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Ethical Approval
All experiments conducted in this research were in accordance with the ethical standards of the hosting institution, and of the 1964 Declaration of Helsinki. The experimental design was approved by the Institutional Review Board (IRB, ethics committee) of the University of Montpellier-Center for Environmental Economics.

Informed Consent
All participants provided informed consent prior to completing the experiment, and could quit the experiment at any time.

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All authors contributed to the conceptualization, conception and design of the experiment, data collection and software analysis, writing – review & editing. Olga Tatarnikova made the writing of the original draft.

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Abstract

Efficiency of SRI portfolios is commonly assessed based on an inconclusive risk-return ratio. We propose to approach the efficiency of portfolios with the notion of instability. Unstable portfolios are characterized by higher transaction costs and human resources costs that justify search for more stable portfolios. We examine the instability of SRI portfolios from the perspective of behavioral finance. Based on data from incentivized experiments with 153 financial professionals and 233 students, we compare a baseline treatment to a ranking treatment in which participants received feedback regarding their average investment in SRI assets. We found that SRI portfolios had significantly lower instability: portfolios with a majority of SRI shares exhibited less instability in both treatments compared to conventional portfolios. Moreover, in the ranking treatment subjects invested more in SRI assets than in the baseline. In addition, the experiment revealed the convergence of professionals' and students' behavioral patterns.

Keywords: behavioral finance, experimental economics, financial asset markets, portfolio instability, socially responsible investment

JEL classification: G11, G40, C9

1 Introduction

The rise of socially responsible investment (SRI)[1] suggests that investors are becoming increasingly conscious of the environmental consequences of their portfolio choices. Besides risk and return objectives, many investors are attracted by environmentally and socially friendly assets. In this context, SRI based on investors' preferences might be regarded as a potential way to mitigate portfolio instability (C. Chen, 2018), which is often generated by behavioral biases (e.g., disposition effect, overconfidence, availability bias, etc.). Portfolio instability is a serious concern for portfolio managers. Indeed, instability entails excessive trading generating higher transaction and human resources costs. Besides the conventional portfolio considerations such as risk-return optimization and diversification, the investors' preference for SRI assets may reduce portfolio instability and its related costs. We hypothesize that investors who exhibit stronger social preferences are more likely, not only to hold larger shares of SRI assets in their portfolios (Riedl and Smeets, 2017; Brodback et al., 2019), but also to keep them for longer periods compared to conventional assets. Lower asset turnover combined with longer holding periods results in higher returns derived from long-term factors and reduced costs (Lake and Oulton, 2016). Consequently, the growing availability of SRI could lead to more stable portfolios that are resilient to financial crises and economic events (Lins et al., 2017). This could also pave the way for the design of public policies aimed at strengthening the pro-sociality of investors, e.g., by nudging them about the SRI performance of their portfolio, to promote financial stability. Yet, in spite of these promising mooted advantages, the existing literature has not directly addressed the impact of SRI investors' preference on portfolio instability. In this paper we fill this gap, by exploring experimentally the link between the share of SRI in a portfolio and its stability.

Our research objective involves two major challenges that will be discussed in the paper: first, relying on an appropriate measure of portfolio instability, and second, properly categorizing portfolios according to their SRI and non-SRI contents. Portfolio instability depends both on the frequency and the magnitude of the changes of the assets' weights in the portfolio over time, induced by portfolio rebalancing. Both the higher frequency and the higher magnitude of weight adjustments lead to higher instability. Potentially, portfolio instability is accompanied by higher transaction costs and lower portfolio performance. The categorization issue arises when there is a wide choice of heterogeneous assets in terms of SRI characteristics. We need therefore to rely on an appropriate SRI index to categorize observed portfolios. We rely on the average share of SRI assets held over time, i.e., a portfolio is categorized as SRI if the mean share of green assets over the investment horizon dominates the share of other assets.

Portfolio instability has been studied from different perspectives in portfolio management and optimization. Kaut et al. (2007) analyzed the stability of a portfolio management model based on the conditional

[1] In 2012, the total value of assets of RI funds managed in Europe was approximately 252 billion euros. Within six years it nearly doubled, reaching 496 billion euros in assets under management on the responsible investing market by the end of 2018 (KPMG, 2019).

value-at-risk (CVaR) measure. Kourtis (2015) investigated the stability approach to mean-variance optimization by introducing a new instability penalty that controls the deviation from the portfolio before rebalancing. Kritzman and Turkington (2016) considered the issue of unstable risk and introduced a methodology for incorporating estimation error in covariances into the portfolio formation process. However, the above studies do not consider SRI as such. In fact, we are aware of only two papers that deal with the issue of the stability of SRI funds: Oikonomou et al. (2015) and Oikonomou et al. (2018). These two empirical papers investigate optimization processes for constructing SRI portfolios and show that a robust SRI approach generates more stable portfolios in comparison to the naïve-deterministic approach. Notably, decreasing instability mechanically reduces transaction costs, which provides a rationale for stability. However, these papers mainly focus on portfolio optimization techniques without investigating the behavior of investors leading to holding and maintaining SRI assets in their portfolios.

Bollen (2007) and Geczy et al. (2021) found that cash flow volatility is lower for SRI funds than for conventional funds, suggesting lower instability for SRI funds. Albuquerque et al. (2019) and Albuquerque et al. (2020) proposed higher customer loyalty as a potential mechanism underlying the lower turnover in SRI funds, and provided some empirical support for their conjecture. Ultimately the higher loyalty is related to some intrinsic preference for the SR dimension of the funds, which consequently offers higher stability (see, e.g., Pástor et al. (2021)).

In this paper, we investigate the portfolio instability of investors dealing with SRI assets among others. We combine data from an online experiment and a lab-in-the-field experiment. Experiments are powerful for analyzing portfolio instability and SRI, as they allow to have control both over treatments and unobservable factors that affect portfolio choices. Furthermore, experimental data is useful for analyzing the trade-offs between SRI, risk and return in a controlled environment with target populations. There are a number of studies that have investigated the impact of SRI on investors' decisions in experimental markets (Nakai et al., 2013; Bartling et al., 2015; Bolton et al., 2015; Døskeland and Pedersen, 2016; Riedl and Smeets, 2017; Bartling et al., 2018). In most cases, the authors used laboratory or field experiments accompanied by survey questionnaires (Døskeland and Pedersen, 2016; Riedl and Smeets, 2017; Brodback et al., 2019; Heeb et al., 2022) and dictator or trust games (Nakai et al., 2013; Riedl and Smeets, 2017). So far, economic experiments have led to controversial results concerning the interplay of material and moral concerns for SRI. Riedl and Smeets (2017) demonstrated the importance of social preferences and social signalling as factors for SRI decisions and claimed that financial motives are of limited importance in comparison to social preferences. In contrast, Døskeland and Pedersen (2016) claimed that wealth is more important than morality, as investors with a wealth frame are more likely to search for further information and invest responsibly than are investors with a moral frame. Apart from that, Bartling et al. (2015) and Bartling et al. (2018) point out that consumers in markets exhibit less social concern than subjects in a comparable individual choice context.

In our experiment, subjects could compose and rebalance their portfolios over a sequence of 10 rounds. Specifically, in each round they had to choose an allocation between four assets: a safe asset (their cash holding), and three risky assets characterized by their risk and return: a neutral asset, a "green" (SRI) and a "brown" (anti-SRI) asset. In contrast to the neutral asset, the green and brown assets were characterized by an indirect environmental impact, a positive externality for the green asset and a negative externality for the brown asset. The positive (negative) externality was framed as a donation by the experimenter to an environmentally friendly (hostile) organization. Participants were aware that the experimenter would make a transfer to the corresponding organization in proportion of the mean capital invested in SRI or anti-SRI assets at the end of the session. As discussed by Duchêne et al. (2022), such framing is akin to delegated philanthropy (misanthropy). We conducted two incentivized experiments: a lab-in-the-field experiment with 153 financial professionals from banks and asset management companies in Paris, Marseille, and Montpellier; and an online experiment with 233 university students. The experiments were performed following the ethical rules of the Laboratory of Experimental Economics of Montpellier (LEEM) and the banks and institutions having participated in the experiments. In addition, the experimental design was approved by the Institutional Review Board (IRB) of the University of Montpellier.

Both experiments involved two treatments: a baseline treatment that corresponded to the previous description and a ranking treatment in which the participants were privately informed about their rank in each round according to their average investment in SRI assets. The aim of the ranking treatment was to stimulate investors' behavioral mechanisms related to self-esteem and competitiveness (Tran and Zeckhauser, 2012; Kirchler et al., 2018; Cadsby et al., 2019), and, thus, increase their investment in SRI assets. Providing ranking information about SRI performance does also stimulate the subjects' awareness of the social impact of their portfolio choices. Reasons for investors' socially responsible behavior and the motives behind their decisions have been analyzed in numerous papers (Bénabou and Tirole, 2006, 2010; Bailey et al., 2011; S.-H. Chen and Tsai, 2011; Nakai et al., 2013; Cohn et al., 2015; Kirchler et al., 2016; Riedl and Smeets, 2017). The extended Markowitz model, which incorporates the variable of social responsibility, Gasser et al. (2017) identifies a clear trade-off between social responsibility and expected returns. Ranking feedback about SRI performance provides therefore a simple and potentially efficient policy tool to encourage SRI.

We report three main findings. First, SRI portfolios exhibited lower instability compared to conventional portfolios, regardless of the treatment. This result complements the findings of Oikonomou et al. (2018) by revealing the stabilizing property of SRI funds. Second, the availability of ranking information increased investments in SRI portfolios in both subject pools in the ranking treatment compared to the baseline. This is in line with the works of Tran and Zeckhauser (2012), Kirchler et al. (2018), and Cadsby et al. (2019), who marked out subjects' increased performance under ranking due to competitive preferences. Third, behavioral patterns were similar in both samples, which provided external validity for our lab findings with student subjects. These converging results between the student and professional samples not only enhance the robustness of our observations but contribute to the recent literature which compares these two subject pools and argues about external validity of lab results based on student subjects (Cohn et al., 2014; Kirchler et al., 2018; Schwaiger et al., 2020; Weitzel et al., 2020; Bottasso et al., 2022).

