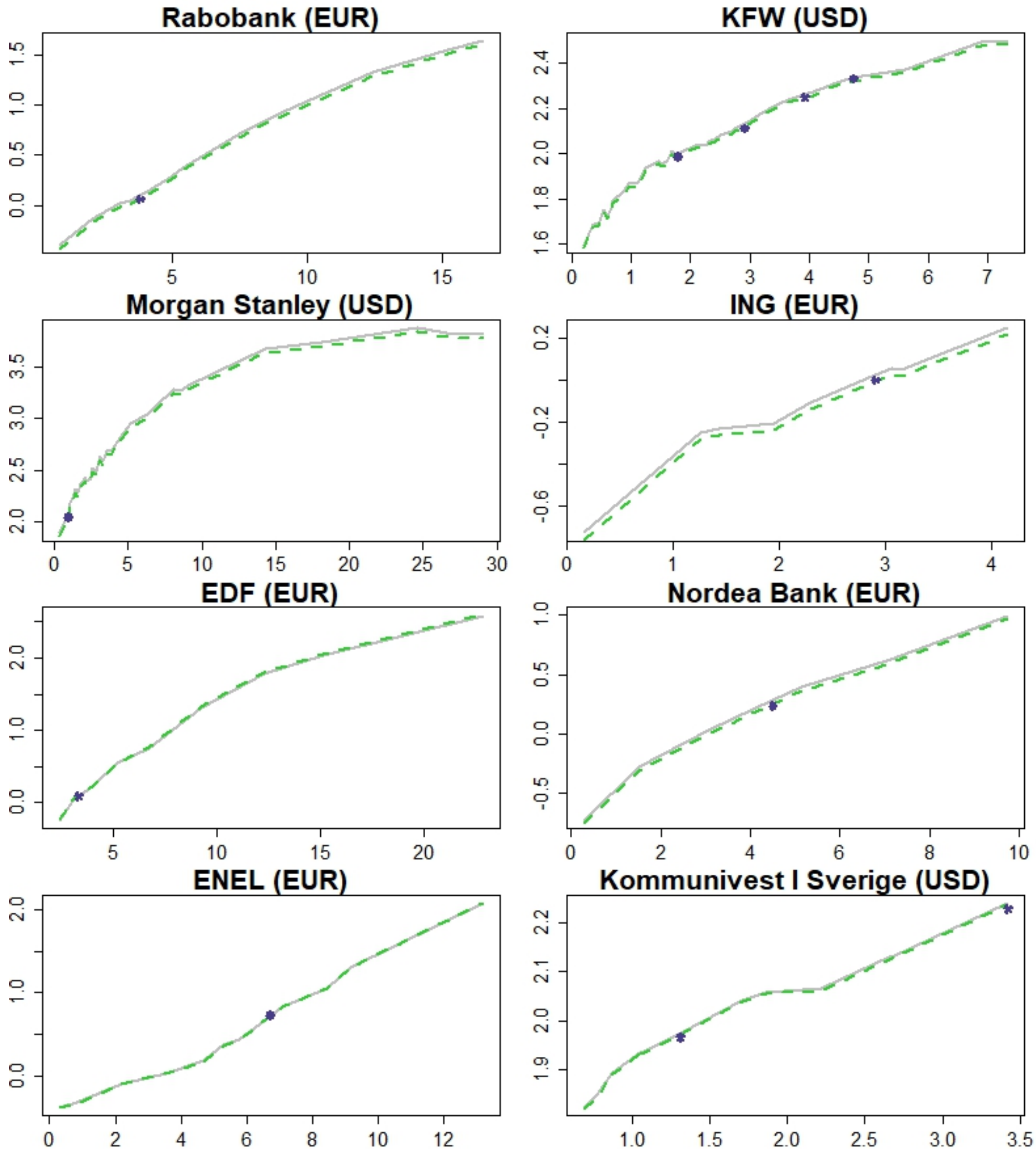
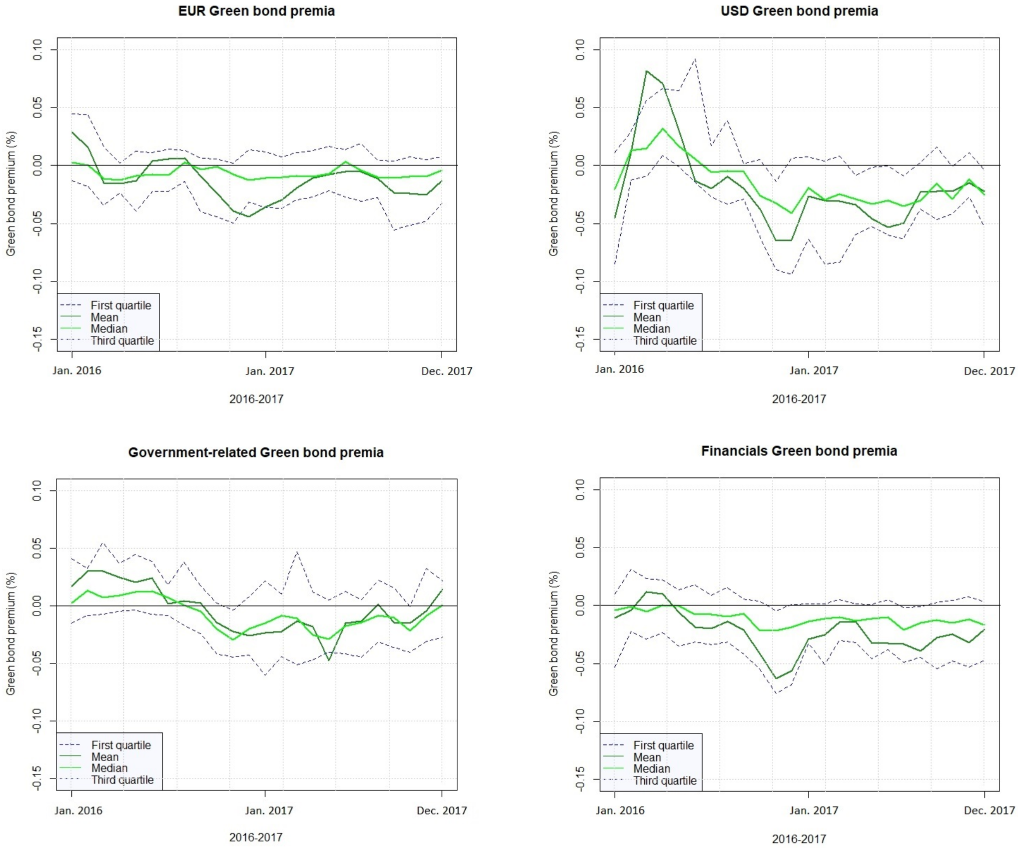


Figure 2.5: **The green bond yield curves.** This figure shows eight green bond curves (green dashed lines) reconstituted from conventional bond curves (grey solid lines) based on the parameters estimated in step 2 of regressions (b) performed on EUR and USD bonds. The market yields of the green bonds are also shown (blue stars).


EUR Green bond premia
USD Green bond premia
Government-related Green bond premia
Financials Green bond premia
Green bond premium (%)
0.10
0.05
0.00
-0.05
-0.10
-0.15
Jan. 2016
Jan. 2017
Dec. 2017
2016-2017
First quartile
Mean
Median
Third quartile

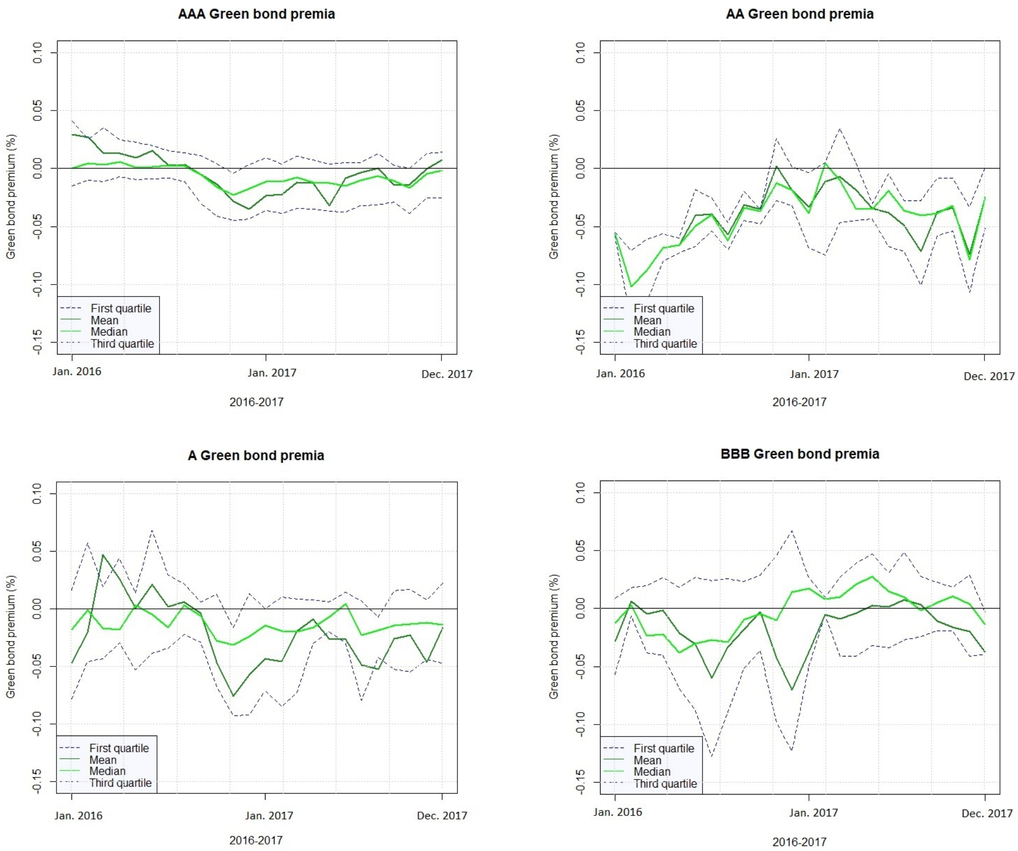


FIGURE 2.6: **Green bond premium dynamics per group.** These figures show the evolution over time of the mean (light green solid line), the median (dark green solid line) and the quartiles (dashed blue lines) of the green bond premia brokend down by groups during the years 2016 and 2017 based on the step 1 regression for the entire sample of green bonds. The groups are as follows: (i) EUR, (ii) USD, (iii) Government-related, (iv) Financials, (v) AAA, (vi) AA, (vii) A, and (viii) BBB green bonds.

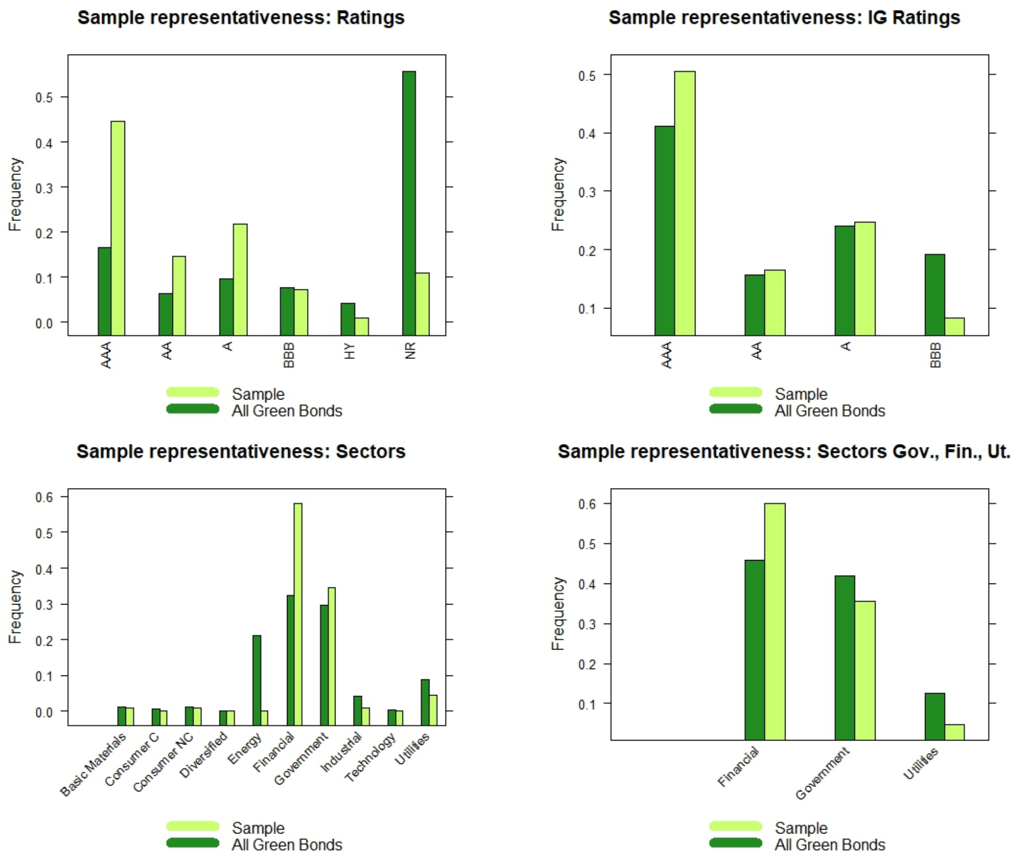


FIGURE 2.7: **Analysis of the representativeness of the matched sample.** This figure shows the distribution, by sector and rating, of green bonds in the matched sample (110 bonds) compared to the distribution of those in the global universe (1065 bonds). The right-hand figures correspond to the left-hand figures, and the comparison is focused on investment-grade bonds for the top figure and the Financial, Government, and Utilities sectors for the bottom figure.

2.10 Appendix B: Internet Appendix

TABLE 2.19: **Meaning of the currency acronyms**. This table gives the currencies and their acronyms.

ID	Currency
AUD	Australian Dollar
CAD	Canadian Dollar
CHF	Swiss Franc
CNY	Chinese Yuan
EUR	Euro
GBP	Great British Pound
INR	Indian Rupee
JPY	Japonese Yen
RUB	Russian Ruble
SEK	Swedish Krona
TRY	Turkish Lira
USD	US Dollar

TABLE 2.20: **Tests of the step 1 regression**. This table shows the tests performed in the step 1 regression controlled by the difference in the bid-ask spread: $\Delta\tilde{y}_{i,t} = p_i + \beta\Delta\text{BA}_{i,t} + \epsilon_{i,t}$. The results of the tests are presented in terms of the statistics, the P-values and their interpretation.

	Panel : $\Delta\tilde{y}$ controlled by ΔBA			
	Test	Statistic	P Value	Conclusion
Strict exogeneity	Su et al. (2016)		73.1%	Strict exogeneity
Fixed vs. Random effect	Hausman	16.011 (df=1)	6.3e-05	Fixed effect
Individual effect	F test	134.93 (df1=109, df2=37933)	<2.2e-16	Individual effect
	Wooldridge	3.5746	0.0004	Individual effect
	Breusch-Pagan	571880 (df=1)	<2.2e-16	Individual effect
	Honda	756.23	<2.2e-16	Individual effect
Serial correlation	Breusch-Godfrey Wooldridge	30717 (df=12)	<2.2e-16	Serial correlation
	Durbin Watson	0.21446	<2.2e-16	Serial correlation
	Wooldridge	1530	<2.2e-16	AR(1) serial correlation
Heteroscedasticity	Breusch-Pagan	129060 (df=110)	<2.2e-16	Heteroscedastitiy

TABLE 2.21: **Tests of the step 2 regression.**. This table presents the results of the tests performed using the step 2 regression (specifications (a), (b), (c) and (d)).

		$\widehat{p_i}$			
		(a)	(b)	(c)	(d)
Breusch-Pagan	Statistic	21.72 (df=11)	19.61 (df=9)	16.92 (df=6)	3.51 (df=5)
	P Value	0.03	0.02	0.01	0.62
Multicolinearity test	GVIF Rating	7.89	5.67	2.08	
	GVIF Sector	2.98	2.76	2.08	
	GVIF Sector × Rating				
	GVIF Currency	8.19	3.64		
	GVIF Maturity	1.35			
	GVIF log(Issue Amount)	4.92			
	$\sqrt{\text{GVIF}^{(1/(2\text{Df}))}}$ Rating	1.29	1.24	1.1	
	$\sqrt{\text{GVIF}^{(1/(2\text{Df}))}}$ Sector	1.31	1.29	1.2	
	$\sqrt{\text{GVIF}^{(1/(2\text{Df}))}}$ Sector × Rating				
	$\sqrt{\text{GVIF}^{(1/(2\text{Df}))}}$ Currency	1.42	1.24		
	$\sqrt{\text{GVIF}^{(1/(2\text{Df}))}}$ Maturity	1.16			
	$\sqrt{\text{GVIF}^{(1/(2\text{Df}))}}$ log(Issue Amount)	2.22			

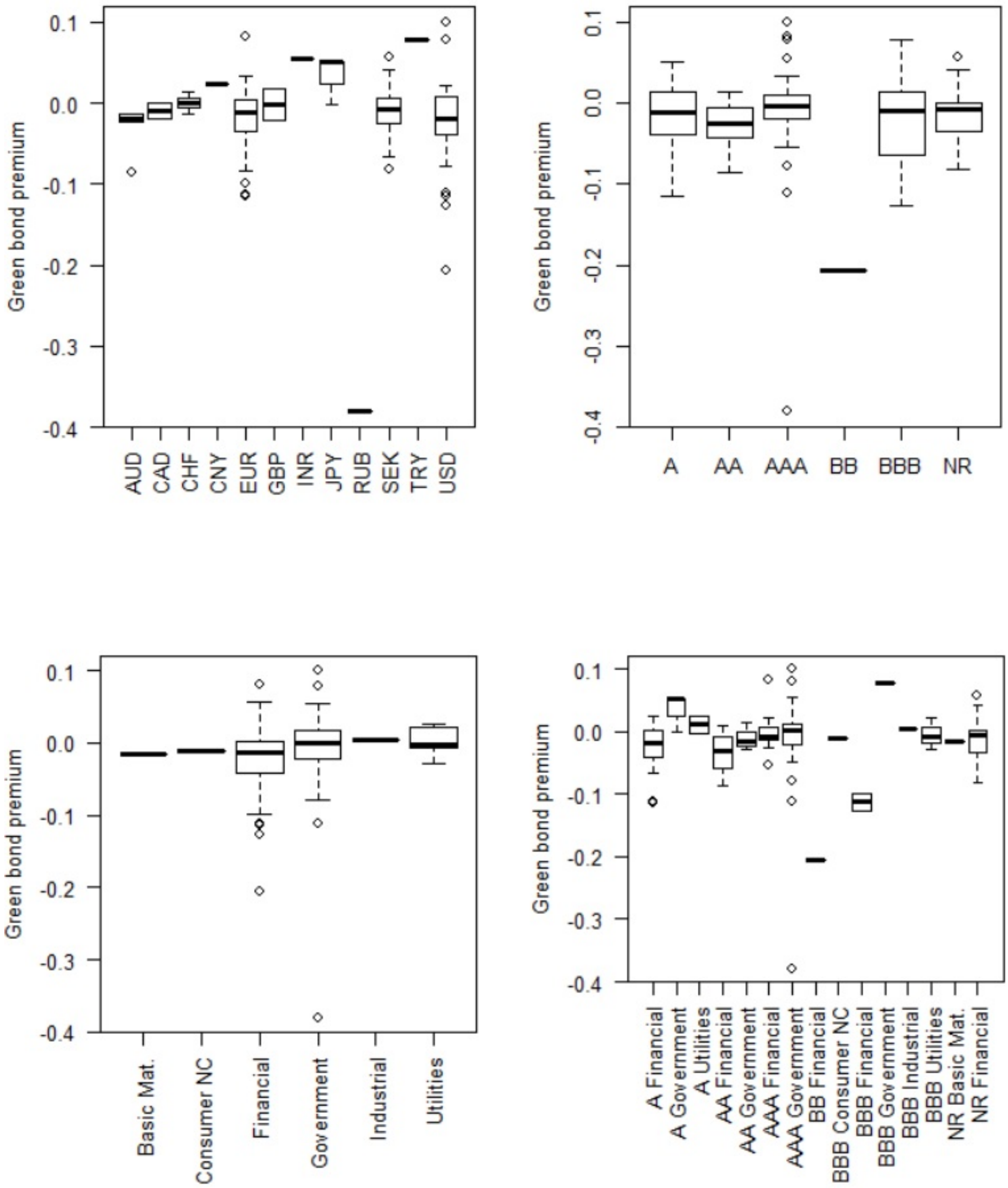


FIGURE 2.8: **Descriptive statistics of the matched sample.** This figure shows the boxplots of the matched sample by currency, rating, sector and sector × rating.

(A) EUR heatmap (B) USD heatmap

FIGURE 2.9: **Heatmaps of the green bond premia.** This figure presents two heatmaps of the green bond premia expressed by rating and sector for EUR and USD bonds, based on the step 2 regression (b).

TABLE 2.22: **Results of the step 1 regression using criteria #1 and #2 for the matching method.** This table gives the results of the step 1 regression: $\Delta\tilde{y}_{i,t} = p_i + \beta\Delta\mathrm{BA}_{i,t} + \epsilon_{i,t}$ using samples from the matching methods with criteria #1 and criteria #2. Newey-West and Beck-Katz robust standard error tests are performed. Matching criteria #1 require the conventional bonds to have (i) a maturity that is neither two years shorter nor two years longer than the green bond's maturity, (ii) an issue amount of less than four times the green bond's issue amount and greater than one-quarter of this amount, and (iii) an issue date that is at most six years earlier or six years later than the green bond's issue date. Matching criteria #2 require the conventional bonds to have (i) a maturity that is neither one (resp. two) year(s) shorter nor one (resp. two) year(s) longer than the green bond's maturity for CB1 (resp. CB2), (ii) an issue amount of less than twice the green bond's issue amount and greater than one-half of this amount, and (iii) an issue date that is at most two years earlier or two years later than the green bond's issue date.

	Dependent variable $\Delta\tilde{y}_{i,t}$	
	Matching 1	Matching 2
ΔBA	-9.881***	-0.039***
	(2.774)	(0.785)
Note:	*p<0.1; **p<0.05; ***p<0.01	

TABLE 2.23: **Results of the step 2 regression using criteria #1 and #2 for the matching method.** This table gives the results of the step 2 regression using samples from the matching methods with criteria #1 and criteria #2. White robust standard error tests are performed. Matching criteria #1 require the conventional bonds to have (i) a maturity that is neither two years shorter nor two years longer than the green bond's maturity, (ii) an issue amount of less than four times the green bond's issue amount and greater than one-quarter of this amount, and (iii) an issue date that is at most six years earlier or six years later than the green bond's issue date. Matching criteria #2 require the conventional bonds to have (i) a maturity that is neither one (resp. two) year(s) shorter nor one (resp. two) year(s) longer than the green bond's maturity for CB1 (resp. CB2), (ii) an issue amount of less than twice the green bond's issue amount and greater than one-half of this amount, and (iii) an issue date that is at most two years earlier or two years later than the green bond's issue date.

	Dependent variable: $\widehat{p_i}$	
	Regression (b)	
	White robust standard errors	
	Matching 2	M1 on M2's sample
Constant	−0.028	−0.021
	(0.017)	(0.016)
Rating AA	0.025	−0.004
	(0.016)	(0.012)
Rating A	0.004	0.002
	(0.028)	(0.026)
Rating BBB	−0.001	0.004
	(0.064)	(0.059)
Non-rated	−0.007	−0.007
	(0.029)	(0.028)
Sector Financial	−0.011	−0.018
	(0.026)	(0.023)
Sector Utilities	0.011	−0.006
	(0.063)	(0.056)
Currency AUD	0.003	0.001
	(0.022)	(0.026)
Currency EUR	0.008	0.019
	(0.019)	(0.020)
Currency SEK	0.038***	0.035**
	(0.013)	(0.016)
Observations	43	43
R^2	0.281	0.107
Adjusted R^2	0.112	−0.103
Residual Std. Error (df = 34)	0.031	0.036
F Statistic (df = 8; 34)	1.665	0.510
Note:		*p<0.1; **p<0.05; ***p<0.01

Chapter 3

Environmental Impact Investing[1]

[1] This chapter, which was co-written with Tiziano De Angelis and Peter Tankov, benefited from the valuable comments of Marco Ceccarelli, Patricia Crifo, Joost Driessen, Caroline Flammer, Ying Jiao, Sonia Jimenez Garces, Frank de Jong, Lionel Melin, Christian Robert, Bert Scholtens, Dimitri Vayanos, as well as participants at the Bachelier Finance Society One World Seminar for their valuable comments and suggestions. It has also been selected for the 2020 PRI Academic Week Conference. This work was supported financially by the Europlace Institute of Finance research grant and the EPSRC Grant EP/R021201/1.

This chapter shows how green investing spurs companies to reduce their greenhouse gas emissions by raising their cost of capital. Companies' emissions decrease when the proportion of green investors and their environmental stringency increase. However, heightened uncertainty regarding future environmental impacts alleviates the pressure on the cost of capital for the most carbon-intensive companies and pushes them to increase their emissions. We provide empirical evidence supporting our results by focusing on United States stocks and using green fund holdings to proxy for green investors' beliefs. When the fraction of assets managed by green investors doubles, companies' carbon intensity drops by 5% per year.

3.1 Introduction

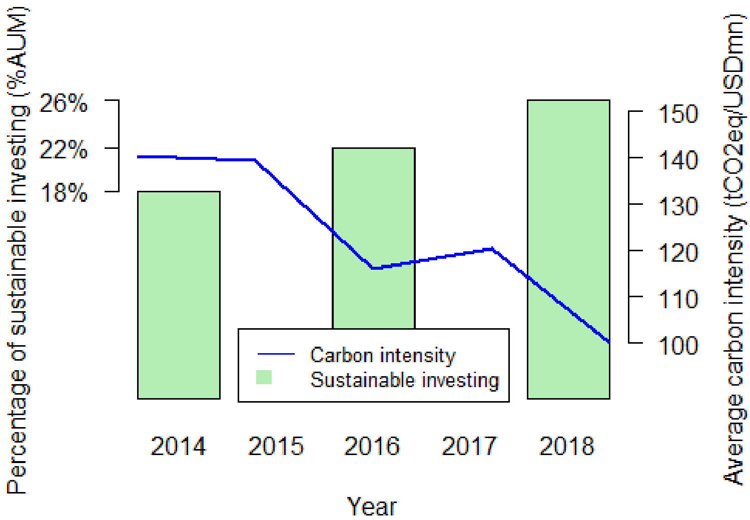


FIGURE 3.1: **Percentage of sustainable investments and average carbon intensity of the AMEX, NASDAQ, and NYSE stocks.** This figure presents the evolution of the proportion of sustainable investing relative to total managed assets over time, according to the Global Sustainable Investment Alliance (2018), as compared to the average carbon intensity of AMEX, NASDAQ and NYSE companies provided by S&P-Trucost between 2014 and 2018. The carbon intensity corresponds to the direct (scope 1 and 2) and indirect (upstream scope 3) greenhouse gas emissions of the companies, expressed in tCO2e per million dollars of revenue generated.

From 2014 to 2018, sustainable investments grew from 18% to 26% of the total assets under management (AUM) in the United States (U.S.) (US SIF, 2018) while, over the same period, the average carbon intensity of the companies listed on the National Association of Securities Dealers Automated Quotations (NASDAQ), American Stock Exchange (AMEX), and New York Stock Exchange (NYSE) decreased from 140 tCO2e/USDmn to 100 tCO2e/USDmn (Figure 3.1).[2] The downward trend in corporate greenhouse gas intensity may be driven by several factors, such as the reduction

[2]The carbon intensity of a company is defined as its emission rate relative to its revenue over one year. This metric is expressed in terms of tons of equivalent carbon dioxide per million dollars.

in green technology prices, tighter environmental regulation, consumer pressure for more sustainable practices, or the pressure exerted by green investors.[3] The two main channels through which green investors can have an impact on companies' practices are *environmental screening* and shareholder engagement. Through environmental screening, by underweighing or excluding the most carbon-intensive[4] companies from their investment scope, green investors increase these companies' cost of capital (Pastor, Stambaugh, and Taylor, 2019; Pedersen, Fitzgibbons, and Pomorski, 2019; Zerbib, 2019a) and can push them to reform. We focus on the specific channel of environmental screening (referred to as *green investing* hereinafter) and address the issue of impact investing by answering the following questions: does green investing push companies to reduce their greenhouse gas emissions? If so, what are the factors that lead companies to mitigate their emissions?

We show that the development of green investing—both in terms of the proportion of AUM and the environmental stringency of green investors—pushes companies to reduce their greenhouse gas emissions by raising their cost of capital. By internalizing the negative impact of green investors on their financial valuation, companies are incentivized to pay a cost to mitigate their emissions by adopting less carbon-intensive technologies and thereby lowering their cost of capital. However, we also show that investors' uncertainty regarding future environmental impacts reduces the incentive for carbon-intensive companies (also referred to as *brown companies* hereinafter) to mitigate their emissions.

We develop a dynamic equilibrium model populated by: (i) 2 different groups of constant absolute risk aversion (CARA) investors who determine their optimal allocation by maximizing their expected wealth at a given terminal date, but differ in their environmental beliefs, and (ii) n companies with different marginal costs of reducing their greenhouse gas emissions (referred to as *marginal abatement cost* hereinafter). Out of the two groups of investors, one is a group of *green investors* and the other of *regular investors*. Green investors differ from regular ones in that they internalize the expected financial impact of future environmental externalities of companies in which they invest.

In the first version of our model, green investors internalize *deterministic* environmental externalities that can be positive or negative and reflect the exposure of companies to: (a) environmental transition risks, such as the rise in the carbon price (Jakob and Hilaire, 2015); (b) physical risks, such as the deterioration of the production fleet due to an increase in the frequency and intensity of natural disasters (Arnell and Gosling, 2016); or (c) litigation risks (Hunter and Salzman, 2007).

At the initial date, $t = 0$, each company chooses a deterministic greenhouse gas emissions schedule—corresponding to a given corporate strategy—up to a final date

[3] Green investing is a form of socially responsible investing aimed at contributing to environmental objectives by internalizing environmental externalities.

[4] We refer to *carbon-intensive* companies and companies with high *greenhouse gas emissions* interchangeably since carbon dioxide is the main gas contributing to global warming. In the United States (U.S.), it accounted for more than 80% of the total emissions in 2018: `https://www.epa.gov/ghgemissions/overview-greenhouse-gases`.

T. This setup is consistent with the fact that a company reforms its environmental practices over a sufficiently long period of time. Choosing the optimal emissions schedule for a company involves a trade-off between reducing its emissions to broaden its investor base and limiting this reduction to contain the cost of reform. Therefore, each company determines its emissions schedule by maximizing its expected utility, which breaks down into two criteria: (i) its future valuation at the targeted emissions schedule irrespective of the cost of reform and (ii) the cost of reform to achieve the targeted emissions schedule. In addition, each company's choice of emissions schedule also accounts for the strategies adopted by all other companies, hence reducing the companies' problem to a nonzero-sum game. This framework notably differs from standard heterogeneous belief models because the choice of each company's emissions schedule directly affects the parameter on which investors disagree—companies' environmental externalities.

We obtain a tractable formula of the equilibrium asset prices and show that they are adjusted by an *externality premium*. Through this premium, the price increases with the *financial impact of future environmental externalities* (referred to as *environmental externalities* hereinafter) internalized by green investors, which can be positive or negative, and with the proportion of green investors' wealth relative to total wealth. Therefore, all else being equal, the asset price of a *brown* company will be lower than that of a *green* company. Conversely, the equilibrium returns increase when the environmental externalities are negative and decrease when they are positive.

We characterize companies' optimal emissions schedule in a general setup and provide their explicit expression when environmental externalities are measured by a quadratic decreasing function of the company's emissions. At equilibrium, emissions decrease as function of the proportion of assets managed by the green investors and their environmental stringency and increase with the cost of reducing environmental externalities. In addition, companies' emissions decline convexly over time, with a slope that becomes steeper with higher time preference rates. We calibrate the model on the AMEX, NASDAQ, and NYSE stocks between 2006 and 2018 using the carbon intensity of companies as a proxy for their emissions. We then simulate the mitigation of emissions in several scenarios by considering a company that reduces its emissions by an average of 1% per year over a 20-year period when green investments account for 25% of the AUM. For example, we show that this company reduces its emissions by an average of 4.4% per year over the same period when green investments account for 50% of the AUM.

These results have a three-fold normative implication for public authorities. First, they highlight their role in supporting the development of green investments—in particular with regard to the definition of rigorous standards for environmental impact assessments—to foster and increase impact investing. This stake is consistent with the recommendations of the European Union High Level Expert Group on Sustainable Finance (2018) and the European Commission (2018)'s Action Plan, particularly regarding the development of a green taxonomy and an official standard for green bonds. Second, these results emphasize the major role of transparency and access to information on the environmental impacts of companies to enable green investors to internalize environmental externalities as accurately as possible, thereby maximizing their impact on the most carbon-intensive companies. Third, they highlight the importance of low-cost access to greener technological solutions (i.e., reducing the marginal abatement cost) as an incentive for companies to mitigate their environmental impacts. Specifically, industries for which green alternatives are limited, such as cement or aircraft, face a structural barrier to which the increase in research and development (R&D) is an essential response.

From the investors' viewpoint, these results suggest that they can increase their impact on companies by raising their environmental requirements, for example by restricting the range of companies which they invest in or by significantly underweighing the most carbon-intensive companies. In addition, impact investing is financially beneficial if investors favor companies that will reduce their environmental footprint, for example companies that will have access to more efficient or cheaper decarbonization technologies.

We extend the first version of our model to the case where green investors also internalize *uncertainty* about the realization of future environmental externalities. Environmental risks, such as a rise in the carbon price or the occurrence of natural disasters, are peculiar in that their distribution is generally non-Gaussian and fat-tailed (Weitzman, 2009; Barnett, Brock, and Hansen, 2020). Therefore, we model future environmental risk internalized by green investors as a stochastic jump process. Since the financial impact associated with the transition risk is more pronounced for the most carbon-intensive companies, we assume that the size of the jumps depends on the companies' emissions. We characterize the optimal allocation of green and regular investors as the unique solution of an equilibrium equation and express the returns in equilibrium. We give a tractable expression of the first-order approximation of equilibrium allocations and expected returns when the frequency of environmental shocks is high, but the financial impact of each shock is small. This setup allows us to analyze the model with environmental uncertainty as a marginal deviation from the deterministic case. The environmental uncertainty pushes green investors to mitigate their absolute allocation to risky assets: on average, they reduce their allocation to green assets and increase their allocation to brown assets. Therefore, compared to the deterministic setup, the equilibrium expected returns decrease for brown companies and increase for green companies because the pressure exerted by green investors lessens. As a consequence, compared to the first version of our model, the companies with the highest emissions adjust their greenhouse gas emissions upwards to benefit from the narrowing of the cost of capital differential with the companies with the least emissions. These results suggest that green investors can increase their impact by pushing companies to enhance disclosure on environmental issues, thereby reducing uncertainty about future environmental externalities. In addition, green investors can benefit from financial gains by investing in green companies for which information on their environmental footprint is still poorly available.

We support our results with empirical evidence. Focusing on the case where green investors internalize deterministic environmental externalities, we estimate both the asset pricing and the emissions schedule equations for the AMEX-, NASDAQ- and NYSE-listed companies between 2006 and 2018. First, we follow Zerbib (2019a) to construct a proxy for the environmental externalities from the holdings of 348 green funds investing in U.S. equities as of December 2018. For each industry at each date, we define this proxy as the relative difference in weight of the industry under consideration between the allocation of the aggregated green funds and the industry breakdown of the investment universe. The more green funds underweigh an industry, the more they internalize a negative financial impact of environmental externalities; the converse is true when they overweigh an industry. We show that the environmental externality premium is significant, and we estimate it for each Standard Industrial Classification (SIC) industry. For example, because they internalize large negative externalities for the coal industry, green investors induce a 0.84% annual increase in returns on the coal industry compared to the electrical equipment industry. Second, to estimate the dynamics of companies' emissions over a one-year horizon, we construct a proxy for the proportion of green investors' AUM as the proportion of the market value of the U.S. stocks in the 348 green funds relative to the market value of the investment universe. We approximate the emissions of companies using their carbon intensity. By estimating the specification derived from the model, we show that the proportion of green investments has a significant negative impact on the carbon intensities of the companies: when the former doubles, the latter falls by 5% over a one-year horizon.

Related literature. This paper contributes to two strands of existing literature on sustainable investing. First, from an asset pricing perspective, we clarify the relationship between the development of sustainable investing[5] and asset returns. The empirical literature on the effects of Environment, Social and Governance (ESG) integration on asset returns is mixed: some authors highlight the negative impact of ESG performance on asset returns, while others suggest a positive relationship or find no significant impact.[6] Three recent papers by Pastor, Stambaugh, and Taylor (2019), Pedersen, Fitzgibbons, and Pomorski (2019) and Zerbib (2019a) study this relationship using a single-period model with investor disagreement. They show that the stock

[5]Sustainable investing can be motivated by pecuniary or non-pecuniary motives (Krüger, Sautner, and Starks, 2020). Riedl and Smeets (2017) and Hartzmark and Sussman (2020) highlight the positive effect of sustainable preferences on sustainable fund flows. Pro-social and pro-environmental preferences also impact asset returns since they induce an increase in the return on sin stocks (Hong and Kacperczyk, 2009), a decrease in the return on impact funds (Barber, Morse, and Yasuda, 2018) and a decrease in the return on bonds (Baker et al., 2018; Zerbib, 2019b).

[6]For negative impacts, see Brammer, Brooks, and Pavelin (2006), Renneboog, Ter Horst, and Zhang (2008), Sharfman and Fernando (2008), ElGhoul et al. (2011), Chava (2014), Barber, Morse, and Yasuda (2018), Bolton and Kacperczyk (2020) and Hsu, Li, and Tsou (2019). For positive impacts, see Derwall et al. (2005), Statman and Glushkov (2009), Edmans (2011), Eccles, Ioannou, and Serafeim (2014), Krüger (2015) and Statman and Glushkov (2016). Finally, Bauer, Koedijk, and Otten (2005), Galema, Plantinga, and Scholtens (2008) and Trinks et al. (2018) find no significant impact.

returns of the most carbon-intensive companies are increased by a positive premium. We contribute to this emerging literature by developing a dynamic model in which green investors internalize non-Gaussian environmental uncertainty. Compared to the case where green investors internalize deterministic externalities, we show that the environmental risk uncertainty internalized by green investors increases asset returns but narrows the return differential between the most and least polluting companies.

We also contribute to the emerging literature on impact investing. In a seminal paper, by constructing a single-period model in which green investors have the ability to exclude the most polluting companies, Heinkel, Kraus, and Zechner (2001) show that the latter are pushed to reform because exclusionary screening negatively impacts their valuations. Chowdhry, Davies, and Waters (2018) study the optimal contracting for a company that cannot commit to social objectives and show that impact investors must hold a large enough financial claim to incentivize the company to internalize social externalities. Oehmke and Opp (2019) develop a general equilibrium model and show that, in addition to regular investors, sustainable investors enable a scale increase for clean production by internalizing social costs. Landier and Lovo (2020) also build a general equilibrium model where sustainable investors have the same return as regular investors and where markets are subject to search friction. They show that the presence of an ESG fund forces companies to partially internalize externalities. Through an asset pricing model, Pastor, Stambaugh, and Taylor (2019) show that green investors increase firms social impact through two channels: greener firms have higher market values and lower cost of capital. We also address the problem from an asset pricing perspective by constructing a dynamic multiperiod model in which returns are stochastic and the environmental risk internalized by green investors is stochastic and non-Gaussian. In our framework, investors and companies enter into a dynamic nonzero-sum game to determine their equilibrium strategies. We show that the increase in the proportion of green investments and the environmental stringency of green investors affect companies' emissions from the first dollar invested and that the dynamic of emission mitigation is convex over time. In addition, when the environmental risk uncertainty is internalized by green investors, brown companies have less incentive to mitigate their emissions. We provide empirical evidence supporting our results by using green fund holdings to proxy for green investors' beliefs.

The remainder of this paper is structured as follows. The second section presents an economy with greenhouse gas emitting companies and heterogeneous beliefs. Section 3 details the equilibrium pricing equations and companies' emissions schedules when green investors internalize deterministic environmental externalities. Section 4 extends the model to non-Gaussian stochastic environmental externalities. Section 5 provides empirical evidence and present the calibration of the model. Section 6 concludes the paper. The proofs are detailed in the Appendix.

3.2 A simple economy with greenhouse gas emitting companies and heterogeneous beliefs

We develop a simple model of heterogeneous beliefs in which the environmental externalities are internalized by green investors as deterministic. We introduce the dynamics of the assets available on the market and the heterogeneous beliefs about environmental externalities of three types of agents—a group of regular investors, a group of green investors and n companies. We then present the investors' and companies' optimization programs.

3.2.1 Securities market

In this section, we consider a financial market consisting of n risky stocks and a risk-free asset, which is assumed to be free of arbitrage and complete. The risk-free asset is in zero net supply and we assume that the risk-free rate is zero without loss of generality. Each stock $i \in \{1, \ldots, n\}$ is in positive net supply of one unit and is a claim on a single liquidating dividend D_T^i at horizon T. We denote by $D_T \in \mathbb{R}^n$ the vector of dividends paid at date T. The terminal dividend is only driven by the sequence of cash flow news, $\sigma_t dB_t$ ($t \in [0, T]$), and reads

$$D_T = D_0 + \int_0^T \sigma_t dB_t. \tag{3.1}$$

Here, $(B_s)_{s\in[0,T]}$ is a standard n-dimensional Brownian motion defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ equipped with a filtration $(\mathcal{F}_s)_{s\in\mathbb{R}_+}$. For each $s \in [0, T]$, σ_s is a deterministic, $n \times n$, invertible matrix; and D_0 is the vector of the initial dividend forecast (i.e., $D_0 = \mathbb{E}[D_T|\mathcal{F}_0]$), of which the value is public information at time $t = 0$. To simplify the analysis without loss of generality, we assume that the dividend trend is zero under the probability $\mathbb{P}$. Denoting by $(p_t)_{t\in[0,T]}$ the equilibrium price process in $\mathbb{R}^n$, we assume $p_T = D_T$. We also denote the dividend forecast in $t \in [0, T]$ by

$$D_t = \mathbb{E}[D_T|\mathcal{F}_t] = D_0 + \int_0^t \sigma_s dB_s. \tag{3.2}$$

This Gaussian continuous-time specification of the dividend dynamics is consistent with previous literature on heterogeneous beliefs dealing with investors' reaction to good and bad news (Veronesi, 1999), excess confidence (Scheinkman and Xiong, 2003) and extrapolation bias (Barberis et al., 2015).[7] We choose a setup with Gaussian dividends and prices because we seek to explicitly characterize the equilibrium price, which is used by companies to endogenously determine their prospective greenhouse gas emissions.

[7] Other articles on heterogeneous beliefs adopt this same setup in discrete time such as Hong and Stein (1999), Barberis and Shleifer (2003) and Barberis et al. (2018).

3.2.2 Investors' and companies' beliefs

The market is populated by two types of investors, *regular* and *green*, who have different expectations regarding companies' future cash flow news. Regular investors only consider the information related to the flow of financial news. Therefore, under their probability measure $\mathbb{P}^r$, B_t is a Brownian motion, and, conditional on the information in t, the expectation of the future cash flow news, $\int_0^t \sigma_s dB_s$, is zero. Denoting by $\mathbb{E}_t^r$ this conditional expectation,

$$\mathbb{E}_t^r(D_T) = D_t. \tag{3.3}$$

From the point of view of the properties of the cash flow news, $\sigma_s dB_s$, there is no difference between measures $\mathbb{P}$ and $\mathbb{P}^r$, and we can simply assume $\mathbb{P} = \mathbb{P}^r$. However, it should be noted that $\mathbb{P}$ is a technical device and, as such, we make no assumptions about the realistic nature of this measure, which means that the expectations of regular investors are not necessarily consistent with the realized events.

In contrast, green investors internalize the financial impact of the expected environmental externalities of the companies in which they invest. These environmental externalities can be negative and correspond to several types of risks: an environmental transition risk related to a rise in carbon price (Jakob and Hilaire, 2015; Battiston et al., 2017) or the change in consumer practices (Welsch and Kühling, 2009); the exposure of a company to physical risks, which are essentially the expected impact of natural disasters on its infrastructure (Mendelsohn et al., 2012; Arnell and Gosling, 2016); and the litigation risk related to the company's environmental impact (Hunter and Salzman, 2007). These externalities can also be positive and reflect, for example, a company's pioneering environmental positioning in an economic segment or its limited exposure to physical risks. The internalization of such environmental externalities may also be driven by non-pecuniary motives (Riedl and Smeets, 2017; Hartzmark and Sussman, 2020) and be characterized by the overweight and underweight of financial assets on ethical grounds. As a result, in addition to the cash flow news, green investors internalize, under their probability measure, the expected financial impact of future environmental externalites at date $t \in [0, T]$. The latter is expressed by

$$\int_t^T \theta(\psi_s) ds. \tag{3.4}$$

Here, $\theta(\psi_t) \in \mathbb{R}^n$ is the vector of the *financial impact of environmental externalities* (referred to as *environmental externalities* hereinafter), and ψ_t is the vector of the greenhouse gas emissions at date t. We refer to greenhouse gas emissions for simplicity, but ψ can be seen as a measure of relative emissions compared to a level of production (e.g., carbon intensity) or a sector average (e.g., *avoided emissions*), or more generally as an environmental rating. We assume $\psi \in F([0, T], \mathbb{R}_+^n)$, where $F([0, T], \mathbb{R}_+^n)$ is the set of Borel-measurable functions of $[0, T]$ in $\mathbb{R}_+^n$. For each $i \in \{1, ..., n\}$, we assume that the i-th coordinate of vector θ is of the form $\theta_i(\psi_t^i)$. This means that the i-th asset is affected by the emissions of the i-th company at time t. Naturally, we also assume that θ_i is a decreasing function of ψ_t^i so that higher emissions correspond to stronger negative externalities. As a consequence, green investors internalize their environmental beliefs regarding the i-th company by paying a price for the i-th stock at time t that is higher (if $\int_t^T \theta_i(\psi_s^i)ds$ is positive) or lower (if $\int_t^T \theta_i(\psi_s^i)ds$ is negative) than the value of the future dividend (see Equation (3.2)). Under the green investors' probability measure, $\mathbb{P}^g$, the process D_t has deterministic drift $\int_0^t \theta(\psi_s)ds$. Denoting by $\mathbb{E}_t^g$ the expectation of the green investors conditional on the information in t, we have

$$\mathbb{E}_t^g(D_T) = D_t + \int_t^T \theta(\psi_s)ds. \tag{3.5}$$

Along with the two types of investors, we also introduce the productive sector by modelling the views of the companies about the n assets available on the market. As in Oehmke and Opp (2019), company managers (referred to as *companies* hereinafter) also have subjective beliefs about the impact of environmental externalities on the dividend dynamics of each of the n companies. We denote by $\theta^c(\psi_t)$ the vector of the environmental externalities internalized by all companies. Under the companies' probability measure, $\mathbb{P}^c$, the process D_t has deterministic drift $\int_0^t \theta(\psi_s)ds$. Denoting by $\mathbb{E}_t^c$ the expectation of the companies conditional on the information in t, we have

$$\mathbb{E}_t^c(D_T) = D_t + \int_t^T \theta^c(\psi_s)ds. \tag{3.6}$$

3.2.3 Investors' preferences and optimization

Regular and green investors have CARA preferences. Subject to their budget constraints, investors maximize the expected exponential utility of their terminal wealth[8] W_T, which reads

$$\mathbb{E}^j(1 - e^{-\gamma^j W_T^j}), \quad \gamma^j > 0, \quad j \in \{r, g\},$$

where the superscripts r and g refer to the regular and green investors, respectively, and γ^js are their absolute risk aversions. The wealth processes follow the dynamics

$$W_t^r = w^r + \int_0^t (N_s^r)^\top dp_s, \qquad W_t^g = w^g + \int_0^t (N_s^g)^\top dp_s, \tag{3.7}$$

where N_t^r and N_t^g are quantities of assets held by the regular and green investors, respectively, at time t, and prices $(p_t)_{t\in[0,T]}$ are determined by the market clearing condition. The initial wealth levels of regular and green investors are denoted by w^r and w^g, respectively, and symbol $\top$ stands for the transposition operator.