Our findings contribute to the literature about portfolio instability in several ways. We have noticed a major lack of studies addressing the issue of portfolio instability in the context of growing SRI funds. Our study is the first, to our knowledge, to rely on controlled online lab experiments to investigate this issue. First, it is often difficult to empirically observe the instability of portfolios due to the limited access to the data of fund managers. Therefore, experiments offer a way to produce meaningful data that allow us to investigate portfolio instability free of the influence of confounding factors. Second, experiments offer the necessary control to establish causality between social influence in the form of ranking and socially responsible portfolio choices. Thus, our research contributes to the existing literature by providing causal evidence on the impact of ranking on allocation of socially responsible assets through an experimental economics methodology. Third, we also contribute to the empirical literature on SRI. The current literature does not provide a consensus on the performance of SRI with regards to conventional funds.[2] By taking into account portfolio instability, we may be able to improve the general understanding of the performance of SRI. Finally, we contribute to the burgeoning literature about investor morality (Hong and Kacperczyk, 2009; Døskeland and Pedersen, 2016; Moisson, 2020; Chew and Li, 2021; Green and Roth, 2021). We found that by making SRI performance salient, through ranking feedback, investments in virtuous (vicious) assets

[2]One of the latest empirical analyses, covering the period 1990–2014 (Jedynak, 2017), concluded that using SRI strategies does not result in any statistically significant over- or underperformance of portfolios. This is consistent with the findings of Rathner (2012)'s meta-analysis, which reported that almost 75% of its performance comparisons (SRI with conventional funds) did not show any tangible performance difference. A significant over- and underperformance is virtually found to the same degree (13%–14%). In contrast, Revelli and Viviani (2015) reported multiple effects of SRI on financial performance on the basis of 85 studies and 190 experiments, demonstrating that SRI performance heavily depends on the empirical methods employed by researchers. Lean et al. (2015) found that SRI funds outperformed the market benchmark in Europe and North America from 2001 to 2011, and that North American SRI funds performed better than the European ones.

In this vein, volatility of green funds, often accompanied by changing transaction volumes, can be considered as a proxy of portfolio instability. Though a few studies demonstrated a risk-reducing effect and lower volatility of high ESG ranked funds compared to low ESG funds (Engelhardt et al., 2021; Burger et al., 2022; Prol and Kim, 2022), there is scarce evidence related to volatility difference between ESG and conventional mutual funds (or ETFs). Kumar et al. (2016) found that, despite the conventional finance principle "less risk leads to lower return", ESG stocks are able to generate higher returns along with lower volatility if compared to non-ESG assets. In line with the above, Ouchen (2022) compared ESG portfolio "MSCI USA ESG Select" to the market benchmark portfolio "S&P 500" and by means of the Markov-switching GARCH model showed the lower volatility of the first. Yet, Kanuri (2020), comparing ESG ETFs to the US and global equity markets, identified higher volatility of ESG portfolios that outperformed US IWV and DGT portfolios in some periods.

are favored (penalized).

The remainder of the paper is organized as follows. Section 2 defines the notion of portfolio instability and introduces our main hypotheses. Section 3 summarizes the data and the experimental design. Section 4 contains the experimental results and their analysis. Section 5 discusses the issue of rationality and decision errors in economic experiments, while section 6 concludes.

2 Portfolio instability definitions and hypotheses

Throughout our experiments we measured portfolio instability by tracking the changes in asset weights in a portfolio (Kourtis, 2015; Oikonomou et al., 2015, 2018), and, thus, the changes in the subjects' investment behavior. We define two notions of portfolio instability: "instantaneous instability" and "long-term instability". The first one refers to portfolio rebalancing between two successive periods. We measure it by the sum of the squared differences of each asset's portfolio weights $\omega_{i,t}$ between two successive periods *t-1* and t:

$$Instability_{t-1\rightarrow t} = \sum_{i=1}^{N}(\omega_{i,t} - \omega_{i,t-1})^2 \tag{1}$$

Long-term instability corresponds to the tendency for investors to adjust their portfolio asset weights over time, in order to restore target allocations, or risk levels, during the process of portfolio rebalancing. Lower long-term instability means fewer changes in portfolio weights, lower transaction costs during rebalancing, and more sustainable investments in the long run (Oikonomou et al., 2015; Lake and Oulton, 2016; Lins et al., 2017; Oikonomou et al., 2018). Thus, lower long-term instability is equivalent to higher portfolio stability. We can also describe portfolio instability as the propensity to rebalance a portfolio. Some subjects favor portfolio rebalancing and change portfolio weights regularly, contributing to various levels of positive portfolio instability scores. Other people can be mildly or strongly averse to portfolio rebalancing both being observed with a zero score of portfolio instability (as it cannot be negative by definition).

In our experiment we consider a finite number of investment periods ($t = 1, ..., T = 10$) and three different asset types: green (SRI), brown (anti-SRI), and neutral. We therefore capture long-term instability by defining an instability index as follows:

$$Instability_{t\rightarrow T} = \sum_{t=1}^{T}(\bar{\omega}_{g_t} - \bar{\omega}_{g_{t-1}})^2 + \sum_{t=1}^{T}(\bar{\omega}_{b_t} - \bar{\omega}_{b_{t-1}})^2 + \sum_{t=1}^{T}(\bar{\omega}_{n_t} - \bar{\omega}_{n_{t-1}})^2 \tag{2}$$

where $\bar{\omega}_{g_t}$, $\bar{\omega}_{b_t}$, $\bar{\omega}_{n_t}$ are the weights of green, brown, and neutral assets in a portfolio in terms of asset values.

The weight of green assets in a portfolio at period t is calculated as:

$$\bar{\omega}_{g_t} = \frac{g_t}{g_t + b_t + n_t} \tag{3}$$

where g_t, b_t and n_t are correspondingly the values of green, brown, and neutral assets (i.e., the number of assets multiplied by the asset price). Similarly, we can calculate the weight of brown and neutral assets.

We hypothesize that the instability level of a portfolio is negatively correlated with the share of green assets. We state it as hypothesis 1:

Hypothesis 1: The greater the share of SRI (anti-SRI) assets in a portfolio, the lower (higher) the portfolio instability.

To test hypothesis 1 we rely on the following definition of an SRI portfolio: a portfolio is categorized as SRI, if the average share of green assets over the 10 periods is both larger than that of brown assets and than that of neutral assets. Because we cannot exclude that our findings are dependent on this definition of SRI portfolios, we will perform two robustness analyses. First, we rely on the more stringent definition that an SRI portfolio should contain at least 50% of green assets, over the 10 periods on average. Second, we replicate the analysis by dividing the 10 periods into two sub-sequences of 5 periods each (periods 1-5 and periods 6-10) and analyze the instability index for each sub-sequence.[3]

We propose two arguments in favor of hypothesis 1. First, each asset is characterized by three parameters: a fixed characteristic, the color of the asset (green/neutral/brown), which reflects its social externality and remains constant over the investment sequence, and two variable characteristics, risk and return, that evolve randomly throughout the sequence. With this design, we aimed to be as close as possible to the real life financial markets, as the realized return of an asset fluctuates much more frequently than its socially responsible rating. In this context, we hypothesize that an investor who foregoes higher returns in order to invest in green assets will tend, all other things being equal, to overweight the color dimension in the valuation of the assets and, therefore, in her portfolio choices. Conversely, a participant investing more in brown assets will underweight the color dimension in favor of the asset profitability dimension. Thus, greener investors who are more strongly oriented towards the asset color will have much more stable green portfolios (with asset colors remaining fixed over time), while browner investors will be mainly concerned with asset profitability and will be more likely to change their portfolio allocation according to the realized returns in each period.[4]

Second, we rely on Andreoni (1989, 1990)'s theory of impure altruism according to which individuals feel joy and satisfaction when they did "their part to help others". This positive feeling of pleasure - or "warm glow" - stands for the selfish satisfaction obtained from "doing good", from the act itself of giving to others. This positive emotion created in our experiment by assets with a positive environmental externality, could largely compensate for the potential experience of negative returns, or lower returns, thus reducing reactions to return variations and promoting greater portfolio stability. This would no longer be the case with neutral or brown assets that do not generate any positive externality, and thus, are not related to positive emotions. As a result, when investors have brown or neutral portfolios, and cannot emotionally compensate for low or negative returns, they are likely to revise their portfolio compositions more frequently. Recently Heeb et al. (2022) confirmed the warm glow effect in an investment experiment. They showed that participants felt good (i.e., experienced a positive emotion) after investing in an asset with a positive environmental externality, and felt better than when investing in a conventional asset.

For these two reasons, we conjecture that portfolios containing a larger portion of SRI assets would be more stable, owing to a lesser need of rebalancing, implying lower transaction costs and lower cost of capital.

In order to assess our participants' other-regarding preferences, we combined two methods. First, at the very beginning of the experiment each participant was asked to select an initial portfolio out of three possibilities: the optimal portfolio, a green portfolio, or a brown portfolio. This initial choice was intended to reveal participants' SRI preferences. Second, we asked our participants to answer the NEP (New Ecological Paradigm Scale) questionnaire (Dunlap et al., 2000)[5] to collect information about their pro-environmental orientation. The NEP questionnaire was provided at the end of the experiment. We expected that both the initial portfolio choice, as well as the NEP score, would exhibit positive correlation with investments in green assets and, consequently, the share of SRI assets, and negative correlation with the level of portfolio instability.

In line with behavioral portfolio theory, some authors suggest that socially responsible traders and asset managers may prefer to forgo financial performance and choose an "SRI portfolio", a portfolio with a high share of SRI assets (Consolandi et al., 2009; Riedl and Smeets, 2017). Thus, in the frame of portfolio optimization and investment efficiency we compare optimal (i.e., the market portfolio defined by CAPM, providing the maximum expected return with the lowest risk level), conventional (anti-SRI) and SRI portfolios

[3] See Appendix 7.7 for details.

[4] As mentioned earlier, the present literature has no common view on the performance of green funds compared to conventional assets (Rathner, 2012; Revelli and Viviani, 2015; Jedynak, 2017). Thus, the relationship between profitability and sustainability of SRI is not always negative. In our experiment we wanted to study a context in which the returns between green and brown assets differ. Based on this design feature we observed a significantly low instability when the green asset has a low return. We therefore conjecture that this result would be reinforced, and become even more significant, when the green asset has a higher return.

[5] The NEP questionnaire is considered as a measure of environmental world view and designed as a questionnaire with 15 statements. The individual responses to these statements in the form of agreement or disagreement (with different degrees) reflect people's environmental concern.

and state hypothesis 2:

Hypothesis 2: Despite the higher performance of optimal portfolios, SRI portfolios provide lower instability than optimal and conventional portfolios.

Although standard financial models assume that investors are solely motivated by risk and return, Bénabou and Tirole (2006) and Bénabou and Tirole (2010) have proposed that financial professionals' behavior is driven by a complex set of motives, including intrinsic altruism, material incentives (defined by laws and taxes), and concerns about social status or self-esteem based on relative judgements. The importance of such social comparisons has been well understood since the seminal theory of Festinger (1954). Indeed, in line with Festinger's theory, Tran and Zeckhauser (2012) found that students seek a high rank among their peers, as evidenced by the fact that their performance increased when they were informed of their ranking on practice tests. Cadsby et al. (2019) have also shown a positive effect of ranking on performance in a real effort experiment on university students and full-time employees. Moreover, as documented recently by Kirchler et al. (2018) and Liu and Ma (2020), performance ranking also affects financial traders. Kirchler et al. (2018) observed that investors' decisions are significantly impacted by ranking, leading to additional risk-taking among underperforming investors. In order to further study the importance of social ranking on investors' decisions, we introduce a ranking treatment in which professionals receive private feedback on the level of their investments in SRI assets.[6] In our experiment we target the ranking on the average amount of money invested in SRI assets rather than on the overall portfolio performance. By doing this, we can trace changes in investors' behavior and increases in their share of SRI assets as a consequence of the ranking feedback.

Hypothesis 3: Investors tend to increase the share of SRI assets and, consequently, decrease the instability of their portfolio, when they receive ranking feedback about their level of investment in SRI assets.

Finally, as exploratory research, we investigate potential behavioral differences between student subjects and financial professionals. There is a specific interest to compare these two populations, as contradictory findings have been reported in the literature. On the one hand, the experimental finance literature reported similar market patterns with finance professionals and with students, in particular price bubbles (Weitzel et al., 2020). More generally, it seems that student subjects, who self-select into experiments, do not behave differently from other types of subjects in classical experimental games (Exadaktylos et al., 2013; Abeler and Nosenzo, 2015). On the other hand, there is strong evidence that students behave more selfish than other types of subjects (Engel, 2011; Belot et al., 2015) and economics students even more so (Gerlach, 2017). Given that our experiment is based on delegated philanthropy (misanthropy), generosity is likely to play an important role. It is therefore likely that the student subjects invest less in green assets that generate positive externalities and favor the more rewarding neutral and brown assets. However, given the mixed evidence about differences between students and professionals, we state the following conservative exploratory hypothesis:

Hypothesis 4: Professionals and students behave similarly with respect to portfolio selection and react similarly with respect to the ranking feedback.

3 Experimental design

The portfolio choice task was a part of a larger experimental set up containing several other parts. Besides the main task, the experiment contained an additional experimental task, the Bomb Risk Elicitation Task (BRET) (Crosetto and Filippin, 2013) and two questionnaires, the New Ecological Paradigm Scale (NEP) (Dunlap et al., 2000) and a socio-economic background questionnaire. The experiment was administered with the help of the O-tree software (Chen et al., 2016). On average the overall experiment lasted 20 minutes.

We designed our experiment in such a way as to account for several potentially relevant features. First, we wanted to measure the instability level of different portfolio types, related to possible intrinsic attraction (repulsion) for SRI (anti-SRI) assets. Thus, we defined three types of assets (green, brown, and neutral)[7]

[6] Providing private rather than public feedback should stimulate behavioral mechanisms related to self-esteem and competitive preferences and prevent potential status-seeking behavior typically brought about by public rankings (Villeval, 2020).

[7] In the instructions the assets were referred to as A (neutral), B (brown) and C (green).

that could be allocated in different portfolios. Second, we wanted to account for a potential variation in the instability level due to awareness of social ranking with respect to virtuous (SRI) investments. Third, we wanted to confer external validity to our experimental setting. These features are discussed in the subsections below.

3.1 Asset types

In order to implement the SRI (anti-SRI) feature, realistically and credibly, we attached either a negative or a positive externality to each asset type (Kirchler et al., 2016; Bartling et al., 2018). We informed the participants that investing in brown assets would oblige the university to transfer 20% of the average capital invested in this asset, over the 10 periods, to an international organization which is aimed at the world's oil and gas exploration and production, including shale gas. All things being equal, we expected that socially responsible investors would prefer not to invest in such an asset, even if it offered higher returns compared to alternative assets. In contrast, investing in green assets resulted in a transfer of 20% of the capital invested in this asset to a social enterprise, whose primary goals are to raise awareness of the power of forests and to restore forests around the world.[8] All things being equal, we expected a socially responsible investor to be more likely to choose such an asset because it includes a virtuous component. Put another way, socially responsible investors could be willing to sacrifice some monetary returns either to generate positive externalities or to avoid negative externalities for the environment (Koppel and Regner, 2014; Eckel et al., 2017; Guenster et al., 2022). Finally, neutral assets did not entail any externality.

In order to test the extent to which a person is ready to sacrifice profits and invest in the asset providing positive environmental externality, we deliberately suggested that a green asset should be less profitable than a neutral asset. Similarly, to test if investors are ready to forgo financial profits to avoid negative externality, we designed a brown asset as more profitable compared to a neutral asset. Besides, in order to respect the Markowitz's portfolio theory, we vary the risk parameter depending on the asset's return and fixed the values of the risk and return parameters such as to equalize the return per unit of standard deviation across asset types[9]. In addition, offering assets with different parameters provides an experiment that comes close to the realism of the financial markets and gives an external validity to this design. Finally, the implementation of an adequate econometric model provides a way to test the impact of difference in returns, all things being equal (i.e., for a given level of risk). Therefore, the green asset had both the lowest return (2%) and the lowest risk (1%), while the brown asset had the highest return (6%) and the highest risk (3%). Finally, the neutral asset had an intermediary return (4%) and risk (2%). The return in each period for each asset is randomly drawn following a normal distribution (μ, σ).

Subjects were aware of each asset's expected return (μ), their risk, measured by a standard deviation (σ), zero correlation between assets, and their type of externality. Table 1 summarizes the characteristics of the assets.

Table 1: Assets characteristics

Asset type	**Return (μ)**	**Risk (σ)**	**Externality**
Green (SRI)	2%	1%	Positive
Brown (anti-SRI)	6%	3%	Negative
Neutral	4%	2%	Neutral

3.2 Initial portfolios

At the beginning of the experiment, subjects had to choose between three initial portfolios, called X, Y, and Z. After their initial portfolio selection, subjects could update its' composition, period by period, after

[8]The above associations were chosen due to their direct impact on the environment (socially destructive and socially responsible) as well as their international character.

[9]The calculations are based on Markowitz's portfolio theory (Markowitz, 1991). Appendix 7.5 details these calculations.

having received return feedback for the current period. According to the CAPM, portfolio X is the optimal portfolio, i.e., it is the portfolio that maximizes the expected return at the lowest risk[10]. The two other initial portfolios, i.e., the portfolios named Y and Z, represented a socially responsible and a socially irresponsible portfolio, respectively. Portfolio Y (Z) contained a majority of green (brown) assets. Based on the provided information (asset returns, risks, and zero correlation) the subjects could infer and compute the risk-return characteristics of the suggested portfolios.[11]

The initial choice of portfolios was intended to reveal subjects' intrinsic SRI preferences before starting the portfolio allocation task. In addition, it allows us to check whether their revealed preferences are stable, in particular, for subjects who choose the initial portfolio X. If subjects consider exclusively the best asset allocations, i.e., behave according to finance theory, they should choose portfolio X, as the externality is irrelevant for portfolio optimization. Therefore, a subject who selects portfolio Y reveals an intrinsic preference for SRI as he is willing to trade off return (per unit of standard deviation) against a positive externality. Notably, this kind of investor demonstrates very high SRI preferences as the difference in green asset weights of optimal and green portfolios rests relevantly small. In contrast, someone who chooses portfolio Z is accepting a higher return (per unit of standard deviation) but at the cost of a negative externality imposed onto others. Externalities matter as shown by Consolandi et al. (2009) and Riedl and Smeets (2017) who documented that traders with stronger social preferences are willing to sacrifice some financial performance in order to invest in portfolios with a higher share of SRI assets.

Additionally, the initial choice of portfolios provided the participants with the possibility to invest in the optimal portfolio offering the best risk-return allocation that the participants could not calculate themselves during the experiment.

In addition to the three assets (green, brown, and neutral), initial portfolios also contained a fraction of riskless asset (cash). The amount of the riskless asset was equalized across initial portfolios, so that the initial value of all portfolios was the same. Thus, each portfolio value was equal to 70 euros, comprising 50 euros allocated according to three types of assets (green, brown, and neutral) and 20 euros in cash. The composition of portfolios is presented in Table 2 below.

Table 2: Composition of initial portfolios and asset allocation

Portfolio	**Value (euros)**	**Composition**		**Asset allocation**		
		Cash (euros)	**Assets (euros)**	**Green**	**Brown**	**Neutral**
Optimal (X)	70	20	50	55%	18%	27%
Green (Y)	70	20	50	60%	20%	20%
Brown (Z)	70	20	50	20%	60%	20%

The choice of the initial portfolio is subject not only to participants' SRI (anti-SRI) preferences but also to the risk-return characteristics of the available portfolios. Although the optimal portfolio offers the best rational proportions of assets, the motives for selecting the green or brown portfolio are arguable. The green portfolio is suboptimal and presents the lowest return and standard deviation compared to the optimal and brown portfolios.[12] Thus, an investor choosing the green portfolio is not necessarily a risk-averse investor, but an investor with an intrinsic preference for green assets. Similarly, the brown portfolio is also suboptimal. However, an investor choosing the brown portfolio, which offers both the highest risk and the highest return, is clearly a risk taker with a strong preference for portfolio profitability. Therefore, when analyzing and interpreting our results, we need to carefully distinguish and control for the impact of risk preferences and environmental preferences on the choice of the initial portfolio.[13]

[10]The optimal portfolio represents the market portfolio providing the maximum expected return with the lowest risk level. See Appendix 7.5 for the calculations.