In what follows, we denote by γ^* the global risk aversion, defined by $\frac{1}{\gamma^*} = \frac{1}{\gamma^r} + \frac{1}{\gamma^g}$, and set $\alpha = \frac{\gamma^r}{\gamma^r+\gamma^g}$ and $1 - \alpha = \frac{\gamma^g}{\gamma^r+\gamma^g}$. To simplify the interpretation of the impact

[8] As Atmaz and Basak (2018) point out, investors' preferences are based on their wealth at the terminal date rather than on intermediate dates, which would have led to endogenizing the interest rate in equilibrium.

of green and regular investors' wealth on the variables in equilibrium, and without losing generality, we assume that green and regular investors have equal relative risk aversions; that is, $\gamma^R = \gamma^g w^g = \gamma^r w^r$, where γ^R denotes the relative risk aversion. In this case, α is the proportion of the green investors' initial wealth at $t = 0$, and $1 - \alpha$ is that of the regular investors; that is, $\alpha = \frac{w^g}{w^g + w^r}$ and $1 - \alpha = \frac{w^r}{w^g + w^r}$.

3.2.4 Companies' utility and optimization

As we are interested in the impact of green investors on corporate emissions, we focus on the financial motives of companies and do not build a model incorporating the effect of consumer preferences or regulatory pressure. A company's decision to reform so as to reduce its emissions is usually made over a sufficiently long period of time. For example, the transformation of a generating fleet by an electric utility or the development of a line of electric vehicles by a car manufacturer is the result of a long-term decision. Therefore, at $t = 0$, the i-th company chooses its emissions schedule $(\psi_t^i)_{t\in[0,T]}$ up to the horizon T so as to optimize two criteria throughout the period: (i) maximize its future valuation at the targeted emissions schedule irrespective of the cost of reform and (ii) minimize the cost of reform to achieve the targeted emissions schedule. In our setup, we endogenize companies' emissions through their market value: the asset price of the i-th company, $p^i(\psi)$, is a function of the vector of all companies' emissions because green investors allocate their wealth according to the whole vector of environmental externalities, $\theta(\psi)$, which also affects the price of the i-th asset. For the i-th company, we denote by c_i the marginal abatement cost in $t = 0$ related to a decrease in its emissions over the period $[0, T]$,[9] and by ρ the rate of time preference; $\bar{\psi}^i$ is the company's initial level of emissions, and ψ^{-i} represents the emissions schedule of the other companies. The companies have a linear utility and risk neutral preferences (Lambrecht and Myers, 2017; Binsbergen and Opp, 2019). Therefore, at $t = 0$, the i-th company chooses $(\psi_t^i)_{t\in[0,T]}$ so as to maximize the following objective function:

$$\mathcal{J}^i(\psi^i, \psi^{-i}) = \mathbb{E}^c \left[\int_0^T e^{-\rho t} \Big(p_t^i(\psi^i, \psi^{-i}) + c_i \left(\psi_t^i - \bar{\psi}^i \right) \Big) dt \right]. \tag{3.8}$$

This optimization program is in line with the approach of Heinkel, Kraus, and Zechner (2001) in the context of a multi-period model where the company's environmental impact is endogenized.

Maximizing the sum of the market values over the entire period is consistent with Pastor, Stambaugh, and Taylor (2019) as well as recent studies on Chief Executive Officers' (CEO) compensation plans: Larcker and Tayan (2019) report that "stock-based performance awards have replaced stock options as the most prevalent form of equity-based pay." In addition, CEOs are generally required to hold their companies' stocks. Managers are therefore directly interested in the valuation of their company's

[9] A non-constant marginal abatement cost can be considered without complicating the calculations. To simplify the interpretation, we present the case where the marginal abatement cost is constant.

stock price at each date, which endogenizes the financial impact of the company's emissions schedule.

The marginal abatement cost, c_i, corresponds to the company's benefit from not reducing its emissions by one unit over the period. Thus, by reducing its emissions by x, the company reduces its utility by $c_i x$. It should be noted that a company's motivations for reform in this model can be interpreted more broadly than solely in pecuniary terms. Indeed, the cost, c_i, can be regarded as a financial cost net of (i) the non-pecuniary motives of shareholders or managers and (ii) the incentives to reform due to consumer and regulatory pressure.

The optimal emissions schedule, ψ^*, corresponds to the Nash equilibrium where each company $i \in \{1, ..., n\}$ determines $\psi^{i,*}$ in $t = 0$, such that

$$\mathcal{J}^i(\psi^{*,i}, \psi^{*,-i}) \geq \mathcal{J}^i(\psi^i, \psi^{*,-i}), \quad \text{for all } \psi^i \in F([0,T], \mathbb{R}_+). \tag{3.9}$$

Table 3.1 summarizes the preferences and optimization programs of the different players and their interactions in the economy we model.

TABLE 3.1: **Summary of agents' actions.** This table summarizes the optimization programs of each agent as well as their interactions between $t = 0$ and $t = T$.

Date	Agent	Choose	Given
At $t = 0$	Companies	Their deterministic emissions schedule from 0 to T	- Their expected market capitalization between 0 and T - The cost of reducing their emissions
$\forall t \in [0, T]$	Regular investors	Their asset allocation	- The observed cash flow news between 0 and t, and the expected cash flow news between t and T
$\forall t \in [0, T]$	Green investors	Their asset allocation	- The observed cash flow news between 0 and t, and the expected cash flow news between t and T - Companies' emissions schedule between t and T

3.3 Equilibrium in the presence of greenhouse gas emitting companies and heterogeneous beliefs

This section presents the asset prices and returns in equilibrium in the simple model developed in Section 3.2. The optimal allocations of regular and green investors are also detailed. Finally, we characterize the optimal dynamics of companies' emissions, for which we give a tractable formula when the environmental externalities are quadratic.

3.3.1 Equilibrium stock price and return

In equilibrium, investors choose their allocations to maximize their expected utility, and equilibrium prices are determined such that the market clears. Denoting $\Sigma_t = \sigma_t^\top \sigma_t$, and letting $\mathbf{1}$ be the vector of ones of length n, Proposition 7 gives the equilibrium prices and allocations.

Proposition 7. *Given an emissions schedule $(\psi_t)_{t\in[0,T]}$, the asset price in equilibrium reads*

$$p_t = D_t - \int_t^T \mu_s ds \quad \textit{with} \quad \mu_t = \gamma^* \Sigma_t \mathbf{1} - \alpha\theta(\psi_t), \tag{3.10}$$

where $-\alpha\theta(\psi_t)$ is the externality premium. The optimal number of shares for the regular and green investors are

$$N_t^r = (1-\alpha)\left(\mathbf{1} - \frac{1}{\gamma^g}\Sigma_t^{-1}\theta(\psi_t)\right) \quad \textit{and} \quad N_t^g = \alpha\left(\mathbf{1} + \frac{1}{\gamma^r}\Sigma_t^{-1}\theta(\psi_t)\right), \tag{3.11}$$

respectively.

The different beliefs of green investors introduce an *externality premium*, which is an additional drift in the price dynamics. When future environmental externalities are negative, the price is adjusted downward proportionally to the fraction of the initial wealth held by the green investors, α. Conversely, when future externalities are positive, green investors bid up the price, which is adjusted upwards. This same dynamic can be expressed in terms of expected dollar returns (referred to as *expected returns* hereinafter), $\mu_t dt$. Since θ_i is a decreasing function of ψ_t^i, expected returns increase with companies' emissions. The externality premium on asset returns can be positive ($\theta_i(\psi^i) < 0$) or negative ($\theta_i(\psi^i) > 0$). This result is supported by extensive empirical evidence, including Renneboog, Ter Horst, and Zhang (2008), Sharfman and Fernando (2008), Chava (2014), Barber, Morse, and Yasuda (2018), Bolton and Kacperczyk (2020) and Hsu, Li, and Tsou (2019). It is also consistent with the theoretical works of Pastor, Stambaugh, and Taylor (2019), Pedersen, Fitzgibbons, and Pomorski (2019) and Zerbib (2019a), who show, through a single-period model, that expected returns increase along with a company's environmental impact as green investors require a higher cost of capital. Therefore, investors can increase their profits by investing in companies that will mitigate their carbon emissions, ψ.

The number of shares purchased by investors is also adjusted by the environmental externalities. Green investors overweigh assets with the higher positive externalities and underweigh or short assets with the higher negative externalities. Regular investors have a symmetrical allocation by providing liquidity to green investors. This result is consistent with optimal allocations in disagreement models where some investors have an optimistic market view and others a pessimistic one (Osambela, 2015; Atmaz and Basak, 2018): the risk is transferred from pessimists to optimists who increase their holding of the asset under consideration.

3.3.2 Equilibrium emissions schedule

At the initial date, companies choose their optimal emissions schedules, taking into account their expected market value between times 0 and T. In this simple economy where prices and dividends are Gaussian, the optimal emissions schedule of a company (determined from the program in Equation (3.9)) does not depend on those of the other companies, ψ^{-i}.

Proposition 8. *The optimal emissions schedule of the i-th company is the one that maximizes for all $t \in [0, T]$*

$$c_i \psi_t^i + \beta_t^c \theta_i^c(\psi_t^i) + \alpha \beta_t \theta_i(\psi_t^i), \tag{3.12}$$

where

$$\beta_t^c = \frac{1 - e^{-\rho(T-t)}}{\rho} \quad \text{and} \quad \beta_t = \frac{e^{\rho t} - 1}{\rho}.$$

At each date, the i-th company maximizes the sum of the benefits from not reducing its emissions ($c_i \psi_t^i$) and from the two environmental externalities premia, that is, the one endogenized by the company ($\theta_i^c(\psi_t^i)$) and the one by the green investors ($\alpha\theta_i(\psi_t^i)$) adjusted by a discount factor (β_t^c and β_t, respectively). The optimal schedule is a trade-off between the positive benefit of not reducing the emissions and the negative effect of decreasing (i.e., deteriorating) the environmental externalities.

Research in environmental economics consensually suggests the use of a convex specification to model the economic damage associated with environmental risks (Dietz and Stern (2015), Burke, Hsiang, and Miguel (2015), and Burke, Davis, and Diffenbaugh (2018)). Particularly, Barnett, Brock, and Hansen (2020) use a quadratic environmental damage function to model the economic impact associated with climate change. Assuming that the environmental externalities are quadratic, Proposition 8 has a simple solution outlined in Corollary 9.

Corollary 9. *Assuming $\theta_i(x) = \kappa_0 - \frac{\kappa}{2}x^2$ and $\theta_i^c(x) = \kappa_0^c - \frac{\kappa^c}{2}x^2$, for $x \geq 0$, where κ, κ^c, κ_0 and κ_0^c are positive constants,*[10] *the optimal emissions schedule for the i-th company is*

$$\psi_t^{*,i} = \frac{c_i}{\beta_t^c \kappa^c + \alpha \beta_t \kappa} \tag{3.13}$$

The emissions schedule declines as the proportion of green investors, α, increases. Parameters κ and κ^c reflect the stringency with which green investors and companies, respectively, internalize the externalities. For example, κ can be interpreted as the inverse of the maximum carbon intensity at which green investors will still purchase an asset. The emissions schedule also declines as green investors and companies internalize the externalities more stringently. Therefore, green investors can increase their

[10] For simplicity we assume that κ, κ^c, κ_0 and κ_0^c are the same for all companies but the generalisation to different constants is straightforward.

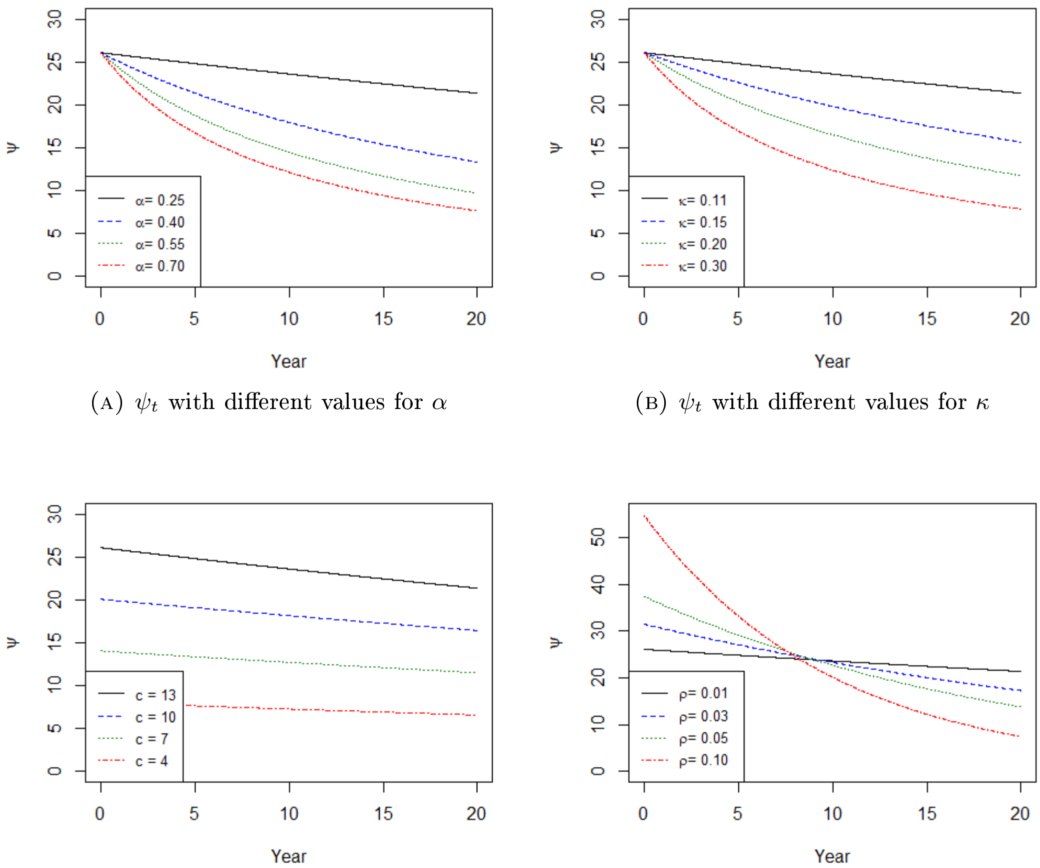
impact on companies by raising their environmental requirements, for example by restricting the range of companies which they invest in or by significantly underweighing the most carbon-intensive companies. Since the discount factor β_t (β_t^c) increases (decreases) with time t, green investors have an even greater influence on the company's emissions in the long run.[11] In addition, the emissions of the i-th company logically decrease with its marginal abatement cost, c_i. In the special case where the marginal abatement cost is zero, the company cuts its emissions to zero. Finally, it should be noted that even if the company does not internalize environmental externalities ($\kappa^c = 0$), green investors' beliefs and the threat they pose to a company's market value are sufficient to prompt a company to reduce its environmental impact. In such a case, the optimal emissions schedule is simplified as

$$\psi_t^{*,i} = \frac{c_i}{\alpha \beta_t \kappa}. \tag{3.14}$$

As a feedback effect, the increase in the proportion of initial wealth held by the green investors (α), their environmental stringency (κ) as well as that of the companies (κ^c) have a positive impact on asset prices and a negative impact on expected returns (Equation (3.10)). The same effects on prices and returns occur when the marginal abatement cost, c_i, decreases. The marginal abatement cost is a company (or industry) specific factor that plays an important role in the greening dynamics of the economy. Research and development in industries where green alternatives are still limited (e.g., cement, aviation) is therefore a major instrument to foster the environmental transition.

Figure 3.2 presents the optimal emissions schedules of a company whose parameters are calibrated in Section 3.4. It should be noted that the starting point of these optimal trajectories is not the company's initial level of emissions. Therefore, when the company emits more than the initial optimal emissions level, it is incentivized to reduce its emissions. Conversely, the company has an incentive to increase its emissions when its initial level of emissions is lower than the initial optimal level. The increase in the share of green investments and the environmental stringency of green investors lead to a faster and more convex decrease in the company's emissions. For example, when 25% of the AUM are managed by green investors, the company reduces its emissions by 1% per year on average. This drop increases to 4.4% per year on average when green investments account for 50% of the AUM. The rate of time preference affects the slope of the curve: a low rate encourages companies to reduce their emissions very early on and to maintain this low level over the entire period; a high rate encourages companies to emit more in the short run and to reduce their emissions more steeply over time. Finally, the marginal abatement cost plays an important role since it shifts the emissions dynamics upwards when the cost is high and

[11] The importance of the long run in environmental matters justifies the use of low discount rates (Gollier, 2002; Gollier, 2010). This is all the more appropriate in the context of current low financial rates. When the time preference rate ρ is close to zero (i.e., $\rho \simeq 0$), the discount factors are $\beta_t^c \simeq T-t$ and $\beta_t \simeq t$, respectively.



(A) ψ_t with different values for α

(B) ψ_t with different values for κ

(C) ψ_t with different values for c

(D) ψ_t with different values for ρ

FIGURE 3.2: **Emissions schedules.** This figure shows the emissions schedules, ψ_t, according to several values of the proportion of green investors (α, sub-figure (a)), the green investors stringency (κ, sub-figure (b)), the marginal abatement cost (c, sub-figure (c)), and the rate of time preference (ρ, sub-figure (d)). The parameters are calibrated according to the values estimated in Section 3.4: $\alpha = 0.25$, $\rho = 0.01$, $\kappa = 0.11$, $\kappa^c = \alpha\kappa$, $c = 13$.

downwards when it is low.

This model extends the work of Heinkel, Kraus, and Zechner (2001) by endogenously characterizing the dynamics of companies' environmental impacts. In addition, in our model, companies can choose a continuum of environmental impacts over a temporal schedule, in contrast to Heinkel, Kraus, and Zechner (2001) where companies reform in a binary way (from *brown* to *green*) in a single-period model.

3.4 Equilibrium with environmental uncertainty

We extend the model presented in Section 3.2 to the case where the environmental externalities are internalized by green investors as a stochastic and non-Gaussian process. Compared with the equilibrium with deterministic externalities we obtained above, the uncertainty about future environmental externalities alleviates the pressure on the cost of capital of the most carbon-intensive companies and pushes them to increase their emissions.

3.4.1 Environmental uncertainty

The internalization of deterministic environmental externalities is an imperfect approach. Barnett, Brock, and Hansen (2020) note that "given historical evidence alone it is likely to be challenging to extrapolate climate impacts on a world scale to ranges in which many economies have yet to experience. Both richer dynamics and alternative nonlinearities may well be essential features of the damages that we experience in the future due to global warming." Indeed, climate risks are characterized by fat tails (Weitzman, 2009; Weitzman, 2011) and abrupt changes beyond tipping points (Alley et al., 2003; Lontzek et al., 2015; Cai et al., 2015) that will severely impact the world economy (Dietz, 2011).

We therefore extend our model to the case where green investors internalize uncertainty about the environment-related financial risks. In this subsection, we model the effect of the environmental uncertainty on the dividend process and we will focus on investors' beliefs in the next subsection. As this uncertainty is not Gaussian and occurs in jerks and turns, we model environment-related financial risks by a time-inhomogeneous compound Poisson process. On the same filtered probability space, $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{P})$, we define a time-inhomogeneous Poisson process $\mathcal{N}$ (counter of the shocks) and a sequence of $\mathbb{R}^n$-valued integrable independent random variables $(Y_k)_{k\geq 1}$ (shock sizes). We denote by $(\Lambda_t)_{t\in[0,T]}$ the time-dependent intensity of the Poisson process and by ν_t the distribution of Y_k, when the shock occurs at time $t \in [0, T]$. The distribution of Y_k describes the impact of the k-th shock on the expected dividend of each company. In particular, Y_k is negative (positive) if the environment-related financial risk is negative (positive).

As before, the fundamental value of each asset at time T is denoted by D^i_T. The vector of terminal dividends is now expressed as follows:

$$D_T = D_0 + \int_0^T \sigma_t dB_t + \sum_{k=1}^{\mathcal{N}_T} Y_k.$$

The actual *equilibrium price process* is denoted by $(p_t)_{t\in[0,T]}$, and it is assumed that $p_T = D_T$.

3.4.2 Investors' and companies' beliefs

The probability of regular investors, $\mathbb{P}^r$, is equal to the original probability measure $\mathbb{P}$. In this general case, we consider that regular investors can internalize the uncertainty about environment-related financial impacts, which are modelled through a jump with time-dependent intensity Λ_t, at time $t \in [0, T]$. Therefore, as a first approach, green and regular investors internalize the uncertainty of environmental shocks but with a different intensity. Further on in this section, we will focus on the particular case where the environmental externalities that regular investors anticipate are zero.