[11]Optionally, as suggested by a reviewer, the participants could have been provided with the portfolio risk-return characteristics.

[12]See Appendix 7.5 for the calculations.

[13]We run multinomial logistic regressions with the initial portfolio choice as a dependent variable, and individual character-

3.3 Treatments

We considered two treatments: baseline and ranking. In the baseline treatment the subjects were asked to participate in an individual choice investment task which included 10 interdependent periods. The design for the ranking treatment was the same but, at the end of each period, the subjects were privately informed about their rank, based on their average investment in SRI assets, in comparison to other participants from the baseline treatment. In light of the findings about the impact of social ranking, by Tran and Zeckhauser (2012), Kirchler et al. (2018), and Cadsby et al. (2019), we conjectured that providing feedback about the ranking, would activate the subjects' behavioral mechanisms related to self-esteem and competitiveness, and, thereby, increase their investment in SRI assets. Consequently, the increased volume of SRI should result in an improved stability level for portfolios.

3.4 Subject pool

We performed two experiments with two different subject pools: students and financial professionals. The main reason for involving financial professionals is external validity. Despite a few recent studies comparing students' and professionals' behavior (Schwaiger et al., 2020; Weitzel et al., 2020; Bottasso et al., 2022), the convergence and replicability of the results of these two population samples are still arguable. It remains desirable, however, to involve students in an online lab experiment because of the high degree of control that the lab environment can provide.[14] Financial professionals are scarcely involved in such experiments. Therefore, we needed to adapt the lab experimental design to a lab-in-the-field setting. This inevitably entails a trade-off between validity and control.

The experiment with 153 financial professionals was held from October 2019 to January 2020 in Paris, Marseille, and Montpellier. Half of the professionals worked in the asset management industry, the other half in bank branches.[15] The replication of the experiment with 233 students was conducted in July 2020 by means of an online experiment with participants selected from the subject pool of the Laboratory of Experimental Economics of Montpellier (LEEM).

Among the 153 professionals, 83 were involved in the baseline treatment and 64 in the ranking treatment. The average age of the professionals was 43, most of them were French, and there was a slight majority of female participants (54%). 75% of the participants had a master's degree and 54% had an annual income greater than 50000 euros. Their mean BRET score was 34 with a maximum of 100, and their mean NEP score was 58 with a maximum of 74 out of 75.

In the online experiment, 129 university students took part in the baseline and 104 in the ranking treatment. The student sample consisted mostly of French students with an average age of 25 and a slight majority of females (55%). Most students had a bachelor or master's degree, and were majoring in Economics, Management, or Biology. 61% of them had an annual income of less than 12000 euros. The mean BRET score was 40 with a maximum of 100, and the mean NEP score was 41 with a maximum of 65 out of 75.

Appendices 7.1 and 7.2 provide details on descriptive statistics and test results regarding the differences between the two samples.

3.5 Practical procedures

Having chosen their initial portfolio, the participants could rebalance their portfolio period after period by performing an allocation task at the end of each period. The allocation task consisted either in investing, by converting some of the cash holdings into units of assets (with the constraint that the proportions of assets sum to 100%), or divesting, by converting units of assets into cash (1 unit of cash = 1 unit of asset, whatever the asset type). Note that we opted for an allocation procedure that agrees with our narrow definition of

istics as regressors, i.e., the BRET score, the NEP score, gender and age. The results clearly show that the choice probabilities of the initial portfolios are not determined by the participants' risk tolerance measured by the BRET score. See Appendix 7.6 for the detailed results.

[14] Though the lack of control is an acute topic, recent studies show no or weakly significant difference between the results of online and lab experiments (Buso et al., 2021; Prissé and Jorrat, 2022).

[15] Please, see Appendix 7.9 for more details on professionals' job functions and employers.

the instability index, which depends exclusively on the relative weights of the risky assets in the portfolio. A broader definition of instability could have been proposed by including the riskless asset. But this would have required a treatment of the riskless asset equal to that of the risky assets, i.e., as a percentage of the total portfolio value. Having chosen their current allocation, participants were invited to press the button “next” to switch to the next period.

At the end of each period the subjects could see a dashboard on their screen, showing their current portfolio composition and the corresponding financial results (realized returns of assets and portfolio value). We provided the participants with asset results instead of overall portfolio results to assure that they were impacted by risk-return characteristics of particular assets and to nudge them to change their portfolio allocation. Whereas, portfolio risk-return real time results could have provided a general information which is not specific to a particular asset type. Besides, we deliberately chose to reduce the quantity of information on screens, having specified in the instructions that the optimal portfolio gave the best maximum expected return for a given level for risk.[16]

The gain of each period was equal to the sum of cash holdings and the value of assets (the volume of each asset type multiplied by its value plus a random period return on each asset). The random returns on assets were added to or subtracted from cash holdings at the end of each period and, thus, could be reinvested in assets during the next periods.

At the end of the 10 periods, the participants were informed of their portfolio results and the transfer to each association. The final gain of the investment task represented the gain of the 10th period and equaled the portfolio value (sum of cash holdings and the value of assets). For the professional sample, 1 out of 10 participants was randomly selected for payment. A participant who was selected for payment earned the total gain. The total gain was equal to the sum of a participant’s gain in one of the investment tasks with equal chances to be chosen (probability = 0.5) and the gain of the control task. The payment was the same for the student subjects, except that all of them were paid. Using the random payment method has become standard in economic experiments, in particular, because it allows to provide high stakes (Cohn et al., 2014; March et al., 2016; Cohn et al., 2017; Kirchler et al., 2018). It has been shown that the random payment method does not affect participants incentives (Charness et al., 2016; Clot et al., 2018).

Based on our previous discussion, we hypothesized that participants’ allocation choices would mainly depend on their risk-return preferences and their environmental sensitivity. Therefore, we added the following control tasks to measure subjects’ risk tolerance and environmental preferences. Firstly, we relied on the Bomb Risk Elicitation Task (BRET) (Crosetto and Filippin, 2013) in order to elicit risk tolerance. In the BRET, subjects choose the number of boxes to open, out of 100, with one of the boxes containing a bomb. Earnings are equal to the number of open boxes multiplied by a constant if the bomb is not collected, or zero if the bomb is collected.[17] The chosen number or boxes is an index of risk-tolerance. We captured the participants’ socially responsible orientation based on the New Ecological Paradigm Scale (NEP) (Dunlap et al., 2000). The NEP measures participants’ environmental worldview and involves 15 statements. A participant’s responses to these statements in the form of agreement or disagreement (with different degrees) reflect his environmental concern. Finally, before leaving the sessions, participants had to complete a short questionnaire on socio-economic background (see Appendix for instructions).

For the investment task (for both treatments) professionals selected for payout received an average payoff of 94 euros, while students received 15 euros.[18] The average payment for BRET amounted to 8 euros with a maximum of 35 euros for professionals and 1.3 euros with a maximum of 6 euros for students. The average final gain was equal to 92 euros for professionals[19] and 21 euros for students. The average transfer to the

[16] We thank the reviewer for suggesting an alternative design where the portfolio risk-return characteristics could have been communicated to participants in real time depending on their portfolio allocation choices.

[17] Choosing 100 is irrational. One student subject (0,4%) and six professional subjects (4%) chose this number.

[18] The difference in payment between professionals and students in our experiment is comparable to the payoff difference of other experiments involving these two types of subjects (Alevy et al., 2007; Cohn et al., 2014; Kirchler et al., 2018). The students’ payment level in our experiment corresponds to 16% of the professionals’ level and is based on the relationship of the students’ average income (OVE, 2018) to the professionals’ average income level in the experiment.

[19] The final gain was equal to the sum of a participant’s gain in one of the investment tasks with equal chances to be chosen (probability = 0.5) and the gain of the control task. The final gain of 92 euros is lower than the average gain of 94 euros from the investment task as it contains the results chosen from the second investment game, with a lower mean profit.

international organization specialized in reforestation was equal to 5 and 0.52 euros for professionals and students, respectively. The corresponding average transfer to the international organization aimed at the world's oil and gas exploration and production was 3 euros for professionals and 0.55 euros for students. All payments, both for professionals and students, were made privately, using closed envelopes.

4 Experimental results

In this section we present our main findings. We start with descriptive results based on non-parametric tests on the initial portfolio choice and the portfolio types. Then we present the key findings about the instability index (result 1) and the ranking effect on the level of SRI investments (result 2). Support will be provided by non-parametric tests, average marginal effects (AME) for tobit regressions (for result 1), and panel data regressions with random effects (for result 2). Statements about behavioral differences between professionals and students will be directly added in results 1 and 2 and discussed simultaneously. We separate the regression results for the professional and the student samples for two reasons: first, we collected different control variables in the two samples, and, second, we relied on different methodologies (lab-in-the-field versus lab online).

At the beginning of the main task participants chose one of the three portfolios: optimal, green, or brown. As shown in Figure 1 and Figure 2, most participants, professionals and students, selected the optimal portfolios in both treatments. Professionals' second position choice was the green portfolio, while the brown portfolio came last. In contrast, for the secondary choice, students preferred the brown portfolio in the baseline and the green portfolio in the ranking treatment.

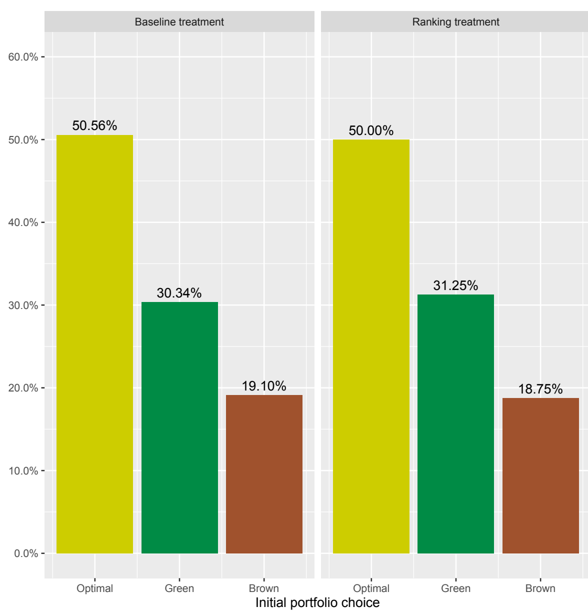


Figure 1: Professionals' choice of initial portfolios by treatment.

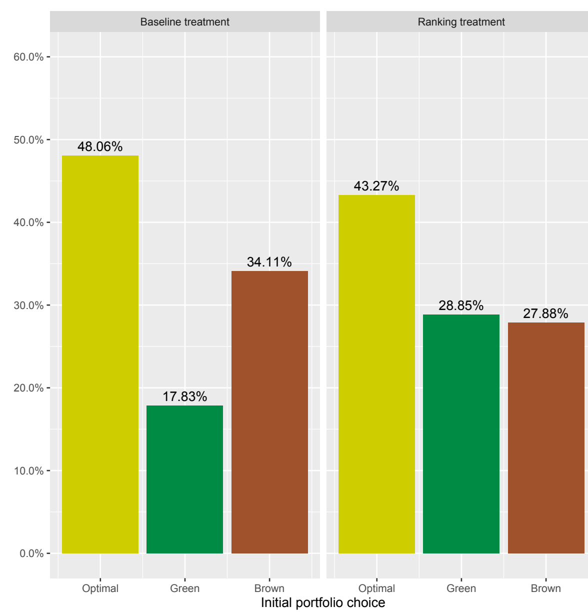


Figure 2: Students' choice of initial portfolios by treatment.

Over the 10 periods, subjects actively invested in assets and, consequently, adjusted their initial portfolio type. In order to compare the instability index of different portfolios, we categorized them into 4 types according to the average value of assets over the 10 periods: green, brown, neutral, and optimal. A portfolio is categorized as a "green" portfolio if the mean value of the green assets over the 10 periods is larger than the mean value of the brown and the mean value of the neutral assets. Similarly, a "brown" (or "neutral") portfolio was defined as a portfolio with the mean value of the brown (neutral) assets superior the mean value of the green and the mean value of the neutral (brown) assets.

It should be noted that the optimal portfolio is included in the set of green portfolios. Indeed, the share of green assets in the optimal portfolio accounts for 55% (based on the initial CAPM calculations) which is superior to the shares of brown and neutral assets. The choice of a green portfolio is rationalizable based on augmented Markowitz models (e.g., Gasser et al., 2017) or models that include a socially responsible criterion in the optimization process (Ballestero et al., 2012; Calvo et al., 2015; Utz et al., 2015). Subjects who deviate from the optimal portfolio (in the narrow sense) by over-investing in the green asset simply reveal a strong social preference.

While defining portfolio types for further analysis, we distinguished the optimal portfolio from others based on the initial CAPM calculations (55% of green, 18% of brown and 27% of neutral assets) with a tolerance of five percentage points, i.e., portfolios containing between 50% and 60% of green assets were categorized as optimal portfolios (provided that these portfolios also satisfied the criteria for brown and neutral).[20] Further, we compared the level of instability of green portfolios to other portfolio types, considering optimal portfolios as a separate category. We did not want to pool green and optimal portfolios as this would have artificially favored hypothesis 1. Indeed, as we will see later, optimal portfolios are also the most stable ones, as one would expect.

Figure 3 and Figure 4 below show the distribution of portfolio types in the baseline (0) and ranking (1) treatments. In both treatments the professionals preferred to invest more in green assets than in brown and neutral. As for the students, in the baseline their environmental preferences were less pronounced: they invested more in brown assets. However, in the ranking treatment, they clearly opted for green assets (which is further discussed in result 2).

Overall, professionals' and students' choice of initial portfolios was not significantly different (Two-sample Kolmogorov-Smirnov test, p-value (baseline) = 0.186, p-value (ranking) = 0.896). As for the distribution of portfolio types defined over the 10 periods, professionals' and students' portfolios differed significantly in the baseline, but converged in the ranking treatment (Two-sample Kolmogorov-Smirnov test, p-value (baseline) = 0.014, p-value (ranking) = 0.333).

[20] Between 13% and 23% for brown assets and between 22% and 32% for neutral assets.

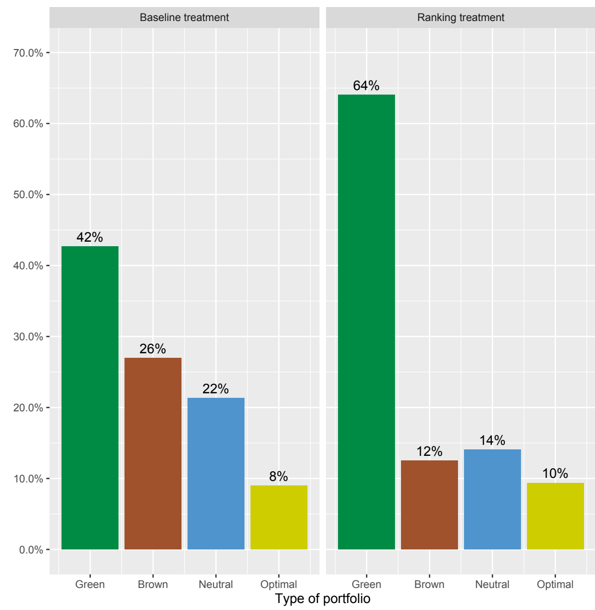


Figure 3: Professionals' portfolio types by treatment.

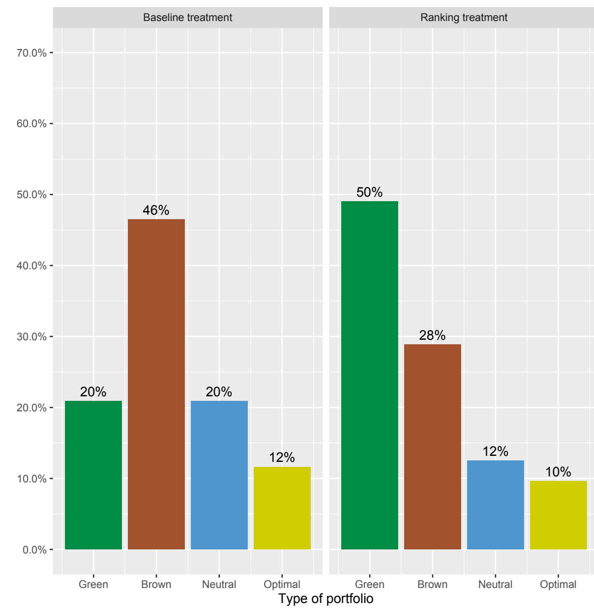


Figure 4: Students' portfolio types by treatment.

Result 1: Green portfolios exhibit lower instability compared to brown and neutral portfolios, but do not outperform optimal portfolios.

Table 3 reports the test results (Mann-Whitney tests) for differences in instability index by portfolio type, sample, and treatment. We observe that the instability index is lower for green portfolios than for brown and neutral portfolios. For the baseline treatment, we observed in both samples (professionals and students) a statistically lower instability index for green portfolios ($p < 0.05$) compared to brown, neutral, and optimal portfolios in the baseline (except for the difference between green and optimal portfolios for professionals). For the ranking treatment, none of the differences was significant (except in the student sample, for the comparison between green and optimal portfolios). In addition, there was no significant difference in instability index between treatments, both for professionals and students. Finally, we observed similar instability results in both samples (professionals and students) and for both treatments.

Table 3: Mann-Whitney test results for differences in instability index

Treatment	**Sample**	**Portfolios**			
		Green vs brown	**Green vs neutral**	**Green vs optimal**	**All portfolios**
Baseline	*Professionals*	0.005 (-2.808)	0.000 (-4.152)	0.366 (0.903)	-
	Students	0.007 (-2.721)	0.042 (-2.035)	0.001 (3.219)	-
	Profs vs students	-	-	-	0.743 (-0.328)
Ranking	*Professionals*	0.068 (-1.828)	0.519 (-0.645)	0.482 (0.703)	-
	Students	0.486 (0.696)	0.066 (-1.836)	0.005 (2.833)	-
	Profs vs students	-	-	-	0.189 (-1.315)
Baseline vs Ranking	*Professionals*	-	-	-	0.894 (-0.133)
	Students	-	-	-	0.190 (-1.310)

Notes: Table 3 reports the p-values (z-scores in parentheses) of Mann-Whitney tests for the instability index of different portfolio types for both samples and both treatments. We observe significant differences ($p < 0.05$) in instability index for green portfolios if compared to brown, neutral and optimal portfolios in the baseline except green vs optimal for professionals (green vs brown: prof p-value = 0.005, stud p-value = 0.005; green vs neutral: prof p-value = 0.000, stud p-value = 0.042; green vs optimal: prof p-value = 0.366, stud p-value = 0.001). There is no significant difference in the ranking treatment except green vs optimal for students (green vs brown: prof p-value = 0.068, stud p-value = 0.486; green vs neutral: prof p-value = 0.527; stud p-value = 0.066; green vs optimal: prof p-value = 0.482, stud p-value = 0.005). There is no significant difference in instability index between treatments for both professionals (p-value = 0.894) and students (p-value = 0.190), as well as between two samples in the baseline (p-value = 0.743) and the ranking treatments (p-value = 0.189).

We provide additional support for result 1 based on multivariate analysis. For ease of interpretation, we rely mainly on average marginal effects (AME) for tobit regressions as the dependent variable (instability index) cannot be less than 0, and, therefore, is left-censored.[21] Figure 5 and Figure 6 clearly show that numerous values of the distributions are left-censored in both samples (22 out of 153 for professionals, 47 out of 233 for students). The detailed descriptive statistics on the instability index is provided in Appendix 7.1. (in the professional sample the mean is 0.46, the median is 0.16, and the standard deviation is 0.80; in the student sample the mean is 0.87, the median is 0.20, and the standard deviation is 1.56)

[21] Results of tobit coefficients and OLS regressions are additionally reported in Appendices 7.3 and 7.4 correspondingly.