In contrast to the setting of Section 3.2, the Brownian motion in the dividends' dynamic does not change under the green investors' measure, $\mathbb{P}^g$. Instead, the intensity of the shocks changes from Λ_t to Λ^g_t, while the distribution of the magnitude of shocks ν_t remains the same under the measures $\mathbb{P}$ and $\mathbb{P}^g$. Consistent with the transition and litigation risks, according to which companies are more exposed to environment-related financial risks as the greenhouse gas emissions are significant,[12] this distribution depends on the emissions, ψ_t. To reflect this dependence, we shall from now on denote it by ν^ψ_t. To summarize, the distribution ν^ψ_t models how environmental risk affects different companies, and does not depend on the probability measure. By contrast, the intensity of shock occurence describes how different investors internalize the environmental risk: it does not depend on the emissions ψ, but takes different values Λ_t and Λ^g_t under the measures $\mathbb{P} = \mathbb{P}^r$ and $\mathbb{P}^g$, respectively. We denote by

$$e^\psi_t = \int_{\mathbb{R}^n} z\nu^\psi_t(dz), \quad t \in [0, T], \tag{3.15}$$

the expectation of environmental shocks on all assets. We draw a parallel with the previous setup where the internalized environmental externalities are deterministic by expressing the expected environmental shocks (per unit time) as a function of the emissions schedule:

$$\theta(\psi_t) := \Lambda^g_t e^\psi_t.$$

In a similar way, we assume that under the probability measure of the companies, $\mathbb{P}^c$, the jump intensity is Λ^c_t, whereas the jump-size distribution and the Brownian motion do not change. Moreover, we can once again express the expected environmental

[12] The reasoning is transposable to physical risks by considering ψ as the exposure to physical risks.

externalities (per unit time) as a function of the emissions:

$$\theta^c(\psi_t) := \Lambda_t^c e_t^\psi.$$

3.4.3 Equilibrium stock price and return

We make the following technical assumption about the Laplace transform of ν_t^ψ which guarantees that environmental shocks do not have an infinite impact.

Assumption 7. *Let $L_t^\psi(u) := \int_{\mathbb{R}^n} e^{u^\top z}\nu_t^\psi(dz)$, for $t \in [0,T]$ and $u \in \mathbb{R}^n$. We assume that*

$$L_t(u) < \infty, \quad \textit{for all } t \in [0,T] \textit{ and } u \in \mathbb{R}^n.$$

The optimization framework and notation remain similar to the case where green investors internalize deterministic environmental externalities. In equilibrium, investors choose their allocation to maximize the expected exponential utility of their terminal wealth (recall (3.7)). Prices $(p_t)_{t\in[0,T]}$ are determined by the market clearing condition.

Theorem 10 gives the equilibrium price and allocations. In the theorem's statement, ∇L_t stands for the gradient of $u \mapsto L_t(u)$ and

$$D_t = D_0 + \int_0^t \sigma_s dB_s + \sum_{k=1}^{\mathcal{N}_t} Y_k. \tag{3.16}$$

Theorem 10. *Suppose that Assumption 7 holds true. The optimal quantity of assets for the regular investors is given, at all times t, by the unique solution, N_t^r, of the following equation.*

$$\Lambda_t^g \nabla L_t(-\gamma^g(\mathbf{1} - N_t^r)) - \gamma^g \Sigma_t(\mathbf{1} - N_t^r) - \Lambda_t \nabla L_t(-\gamma^r N_t^r) + \gamma^r \Sigma_t N_t^r = 0, \tag{3.17}$$

Moreover, the optimal quantity of assets for the green investors is given at all times t by $N_t^g = \mathbf{1} - N_t^r$, and the price process is given by

$$p_t = D_t - \int_t^T \mu_s ds \tag{3.18}$$

with drift

$$\mu_t = \gamma^r \Sigma_t N_t^r - \Lambda_t \nabla L_t(-\gamma^r N_t^r). \tag{3.19}$$

The price drift, μ, breaks down into a first term that is written similarly to the drift in the case with deterministic externalities, $\gamma^r \Sigma_t N^r$, and an additional term, $-\Lambda_t \nabla L_t(-\gamma^r N^r)$. Indeed, in the case with deterministic environmental externalities (see Equations (3.10) and (3.11)), the drift of the equilibrium price process also writes as follows:

$$\mu_t = \gamma^* \Sigma_t \mathbf{1} - \alpha\theta(\psi_t) = \gamma^r \Sigma_t N_t^r.$$

From now on, for consistency with the case where green investors internalize deterministic environmental externalities, we assume that the jump intensity for regular investors is zero. Therefore, the dividend dynamic under regular investors' probability is equal to that in the first version of our model.

Assumption 8. $\Lambda_t \equiv 0$.

In equilibrium, under Assumption 8, Equation (3.17) becomes

$$-\gamma^g \Sigma_t \mathbf{1} + (\gamma^g + \gamma^r)\Sigma_t N_t^r + \Lambda_t^g \nabla L_t\big(-\gamma^g(\mathbf{1} - N_t^r)\big) = 0. \tag{3.20}$$

We now restrict our attention to the case where the probability of environmental risk is high, and the financial impacts are small. We focus on this particular case for two reasons: to analyze the model with environmental uncertainty as a marginal deviation from the deterministic case, and to obtain a tractable approximation of prices, returns and asset allocations in equilibrium. This setup is also consistent with environmental transition risks, which are likely to occur as a succession of small shocks. To this end, we introduce a small parameter h, and assume that the jump intensity is given by $\Lambda_t^{g,h} := h^{-1}\Lambda_t^g$ and the jump sizes are multiplied by h, so that the expected jump size reads $e_t^{h,\psi} := h e_t^{\psi}$. Therefore, when $h \to 0$, the current setup converges towards the setup from Section 3.2, where the externalities are deterministic.

We recall that $\Lambda_t^g e_t^{\psi} = \theta(\psi_t)$ for a given emissions schedule $(\psi_t)_{t\in[0,T]}$ and notice that $\theta(\psi_t)$ is invariant with respect to h, as indeed $\Lambda_t^g e_t^{\psi} = \Lambda_t^{g,h} e_t^{h,\psi}$. Similarly to θ, we introduce the variable $\pi(\psi_t)$ that represents environmental risk, which is defined as the product of the frequency by the second moment of environmental shocks:

$$\pi(\psi_t) := \Lambda_t^g \int_{\mathbb{R}^n} z\, z^\top \nu_t^{\psi}(dz), \qquad \text{for } t \in [0,T]. \tag{3.21}$$

Proposition 11 gives an explicit formula for the solution to Equation (3.20) in the asymptotic limit of $h \to 0$.

Proposition 11. *Suppose that Assumptions 7 and 8 hold true and fix an emissions schedule $(\psi_t)_{t\in[0,T]}$. As $h \to 0$, the vector of the quantities of assets held by the green investors is given by*

$$N_t^{g,h} = N^{g,0} - h(1-\alpha)\alpha\Sigma_t^{-1}\pi(\psi_t)\left(\mathbf{1} + \frac{1}{\gamma^r}\Sigma_t^{-1}\theta(\psi_t)\right) + O(h^2),$$

and the vector of the quantities of assets held by the regular investors is given by

$$N_t^{r,h} = N^{r,0} + h(1-\alpha)\alpha\Sigma_t^{-1}\pi(\psi_t)\left(\mathbf{1} + \frac{1}{\gamma^r}\Sigma_t^{-1}\theta(\psi_t)\right) + O(h^2),$$

where $N^{g,0} = \alpha\left(\mathbf{1} + \frac{1}{\gamma^r}\Sigma_t^{-1}\theta(\psi_t)\right)$ *and* $N^{r,0} = (1-\alpha)\left(\mathbf{1} - \frac{1}{\gamma^g}\Sigma_t^{-1}\theta(\psi_t)\right)$ *coincide with the quantities of assets held by green and regular investors, respectively, in the case of deterministic environmental externalities.*

Finally, the drift of the equilibrium price is given by

$$\mu_t^h = \mu_t^0 + h(1-\alpha)\alpha\pi(\psi_t)\,\left(\gamma^r\mathbf{1} + \Sigma_t^{-1}\theta(\psi_t)\right) + O(h^2), \tag{3.22}$$

where $\mu_t^0 = \alpha\gamma^g\Sigma_t\mathbf{1} - \alpha\theta(\psi_t)$ *coincides with the drift in the case of deterministic environmental externalities (see* (3.10)*).*

The uncertainty associated with environmental risk induces corrections of investors' asset allocations and companies' cost of capital. Denoting the diagonal matrix of 'ones' by $\mathbf{I}$, the quantity of assets held by green investors can be written in relation to this same quantity in the case where environmental externalities are deterministic as:

$$N^{g,h} = \left(\mathbf{I} - h(1-\alpha)\Sigma_t^{-1}\pi(\psi_t)\right)N^{g,0} + O(h^2).$$

The adjustment of the quantity of assets depends on the matrix of environmental risks normalized by the covariance matrix, $\Sigma_t^{-1}\pi(\psi_t)$, and on the proportion of wealth of regular investors, $(1-\alpha)$. In the case where green investors internalize uncertainty about environmental risks, and by comparison with the deterministic case, they decrease their overall absolute allocation to risky assets, since $\|N^{g,h}\| < \|N^{g,0}\|$. Thus, on average, they will reduce their allocation to green assets (long positions in their portfolio) and increase their allocation to brown assets (short positions). This adjustment is proportional to the frequency of the risk (Λ_t^g) and its second moment. The adjustment of green investors' allocations is offset by the adjustment of regular investors' allocations since regular investors provide green investors with the needed liquidity. As a result, since the pressure exerted by the green investors weakens, the cost of capital increases for the greenest assets and decreases for the brownest assets by an adjustment commensurate with environmental risks (in terms of frequency and second moment).

Remark 12. *Letting*

$$\overline{\theta}(\psi_t) = \theta(\psi_t) - h(1-\alpha)\gamma^g\pi(\psi_t)\mathbf{1} \quad \textit{and} \quad \overline{\Sigma}_t = \Sigma_t + h(1-\alpha)\pi(\psi_t),$$

the vector of quantities of assets held by the regular and green investors, respectively, can be written as

$$N_t^r = (1-\alpha)\left(\mathbf{1} - \frac{1}{\gamma^g}\overline{\Sigma}_t^{-1}\overline{\theta}(\psi_t)\right) + O(h^2),$$
$$N_t^g = \alpha\left(\mathbf{1} + \frac{1}{\gamma^r}\overline{\Sigma}_t^{-1}\overline{\theta}(\psi_t)\right) + O(h^2).$$

Up to a correction term of order $O(h^2)$ *the above expressions are the same as in the deterministic case, but with drift* $\overline{\theta}$ *and covariance matrix* $\overline{\Sigma}$*. Therefore, for the* *green investors, the effect of the environmental uncertainty at the first order in h is to decrease the value of the drift in the equilibrium price (from θ to $\overline{\theta}$) and to increase the values of the covariance matrix (from Σ to $\overline{\Sigma}$).*

3.4.4 Equilibrium emissions schedule

Companies fix their emissions schedules by optimizing the same gain function as in the deterministic case (Equation (3.8)): they maximize their future market value irrespective of the cost of reform and minimize their abatement cost. The main difference with the case where environmental externalities are deterministic is that the optimal emissions schedule of the i-th company depends on those of the other companies, ψ^{-i}.

To simplify the model and focus on the effect of the uncertain arrival of the shocks, we now assume that the size of the environmental shocks is deterministic. In particular, we let $(y_t)_{t\in[0,T]}$ be a deterministic, $\mathbb{R}^n$-valued process and assume that the shocks' distribution is concentrated on y_t at each time $t \in [0,T]$.

Assumption 9. *Recall the sequence of random shocks $(Y_k)_{k\geq 1}$ and assume $Y_k = y_t$ if the shock occurs at time $t \in [0,T]$.*[13]

It then follows from Equation (3.15) that $e_t^{\psi} = y_t$, so in our formulae below we continue to use the average shock size e_t^{ψ}. Moreover, in this special case we have

$$\pi_t(\psi) = \Lambda_t^g \, e_t^{\psi} (e_t^{\psi})^\top,$$

which will be needed for the proof of the next result.

In Proposition 13, we give a tractable expression of the approximation of the emissions schedule of the i-th company when the environmental shocks are small but frequent.

Proposition 13. *Let Assumptions 7, 8 and 9 hold. Moreover, assume that Λ_t^g and Λ_t^c are independent of the emissions schedule and e_t^{ψ} is such that $\theta(\psi)$ and $\theta^c(\psi)$ are as in Corollary 9. As $h \to 0$, the optimal emissions schedule of the i-th company reads*

$$\psi_t^{*,i} = \psi_t^{*,0,i}\left(1 - h\,\Gamma_t^i\,\psi_t^{*,0,i}\right)^{-1} + O(h^2), \quad \textit{for } i{=}1,\dots n, \tag{3.23}$$

with $\psi_t^{*,0,i} = c_i(\beta_t^c\kappa^c + \alpha\beta_t\kappa)^{-1}$ being the emissions schedule in the deterministic case (Corollary 9) and

$$\Gamma_t^i := \kappa\beta_t\frac{\alpha(1-\alpha)}{c_i\Lambda_t^g}\Bigg[\underbrace{\left(\gamma^r\mathbf{1}^\top\theta(\psi_t^{*,0}) + \theta^\top(\psi_t^{*,0})\Sigma_t^{-1}\theta(\psi_t^{*,0})\right)}_{\textit{Market adjustment}}$$
$$+\underbrace{\left(\gamma^r\theta_i(\psi_t^{*,0}) + 2\theta^\top(\psi_t^{*,0})\Sigma_t^{-1}\delta_i\theta_i(\psi_t^{*,0})\right)}_{\textit{Stock adjustment}}\Bigg],$$

[13]Notice that, in terms of the distribution ν_t, this assumption is equivalent to $\nu_t(dz) = \delta(y_t - z)dz$, where $\delta(y_t - \cdot)$ is a Dirac delta concentrated on y_t.

where δ_i is a vector whose i-th coordinate is equal to one and all other coordinates are zero.

Compared to the equilibrium in the deterministic case, the emissions schedule is adjusted by a correction factor that is a function of Γ_t^i. Γ_t^i breaks down into a *market adjustment* that is driven by the externalities of all stocks in the market and a *stock adjustment* that is driven by the externality of the i-th stock, each of the two adjustments being decomposed into a linear and a quadratic effect.

As the adjustment is inhomogeneous depending on the market structure, the correlation between the assets and their environmental externalities, we illustrate its effect by considering a simple market made up of two assets and using the parameters calibrated in Section 3.5. The first asset is a green asset, through a low marginal abatement cost ($c_1 = 0.5$), and the second is a brown asset, through a high marginal abatement cost ($c = 13$). Figure 3.3 shows the emissions schedule with environmental uncertainty of the brown company compared to the emissions schedule with deterministic environmental externalities. For all levels of correlation considered, the brown company increases its carbon emissions as compared to the deterministic case. Indeed, green investors increase their allocation to the brown company's assets—of which they were short in the deterministic case—thereby mitigating the pressure they exert on the cost of capital of the brown company, which therefore incentivizes it to increase its emissions. The opposite effect arises for the green company: it cuts its emissions because green investors—who were long on the company's assets in the deterministic case—reduce their asset allocation to the green company and increase its cost of capital.

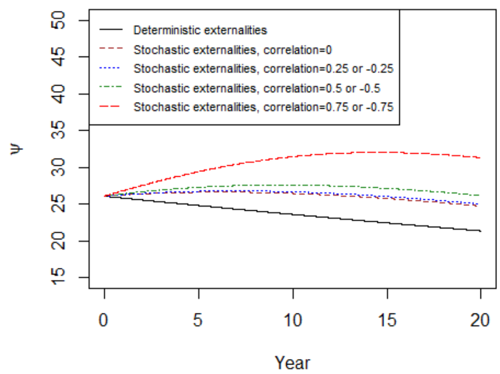


FIGURE 3.3: **Emissions schedules with stochastic environmental externalities.** This figure shows the emissions schedules of a brown company (marginal abatement cost $c_2 = 13$) in the deterministic case and in the stochastic case for different levels of correlation with the asset of the second company in the market. The market is made up of two assets and the second asset is that of a green company, with a marginal abatement cost of $c_1 = 0.5$. The correlation is the nondiagonal element in Σ. The parameters are calibrated according to the values estimated in Section 3.4: $\alpha = 0.25$, $\rho = 0.01$, $\kappa = 0.11$, $\kappa^c = \alpha\kappa$, $\kappa_0 = 0.1$, $\gamma^r = \gamma^g = 1$ and $\Lambda = 1$. We take $h = 10^{-4}$.

This result underscores the value of increasing the transparency of companies' environmental impacts as well as improving the forecasting of environment-related financial risks. It also emphasizes the importance of predictability of public policies in favor of environmental transition, notably, the upward trajectory of the carbon price. Transparency and predictability are key pillars for a better integration of environment-related financial risks by green investors, which provides incentives for companies to better internalize their environmental externalities and thus reduce their environmental impact more rapidly.

3.5 Empirical evidence

In this section we provide empirical evidence of (i) the asset pricing equation (Equation (3.10)) and (ii) the dynamics of companies' emissions (Equation (3.14)) in the case where green investors internalize *deterministic* environmental externalities. We calibrate the parameters of interest on U.S. stocks between 2006 and 2018 using green fund holdings.

3.5.1 Asset pricing with green investors

As previously demonstrated, with or without uncertainty about environmental risks, a corrective factor, known as the externality premium, applies to asset returns. We focus on the case where green investors internalize environmental externalities without uncertainty regarding future environmental impacts (Section 3.3) and take expectations of asset returns (μ_t in Equation (3.10)) with respect to the regular investors' probability measure $\mathbb{P}^r$. Consistent with Pedersen, Fitzgibbons, and Pomorski (2019) and Zerbib (2019a) who test a negative effect of companies' environmental performance on asset returns, we assume that the probability measure of regular investors is the real world probability and we test the existence of the negative externality premium on asset returns, that is, the presence of the correction term $-\alpha\theta_i(\psi_t^i)dt$ in the expected returns:[14]

$$\mathbb{E}(dp_t^i) = \gamma^* \Sigma_t^i dt - \alpha\theta_i(\psi_t^i)dt. \tag{3.24}$$

Since the dollar returns, dp_t^i, are non-stationary we cannot reasonably perform an estimation based on our theoretical model that uses normally distributed prices and dividends. Facing the same challenge, Banerjee (2011) performs the estimations on *rates of return*. The author claims that the empirical predictions of his model are robust to using rates of return instead of dollar returns and supports the assertion with descriptive statistics. We go a step further by showing that the pricing equation is written similarly when returns are Gaussian, and, therefore, we perform the

[14]Under $\mathbb{P}^G$, the externality premium has a positive effect on expected returns, which read

$$\mathbb{E}^g(dp_t^i) = \gamma^* \Sigma_t^i dt + (1-\alpha)\theta_i(\psi_t^i)dt$$

.

empirical analysis on rates of return. Indeed, by using a one-period model with normally distributed returns, in which green investors disagree with regular investors by internalizing a private externality factor, $\theta(\psi)$, the analogue of Equation (3.24) reads

$$\mathbb{E}(r^i) = \gamma\,\mathbb{C}\mathrm{ov}(r^i, r^m) - \alpha\theta_i(\psi^i), \tag{3.25}$$

where r^i and r^m denote the rates of returns in excess of the risk-free rate on the i-th asset and the market, respectively.[15] The time subscripts are omitted for simplicity.

We perform the estimation on U.S. data from the common stocks (share type codes 10 and 11) listed on the NYSE, AMEX and NASDAQ (exchanges codes 1, 2 and 3) in the Centre for Research in Security Prices (CRSP) database. Given the recent development of green investing, and in line with Zerbib (2019a), the estimation is performed from December 31, 2006 to December 31, 2018 on 48 industry-sorted portfolios using the SIC classification based on a total number of 6019 stocks.

The environmental externalities internalized by green investors are both the key variable and the most complex one to approximate. Indeed, the environmental ratings provided by the numerous data providers are an imperfect proxy for green investors' tastes and beliefs, given the lack of a common definition (Chatterji et al., 2016) and their low commensurability (Gibson et al., 2019). Moreover, the environmental ratings and carbon intensities are available at an annual frequency and do not allow the estimation to be performed on a monthly basis. Therefore, we follow Zerbib (2019a) to construct a monthly proxy for the revealed environmental externalities internalized by green investors from the holdings of the 348 listed green funds worldwide investing in U.S. equities in December 2018. We identify these funds via Bloomberg and download the fund holdings from FactSet on a quarterly basis. We aggregate the green funds' holdings and denote by $w_{i,t}$ the weight of the i-th industry in the U.S. allocation of the green funds as of month t. Denoting by $w^b_{i,t}$ the weight of the i-th industry in the CRSP universe on date t, we define the instrument for the i-th industry in t as

$$\tilde{\theta}_i(\psi^i_t) = \frac{w_{i,t} - w^b_{i,t}}{w^b_{i,t}}.$$

A large value of $\tilde{\theta}_i$ means that green funds allocate a larger proportion of their portfolios' wealth to stocks from the i-th industry relative to the market, reflecting higher positive environmental externalities of the i-th industry. Conversely, when $\tilde{\theta}_i$ is negative, green investors reduce their holdings in stocks from the i-th industry because they internalize negative externalities. The instrument defined, $\tilde{\theta}$, is the opposite of the one constructed by Zerbib (2019a), who proxies a cost of externalities. We then extend this value over the next two months of the year in which no holdings data are available. Assuming that $\theta = \delta\tilde{\theta}$, $\delta \geq 0$, we therefore perform the estimation on the

[15] See Zerbib (2019a), Appendix, Equation (9), where the market is not segmented (i.e., taking $q = 0$).

following econometric specification:

$$\mathbb{E}(r^i) = \iota + \gamma\, \mathbb{C}\mathrm{ov}(r^i, r^m) - \alpha\delta\tilde{\theta}_i(\psi^i), \tag{3.26}$$

where ι is the constant term. We estimate the parameters in (3.26) by performing a two-step cross-sectional regression (Fama and MacBeth, 1973). In the first step, we estimate variables $\mathbb{E}(r^i)$, $\mathbb{C}\mathrm{ov}(r^i, r^m)$ and $\tilde{\theta}_i(\psi^i)$ over a 3-year rolling period at a monthly frequency, yielding time series of 109 dates for each of the three variables. In the second step, we perform 109 cross-sectional regressions on the 48 portfolios considered. The estimated loadings correspond to their average over the 109 dates. Standard errors are adjusted following Newey and West (1987) to account for heteroskedasticity and serial correlation. We report the ordinary least squares (OLS) adjusted-R^2 of the cross-sectional regressions as well as the generalized least squares (GLS) R^2, which is a suitable measure of model fit because it is determined by the factor's proximity to the minimum-variance boundary (Lewellen, Nagel, and Jay, 2010).

The estimates are presented in Table 3.2. The environmental externality premium is significant and the estimate is robust to the inclusion of the size factor (SMB), book-to-market factor (HML) (Fama and French, 1992) and the momentum factor (MOM) (Carhart, 1997) betas. The average effect is close to zero because green investors are unlikely to overweigh or underweigh the market as a whole (Pastor, Stambaugh, and Taylor, 2019; Zerbib, 2019a). However, the externality premium varies from one industry to another (see Table 3.5 in the Appendix). For example, green investors induce a 0.84% annual increase in returns on the coal industry compared to the electrical equipment industry. Consistent with Zerbib (2019a) who estimates a capital asset pricing model (CAPM)-like specification, these results illustrate the fact that green investors require a higher return on the most polluting companies and support the asset pricing predictions of our model.