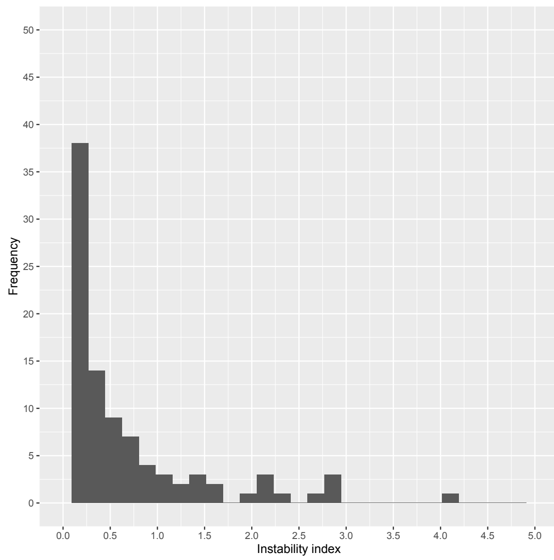


Figure 5: Professionals. Histogram of instability index.

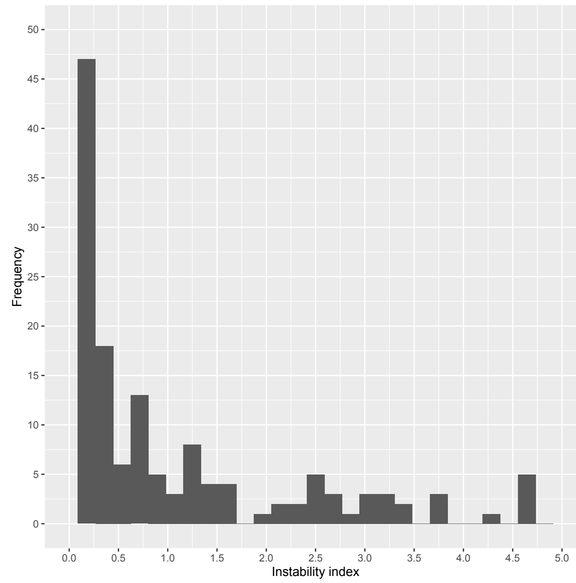


Figure 6: Students. Histogram of instability index.

In Table 4 and Table 5 we report the AME of the tobit models for the instability index, for both samples.[22] Note that AME for tobit models are interpreted comparably to β-coefficients of a linear regression, i.e., as the predicted change in the instability index associated with the changes in the other variables.

For the professional sample, as shown in models (1–2) of Table 4, we observe that the instability index of brown portfolios is on average 0.2 points higher than that of green portfolios. Yet, there is no significant ($p < 0.05$) difference in the instability index between green and neutral portfolios. In the student sample (Table 5), we observe that the instability index of optimal portfolios is 0.7 points lower than that of green portfolios. However, we do not find any significant ($p < 0.05$) difference in instability indices of green and conventional (brown and neutral) portfolios.

In models (2–3) of Table 4, we observe a lower instability index whenever the brown portfolio was initially selected over the optimal portfolio: the instability index is 0.2 points lower for professionals. Participants who initially selected the optimal portfolio (roughly 50% of the professionals and 45% of the students), on the other hand, actively rebalanced their portfolios throughout the experiment, resulting in just 9% of optimal portfolios for the professionals and 11% for the students at the end of the 10 periods. We find no significant difference in the instability index in cases when participants initially chose the green or the optimal portfolios.

From Table 4, models (2–3), it can be seen that the variable BRET has a significant positive coefficient in the professional sample, implying higher portfolio instability for more risk-loving participants: a 1-point increase of the BRET score increases the mean instability by 0.007. This effect is specific to the professionals since the students' instability index is not affected by BRET.

Table 4, model (3), meanwhile, reveals an "age effect". The coefficient of the birth year indicates that younger professionals have less stable portfolios: an additional year of birth year increases the instability index by 0.012.

Result 1 confirms our main hypothesis: portfolios with a higher share of SRI assets have lower instability. However, our second hypothesis is confirmed only partially: though the instability of SRI portfolios is lower

[22] Additionally, in Appendix 7.7 we present the robustness check of our results. First, we analyze the portfolio instability by suggesting a more demanding definition of a green portfolio and, second, by dividing the investment game in two subsequent parts.

than that of conventional (brown and neutral) portfolios, it is still higher than the instability of optimal portfolios.

The latter outcome could be due to two reasons. First, optimal portfolios are defined by a narrow percentage range which contributed to their stability. In particular, portfolios characterized as optimal over 10 periods were mostly those that rested optimal during the game. Second, this result should be contrasted with the sharp decline in the proportion of optimal portfolios over time. Most participants revealed their preferences across time and voluntary abandoned the optimal allocation with the highest Sharpe ratio, favoring green portfolios (professionals and students in the ranking treatment) or brown portfolios (students in the baseline). Notably, this was not the case for asset allocation in the opposite direction: from green or brown portfolios to optimal ones.

Finally, these pieces of evidence are similar between the professional and student samples, supporting hypothesis 4 that behavioral patterns of professionals and students are concordant. Indeed, we found no significant difference in the initial portfolio choice and the instability index between professionals and students in both treatments.

Table 4: Portfolio instability - Professionals (average marginal effects, Tobit estimates)

	Dependent variable:		
	Instability index		
	(1)	(2)	(3)
Brown portfolio	0.254*	0.230*	0.189
	(0.111)	(0.104)	(0.102)
Neutral portfolio	0.301	0.270	0.238
	(0.183)	(0.161)	(0.159)
Optimal portfolio	−0.137	−0.088	−0.081
	(0.153)	(0.146)	(0.144)
Initial choice of green portfolio	−0.087	−0.087	−0.092
	(0.113)	(0.106)	(0.103)
Initial choice of brown portfolio	−0.200	−0.205*	−0.190*
	(0.106)	(0.100)	(0.096)
Ranking	0.151	0.135	0.117
	(0.099)	(0.097)	(0.093)
BRET score		0.007**	0.007**
		(0.003)	(0.002)
NEP score		−0.010	−0.010
		(0.007)	(0.007)
Birth year			0.012**
			(0.004)
Gender			0.078
			(0.088)
Observations	153	153	153

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 4 shows AME for tobit models on instability index with robust standard errors in parentheses for professional sample. Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for female and 0 for male gender. Finally, Ranking is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 153. Tobit estimated coefficients are displayed in Appendix 7.3.

Table 5: Portfolio instability - Students (average marginal effects, Tobit estimates)

	Dependent variable:		
	Instability index		
	(1)	(2)	(3)
Brown portfolio	0.428	0.427	0.437
	(0.247)	(0.242)	(0.246)
Neutral portfolio	0.332	0.300	0.312
	(0.191)	(0.192)	(0.194)
Optimal portfolio	-0.667^{**}	-0.664^{**}	-0.661^{**}
	(0.163)	(0.164)	(0.164)
Initial choice of green portfolio	−0.079	−0.069	−0.041
	(0.205)	(0.206)	(0.211)
Initial choice of brown portfolio	−0.417	−0.405	−0.414
	(0.225)	(0.239)	(0.231)
Ranking	0.214	0.201	0.206
	(0.147)	(0.148)	(0.146)
BRET score		−0.002	−0.002
		(0.004)	(0.005)
NEP score		0.013	0.015
		(0.015)	(0.015)
Birth year			0.017
			(0.013)
Gender			0.051
			(0.165)
Observations	233	233	233

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 5 shows AME for tobit models on instability index with robust standard errors in parentheses for student sample. Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for male and 0 for female gender. Finally, Ranking is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 233. Tobit estimated coefficients are displayed in Appendix 7.3.

Result 2: Participants invested more in green assets in the ranking treatment than in the baseline treatment, in both samples. However, students' reaction to the ranking feedback was stronger than that of professionals.

We observe that professionals' and students' mean investments in green assets largely increased in the ranking treatment in comparison to the baseline treatment (by 21% and 44%, respectively). The difference in investments in green assets between the baseline and the ranking treatment is significant ($p < 0.05$) both for the professional and the student samples. The difference in investments in brown and neutral assets between the treatments is significant only for the student sample. Comparing professionals and students, we also observe a significant difference in investments in green and brown assets between these samples in both treatments ($p < 0.05$). Table 6 summarizes the results of Mann-Whitney tests for differences in investments for the three asset types for both treatments.

Table 6: Mann-Whitney test results for differences in investments in green, brown and neutral assets.

	Baseline	**Ranking**	**Baseline vs Ranking**	
Assets	*Prof vs Stud*	*Prof vs Stud*	*Prof*	*Stud*
Green	0.000 (3.770)	0.049 (1.965)	0.006 (-2.767)	0.000 (-4.658)
Brown	0.005 (-2.855)	0.030 (-2.165)	0.071 (1.803)	0.009 (2.610)
Neutral	0.802 (-0.250)	0.606 (-0.516)	0.100 (1.646)	0.038 (2.076)

Notes: Table 6 shows the p-values (z-scores) for Mann-Whitney tests for investments in the three asset types for both samples and the two treatments. Professional and student samples differ significantly (p < 0.05) in their investments in green assets in both treatments (p-value (baseline) = 0.000 and p-value (ranking) = 0.049), as well as in brown assets (p-value (baseline) = 0.005, p-value (ranking) = 0.030), but not in neutral assets (p-value (baseline) = 0.802, p-value (ranking) = 0.606). Investments in green assets differ significantly (p < 0.05) in baseline vs ranking treatment for professionals (p-value = 0.006) and students (p-value = 0.000), in brown assets - for students (p-value = 0.009) but not for professionals (p-value = 0.071); investments in neutral assets do not differ for professionals (p-value = 0.100), but do for students (p-value = 0.038).

Figure 7 and Figure 8 below show the dynamics of the investments in each asset type over time in relative portfolio weights (mean and median). We observe the same behavioral pattern in the investments of the professionals and students: their mean and median investments in green assets are significantly ($p < 0.05$) higher in the ranking treatment than in the baseline. On the contrary, the mean and median investments in brown and neutral assets over the 10 periods are relatively lower in the ranking treatment than in the baseline.[23] Apart from that, we can note a gradual decline in green investments during the game in the baseline treatment in both samples: students and professionals opt for more profitable brown and neutral investments by the end of the experiment. However, in the ranking treatment students and professionals tend to increase their green investments over time seeking for a higher rank. Consequently, their investments in brown and neutral assets diminish by the end of the game.