Pastor, Stambaugh, and Taylor (2019) point out that approximating expected returns by realized returns fails to account for the unexpected changes in investors' tastes or beliefs which, however, impact realized returns. Indeed, a green stock may have a lower externality premium than a brown stock and yet have a higher realized return because green investors reinforce their pro-environmental beliefs. Therefore, we estimate the main specification by adding instrument $\Delta\tilde{\theta}_i(\psi^i)$ to control for the unexpected changes in beliefs, defined as

$$\Delta\tilde{\theta}_{i,t}(\psi^{i,t}) = \tilde{\theta}_{i,t}(\psi^{i,t}) - \tilde{\theta}_{i,t-1}(\psi^{i,t-1})$$

As expected, the estimate of instrument $\Delta\tilde{\theta}_i(\psi^i)$ is positive and significant: when green investors' pro-environmental beliefs reinforce unexpectedly ($\Delta\tilde{\theta}_i(\psi^i) > 0$), realized returns increase. However, the externality premium remains significant and its loading is consistent with that of the main estimation.

TABLE 3.2: **Estimation of the asset pricing equation.** This table presents the estimates of the asset pricing Equation (3.26): $\mathbb{E}(r^i) = \iota + \gamma\,\mathbb{C}\mathrm{ov}(r^i, r^m) - \alpha\delta\tilde{\theta}_i(\psi^i)$. The estimation is performed using value-weighted monthly returns in excess of the 1-month T-Bill for the 48 SIC industry-sorted portfolios between December 31, 2006, and December 31, 2018. r^i is the value-weighted excess return on industry i ($i = 1, ..., n$), r^m is the market excess return, and $\tilde{\theta}_i(\psi^i)$ is the proxy for the environmental externalities of industry I_i. This specification is compared with two other specifications: (i) we add to our model the beta of the Carhart (1997) momentum factor and betas of the Fama and French (1993) size and value factors, of which the loadings are denoted by u_{SMB}, u_{HML}, and u_{MOM}, respectively; (ii) we add to specification (i) the unexpected shifts in beliefs $\Delta\tilde{\theta}_i(\psi^i)$, of which the loading is denoted by $u_{\Delta\theta}$. First, the variables are estimated by industry in a 3-year rolling window at monthly intervals. In the second step, a cross-sectional regression is performed by month on all the industries. The estimated parameter is the average value of the estimates obtained on all months during the period. t-values, estimated following Newey and West (1987) with three lags, are reported in round brackets. The last column reports the average OLS adjusted-R^2 and the GLS R^2 on the row underneath. The 95% confidence intervals are shown in square brackets.

	ι	γ	$\alpha\delta$	β_{SMB}	u_{HML}	u_{MOM}	$u_{\Delta\theta}$	Adj OLS/GLS R^2
Estimation of the market and externality premia separately								
Estimate	0.0141	-0.6871						0.05 [0.03,0.07]
t-value	(11.54)	(-0.94)						0.07 [0.05,0.09]
Estimate	0.0142		-0.0002					-0.01 [-0.02,-0.01]
t-value	(18.16)		(-3.41)					0.01 [0.01,0.01]
Main estimation								
Estimate	0.0142	-0.6855	-0.0002					0.04 [0.02,0.05]
t-value	(11.73)	(-0.92)	(-3.6)					0.08 [0.06,0.09]
Main estimation with SMB, HML and MOM betas								
Estimate	0.0138	0.4387	-0.0003	-0.00004	0.0002	-0.0001		0.22 [0.18,0.26]
t-value	(12.38)	(0.59)	(-5.6)	(-0.33)	(1.27)	(-1.36)		0.31 [0.27,0.34]
Main estimation with SMB, HML and MOM betas, and control for unexpected shifts in beliefs								
Estimate	0.014	0.2866	-0.0002	-0.00005	0.0002	-0.0001	0.0138	0.22 [0.18,0.26]
t-value	(12.43)	(0.38)	(-1.95)	(-0.38)	(1.09)	(-1.41)	(3.89)	0.32 [0.28,0.35]

3.5.2 Companies' emissions schedule

The second estimation concerns the companies' greening dynamics as expressed by their greenhouse gas emissions: we test the accuracy of the emissions schedule $t \mapsto \psi_t^*$ obtained in Equation (3.14). The latter gives the companies' optimal emissions schedule as a function of the proportion of green investors at the optimization date, α, their environmental stringency, κ, the marginal abatement cost of the i-th company, c_i, and the discount factor, β_t. Assuming that companies have a one-year optimization horizon and that the rate of time preference is close to zero at that horizon, the discount factor is reduced to $\beta_1 \simeq 1$. Taking the logarithm of the equilibrium equation between t and $t+1$, Equation (3.14) is rewritten as follows:

$$log(\psi_{i,t+1}) \simeq log(c_i) - log(\kappa) - log(\alpha_t). \tag{3.27}$$

As a proxy for the companies' emissions, we use their carbon intensity, which is the environmental metric most used by investors (Gibson et al., 2019). Provided by S&P–Trucost, the carbon intensity of the i-th company on year t is defined as the amount of greenhouse gases emitted by that company during that year divided by its annual revenue. We construct a proxy for the percentage of green investors in each period, $\tilde{\alpha}_t$, as the market value of the U.S. stocks in the CRSP investment universe held by the 348 green funds divided by the total market value of the U.S. investment universe:

$$\tilde{\alpha}_t = \frac{\text{Market value of U.S. stocks in green funds holdings in } t}{\text{Total market value of U.S. stocks in } t}. \tag{3.28}$$

Figure 3.4 shows the evolution of $\tilde{\alpha}$, which reaches 0.10% at the end of 2018.

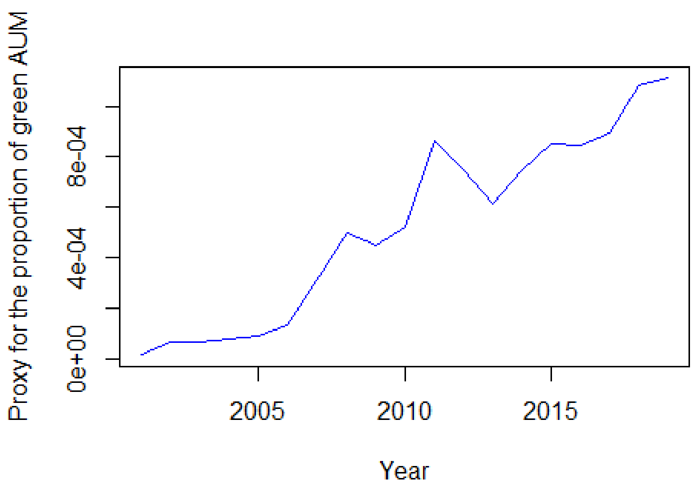


FIGURE 3.4: **Evolution of $\tilde{\alpha}$.** This figure shows the evolution of the proxy for the proportion of green AUM, $\tilde{\alpha}$, defined in Equation (3.28).

We assume that $\alpha = \lambda\tilde{\alpha}$, $\lambda > 0$, and we estimate the following econometric specification on a set of 48 portfolios sorted by industry according to the SIC classification, at an annual frequency, between December 2006 and December 2018:

$$log(\psi_{i,t+1}) = \iota + f_i + \beta_\alpha log(\tilde{\alpha}_t) + \epsilon_{i,t}, \tag{3.29}$$

where $\psi_{i,t}$ is the carbon intensity of the i-th industry at time t, f_i is the industry fixed effect, $\tilde{\alpha}_t$ is the proxy for the proportion of green investors at time t, and ι and $\epsilon_{i,t}$ stand for the constant and the error terms, respectively. In the estimation, $\tilde{\alpha}$ is lagged by one year as compared to the dependent variable. Since $\alpha = \lambda\tilde{\alpha}$, the term $log(\lambda)$ is absorbed in the constant.

We estimate the parameters in Equation (3.29) using an OLS regression with industry fixed effects and White standard errors. Table 3.3 presents the results of the estimation. As predicted by the model, the loading of $log(\tilde{\alpha}_t)$ is negative and highly significant. However, β_α is not equal to -1 for three main reasons : in the theory, we make several simplifying assumptions (θ is a quadratic function of ψ, $\rho \simeq 0$, and $\kappa^c = 0$) that do not accurately reflect financial reality; we estimate the equation over a one-year horizon ($T = 1$); furthermore, the model reflects a partial equilibrium because environmental screening is not the only channel that explains the effect of the share of green investors, α, on companies' emissions, ψ. Therefore, this section is for illustrative purposes and shows that the effect is indeed negative and of an acceptable order of magnitude. Under the considered specification, when the proxy for the percentage of green assets, $\tilde{\alpha}$, doubles, the carbon intensity, ψ, drops by 5% the following year.[16] The estimation is robust to the use of $\tilde{\alpha}_t$ lagged by two years.

Table 3.6 in the Appendix reports the estimated fixed effects by industry in descending order. As the cross-sectional heterogeneous effect, the industry fixed effect differs according to the marginal abatement cost in each industry i:

$$f_i = log(c_i).$$

The industries with the highest marginal abatement cost are at the top of this ranking and include, for example, mining, fossil fuel and polluting transport industries.

3.5.3 Calibration

We choose the rate of time preference, ρ, equal to 0.01 (Gollier, 2002; Gollier and Weitzman, 2010). We estimate the proportion of assets managed by taking into account environmental criteria, α, at 25% (US SIF, 2018). We use the carbon intensities as a measure of greenhouse gas emissions, and we estimate c_i by industry as the exponential of the industry fixed effects estimated via specification (3.29). Table 3.6 in the Appendix reports the average values of ψ_i and the estimates of c_i by industry between 2006 and 2018. The marginal abatement cost of the banking industry, which is the

[16]Denoting by ψ_1 the current emissions and ψ_2 the emissions when the percentage of green assets doubles, $\frac{\psi_2-\psi_1}{\psi_1} = e^{-0.079log(2)} - 1 = -0.053$.

TABLE 3.3: **Estimation of the emissions schedule.** This table presents the estimates of the emissions schedule (Equation (3.29)): $log(\psi_{i,t+1}) = \iota + f_i + \beta_\alpha log(\tilde{\alpha}_t) + \epsilon_{i,t}$. $\psi_{i,t+1}$ is the carbon intensity of the i-th industry at time $t+1$ provided by S&P–Trucost and defined as the greenhouse gas emissions emitted by the companies including scope 1, scope 2 and upstream scope 3 expressed in tCO2e per million dollars of revenue generated. $\tilde{\alpha}_t$ is the proxy for the proportion of green AUM in t, defined in Equation (3.28), f_i is the industry fixed effect, ι is the constant and $\epsilon_{i,t}$ is the error term. The equation is estimated using an OLS regression with industry fixed effects and White standard errors.

	Dependent variable: $log(\psi_{i,t+1})$
$log(\tilde{\alpha}_t)$	-0.079^{***}
	(0.014)
Industry FE	Yes
Observations	564
R^2	0.964
Adjusted R^2	0.961
F Statistic	297.502^{***} (df = 47; 516)
Note:	*p<0.1; **p<0.05; ***p<0.01

least carbon-intensive, is close to zero, while it is 17.12 for precious metals, which is the most carbon-intensive industry. Using Equation (3.14) and assuming $\beta_t \simeq 1$ (see subsection 3.5.2), we estimate κ as:

$$\kappa = \frac{1}{n}\sum_{i=1}^{n}\frac{c_i}{\alpha\psi_i} = 0.11.$$

We assume that companies internalize their environmental externalities as the proportion of those internalized by all the investors in the market, that is, $\kappa^c = \alpha \times \kappa = 0.03$. The externality premium estimated in Table 3.5 for different industries is $-\alpha\theta(\psi)$. To obtain an order of magnitude of $\kappa_0 = \theta(0)$ that we cannot directly estimate, we approximate $\theta(\psi)$ by dividing the externality premium by $-\alpha$ and choosing a value slightly larger than the largest value of $\theta(\psi)$, which is 0.08. We therefore set $\kappa_0 = 0.1$. For the section dealing with environmental uncertainty, we set jump intensity $\Lambda = 1$, which corresponds to one jump per year on average. Table 3.4 summarizes the calibrated parameters.

3.6 Conclusion

In this paper we show how green investing impacts companies' practices by increasing their cost of capital. Companies are pushed to internalize their environmental externalities and thereby reduce their greenhouse gas emissions. They are more inclined to do so if their marginal abatement costs are low and the proportion and stringency

TABLE 3.4: **Calibrated parameters.** This table gives the value of the parameters calibrated based on the estimates in this section and used for the simulations presented in Figure 3.2.

Parameter	Value
α	0.25
ρ	0.01
κ	0.11
κ^c	$\alpha\kappa$
κ_0	0.1
c_i	See Table 3.6
Λ	1

of green investors is high. However, uncertainty about environmental risks pushes green investors to mitigate their exposure compared to the deterministic case: green investors increase their allocation to brown companies, thereby reducing their cost of capital and encouraging them to increase their emissions relative to the deterministic case. The opposite effect arises for green companies. We support our main results by estimating our model on U.S. data. By estimating the specification derived from the model, we show that when the fraction of assets managed by green investors doubles, companies' carbon intensity drops by 5% per year.

These results suggest two main normative implications for public authorities; they emphasize the importance of establishing conditions for the development of green investments, and they highlight the need to promote transparency and disclosure of companies' environmental impacts to minimize uncertainty of future environmental impacts that green investors internalize. From the investors' viewpoint, these results suggest that they can increase their impact on companies by raising their environmental requirements as well as prompting companies to enhance disclosure on environmental issues. In addition, impact investing is financially beneficial if green investors favor companies that will reduce their environmental footprint or green companies for which information on their environmental footprint is still poorly available.

Future research may develop along two main avenues. Shareholder engagement seeks to achieve the same goals as the internalization of environmental externalities in the asset allocation by using opposite means: instead of divesting from the assets of a polluting company, the investors push companies to reform by holding part of their capital. A first line of research could jointly analyze these two mechanisms to disentangle their respective impacts and their interaction. A second line of research could introduce the ability for companies to reform dynamically to determine whether they have an incentive to maintain a stable emissions schedule or to regularly change their objectives.

3.7 Appendix A: Proofs

In this appendix we collect proofs and some supporting mathematical materials, needed to justify rigorously our claims.

Proof of Proposition 7

Since the market is assumed to be free of arbitrage and complete, there exists a unique *state price density* ξ_T, i.e., a positive $\mathcal{F}_T$-measurable integrable random variable such that the market price at time t of every contingent claim with terminal value X_T, satisfying $\mathbb{E}[\xi_T|X_T|] < \infty$, is given by

$$\xi_t^{-1}\mathbb{E}[\xi_T X_T|\mathcal{F}_t], \tag{3.30}$$

where $\xi_t := \mathbb{E}[\xi_T|\mathcal{F}_t] = \mathbb{E}_t[\xi_T]$. In particular, since the interest rate is zero, $\mathbb{E}[\xi_T] = 1$. It is worth recalling that $\mathbb{P} = \mathbb{P}^r$ and that $(B_t)_{t\in[0,T]}$ is a Brownian motion under this measure.

The optimization problems of the two investors read:

$$\min_{W_T^r\in\mathcal{A}_T} \mathbb{E}^r\left[e^{-\gamma^r W_T^r}\right], \qquad \min_{W_T^g\in\mathcal{A}_T} \mathbb{E}^g\left[Z_T e^{-\gamma^g W_T^g}\right], \tag{3.31}$$

subject to the budget constraints

$$\mathbb{E}[\xi_T W_T^r] = w^r, \qquad \mathbb{E}[\xi_T W_T^g] = w^g, \tag{3.32}$$

where $w^r > 0$ and $w^g > 0$ are the initial wealth of the regular and green investor, respectively. Both investors use the real-world probability measure for pricing but every investor uses her subjective measure for computing the utility function. Here we consider admissible controls from the class

$$\mathcal{A}_T := \{X \in \mathcal{F}_T : \mathbb{E}^r[\xi_T|X|] < \infty\}$$

and denote by Z_T the Radon-Nikodym density that connects the two probability measures $\mathbb{P}^g$ and $\mathbb{P}^r$. More precisely, recalling (3.3) and (3.5), we have

$$Z_T = e^{\int_0^T \lambda_s^\top dB_s - \frac{1}{2}\int_0^T \|\lambda_s\|^2 ds}, \tag{3.33}$$

where we set $\lambda_t := \sigma_t^{-1}\theta(\psi_t)$, to simplify the notation, and $\|\cdot\|$ is the Euclidean norm in $\mathbb{R}^n$.

The optimization problem is over the set of all admissible contingent claims, but we shall see later that the optimal claims will be attainable. Moreover, we assume that

$$\mathbb{E}^r[\xi_T|\log\xi_T|] < \infty \quad \text{and} \quad \mathbb{E}^r[\xi_T|\log Z_T|]. \tag{3.34}$$

This assumption will be checked a posteriori for the equilibrium state price density.

By the standard Lagrange multiplier argument, the solutions to problems (3.31)-(3.32) are given by

$$W_T^r = w^r - \frac{1}{\gamma^r}\log \xi_T + \frac{1}{\gamma^r}\mathbb{E}^r\left[\xi_T \log \xi_T\right], \quad W_T^g = w^g - \frac{1}{\gamma^g}\log\frac{\xi_T}{Z_T} + \frac{1}{\gamma^g}\mathbb{E}^r\left[\xi_T \log\frac{\xi_T}{Z_T}\right]. \tag{3.35}$$

The equilibrium state price density ξ_T is found from the market clearing condition

$$W_T^r + W_T^g = \mathbf{1}^\top D_T.$$

Substituting the formulas for W_T^r and W_T^g, yields

$$\xi_T = c\exp\left(-\gamma^*\mathbf{1}^\top D_T + \frac{\gamma^*}{\gamma^g}\log Z_T\right)$$

for some constant c, where we recall $\frac{1}{\gamma^*} = \frac{1}{\gamma^r} + \frac{1}{\gamma^g}$. Note that since D_T and $\log Z_T$ are Gaussian, our a priori assumptions (3.34) are satisfied.

We can now use the fact that $\mathbb{E}^r[\xi_T] = 1$ to conclude that:

$$\xi_T = \frac{\exp\left(-\gamma^*\mathbf{1}^\top D_T + \frac{\gamma^*}{\gamma^g}\log Z_T\right)}{\mathbb{E}^r\left[\exp\left(-\gamma^*\mathbf{1}^\top D_T + \frac{\gamma^*}{\gamma^g}\log Z_T\right)\right]}.$$

Substituting the explicit formulae for D_T and Z_T (see (3.1) and (3.33)) and using that

$$\int_0^T \left(-\gamma^*\mathbf{1}^\top\sigma_t + \frac{\gamma^*}{\gamma^g}\lambda_t^\top\right) dB_t$$

is normally distributed with zero mean and variance

$$\int_0^T \left\|-\gamma^*\mathbf{1}^\top\sigma_t + \frac{\gamma^*}{\gamma^g}\lambda_t^\top\right\|^2 dt,$$

because $(\sigma_t)_{t\in[0,T]}$ and $(\lambda_t)_{t\in[0,T]}$ are deterministic, we have:

$$\xi_T = \mathcal{E}\left(\int_0^\cdot \left\{-\gamma^*\mathbf{1}^\top\sigma_t + \frac{\gamma^*}{\gamma^g}\lambda_t^\top\right\} dB_t\right)_T. \tag{3.36}$$

Here $\mathcal{E}$ denotes the stochastic exponential, i.e., for any adapted square integrable process $X \in \mathbb{R}^n$,

$$\mathcal{E}\left(\int_0^\cdot X_s dB_s\right)_t = \exp\left(\int_0^t X_s dB_s - \frac{1}{2}\int_0^t \|X_s\|^2 ds\right).$$

From (3.36) and (3.33) we can easily verify that (3.34) holds, since (σ_t) and (λ_t) are deterministic.

Using the no-arbitrage pricing rule (3.30), the vector of equilibrium prices is then given by

$$p_t = \xi_t^{-1}\mathbb{E}_t^r[\xi_T D_T] = D_0 + \int_0^t \sigma_s dB_s + \mathbb{E}_t^{\mathbb{Q}}\left[\int_t^T \sigma_s dB_s\right],$$

where $\mathbb{Q}$ is the risk-neutral measure defined by

$$\frac{d\mathbb{Q}}{d\mathbb{P}^r}\bigg|_{\mathcal{F}_T} = \xi_T.$$

Under $\mathbb{Q}$, the process

$$\widetilde{B}_t = B_t - \int_0^t \left\{-\gamma^*\sigma_s^\top \mathbf{1} + \frac{\gamma^*}{\gamma^g}\lambda_s\right\} ds$$

is a standard Brownian motion. Hence, the equilibrium prices are computed as follows.

$$\begin{aligned} p_t &= \xi_t^{-1}\mathbb{E}_t^r[\xi_T D_T] \\ &= D_0 + \int_0^t \sigma_s dB_s + \int_t^T \sigma_s \left\{-\gamma^*\sigma_s^\top \mathbf{1} + \frac{\gamma^*}{\gamma^g}\lambda_s\right\} ds \\ &= D_t + \int_t^T \{-\gamma^*\Sigma_s \mathbf{1} + \alpha\theta(\psi_s)\}\, ds, \end{aligned} \tag{3.37}$$

with

$$D_t = D_0 + \int_0^t \sigma_s dB_s, \quad \Sigma_t = \sigma_t\sigma_t^\top, \qquad \theta(\psi_t) = \sigma_t\lambda_t, \quad \text{and} \quad \alpha = \frac{\gamma^r}{\gamma^r + \gamma^g}.$$

This completes the proof of (3.10).

Next we determine the number of shares that each investor holds in her portfolio. The values of the investors' portfolios are determined through the no-arbitrage pricing rule (3.30). In particular, we have

$$\begin{aligned} W_t^r &= \xi_t^{-1}\mathbb{E}_t^r[\xi_T W_T^r] \\ &= w^r - \frac{1}{\gamma^r}\mathbb{E}_t^r\left[\frac{\xi_T}{\xi_t}\left(\log\frac{\xi_T}{\xi_t} + \log\xi_t\right)\right] + \frac{1}{\gamma^r}\mathbb{E}^r\left[\xi_t\left(\frac{\xi_T}{\xi_t}\log\frac{\xi_T}{\xi_t}\right) + \left(\frac{\xi_T}{\xi_t}\right)\xi_t\log\xi_t\right], \end{aligned}$$

by simple algebraic manipulations. Then, using that ξ_T/ξ_t is independent of $\mathcal{F}_t$ (hence of ξ_t) and that $\mathbb{E}^r[\xi_t] = \mathbb{E}^r[\xi_T] = \mathbb{E}_t^r[\xi_T/\xi_t] = 1$ we obtain the wealth at time t of the regular investor

$$W_t^r = w^r - \frac{1}{\gamma^r}\log\xi_t + \frac{1}{\gamma^r}\mathbb{E}^r\left[\xi_t\log\xi_t\right]. \tag{3.38}$$

By construction $W_t^r = \mathbb{E}^{\mathbb{Q}}[W_T^r|\mathcal{F}_t]$, hence it is a $\mathbb{Q}$-martingale. Moreover, by (3.38) we see that the only stochastic term in the dynamics of (W_t^r) is $-1/\gamma^r\log\xi_t$. Then, using

$$\xi_t = \mathcal{E}\left(\int_0^\cdot \left\{-\gamma^*\mathbf{1}^\top\sigma_s + \frac{\gamma^*}{\gamma^g}\lambda_s^\top\right\} dB_s\right)_t,$$

we can conclude that, under the measure $\mathbb{Q}$, the process (W_t^r) has martingale dynamics

$$W_t^r = w^r + (1-\alpha)\int_0^t \left\{ \mathbf{1}^\top \sigma_s - \frac{1}{\gamma^g}\lambda_s^\top \right\} d\widetilde{B}_s.$$

The price derived in (3.37), on the other hand, has martingale dynamics under the measure $\mathbb{Q}$ given by

$$p_t = p_0 + \int_0^t \sigma_s d\widetilde{B}_s,$$

where

$$p_0 = D_0 + \int_0^T \left(-\gamma^* \Sigma_s \mathbf{1} + \alpha\theta(\psi_s)\right) ds.$$

It follows that the optimal claim for the investor is replicable by a self-financing portfolio whose value can be written as follows:

$$\begin{aligned} W_t^r &= w^r + (1-\alpha)\int_0^t \left\{ \mathbf{1}^\top \sigma_s - \frac{1}{\gamma^g}\lambda_s^\top \right\} \sigma_s^{-1} dp_s \\ &= w^r + (1-\alpha)\int_0^t \left\{ \mathbf{1}^\top - \frac{1}{\gamma^g}\theta(\psi_s)^\top \Sigma_s^{-1} \right\} dp_s. \end{aligned}$$

We conclude that the vector of quantities of shares held by the regular investor at time t is given by

$$N_t^r = (1-\alpha)\left\{ \mathbf{1} - \frac{1}{\gamma^g}\Sigma_t^{-1}\theta(\psi_t) \right\},$$

while that of the green investor is given by

$$N_t^g = \alpha\left\{ \mathbf{1} + \frac{1}{\gamma^r}\Sigma_t^{-1}\theta(\psi_t) \right\}.$$

The latter can be obtained by the former and the market clearing condition. Alternatively, the risk-neutral pricing principle and calculations analogous to the ones above allow us to deduce that

$$W_t^g = \xi_t^{-1}\,\mathbb{E}_t^r[\xi_T W_T^g] = w^g + \alpha \int_0^t \left\{ \mathbf{1}^\top + \frac{1}{\gamma^r}\theta(\psi_s)^\top \Sigma_s^{-1} \right\} dp_s$$

from the formula in (3.35). Hence, the expression of N_t^g follows.

Proof of Proposition 8

Recalling (3.6), the measure $\mathbb{P}^c$ has density with respect to the measure $\mathbb{P}^r$ given by

$$Z_T^c = e^{\int_0^T (\lambda_s^c)^\top dW_s - \frac{1}{2}\int_0^T \|\lambda_s^c\|^2 ds},$$

where $\lambda_t^c := \sigma_t^{-1}\theta^c(\psi_t)$.

Using (3.37) and Girsanov theorem, the vector of expected equilibrium prices under the measure $\mathbb{P}^c$ reads

$$\mathbb{E}^c(p_t) = D_0 + \int_0^t \theta^c(\psi_s)ds + \alpha \int_t^T \theta(\psi_s) - \gamma^* \int_t^T \Sigma_s \mathbf{1}\, ds.$$

Then, the profit function of the i-th company reads

$$\begin{aligned}\mathcal{J}^i(\psi^i, \psi^{-i}) = &\int_0^T e^{-\rho t}\left(D_0^i + \int_0^t \theta_i^c(\psi_s^i)ds + \alpha \int_t^T \theta_i(\psi_s^i)ds - \gamma^* \int_t^T [\Sigma_s \mathbf{1}]_i ds\right)dt \\ &+ c_i \int_0^T e^{-\rho t}(\psi_t^i - \psi_0^i)dt,\end{aligned}$$

where $[\Sigma_s \mathbf{1}]_i$ is the i-th coordinate of the vector $\Sigma_s \mathbf{1}$. Then, each company maximises a function that only depends on its own emissions.

Maximizing $\mathcal{J}^i(\psi^i, \psi^{-i})$ is equivalent to maximizing

$$\tilde{\mathcal{J}}^i(\psi^i, \psi^{-i}) = \int_0^T e^{-\rho t}\left(\int_0^t \theta_i^c(\psi_s^i)ds + \alpha \int_t^T \theta_i(\psi_s^i)ds\right)dt + c_i \int_0^T e^{-\rho t}\psi_t^i dt.$$

Applying integration by parts to the integral with respect to 'dt' we have

$$\tilde{\mathcal{J}}^i(\psi^i, \psi^{-i}) = \int_0^T \left(\frac{e^{-\rho t} - e^{-\rho T}}{\rho}\theta_i^c(\psi_t^i) + \alpha \frac{1 - e^{-\rho t}}{\rho}\theta_i(\psi_t^i) + c_i e^{-\rho t}\psi_t^i\right)dt. \quad (3.39)$$

The problem reduces to maximizing the integrand above along the entire trajectory of $(\psi_t^i)_{t\in[0,T]}$. That is

$$\max_{\psi_t^i}\left(\frac{e^{-\rho t} - e^{-\rho T}}{\rho}\theta_i^c(\psi_t^i) + \alpha \frac{1 - e^{-\rho t}}{\rho}\theta_i(\psi_t^i) + c_i e^{-\rho t}\psi_t^i\right)$$

which, multiplying by $e^{\rho t}$ reads

$$\max_{\psi_t^i}\left(\frac{1 - e^{-\rho(T-t)}}{\rho}\theta_i^c(\psi_t^i) + \alpha \frac{e^{\rho t} - 1}{\rho}\theta_i(\psi_t^i) + c_i \psi_t^i\right)$$

and the claim follows (see (3.12)).

Proof of Theorem 10

The standard approach to the problem, via dynamic programming, requires us to introduce the value processes for the two agents:

$$V_t^r = \min_{N\in\mathcal{A}_{t,T}^r} \mathbb{E}_t^r\left[\exp\left(-\gamma^r W_T^r\right)\right], \qquad V_t^g = \min_{N\in\mathcal{A}_{t,T}^g} \mathbb{E}_t^g\left[\exp\left(-\gamma^g W_T^g\right)\right],$$

where for $t \le T$ and $j \in \{r, g\}$ we define

$$\mathcal{A}_{t,T}^j := \{(N_s)_{t\le s\le T} : N \text{ is } \mathbb{R}^n\text{-valued, } (\mathcal{F}_s)_{t\le s\le T}\text{-adapted and } \mathbb{P}^j\text{-square integrable}\}$$

and $\mathbb{P}^j$-square integrable means

$$\mathbb{E}^j\left[\int_0^T |N_t|^2 dt\right] < +\infty.$$

Moreover, we assume that the equilibrium price has the following dynamics.

$$p_t = p_0 + \int_0^t \mu_s ds + \int_0^t \sigma_s dB_s + \sum_{k=1}^{\mathcal{N}_t} Y_k \tag{3.40}$$

where μ is deterministic and must be found in equilibrium. We shall show a posteriori that an equilibrium price process of this form can indeed be found.

Notice that from $p_T = D_T$ it follows that

$$p_0 + \int_0^T \mu_s ds = D_0,$$

and recalling (3.16) we can equivalently write

$$p_t = D_0 - \int_t^T \mu_s ds + \int_0^t \sigma_s dB_s + \sum_{k=1}^{\mathcal{N}_t} Y_k = D_t - \int_t^T \mu_s ds.$$

Following a well-known ansatz we expect

$$V_t^r = \exp\left(-\gamma^r W_t^r + Q_t^r\right), \qquad V_t^g = \exp\left(-\gamma^g W_t^g + Q_t^g\right),$$

where Q^r and Q^g are absolutely continuous deterministic processes with

$$dQ_t^r = q_t^r dt \quad \text{and} \quad dQ_t^g = q_t^g dt.$$

Applying the Itô's formula for jump processes yields

$$\begin{aligned}
dV_t^r &= V_{t-}^r\left(-\gamma^r dW_t^r + q_t^r dt + \frac{(\gamma^r)^2}{2} d[W^r]_t^c + (e^{-\gamma \Delta W_t^r} - 1 + \gamma \Delta W_t^r)\right) \\
&= V_{t-}^r\Big(- \gamma^r (N_t^r)^\top dp_t + q_t^r dt + \frac{(\gamma^r)^2}{2}(N_t^r)^\top d[p]_t^c N_t^r \\
&+ (e^{-\gamma (N_{t-}^r)^\top \Delta p_t} - 1 + \gamma^r (N_{t-}^r)^\top \Delta p_t)\Big) \\
&= V_{t-}^r\Big(- \gamma^r (N_t^r)^\top \mu_t + q_t^r + \frac{(\gamma^r)^2}{2}(N_t^r)^\top \sigma_t \sigma_t^\top N_t^r \\
&+ \Lambda_t \int_{\mathbb{R}^n} (e^{-\gamma^r (N_t^r)^\top z} - 1)\nu_t^\psi(dz)\Big) dt + M_t,
\end{aligned}$$

where (M_t) is a $\mathbb{P}^r$-martingale on $[0,T]$ and $[W^r]^c$ is the continuous part of the quadratic variation of the process W^r. Since V^r must be a martingale along the trajectory of the optimal process (N_t^r) and a submartingale along every trajectory, we conclude that the drift term in 'dV_t^r' must be non-negative and

$$\min_{N_t}\left(-\gamma^r N_t^\top \mu_t + q_t^r + \frac{(\gamma^r)^2}{2} N_t^\top \Sigma_t N_t + \Lambda_t\big(L_t(-\gamma^r N_t) - 1\big)\right) = 0 \tag{3.41}$$

for each $t \in [0,T]$. Since Σ is nondegenerate, the function to be maximized is strictly convex and coercive (i.e., it tends to $+\infty$ as $\|N_t\| \to \infty$; notice that $L_t(-\gamma^r N_t) > 0$), thus the unique maximum is always attained. With a slight abuse of notation, we denote the minimizer of (3.41) (which does not depend on q_t) by N_t^r, as this will be the number of assets held by the regular investors. By imposing first order conditions we have that N_t^r must be the unique solution of

$$\mu_t - \gamma^r \Sigma_t N_t + \Lambda_t \nabla L_t(-\gamma N_t) = 0.$$

By the same logic, the green investors use the measure $\mathbb{P}^g$ to compute the dynamic 'dV_t^g' and find the optimal quantity of assets. In particular, the optimal quantity N_t^g is the minimizer of

$$\min_{N_t}\left(-\gamma^g N_t^\top \mu_t + q_t^g + \frac{(\gamma^g)^2}{2} N_t^\top \Sigma_t N_t + \Lambda_t^g\big(L_t(-\gamma^g N_t) - 1\big)\right) = 0.$$

The market clearing condition therefore allows to compute (μ, N^r, N^g) by solving the following system of equations:

$$\begin{aligned} &\mu_t - \gamma^r \Sigma_t N_t^r + \Lambda_t \nabla L_t(-\gamma^r N_t^r) = 0; \\ &\mu_t - \gamma^g \Sigma_t N_t^g + \Lambda_t^g \nabla L_t(-\gamma^g N_t^g) = 0; \\ &N_t^r + N_t^g = \mathbf{1}. \end{aligned} \tag{3.42}$$

Substituting μ_t from the second equation into the first one, allows to eliminate it, obtaining Equation (3.17) in our theorem. The left-hand side of Equation (3.17) coincides with the gradient of the strictly convex, differentiable and coercive function

$$f(N) := -\gamma^g \Sigma_t \mathbf{1} N + \frac{\gamma^r + \gamma^g}{2} N^\top \Sigma_t N + \frac{\Lambda_t}{\gamma^r} L_t(-\gamma^r N) + \frac{\Lambda_t^g}{\gamma^g} L_t(-\gamma^g(\mathbf{1} - N)),$$

which proves existence and uniqueness of the solution of (3.17).

Proof of Proposition 11

The Laplace transform of the shock size distribution, scaled by h, reads

$$L_t^h(u) = \int_{\mathbb{R}^n} e^{hu^\top z} \nu_t^\psi(dz), \quad t \in [0,T].$$

If we denote the quantities of assets held by the regular investor by $N^{r,h}$, then by Theorem 10 (see also (3.20)) we have

$$-\gamma^g \Sigma_t \mathbf{1} + (\gamma^g + \gamma^r)\Sigma_t N_t^{r,h} + \Lambda^{g,h}\nabla L_t^h(-\gamma^g(\mathbf{1} - N_t^{r,h})) = 0. \tag{3.43}$$

Consider now the function $f_h : \mathbb{R}^n \to \mathbb{R}$ defined by

$$\begin{aligned} f_h(N) &:= -\gamma^g \mathbf{1}^\top \Sigma_t N + \frac{\gamma^r + \gamma^g}{2} N^\top \Sigma_t N + \frac{\Lambda_t^{g,h}}{\gamma^g}\Big(L_t^h(-\gamma^g(\mathbf{1} - N)) - 1\Big), \\ &= -\gamma^g \mathbf{1}^\top \Sigma_t N + \frac{\gamma^r + \gamma^g}{2} N^\top \Sigma_t N - \theta(\psi_t)^\top(\mathbf{1} - N) \\ &\quad + \frac{\Lambda^{g,h}}{\gamma^g}\Big(L_t^h(-\gamma^g(\mathbf{1} - N)) + h\gamma^g(e_t^\psi)^\top(\mathbf{1} - N) - 1\Big). \end{aligned}$$

On the one hand, this function satisfies $f_h(\mathbf{1}) = \frac{\gamma^r - \gamma^g}{2}\mathbf{1}^\top \Sigma_t \mathbf{1}$. On the other hand, since the Laplace transform is positive and the only quadratic term in N is positive, it is clear that there exists a constant k, independent of h such that, for $\|N\|$ large enough,

$$f_h(N) \geq k\|N\|^2. \tag{3.44}$$

Since $N_t^{r,h}$ minimizes $f_h(N)$ (see Theorem 10) we have

$$f_h(\mathbf{1}) \geq f_h(N_t^{r,h}) \geq k\|N_t^{r,h}\|^2,$$

where the final inequality holds if $\|N_t^{r,h}\|$ is large. So, either way the norm of $N_t^{r,h}$ is bounded from above by a constant independent of h. Now, let

$$N_t^{r,h} = N_t^{r,0} + N_t^{r,1}(h) \quad \text{with} \quad N_t^{r,0} := (1-\alpha)\left\{\mathbf{1} - \frac{1}{\gamma^g}\Sigma_t^{-1}\theta(\psi_t)\right\}. \tag{3.45}$$

It follows from (3.44) that the norm of $N_t^{r,1}(h)$ is also bounded from above. Substituting (3.45) into (3.43) we obtain an equation for $N_t^{r,1}(h)$:

$$-(\gamma^r + \gamma^g)\Sigma_t N_t^{r,1}(h) + \Lambda_t^{g,h}\nabla L_t^h\Big(-\gamma^g\big(\mathbf{1} - N_t^{r,0} - N_t^{r,1}(h)\big)\Big) - \theta(\psi_t) = 0 \tag{3.46}$$

To proceed we shall use the next lemma.

Lemma 2. *Fix $t \in [0,T]$. As $h \to 0$, the following limit holds uniformly for $u \in \mathbb{R}^n$ lying in a compact:*

$$\lim_{h\to 0}\frac{1}{h}\left\{\Lambda_t^{g,h}\nabla L_t^h(u) - \theta(\psi_t)\right\} = \pi(\psi_t)u.$$

with $\pi(\psi_t)$ as in (3.21).

Proof. The expression under the limit is computed as follows.

$$\begin{aligned}\frac{1}{h}\left\{\Lambda^{g,h}\nabla L_t^h(u)-\theta(\psi_t)\right\} &= \frac{1}{h}\left\{\Lambda^{g,h}\nabla L_t^h(u)-\Lambda_t^g e_t^\psi\right\}\\ &= \Lambda_t^g\int_{\mathbb{R}^n} u^\top z\, z\left(\int_0^1 e^{\zeta\, h\, u^\top z}d\zeta\right)\nu_t^\psi(dz).\end{aligned}$$

To prove the lemma, it is enough to show that

$$\int_{\mathbb{R}^n} z_i\, z_j\left(\int_0^1 e^{\zeta\, h\, u^\top z}d\zeta\right)\nu_t^\psi(dz)\to\int_{\mathbb{R}^n} z_i\, z_j\nu_t^\psi(dz)$$

as $h\to 0$, uniformly on $u\in[-U,U]^n$, for $0<U<\infty$. It is also enough, by considering each orthant separately, to show that

$$\int_{\mathbb{R}^n} z_i\, z_j\mathbf{1}_{z_i\ge 0}\mathbf{1}_{z_j\ge 0}\left(\int_0^1 e^{\zeta\, h\, u^\top z}d\zeta\right)\nu_t^\psi(dz)\to\int_{\mathbb{R}^n} z_i\, z_j\mathbf{1}_{z_i\ge 0}\mathbf{1}_{z_j\ge 0}\nu_t^\psi(dz) \qquad (3.47)$$

Assume that $u\in[-U,U]^n$. The integral $\int_0^1 e^{\zeta\, h\, u^\top z}d\zeta$ admits the following bounds:

$$e^{-hU\sum|z_i|}\le\int_0^1 e^{\zeta\, h\, u^\top z}d\zeta\le e^{hU\sum|z_i|}.$$

Then,

$$\int_{\mathbb{R}^n} z_i\, z_j\mathbf{1}_{z_i\ge 0}\mathbf{1}_{z_j\ge 0}\left(\int_0^1 e^{\zeta\, h\, u^\top z}d\zeta\right)\nu_t^\psi(dz)\le\int_{\mathbb{R}^n} z_i\, z_j\mathbf{1}_{z_i\ge 0}\mathbf{1}_{z_j\ge 0}e^{hU\sum|z_i|}\nu_t^\psi(dz),$$

and similarly for the lower bound. If we recall the well-known inequality

$$|z_i\, z_j|e^{hU\sum|z_i|}\le\frac{1}{2\epsilon}|z_i\, z_j|^2+2\epsilon\, e^{2hU\sum|z_i|}\quad\text{for any }\epsilon>0,$$

we can use Assumption 7 (which implies that ν_t^ψ has finite 4-th moment) and the dominated convergence theorem, to conclude that

$$\lim_{h\to 0}\int_{\mathbb{R}^n} z_i\, z_j\mathbf{1}_{z_i\ge 0}\mathbf{1}_{z_j\ge 0}e^{hU\sum|z_i|}\nu_t^\psi(dz)=\int_{\mathbb{R}^n} z_i\, z_j\mathbf{1}_{z_i\ge 0}\mathbf{1}_{z_j\ge 0}\nu_t^\psi(dz).$$

A similar argument holds for lower bound, so that the convergence in (3.47) holds uniformly on $u\in[-U,U]^n$ and the lemma is proved. □

In view of the boundedness of $N_t^{r,1}(h)$, we immediately conclude from the above lemma and (3.46) that $N_t^{r,1}(h)\to 0$ as $h\to 0$. But then, we can divide both sides of (3.46) by h and take the limit:

$$-(\gamma^r+\gamma^g)\Sigma_t\lim_{h\to 0}\frac{1}{h}N_t^{r,1}(h)+\lim_{h\to 0}\frac{1}{h}\left\{\Lambda_t^{g,h}\nabla L_t^h\big(-\gamma^g(\mathbf{1}-N_t^{r,0}-N_t^{r,1}(h))\big)-\theta(\psi_t)\right\}=0.$$

Using once again Lemma 2, we conclude that

$$\lim_{h\to 0}\frac{1}{h}N_t^{r,1}(h) = -(1-\alpha)\Lambda_t^g\Sigma_t^{-1}S_t\,(\mathbf{1}-N_t^{r,0}) = (1-\alpha)\alpha\Lambda_t^g\Sigma_t^{-1}S_t\,\left\{\mathbf{1}+\frac{1}{\gamma^r}\Sigma_t^{-1}\theta(\psi_t)\right\}.$$

This shows that $N_t^{r,1}(h)$ is differentiable at $h=0$ and allows to write down its first order Taylor expansion up to a remainder of order $O(h^2)$. Recalling the expression for the drift μ_t from (3.19) and that $\Lambda_t\equiv 0$, we have $\mu_t^h = \gamma^r\Sigma_t N_t^{r,h}$. Then, using the first order expansion of $N_t^{r,h}$ we obtain (3.22).

Proof of Proposition 13

We start by recalling that the equilibrium price dynamics reads (see (3.40) and (3.18))

$$p_t = p_0 + \int_0^t \mu_s ds + \int_0^t \sigma_s dB_s + \sum_{k=1}^{\mathcal{N}_t} Y_k = D_0 - \int_t^T \mu_s ds + \int_0^t \sigma_s dB_s + \sum_{k=1}^{\mathcal{N}_t} Y_k.$$

In order to compute the objective function of the i-th company (see (3.8)) we first notice that recalling (3.40) we have

$$\mathbb{E}^c[p_t^i(\psi^i,\psi^{-i})] = D_0 - \int_t^T \mu_s^i ds + \mathbb{E}^c\left[\sum_{k=1}^{\mathcal{N}_t} Y_k\right] \sim -\int_t^T \mu_s^i ds + \int_0^t \theta_i^c(\psi_s)ds, \quad (3.48)$$

where the sign "$\sim$" means that the two sides are equal up to terms which do not depend on the emissions schedule[17]. In particular the integral of $\theta_i^c(\psi_s) = \Lambda_t^c e_t^{\psi}$ appears due to the following calculations:

$$\mathbb{E}^c\left[\sum_{k=1}^{\mathcal{N}_t} Y_k\right] = \mathbb{E}^c\left[\int_0^t Y_s d\mathcal{N}_s\right] = \int_0^t \mathbb{E}^c[Y_s]\, d\,\mathbb{E}^c[\mathcal{N}_s],$$

where the final equality uses independence of Y_s and $\mathcal{N}_s$ and we conclude by using $\mathbb{E}^c[Y_s] = e_s^{\psi}$ and $\mathbb{E}^c[\mathcal{N}_s] = \int_0^s \Lambda_u^c du$.

Then, the optimization problem of the i-th company reads

$$\begin{aligned}\mathcal{J}^i(\psi^i,\psi^{-i}) &\sim \int_0^T e^{-\rho t}\left\{-\int_t^T \mu_s^i ds + \int_0^t \theta_i^c(\psi_s)ds\right\}dt + c_i\int_0^T e^{-\rho t}\psi_t^i dt\\ &= \int_0^T e^{-\rho t}\{-\beta_t\mu_t^i + \beta_t^c\theta_i^c(\psi_t) + c_i\psi_t^i\}dt, \qquad (3.49)\end{aligned}$$

where the final expression follows by integration by parts as in (3.39). As in Proposition 8, also in this case the problem reduces to a point-wise maximisation along the trajectory of the emissions schedule. Since the problem is too complex in its full generality and we are interested in the asymptotic results as $h\to 0$, we replace μ_t in

[17]We must of course keep the drift term because in general it depends on the emissions by Theorem 10.