[23] This difference is significant ($p < 0.05$) for the student sample, but not for the professional sample as shown further in Table 7 and Table 8.

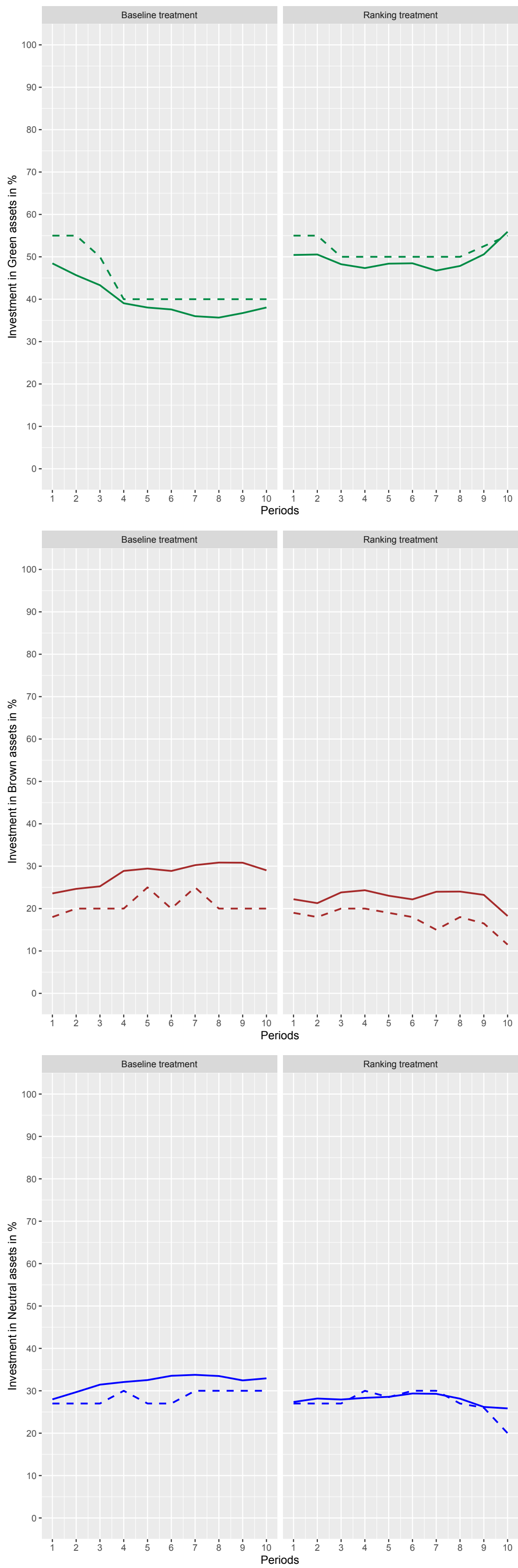


Figure 7: Mean (solid line) and median (dashed line) investments in % by periods. Professionals.

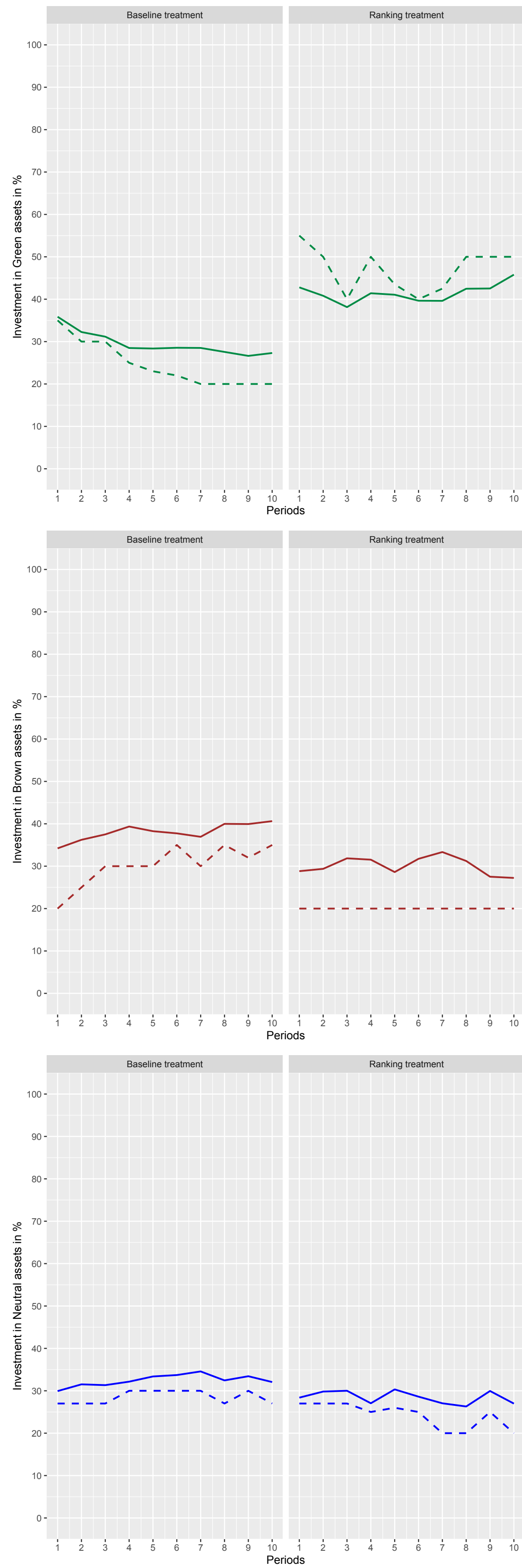


Figure 8: Mean (solid line) and median (dashed line) investments in % by periods. Students.

We provide additional support for result 2 by means of panel data regressions with random effects.[24] The models reported in Table 7 and Table 8 test the difference between investments in green, brown, and neutral assets for the professional and student samples. Investments in green, brown, and neutral assets denote the respective investment weights in terms of their percentage of the total portfolio weight. We take into account the lagged realized return differences, between the brown and the green assets on one hand ("Lag diff of B and G returns"), and between the neutral and the green assets on the other hand ("Lag diff of N and G returns"). We expected that larger differences in lagged returns would favor disinvestment in green assets and favor investment, either in brown or neutral assets.

In both tables we can observe a highly significant ($p < 0.01$) and consistent positive impact of the ranking treatment on investments in green assets. Moreover, there is a highly significant negative impact of the ranking treatment on investments in brown and neutral assets, for the student sample, but not for the professionals. On average, the professionals invested 10% more in green assets in the ranking treatment than in the baseline. The students behaved similarly, investing 11% more in green assets. Apart from that, the students invested 7% less in brown assets, and 4% less in neutral assets.

Table 7 shows that the financial professionals who initially selected the green portfolio invested 11% more in green assets (models (1)) and 11% less in neutral assets (models (3)) compared to those who initially selected the optimal portfolio. Similarly, as we observe in model (2) of Table 8, the students invested 5% less in neutral assets after selecting the initial green portfolio. In Table 7 we can see that the professionals who initially selected the brown portfolio invested 12% more in brown assets (models (2)) compared to the professionals who initially selected the optimal portfolio. Table 8 indicates that there was the similar response in the student sample: they invested 20% less in green assets, 29% more in brown assets, and 9% less in neutral assets if the brown portfolio was initially chosen.

We observe additional significant coefficients in the student sample. Models (1) and (2) of Table 8 affirm the gender effect in investments: men tend to invest 6% less in green assets and, conversely, 6% more in brown assets than women. In the professional sample, however, there is no gender effect.

Result 2 confirms our third hypothesis. The applied incentive, i.e. the ranking feedback, had a substantial impact on investors' behavior and the choice of assets: both students and professionals invested more in SRI assets when they were ranked based on the level of their average investment, and conversely tended to invest less in conventional assets. Though ranking feedback positively affected the "greening" of portfolios, i.e., portfolios contained larger shares of SRI assets in the ranking treatment than in the baseline, this was insufficient to affect the instability index. The reason is that ranking feedback favored portfolio rebalancing, increasing thereby instability.

Finally, result 2 partially agrees with hypothesis 4. Though the ranking treatment generated a large effect in both populations, it was notable that professionals invested more in SRI assets than students, both in their more frequent selection of the green portfolio in the initial choice stage, and by investing more in green over the 10 rounds sequence. Additionally, the students' response to the ranking incentive was stronger than that of the professionals.

Apart from that, we should note that the above results were observed due to the private ranking feedback which is based on subjects' intrinsic motivation and implies no social signaling and external recognition. Therefore, it is likely that the positive effect of ranking on SRI is a lower bound that could be sharply increased if the ranking was made public.

[24] We do not use tobit regressions with the data on investments in green, brown, and neutral assets, as it is not censored. In addition, in Appendix 7.8 we provide fractional probit regressions that confirm the original results.

Table 7: Investment in assets in relative portfolio weights - Professionals (random effects panel data estimates).

	Dependent variable:		
	Investment in green assets	Investment in brown assets	Investment in neutral assets
	(1)	(2)	(3)
Lag diff of B and G returns	−0.183	0.113	0.069
	(0.134)	(0.127)	(0.133)
Lag diff of N and G returns	−0.260	−0.010	0.271
	(0.197)	(0.181)	(0.172)
Ranking	10.023**	−5.791	−4.233
	(3.189)	(3.022)	(2.431)
Initial choice of green portfolio	10.755**	0.139	−10.894**
	(3.513)	(3.323)	(2.432)
Initial choice of brown portfolio	−7.801	12.081*	−4.280
	(4.694)	(4.694)	(4.272)
BRET score	−0.050	0.075	−0.025
	(0.070)	(0.061)	(0.047)
NEP score	0.394	−0.398	0.004
	(0.251)	(0.276)	(0.212)
Gender	−0.402	0.816	−0.415
	(3.169)	(3.097)	(2.519)
Birth year	−0.161	0.079	0.082
	(0.177)	(0.160)	(0.130)
Constant	336.187	−109.969	−126.207
	(349.089)	(314.474)	(255.910)
Observations	1,377	1,377	1,377
R^2	0.027	0.013	0.015
Adjusted R^2	0.021	0.007	0.009
F Statistic	37.986**	18.379*	21.334*

*p<0.05; **p<0.01

Notes: Table 7 shows the random effect panel regressions with robust clustered standard errors (in parentheses) at the subject level. The Hausman test favored a random effect model. Investments in green, brown, and neutral assets denote the respective investment weights in percent of the total portfolio weight. Lag diff of B and G returns and Lag diff of N and G returns represent the difference perceived by professionals between lagged returns on brown and green or neutral and green assets which might change their investment decisions. Ranking is a dummy for the ranking treatment with the baseline as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 0 for male and 1 for female. Sample size N (number of subjects) for each test is 153. There are 9 observations per subject because of the presence of one-period lagged variables.