(3.49) by its first order Taylor expansion, obtained in Proposition 11, i.e.

$$\mu_t^h = \mu_t^0 + h\mu_t^1 + O(h^2),$$

with

$$\mu_t^0 = \alpha\gamma^g\Sigma_t\mathbf{1} - \alpha\theta(\psi_t) \quad \text{and} \quad \mu_t^1 := (1-\alpha)\alpha\pi(\psi_t)\,\left(\gamma^r\mathbf{1} + \Sigma_t^{-1}\theta(\psi_t)\right).$$

Dropping terms of the second order in h the optimization for the i-th company reduces to maximizing over ψ_t^i the functional

$$\int_0^T e^{-\rho t}\{-\beta_t(\mu_t^{0,i} + h\cdot\mu_t^{1,i})(\psi_t) + \beta_t^c\theta_i^c(\psi_t) + c_i\psi_t^i\}dt.$$

After dropping terms independent of ψ, the latter is equivalent to maximizing

$$\alpha\beta_t\theta_i(\psi_t) + \beta_t^c\theta_i^c(\psi_t) + c_i\psi_t - h\beta_t\alpha(1-\alpha)\left[\pi(\psi_t)\left(\gamma^r\mathbf{1} + \Sigma_t^{-1}\theta(\psi_t)\right)\right]_i \tag{3.50}$$

for each $t\in[0,T]$. Due to the fact that $\pi(\psi_t) = \Lambda_t^g\,(e_t^\psi(e_t^\psi)^\top)$, with Λ_t^g independent of ψ_t, and $\theta(\psi_t) = \Lambda_t^g\,e_t^\psi$ we can equivalently write (3.50) in terms of $\theta(\psi_t)$ as

$$\begin{aligned}
&\alpha\beta_t\theta_i(\psi_t) + \beta_t^c\theta_i^c(\psi_t) + c_i\psi_t - h\beta_t\alpha(1-\alpha)\Lambda_t^g\,e_t^{\psi,i}\Big(\gamma^r(e_t^\psi)^\top\mathbf{1} + (e_t^\psi)^\top\Sigma_t^{-1}\theta(\psi_t)\Big)\\
&= \alpha\beta_t\theta_i(\psi) + \beta_t^c\theta_i^c(\psi) + c_i\psi - h\frac{\beta_t\alpha(1-\alpha)}{\Lambda_t^g}\,\theta_i(\psi_t)\Big(\gamma^r\theta^\top(\psi_t)\mathbf{1} + \theta^\top(\psi_t)\Sigma_t^{-1}\theta(\psi_t)\Big)
\end{aligned} \tag{3.51}$$

Clearly, the equilibrium strategy corresponding to the zeroth-order approximation of μ, i.e., taking $h=0$ in (3.51), is given by

$$\psi_t^{*,0,i} = \arg\max_\psi\{\alpha\beta_t\theta_i(\psi) + \beta_t^c\theta_i^c(\psi) + c_i\psi\}$$

In order to find the 'uncertainty correction' to the equilibrium emission strategy, we expand the last term of (3.50) around $\psi^{*,0}$. The maximizer will satisfy

$$\Delta\theta^h := \theta(\psi^*) - \theta(\psi^{*,0}) = O(h)$$

hence we can ignore terms of order higher than one in $\Delta\theta^h$. Then, approximating (3.51) and dropping terms independent of ψ, the i-th player must maximise

$$\begin{aligned}
g_h^i(\psi_t) =& \alpha\beta_t\theta_i(\psi_t) + \beta_t^c\theta_i^c(\psi_t) + c_i\psi_t\\
&- h\frac{\beta_t\alpha(1-\alpha)}{\Lambda_t^g}\,\theta_i(\psi_t)\Big(\gamma^r\theta^\top(\psi_t^{*,0})\mathbf{1} + \theta^\top(\psi_t^{*,0})\Sigma_t^{-1}\theta(\psi_t^{*,0})\Big)\\
&- h\frac{\beta_t\alpha(1-\alpha)}{\Lambda_t^g}\,\theta_i(\psi_t^{*,0})\Big(\gamma^r\mathbf{1}^\top\theta(\psi_t) + 2\theta^\top(\psi_t^{*,0})\Sigma_t^{-1}\theta(\psi_t)\Big).
\end{aligned}$$

Differentiating with respect to ψ_t^i and imposing first order conditions we obtain

$$-\left(\alpha\kappa\beta_t+\kappa^c\beta_t^c\right)\psi_t^i+c_i+h\kappa\beta_t\frac{\alpha(1-\alpha)}{\Lambda_t^g}\left(\gamma^r\mathbf{1}^\top\theta(\psi_t^{*,0})+\theta^\top(\psi_t^{*,0})\Sigma_t^{-1}\theta(\psi_t^{*,0})\right)\psi_t^i$$
$$+h\kappa\beta_t\frac{\alpha(1-\alpha)}{\Lambda_t^g}\,\theta_i(\psi_t^{*,0})\left(\gamma^r\mathbf{1}^\top\delta_i+2\theta^\top(\psi_t^{*,0})\Sigma_t^{-1}\delta_i\right)\psi_t^i=0,$$

where δ_i is a vector whose i-th coordinate is equal to one and all other coordinates are zero. Rearranging terms and recalling that $\psi_t^{*,0,i}=c_i(\alpha\kappa\beta_t+\kappa^c\beta_t^c)$ we obtain

$$\psi_t^i\Bigg(1-h\kappa\beta_t\frac{\alpha(1-\alpha)}{c_i\Lambda_t^g}\Bigg[\left(\gamma^r\mathbf{1}^\top\theta(\psi_t^{*,0})+\theta^\top(\psi_t^{*,0})\Sigma_t^{-1}\theta(\psi_t^{*,0})\right)$$
$$+\theta_i(\psi_t^{*,0})\left(\gamma^r\mathbf{1}^\top\delta_i+2\theta^\top(\psi_t^{*,0})\Sigma_t^{-1}\delta_i\right)\Bigg]\psi_t^{*,0,i}\Bigg)=\psi_t^{*,0,i}.$$

Solving for ψ_t^i concludes the proof given that $\psi^i\mapsto g_h^i(\psi^i)$ is concave for small h (notice also that the denominator in (3.23) is not zero for small h).

3.8 Appendix B: Additional tables

TABLE 3.5: **Externality premia broken down by industry.** This table presents the externalities premia, estimated using specification (3.26), broken down by SIC industry and ranked in descending order.

Industry name	Externality premium
Tobacco products	0.0023^{***}
Defense	0.0022^{***}
Printing and publishing	0.002^{***}
Precious metals	0.0018^{***}
Coal	0.0015^{***}
Aircraft	0.0014^{***}
Non-metallic and industrial metal mining	0.0013^{***}
Cand & Soda	0.0012^{***}
Entertainment	0.0012^{***}
Petroleum and natural gas	0.0011^{***}
Communication	0.0011^{***}
Shipping containers	0.001^{***}
Trading	0.001^{***}
Retail	0.0009^{***}
Meals	0.0009^{***}
Banking	0.0009^{***}
Insurance	0.0009^{***}
Pharmaceutical products	0.0008^{***}
Personal services	0.0008^{***}
Clothes apparel	0.0007^{***}
Real estate	0.0006^{***}
Business services	0.0004^{***}
Recreation	0.0003^{***}
Transportation	0.0001^{**}
Beer & Liquor	0
Chemicals	0
Computers	0
Consumer Goods	-0.0001^{***}
Steel works	-0.0001
Shipbuilding & Railroad equipment	-0.0001
Agriculture	-0.0002
Automobiles and trucks	-0.0002^{***}
Rubber and plastic products	-0.0004^{***}
Healthcare	-0.0006^{***}
Textiles	-0.0006^{***}
Food products	-0.0007^{***}
Medical equipment	-0.0007^{***}
Chips	-0.0012^{***}
Wholesale	-0.0015^{***}
Business supplies	-0.0021^{***}
Utilities	-0.0023^{***}
Machinery	-0.0026^{***}
Fabricated products	-0.0028^{***}
Construction materials	-0.0051^{***}
Electrical equipment	-0.0069^{***}
Measuring and control equipment	-0.0076^{***}
Construction	-0.0083^{***}
Other	-0.0217^{***}
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

TABLE 3.6: **Carbon intensities and marginal abatement costs.** This table gives, for each SIC industry, the average carbon intensity of the companies, ψ, the industry fixed effect estimated via specification (3.29) and the estimated marginal abatement cost, c_i, such that $f_i = log(c_i)$.

Industry	ψ^i	f_i	c_i
Precious metals	566.76	2.84	17.12
Petroleum and natural gas	436.64	2.63	13.87
Non-metallic and industrial metal mining	498.51	2.57	13.07
Shipping containers	540.90	2.53	12.55
Transportation	377.60	2.45	11.59
Steel works	492.61	2.44	11.47
Food products	466.31	2.43	11.36
Chemicals	417.34	2.37	10.70
Utilities	375.12	2.37	10.70
Business supplies	396.08	2.36	10.59
Textiles	364.15	2.30	9.97
Fabricated products	284.29	1.99	7.32
Construction materials	302.78	1.91	6.75
Other	255.54	1.83	6.23
Cand & Soda	220.34	1.78	5.93
Beer & Liquor	208.01	1.58	4.85
Rubber and plastic products	184.31	1.46	4.31
Tobacco products	155.53	1.36	3.90
Consumer Goods	152.09	1.34	3.82
Machinery	176.77	1.34	3.82
Electrical equipment	152.54	1.23	3.42
Meals	146.95	1.23	3.42
Medical equipment	84.90	1.17	3.22
Shipbuilding & Railroad equipment	172.74	1.16	3.19
Automobiles and trucks	168.17	1.09	2.97
Wholesale	123.34	0.99	2.69
Personal services	115.42	0.91	2.48
Recreation	96.41	0.88	2.41
Chips	117.14	0.85	2.34
Aircraft	89.24	0.83	2.29
Defense	130.73	0.80	2.23
Construction	86.40	0.69	1.99
Insurance	15.88	0.69	1.99
Clothes apparel	73.46	0.65	1.92
Measuring and control equipment	78.20	0.62	1.86
Pharmaceutical products	70.44	0.56	1.75
Real estate	74.78	0.44	1.55
Retail	74.72	0.43	1.54
Entertainment	59.26	0.15	1.16
Communication	35.53	0.12	1.13
Printing and publishing	70.85	0.11	1.12
Healthcare	59.20	0.08	1.08
Computers	57.64	-0.17	0.84
Business services	41.21	-0.18	0.84
Trading	26.20	-0.69	0.50
Banking	10.53	-0.86	0.42

Conclusion

In this thesis, I study the effect of investors' pro-environmental preferences on asset prices and companies' practices.

I show that pro-environmental preferences impact asset returns and prices in equilibrium. I characterize the effect in a one-period model (Chapter 1) and a multi-period model (Chapter 3). In equilibrium, asset returns decrease (increase) for green (brown) assets because sustainable investors accept a lower (require a higher) return to hold them. I estimate this effect by constructing a proxy using green fund holdings (Chapters 1 and 3): the average effect between the least and most polluting industries ranged between -1.12% and 0.14% per year between 2007 and 2019 and increased over time (Chapter 1). I also document the effect of exclusionary screening on asset returns. I show that this sustainable investing practice translates into two exclusion premia, one of which is a generalized form of Merton (1987)'s premium on neglected stocks. When applying the model to sin stocks as excluded assets, the exclusion effect was 1.43% per year between 2007 and 2019.

I also estimate the share of the green premium induced by non-pecuniary preferences by focusing on the bond market (Chapter 2). To do so, I use green bonds as an instrument that I compare to a synthetic counterfactual conventional bond, and I derive the yield differential by controlling for the effect of the difference in liquidity. The share of non-pecuniary preferences in the yield differential between green and brown assets is small—approximately 2 bps, which is the yield that green investors are willing to forgo owing to their non-pecuniary preferences. This result suggests that the yield differential between the bond yields of green and brown companies is mainly driven by green investors' expectations of environment-related financial risks being more pronounced for brown companies rather than the effect of non-pecuniary preferences.

Finally, Tiziano De Angelis, Peter Tankov, and I show that by modifying the equilibrium return, and thus companies' cost of capital, investors push them to reform (Chapter 3). Consequently, companies pay a price to mitigate their environmental impact and increase their shareholder base, thereby lowering their cost of capital. In particular, both the increase in the proportion of green investors and their environmental stringency push companies to reduce their carbon footprint. We estimate the equilibrium equation applied to companies' carbon intensity by using the history of green fund holdings. When the share of green investors doubles, the carbon, companies' carbon intensity falls by an average of 5% per year. Extending our analysis to the case where environmental externalities are *uncertain*, we show that green investors reduce their allocation to risky assets, thereby mitigating the pressure they exert on the most polluting companies' cost of capital. As a result, brown companies are incentivized to increase their carbon footprint compared to the equilibrium without uncertainty.

The results of this thesis have several normative implications for investors and public authorities. From the investors' viewpoint, (i) the results show that it is financially profitable to support companies that will become green. Indeed, the direct taste premium decreases when the cost of environmental externalities decreases. Moreover, (ii) we show that green investors have the means to increase their impact on the most polluting companies and push them to reduce their environmental footprint by increasing their environmental requirements. To do so, they can either restrict their investment scope to the most virtuous companies or more significantly underweight the least virtuous companies.

From the viewpoint of the public authorities, (i) the results of this thesis show that supporting the increase in the proportion of green investors contributes to increasing the pressure on the most polluting companies and accelerating the mitigation of their environmental footprint. The consolidation of green finance can be achieved through the development of green stock market indices, environmental taxonomies, green standards and certifications, the improvement of green securities' liquidity, and the raising of retail investors' awareness about the risks and opportunities of environmental issues. Those are levers that contribute to the growth of the share of investors likely to internalize pro-environmental preferences in their investment choices. Moreover, (ii) developing initiatives and regulations to increase transparency on the environmental footprint of companies gives green investors the means to have a stronger impact on companies and thus contribute to accelerating the ecological transition.

Several research avenues are possible building on this thesis. First, another key aspect of green investment is the ability for shareholders to push companies to reform by participating in companies' decisions; this is called shareholder engagement. This practice is not examined in this thesis, and its interaction with ESG integration and divestment practices is not yet developed in the academic literature. However, regarding the analysis of impact investing, it is crucial to take into account shareholder engagement as well, as it aims at the same goals as ESG integration by using opposite means—increasing participation in a brown company to support the reduction of its environmental footprint. This dual approach constitutes a potentially fruitful line of research in the continuity of this thesis. Second, an empirical study could be performed to assess whether the use of green bonds' proceeds has a differentiating impact on the green premium. This would make it possible to identify whether the degree of non-pecuniary preferences induces a differentiating impact on asset returns. Third, a literature that combines asset pricing and climate models is emerging. Such interdisciplinary contributions could shed light on the role that finance could play to support and foster the ecological transition.

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Résumé en français

1. Définitions liminaires

Préférences pro-environnementales. Un investisseur a des préférences pro-environnementales lorsque, dans sa fonction d'utilité, il valorise plus fortement les actifs des entreprises les plus vertes et plus faiblement les actifs des entreprises les plus polluantes. Ces préférences pro-environnementales peuvent être motivées par des enjeux pécuniers ou non-pécuniers.

Préférences non-pécuniaires. Un investisseur a des préférences non-pécuniaires pour certains actifs lorsqu'il valorise plus fortement ces derniers, indépendamment de leur rendement anticipé ou de leur variance anticipée. En particulier, les préférences pro-environnementales non-pécuniaires font références aux motivations des investisseurs à investir dans des actifs verts indépendamment de leurs caractéristiques financières.

Investissement d'impact. Un investissement d'impact vise à « générer un impact social et environnemental positif et mesurable, en complément d'un rendement financier » (Global Impact Investing Network). En particulier, un investissement d'impact environnemental cherche à réduire l'empreinte environnementale des entreprises émettrices des actifs financiers.

2. Enjeux et problématiques

L'urgence environnementale, qui suppose de repenser l'organisation de nos sociétés et le fonctionnement de nos économies, nécessite de mobiliser des capacités de financement considérables. Pour exemple, les seuls besoins d'infrastructure au cours des quinze prochaines années permettant aux pays de l'OCDE d'être cohérents avec la trajectoire 2 degrés Celsius s'élèvent à 6 900 milliards de dollars (OECD, 2017a). En complément du soutien public, les financements privés représentent donc un précieux levier pour parvenir à mobiliser de tels montants.

De manière concomitante, l'intérêt des investisseurs financiers pour les enjeux environnementaux s'est considérablement accru au cours des dernières années. Les investisseurs qualifiés de « verts » adaptent ainsi leur allocation d'actifs en surpondérant les actifs des entreprises les plus vertueuses sur le plan environnemental et en sous-pondérant, voire en excluant, les actifs des entreprises les plus polluantes. L'ajustement de leur allocation d'actifs peut être motivée par deux principaux enjeux : (i) des préférences non-pécuniaires pour les enjeux environnementaux et (ii) l'internalisation du risque financier lié à l'environnement. Dans le premier cas, les investisseurs excluent les entreprises les plus polluantes pour des raisons éthiques et sont prêts à renoncer à une partie de leur rendement espéré au nom de leurs convictions environnementales. Dans le second cas, les investisseurs se couvrent contre un risque financier lié à l'environnement qui est encore imparfaitement valorisé par les marchés financiers. Ce risque peut être un risque de transition environnementale (Jakob and Hilaire, 2015), un risque physique (Arnell and Gosling, 2016) ou un risque légal (Hunter and Salzman, 2007).

Que ce soit pour des motifs non-pécuniers ou pour internaliser un risque financier lié à l'environnement, l'ajustement de l'allocation d'actif des investisseurs verts a une double incidence : (i) elle modifie les prix et les rendements des actifs à l'équilibre et, en conséquence, (ii) elle affecte les pratiques des entreprises en modifiant leur coût du capital. L'analyse de la première conséquence participe d'une approche de valorisation d'actifs, tandis que l'analyse de la seconde conséquence s'inscrit dans le champ de recherche embryonnaire que l'on qualifie d'investissement d'impact.

Dès lors, trois grandes questions se posent :

- Comment les rendements espérés des actifs se déforment-ils lorsqu'un groupe d'investisseurs internalise les enjeux environnementaux dans son allocation d'actifs ? [Chapitre 1]

- Comment se décompose l'ajustement du rendement espéré entre (i) l'impact des préférences non-pécuniaires et (ii) celui de l'internalisation du risque financier lié à l'environnement ? [Chapitre 2]

- Les entreprises les plus polluantes, dont le coût du capital est affecté par les pratiques des investisseurs verts, sont-elles incitées à réduire leur impact environnemental ? [Chapitre 3]

Comme l'illustre la Figure 1, les trois chapitres de cette thèse s'attachent à répondre respectivement à chacune de ces questions.

3. L'investissement environnemental

a. L'approche de valorisation d'actifs

i. Valorisation d'actifs avec préférences pro-environnementales

La théorie moderne du portefeuille, fondée sur le travail séminal de Markowitz (1952), ainsi que le modèle d'évaluation d'actifs, qui s'appuie sur les contributions de Sharpe (1964) et Lintner (1965), n'offrent pas le cadre théorique permettant d'expliquer l'effet des préférences pro-environnementales des investisseurs sur les rendements des actifs à l'équilibre. Si plusieurs facteurs de risque, tels que les facteurs de Fama and French (1993) ou de Carhart (1997), ont été identifiés comme des déterminants de la dynamique des rendements des actifs, ils ne permettent pas non plus d'expliquer l'effet de l'investissement vert sur le rendement des actifs.

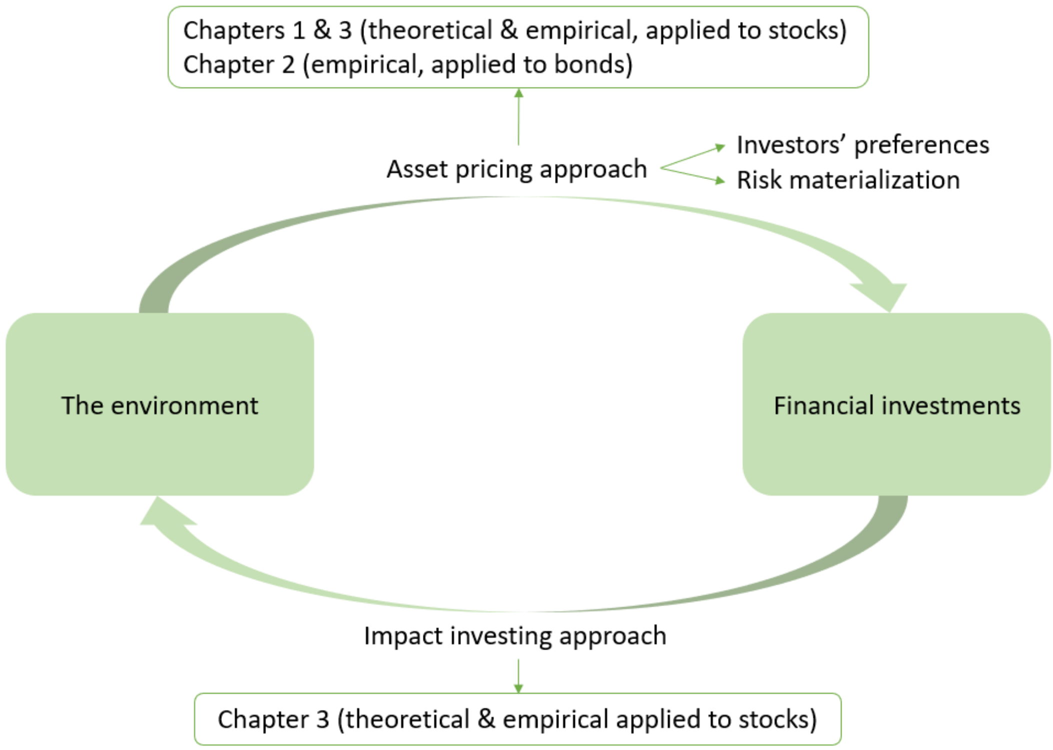

FIGURE 5: **Principales approches de recherche en investissement environnemental** Ce schéma illustre les deux principales approches de recherche dans le champ de l'investissement environnemental: la valorisation d'actifs et l'investissement d'impact.

Une foisonnante littérature empirique a cherché à mettre en évidence l'effet de l'impact environnemental des entreprises sur leurs rendements à l'équilibre. Généralement, ces articles ont cherché à régresser des rendements financiers réalisés sur des notes environnementales. Cependant, les résultats de cette littérature sont non conclusifs :

- Certains articles mettent en évidence une relation négative entre la performance environnementale et la performance financière, notamment Brammer, Brooks, and Pavelin (2006), Renneboog, Ter Horst, and Zhang (2008) et Barber, Morse, and Yasuda (2018). De plus, Sharfman and Fernando, 2008, ElGhoul et al. (2011) et Chava (2014) mettent en évidence ce même effet sur les rendements espérés. Bolton and Kacperczyk (2020), Hsu, Li, and Tsou (2019) et In, Park, and Monk (2019) montrent que les entreprises qui émettent le plus de gaz à effets de serre ont des rendements plus élevés que les entreprises qui en émettent moins.

- D'autres articles trouvent une relation positive, notamment Derwall et al. (2005), Statman and Glushkov (2009), Edmans (2011), Eccles, Ioannou, and Serafeim (2014), Flammer (2015), Krüger (2015) et Statman and Glushkov (2016). En particulier, Krüger (2015) montre que les investisseurs réagissent très négativement aux nouvelles négatives concernant la responsabilité environnementale des entreprises.

- Enfin, d'autres auteurs encore, tels que Bauer, Koedijk, and Otten (2005) et Galema, Plantinga, and Scholtens (2008), ne trouvent pas de relation significative entre performance environnementale et performance financière.

C'est en me basant sur la littérature sur les préférences hétérogènes et le désaccord entre investisseurs,[18] que j'éclaire dans le premier chapitre de cette thèse, d'un point de vue théorique et empirique, l'impact des préférences pro-environnementales sur les rendements des actifs.

ii. Préférences non-pécuniaires pour les actifs verts

L'analyse de l'impact des préférences pro-environnementales sur les rendements des obligations donne des résultats empiriques plus consensuels que cette même analyse sur les actions. En effet, même si les conclusions ne sont pas unanimes, la majorité des travaux suggère que les entreprises ayant une performance environnementale élevée bénéficient d'un coût de la dette plus faible. Les auteurs attribuent principalement ce différentiel de coût du capital à une réalité financière : la création d'actifs intangibles (Porter and Linde, 1995, Hart, 1995, Jones, 1995, Ambec and Lanoie, 2008, Flammer, 2015) ainsi qu'une meilleure gestion du risque (Ambec and Lanoie, 2008; Bauer and Hann, 2014), tous deux étant imparfaitement capturés par les modèles des agences de notation (Ge and Liu, 2015; Oikonomou, Brooks, and Pavelin, 2014). Cependant, la littérature n'identifie pas la part de ce différentiel de rendement qui est imputable aux préférences non-pécuniaires.

L'émergence des obligations vertes (*green bonds*) et la liquidité croissante de ces actifs offre un cadre propice à l'identification de la part du différentiel de rendement obligataire imputable aux préférences pro-environnementales non-pécuniaires des investisseurs. En effet, de même que pour les obligations conventionnelles, le risque des obligations vertes est celui de l'entreprise émettrice. Ainsi, comparer des obligations vertes à des obligations contrefactuelles synthétiques conventionnelles permet d'éliminer le différentiel de risque financier et d'isoler l'impact des préférences non-pécuniaires des investisseurs verts sur le rendement des obligations. C'est l'approche que j'adopte dans le deuxième chapitre de cette thèse.

b. L'approche d'investissement d'impact

Parce que l'investissement vert impacte le rendement espéré des actifs à l'équilibre, comme analysé dans les chapitres 1 et 2 de cette thèse, il modifie le coût du capital des entreprises qui peuvent être incitées à réagir en conséquence. En particulier, elles peuvent être incitées à réduire leur impact environnemental. C'est le mécanisme de

[18] En particulier, Harris and Raviv (1993), Biais and Bossaerts (1998), Scheinkman and Xiong (2003), Fama and French (2007b), Jouini and Napp (2007), David (2008), Dumas, Kurshev, and Uppal (2009), Banerjee and Kremer (2010), Bhamra and Uppal (2014), Carlin, Longstaff, and Matoba (2014), Baker, Hollifield, and Osambela (2016), Atmaz and Basak (2018) and Banerjee, Davis, and Gondhi (2019).

l'investissement d'impact qui a été documenté par les travaux séminaux de Oehmke and Opp (2019), Landier and Lovo (2020) et Pastor, Stambaugh, and Taylor (2019).

Les deux premiers articles développent un modèle d'équilibre général. Oehmke and Opp (2019) introduisent des investisseurs durables qui acceptent de financer des projets moins rentables et montrent que les entreprises réduisent leur empreinte environnementale en étant contraintes d'internaliser leurs coûts sociaux. Landier and Lovo (2020) arrivent à des conclusions similaires en introduisant un fonds qui a des préférences pour les enjeux ESG mais un objectif de rendement financier similaire aux investisseurs standards. Enfin, Pastor, Stambaugh, and Taylor (2019) arrivent également aux mêmes conclusions en montrant que les entreprises les plus polluantes ont un coût du capital plus élevé.

Dans le troisième chapitre de cette thèse, nous abordons le problème sous l'angle de la valorisation d'actifs à travers un modèle dynamique où les investisseurs et les entreprises entrent dans un jeu à somme non-nulle. Nous analysons notamment l'effet de l'incertitude concernant l'impact environnemental futur d'une entreprise sur son incitation à se réformer et à réduire ce dernier.

4. Contributions

Chapitre 1 - A sustainable capital asset pricing model (S-CAPM): Evidence from green investing and sin stock exclusion

Dans le premier chapitre de cette thèse, je montre d'un point de vue théorique comment les pratiques (i) du filtre d'exclusion et (ii) du filtre ESG par les investisseurs « durables » affectent les rendements espérés des actifs à l'équilibre. Je valide empiriquement le modèle appliqué (i) aux « actions du péché » (alcool, jeux, tabac) pour le filtre d'exclusion et (ii) en construisant un proxy du goût des investisseurs verts à partir des détentions d'actifs des fonds verts pour le filtre ESG.

Plus précisément, je montre que les pratiques d'exclusion et d'intégration ESG des investisseurs durables induisent, respectivement, deux « primes d'exclusion » et deux « primes de goût » sur les rendements espérés d'équilibre. Dans ce marché partiellement segmenté (Errunza and Losq, 1985), je montre que ces primes ont des effets croisés entre les actifs exclus et les actifs non-exclus.

Primes d'exclusion

Les deux primes d'exclusion, induites par la réduction de la base d'investisseurs, ont été indépendamment mises en évidence par Errunza and Losq (1985) sur les actifs exclus et Jong and Roon (2005) sur les actifs non-exclus dans le cadre de marchés partiellement segmentés. Je montre que ces deux primes s'appliquent simultanément à l'ensemble des actifs, ce qui reflète notamment l'effet croisé des primes d'exclusion sur les actifs non-exclus. Ces primes d'exclusion sont induites par l'effet de couverture conjoint des investisseurs durables qui pratiquent l'exclusion et des autres investisseurs qui sont contraints de détenir ces actifs. En effet, pour un actif donné, chacune de ces primes peut être décomposée en deux effets : (i) d'une part, contraints de détenir les « actifs exclus », les investisseurs qui ne pratiquent pas l'exclusion valorisent d'autant plus l'actif exclu qu'il est décorrélé des autres actifs exclus; (ii) d'autre part, les investisseurs qui pratiquent l'exclusion cherchent à se couvrir en achetant le portefeuille de réplication de l'actif exclu à partir des actifs non-exclus; ceci induit ainsi une pression d'autant plus forte sur le rendement des actifs exclus dont la dynamique est aisément réplicable à partir des actifs non-exclus.

En relâchant l'hypothèse d'indépendance des rendements, je montre que l'une de ces deux primes généralise la prime des actions « négligés » caractérisée par Merton (1987). Par ailleurs, plusieurs articles empiriques, tels que Hong and Kacperczyk (2009) et Chava (2014), ont mis en évidence l'effet positif de l'exclusion sur le rendement des actions du péché. Je montre d'un point de vue théorique que, si l'effet d'exclusion est bien positif en moyenne, il peut être négatif pour les actifs exclus pris individuellement, notamment lorsqu'ils sont décorrélés des autres actifs exclus. Je valide empiriquement ce résultat théorique en estimant l'équation d'équilibre microfondée sur données américaines entre 2007 et 2019. Je montrant ainsi que, si l'effet d'exclusion moyen annuel est de 1,43%, ce dernier est négatif pour 10 actions du péché parmi 52. La valeur moyenne de l'effet d'exclusion moyen est cohérent avec l'effet estimé par Hong and Kacperczyk (2009).

Enfin, j'analyse la dynamique de l'effet d'exclusion. En régressant la prime d'exclusion que Luo and Balvers (2017) mettent en évidence sur un proxy du cylce économique, ces auteurs affirment que la dynamique d'exclusion est déterminée par les cycles économiques. Je montre que la dynamique de la prime d'exclusion, pour un actif donné, n'est pas directement liée aux cycles économiques mais à la covariance du rendement de cet actif avec les autres actifs, en particulier avec les rendements des autres actifs exclus. Ainsi, lorsque la corrélation entre actifs s'accroît, notamment pendant les périodes de crises, l'effet d'exclusion augmente sensiblement. C'est ce que l'on observe pendant la crise financière de 2008: la prime d'exclusion a fortement cru et s'est effondrée avec la remontée des marchés et la baisse de la corrélation entre les actifs.

Je conduis enfin plusieurs tests de robustesse sur des spécifications alternatives qui valident les résultats principaux résumés ci-avant.

Primes de goût

Les deux primes de goût (prime de goût *directe* et prime de goût *indirecte*) sont induites par l'internalisation des externalités ESG par les investisseurs durables qui modifient leur pondération d'actifs en conséquence. Ces dernières se matérialisent via trois canaux. Premièrement, en cohérence avec les travaux indépendants de Pastor, Stambaugh, and Taylor (2019) et Pedersen, Fitzgibbons, and Pomorski (2019), la prime de goût directe est plus élevée (faible) pour les actifs bruns (verts), car les investisseurs durables requièrent un rendement plus élevé (acceptent un rendement plus faible) pour les détenir. Deuxièmement, et en conséquence, la prime de marché est également ajustée de la prime de goût directe. Troisièmement, la prime de goût indirecte affecte les actifs exclus car les investisseurs pratiquant l'intégration ESG se couvrent en surpondérant les actifs exclus les plus corrélés aux actifs non-exclus des entreprises polluantes qu'ils sous-pondèrent.

D'un point de vue empirique, de nombreux articles ont tâché d'expliquer l'impact des notes ESG sur le rendement réalisé des actifs, avec des résultats non consensuels. Cela s'explique notamment par trois raisons : (i) les notes ESG ou les indicateurs environnementaux sont des proxy imparfaits du goût agrégé des investisseurs durables et sont généralement disponibles uniquement à une fréquence annuelle ; (ii) les équations estimées ne prennent pas en compte l'accroissement de la proportion des investisseurs durables ; (iii) les rendements réalisés sont des proxys imparfaits des rendements espérés car ils ne prennent pas en compte les changements inattendus des préférences des investisseurs durables (Pastor, Stambaugh, and Taylor, 2019). Je contourne cette triple difficulté en estimant l'équation d'équilibre microfondée à partir de proxies (i) du coût d'externalités environnementales, (ii) de la proportion d'investisseurs verts, et (iii) du changement inattendu de leurs préférences, construits à partir de l'historique des détentions d'actifs des fonds verts dans le monde. (i) Le proxy du coût d'externalités environnementales est construit comme la différence relative entre le poids d'un actif dans le portefeuille agrégé des fonds verts et son poids dans l'univers d'investissement; je montre théoriquement que cet instrument approxime bien le coût d'externalités environnementales tel que défini dans le modèle. (ii) Le proxy de la proportion d'investisseurs verts est défini comme la valeur des actifs sous gestion des fonds verts à chaque date divisée par la valeur de marché de l'univers d'investissement. (iii) Enfin, le proxy du changement inattendu des préférences est défini comme la variation du facteur de goût direct construit à partir de (i) et (ii).

En estimant l'équation d'équilibre appliquée à l'intégration des enjeux environnementaux, je montre que l'effet de goût moyen entre les industries les moins et les plus polluantes varie entre -1,12% et 0,14% par an entre 2007 et 2019 et qu'il s'accroît dans le temps.

Je vérifie, à travers plusieurs tests de robustesse, que le résultat principal reste valide en reproduisant l'estimation sur des modèles alternatifs (plus longue durée pour la première passe de l'estimation, rendements équipondérés, portefeuilles doublement triés par taille et par industrie), en écartant la possibilité que la significativité du résultat soit liée à une causalité inverse, en contrôlant le risque de variable omise lié au changement inattendu des préférences, et en conduisant une analyse du risque d'erreur de mesure à partir de l'intensité carbone des entreprises.

Chapitre 2 - The effect of pro-environmental preferences: Evidence from green bonds.

Le deuxième chapitre de cette thèse estime empiriquement la part de l'écart de rendement entre les actifs verts et non-verts qui est induite par les préférences non-pécuniaires des investisseurs. Pour ce faire, je me concentre sur le marché obligataire et j'utilise les obligations vertes (« green bonds ») comme instrument pour estimer cette « prime verte ».

Prime verte

A partir d'une méthode d'appariement, j'identifie les 110 obligations vertes pour lesquelles il est possible de construire un contrefactuel synthétique d'obligations conventionnelles ayant exactement les mêmes caractéristiques (hormis le fait qu'elles ne sont pas vertes). Plus précisément, afin de construire une obligation conventionnelle contrefactuelle synthétique, pour chaque obligation verte, j'identifie d'abord deux obligations conventionnelles du même émetteur, dans la même devise, avec la même notation, la même structure obligataire, le même type de coupon et ayant les maturités les plus proches de celle de l'obligation verte; de plus, je limite l'écart de maturité et de liquidité (à partir de la taille de la souche et de la date d'émission) entre les obligations vertes et les deux obligations conventionnelles appariés. Je construis alors l'obligation conventionnelle contrefactuelle synthétique en interpolant linéairement le rendement des deux obligations conventionnelles à la date de maturité de l'obligation verte; ceci permet d'éliminer le biais de maturité. Enfn, afin d'éliminer le biais de liquidité, je régresse la différence de rendement entre l'obligation verte et l'obligation conventionnelle contrefactuelle synthétique sur un proxy de leur différence de liquidité construit à partir du *bid-ask spread*. Cette régression en données de panel à effets fixes permet d'extraire la prime verte définie comme l'effet spécifique inobservé de la régression.

Utiliser le différentiel de rendement entre obligations vertes et obligations conventionnelles contrefactuelles comme variable dépendante permet de contourner deux biais inhérents à une régression où les rendements des obligations vertes et conventionnelles sont régressés sur les caractéristiques des obligations: un biais de variables omises et un biais lié à la surpondération des actifs ayant l'historique le plus long.

L'analyse porte sur le marché secondaire entre juillet 2013 et décembre 2017. Les 110 obligations représentent 10% du nombre et 17% du montant des obligations vertes émises dans le monde à la fin de l'année 2017. La prime verte est estimée à -2 points de base (bps) en moyenne. Cela signifie que le rendement (prix) des obligations vertes est légèrement plus faible (élevé) que celui des obligations conventionnelles. Cette prime verte reflète le rendement que les investisseurs sont prêts à céder pour détenir des actifs obligataires verts à risque égal. Si elle est statistiquement significative, cette prime demeure économiquement très faible. Elle suggère donc que la différence de rendement entre les obligations d'entreprises vertes et celles d'entreprises brunes, largement mise en évidence dans la littérature,[19] correspond principalement à une différence de risque financier entre les deux types d'entreprises plutôt qu'à l'effet des préférences non-pécuniaires des investisseurs verts.

Du point de vue des praticiens, cette prime verte met en évidence l'appétit des investisseurs pour les obligations vertes et le fait que les entreprises peuvent diversifier leurs bases de créanciers à travers cette classe d'actifs. Cependant, compte tenu de sa très faible valeur, elle ne constitue pas une désincitation pour les investisseurs verts à soutenir le marché des obligations vertes. En outre, du point de vue des autorités de supervision, cette prime ne révèle pas d'écart de valorisation substantiel – donc de bulle – entre les actifs verts et bruns à risque égal.

Tests de robustesse

Je conduis toute une série de tests de robustesse. Premièrement, je vérifie que la prime verte ne correspond pas à une différence de risque financier entre les obligations vertes et conventionnelles. Pour ce faire, je reproduis la régression principale en données de panel augmentée d'une variable correspondant à la différence de volatilité entre l'obligation verte et l'obligation contrefactuelle conventionnelle. Qu'il s'agisse des volatilités 10 jours, 20 jours ou 30 jours annualisées, le différentiel de ces dernières n'a pas de pouvoir explicatif de la prime verte. Ce résultat correspond à ce qui était attendu compte tenu de la similarité du risque entre obligations vertes et conventionnelles du même émetteur. Deuxièmement, j'analyse la dynamique de la prime verte dans le temps. En reproduisant l'analyse mois par mois, je montre que la prime verte est proche de zéro et non significative jusqu'à mai 2016. A partir de cette date, à six mois de la signature des accords de Paris, une prime verte significative de l'ordre de -2 bps se matérialise. L'analyse de différents sous-groupes d'obligations vertes fait apparaître une dynamique similaire. Troisièmement, je m'assure que la prime verte ne correspond pas à une prime de marché en introduisant un effet fixe temps dans la régression en données de panel et en régressant ce dernier sur le rendement de plusieurs indices actions. Aucun effet causal n'apparaît significativement, ce qui permet d'écarter la possibilité que la prime verte capture un facteur de risque de marché. Quatrièmement, je reproduis l'analyse en modulant les critères d'appariement sur les bornes du différentiel de maturité et de liquidité. Avec des critères plus restrictifs, les résultats ne sont pas alterés. Enfin, je teste la représentativité de l'échantillon analysé par rapport à l'univers total d'obligations vertes en comparant les distributions des caractéristiques des obligations vertes dans les deux échantillons à l'aide d'un test du χ^2. Il apparaît que l'échantillon étudié ne diffère pas significativement de l'univers d'obligations vertes; cela suggère donc que cette prime négative de 2 bps en moyenne pourrait être matérielle pour l'ensemble des obligations vertes de l'univers d'investissement.

[19] Par exemple, Bauer and Hann (2014), Oikonomou, Brooks, and Pavelin (2014), Flammer (2015).

Déterminants de la prime verte

Enfin, j'analyse l'hétérogénéité de cette prime parmi l'ensemble des obligations du panel. Plus précisément, je réalise une régression transversale de la prime verte estimée sur les caractéristiques discriminantes des obligations vertes: le type d'émetteur, leur notation, la devise, la maturité et la taille de la souche (comme proxy de la liquidité). Je montre notamment que cette prime est plus prononcée sur les obligations des émetteurs financiers et des émetteurs ayant une faible notation. Par exemple, le rendement d'une obligation financière européenne verte de notation AAA, AA, A, BBB est plus faible que celui d'une obligation conventionnelle équivalente de, respectivement, 0.9 bp, 3.2 bps, 3.2 bps et 4.9 bps. Cette analyse permet de construire une courbe verte pour l'ensemble des émetteurs n'ayant pas encore émis d'obligations vertes à partir de leurs caractéristiques (type d'émetteur, notation, devise, maturité, liquidité) et en utilisant les paramètres estimés via cette dernière régression. Cet exercice est utile, tant pour les émetteurs que pour les investisseurs qui cherchent à estimer, respectivement, un « taux d'endettement juste » et un « rendement juste » lors de l'émission d'une nouvelle souche obligataire verte pour laquelle aucun repère n'est encore disponible.

Chapitre 3 - Environmental Impact Investing

Dans le troisième chapitre de cette thèse, co-écrit avec Tiziano de Angelis et Peter Tankov, nous montrons comment l'investissement vert peut avoir un impact sur la pratique des entreprises, notamment les plus polluantes, qui sont poussées à réduire leur impact environnemental.

Externalités environnementales déterministes

Nous construisons un modèle d'équilibre dans un marché peuplé par (i) un groupe d'investisseurs standards et (ii) un groupe d'investisseurs verts qui internalise l'impact financier des externalités environnementales des actifs dans lesquels ils investissent. Ces externalités sont, dans un premier temps, considérées comme déterministes. En prenant en compte l'effet des préférence des investisseurs, les entreprises choisissent une trajectoire d'émissions carbone jusqu'à une date finale. Elles font ainsi face à un arbitrage entre réduire leurs émissions carbone à un coût financier (par exemple, renouveler leur parc de production) et, ainsi, élargir leur base d'investisseurs, ou bien ne pas réduire leurs émissions carbone et ne pas bénéficier d'un élargissement de leur base d'investisseurs. Les entreprises choisissent donc leur trajectoire d'émissions carbone en maximisant leur espérance d'utilité qui se décompose en deux critères : (i) leur future valorisation à une trajectoire d'émissions carbone donnée, indépendamment du coût de réforme, et (ii) le coût de réforme pour atteindre cette trajectoire d'émissions. Les entreprises prennent également en compte les choix des autres entreprises, ce qui créée un jeu à somme non-nulle auquel participent investisseurs et entreprises. Dans ce modèle, nous endogénéisons donc l'impact environnemental des entreprises et analysons leur trajectoire d'empreinte carbone optimale.

Nous déterminons les rendements d'équilibre dont l'expression est cohérente avec le premier chapitre de cette thèse en temps continu. Nous déterminons également une expression explicite et simple de la trajectoire d'émissions des entreprises dans le cas où les externalités environnementales sont quadratiques en les émissions. Nous montrons que l'augmentation de la proportion d'investisseurs verts ou de leurs exigences environnementales, en augmentant le coût du capital des entreprises les plus polluantes, poussent ces dernières à réduire leur empreinte carbone. Ce résultat souligne l'importance du soutien des personnes publiques au développement de l'investissement vert – par exemple, au travers de la définition de standards rigoureux pour évaluer l'impact environnemental telle la taxonomie sur laquelle travaille actuellemment la Commission Européenne. Du point de vue des investisseurs, ce résultat suggère que ces derniers peuvent accroître leur impact sur les entreprises en élevant leurs exigences environnementales, par exemple en restreignant leur périmètre d'investissement ou en sous-pondérant plus significativement les entreprises les moins vertueuses. De plus, en cohérence avec le premier chapitre de cette thèse, nous montrons que l'investissement vert est bénéfique financièrement lorsque les investisseurs favorisent les entreprises qui vont effectivement baisser leur impact environnemental.

Externalités environnementales incertaines et non-gaussiennes

Nous étendons notre analyse au cas où les investisseurs verts internalisent les externalités environnementales futures avec *incertitude*. En cohérence avec la nature des risques environnementaux, nous modélisons cette incertitude comme non-Gaussienne à travers un processus à saut. Nous montrons que l'augmentation de l'incertitude sur le risque futur pousse les investisseurs verts à réduire leur allocation en actifs risqués, ce qui atténue la pression qu'ils exercent sur le coût du capital des entreprises les plus polluantes et, en conséquence, incite ces dernières à accroître leur empreinte carbone par rapport à l'équilibre sans incertitude. Ce résultat souligne l'importance majeure de la transparence sur l'impact environnemental des entreprises et de l'accès à cette information par les investisseurs : meilleure est l'information, plus les entreprises sont contraintes par les investisseurs verts d'internaliser leurs externalités environnementales et donc de réduire leurs émissions.

Estimation du modèle

Nous estimons empiriquement notre modèle appliqué à l'intensité carbone des entreprises en utilisant, comme dans le premier chapitre, l'historique de détention des fonds verts dans le monde pour approximer la proportion d'investisseurs verts. Nous définissons ce proxy comme la valeur des actifs gérés par les fonds verts rapportée à la valeur de marché de l'univers d'investissement. Nous montrons notamment que lorsque la proportion d'investisseurs verts double, l'intensité carbone des entreprises baisse en moyenne de 5% par an.

5. Principales implications pour l'industrie financière

Les résultats de cette thèse ont des implications concrètes pour l'industrie financière à plusieurs égards.

1. Premièrement, ces travaux montrent que l'investissement dans une entreprise qui est amenée à se verdir est financièrement rentable. Cela souligne l'importance de l'analyse « extra-financière », conduite par les institutions financières ou les agences de notation, afin que les investisseurs soient en mesure d'allouer leur capital sur les entreprises qui seront les plus vertueuses sur le plan environnemental.

2. Deuxièmement, cette thèse souligne la capacité des investisseurs à pousser les entreprises à se réformer en augmentant leurs exigences environnementales. Cela peut se traduire par un ajustement à la baisse de la pondération des entreprises les plus polluantes ou par la restriction du périmètre d'acceptabilité de ces dernières.

3. Troisièmement, ces travaux mettent en évidence l'importance de la transparence sur les informations environnementales des entreprises afin de maximiser l'internalisation par ces dernières de leur coût social et environnemental et, en conséquence, de réduire leur impact environnemental.

4. Enfin, et plus généralement, cette thèse souligne l'importance du soutien des personnes publiques au développement de la finance verte, notamment à travers la définition de normes et de standards rigoureux offrant aux investisseurs une lecture plus précise de l'impact environnemental des entreprises dans lesquelles ils peuvent investir.