Table 8: Investment in assets in relative portfolio weights - Students (random effects panel data estimates).

	Dependent variable:		
	Investment in green assets	Investment in brown assets	Investment in neutral assets
	(1)	(2)	(3)
Lag diff of B and G returns	−0.126	0.241	−0.120
	(0.140)	(0.147)	(0.162)
Lag diff of N and G returns	−0.041	−0.154	0.196
	(0.172)	(0.189)	(0.202)
Ranking	10.882**	−6.671**	−4.212*
	(2.280)	(2.465)	(2.138)
Initial choice of green portfolio	2.824	2.199	−5.023*
	(3.114)	(2.789)	(2.559)
Initial choice of brown portfolio	−20.118**	29.224**	−9.106**
	(2.450)	(3.117)	(2.526)
BRET score	−0.052	0.048	0.004
	(0.053)	(0.053)	(0.043)
NEP score	−0.287	−0.070	0.357
	(0.212)	(0.253)	(0.195)
Gender	−5.627*	6.381*	−0.753
	(2.289)	(2.484)	(2.016)
Birth year	−0.087	0.015	0.072
	(0.162)	(0.146)	(0.134)
Constant	225.241	−3.500	−121.479
	(323.261)	(292.043)	(268.469)
Observations	2,097	2,097	2,097
R^2	0.061	0.070	0.011
Adjusted R^2	0.057	0.066	0.007
F Statistic	136.244**	157.457**	23.155**

*p<0.05; **p<0.01

Notes: Table 8 shows the random effect panel regressions with robust clustered standard errors (in parentheses) at the subject level. The Hausman test favored a random effect model. Investments in green, brown, and neutral assets denote the respective investment weights in percent of the total portfolio weight. Lag diff of B and G returns and Lag diff of N and G returns represent the difference perceived by students between lagged returns on brown and green or neutral and green assets which might change their investment decisions. Ranking is a dummy for the ranking treatment with the baseline as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for male and 0 for female. Sample size N (number of subjects) for each test is 233. There are 9 observations per subject because of the presence of one-period lagged variables.

5 Discussion

There is an old debate about deviations from rationality and decision errors in economic experiments. For instance, cooperation in public goods games was sometimes related to confusion and decision errors (Andreoni, 1995). But later research, showed that a vast majority of subjects' behavior agreed with rational altruistic behavior (Andreoni and Miller, 2002; Charness and Rabin, 2002). It is nowadays admitted that people have social preferences, such as altruism, that can be captured in simple games. People who invest more in green in our experiment are more likely to be of the altruistic type. However, because our portfolio choice task is more complex than a simple division game, we cannot rule out the possibility that some individuals make mistakes or act irrationally.

To what extent could decision errors and irrationality drive our results? A selfish rational agent should always choose the optimal portfolio (i.e., 55% of green, 18% of brown, and 27% of neutral assets). In our analysis we separate optimal portfolios from green portfolios to avoid motives confounds. If all our subjects were selfish rational agents, we should observe a frequency close to 100% of optimal portfolios. In the baseline treatment, only 8% of the professional and 12% of the student portfolios kept the optimal portfolio during the game, and these frequencies are virtually unaffected by our ranking treatment variable (Figure 3 and Figure 4). In contrast, 42% of the professionals and 20% of the students chose a green portfolio in the baseline treatment, and these frequencies go up 64% and 50% respectively, in the ranking treatment. To what extent could these frequencies be explained by irrational behavior? Clearly, as in most other economic experiments, our subjects' choices are not compatible with the selfish rational model, which in our case is the optimal portfolio choice theory. First, the high frequencies of green portfolios could reflect a stronger taste for positive green externalities rather than negative brown externalities, which is more pronounced in professionals than in students. This agrees with previous findings that showed that students represent a special class of subjects as they are more selfish and more rational than non-student subjects (Engel, 2011; Belot et al., 2015; Gerlach, 2017). Second, the strong impact of the ranking treatment on green portfolio choices could be driven by a priming effect of warm glow (Andreoni, 1990) and social influence (Martin and Randal, 2008; Shang and Croson, 2009). By providing private feedback on one's green ranking with respect to a reference with the same identity might have activated a stronger feeling in self-esteem and self-image (Bénabou and Tirole, 2011), leading to more greener choices.

Finally, it remains to explain why we also observe a substantial fraction of neutral and brown portfolios for both types of subjects. Could it reflect mistakes and irrationality? Brown portfolios entail higher returns at the cost of higher risk. It could, therefore, both reflect some propensity to take risk and some anti-social preference. On the other hand, the choice of a neutral asset is more difficult to justify. It is 21% in the baseline and 13% in the ranking treatment (both samples included). Let us assume that these 21% of neutral portfolio choices reflect the error rate. Extrapolating this fraction to the other types of portfolios reduces the purposeful choices of the green and brown portfolios, but we still observe the highest fraction of green for professional in both treatments and for students in the ranking treatment. Therefore, we can safely conclude that professionals' portfolio choices reflect a taste for green but not for student, unless they are primed with ranking feedback.

6 Conclusion

We measured the instability of socially responsible portfolios based on the data collected from a lab-in-the-field experiment with financial professionals and an online experiment with students. Following the work of Kirchler et al. (2018), we compared a treatment in which subjects received feedback regarding their rank related to investment in SRI assets to a baseline treatment without feedback. In line with existing empirical research, we hypothesized that (i) the level of portfolio instability is negatively correlated with the share of SRI assets in a portfolio, (ii) SRI portfolios provide lower instability than optimal and conventional portfolios, (iii) financial professionals and students who receive ranking feedback invest more in SRI assets, and (iv) professionals' and students' behavior is similar in portfolio selection and reaction to the ranking treatment.

Ultimately, we were able to highlight the importance of SRI for the level of portfolio instability, and for portfolio management in general. This is an aspect that has been neglected in previous literature on portfolio management. Furthermore, our work is the first to approach this issue using controlled experiments. In this vein, we provided new experimental evidence regarding financial professionals' preferences for SRI in a controlled environment and enriched the existing methodology by designing SRI and anti-social investment in the lab as a third-party beneficiary.

More specifically, we found that SRI significantly correlated with the level of portfolio instability and the need for portfolio rebalancing. In both treatments, the majority of subjects opted for the optimal portfolio at the beginning of the experiment. Throughout the game, the participants actively changed their portfolios, and, finally, preferred to invest more in green assets than in brown and neutral assets (in both treatments for the financial professionals, and in the ranking treatment for the students). In both treatments, the lower instability was detected in the portfolios containing a prevailing share of SRI assets if compared to the portfolios with the majority of conventional assets. However, SRI portfolios exhibited a slightly higher instability than optimal portfolios. It is worth mentioning that we intentionally analyzed SRI and optimal portfolios as separate portfolio types. Otherwise, the lowest instability level of optimal portfolios could have provided results in favor of the instability of SRI portfolios. As we can observe from the regression analysis, portfolio instability is positively correlated with risk tolerance measured by the BRET score, i.e., risk-loving participants hold less stable portfolios.

As there is no commonly accepted definition for an SRI portfolio, we needed to ensure the robustness of our results and therefore conducted two sensitivity analyses. First, we relied on a more stringent definition by categorizing an SRI portfolio as a portfolio containing at least 50% of green assets on average over the 10 periods. Second, we refined the analysis of the instability index by considering two sub-sequences consisting of periods 1-5 and 6-10. These robustness analyses confirmed the results obtained with the original analysis based on a weaker definition of SRI portfolios and the whole sequence.

With respect to our treatment, we discovered that the feedback on the average investment level in SRI assets had a direct impact on the participants' behavior and asset allocation. In the ranking treatment, the subjects invested more in SRI assets than in the baseline. Conversely, investments in conventional assets diminished in the ranking treatment.

Additionally, it is worth mentioning the convergence of experimental results between the student and professional subject pools. Both samples had a similar portfolio instability index of SRI assets when compared to conventional portfolios, and we observed a strong response in both samples to the ranking treatment. However, professionals' investment in green assets was significantly higher than that of students, the latter being more greatly impacted by the ranking incentive.

Given our findings, additional treatments could be worth investigating to better understand the impact of behavioral mechanisms on SRI. Following Bénabou and Tirole (2006) and Kirchler et al. (2016), one could consider a "responsibility treatment", i.e., a treatment in which participants are reminded during the investment task of the tangible impact of their choices on the environment. Alternatively, a "punishment treatment" could be utilized, i.e., participants are penalized by a tax on investment in non-SRI or anti-SRI assets, which would also be of interest as the threat of monetary punishment should promote moral behavior.

In addition, given the strong impact of the ranking treatment, comparing different ranking feedback systems would be worthwhile. For instance, it would be interesting to know whether an anti-SRI ranking feedback produces the same effect on SRI investments as an SRI ranking feedback. Another option is to consider a public form of ranking in contrast to the private feedback used in the experiment. The public ranking may produce a higher effect on SRI taking into account the role of external recognition and social signalling.

Finally, it should be noted that SRI portfolios possessing lower instability than conventional portfolios can be more resilient in times of economic downturn and thus provide a sustainable investment in the long term. Several papers (Nofsinger and Varma, 2014; Ang, 2015; Lins et al., 2017; Erragragui et al., 2018) have observed that SRI could provide sustainable development to the asset management industry while also being more resilient to financial crises and economic events. The portfolio instability index determined by SRI assets could contribute to a better understanding of the problem of instability of the mean-variance frontier and could be successfully applied in asset management. In particular, this study could be valuable for individual investors and financial managers in developing better investment strategies and in serving as an efficient tool for portfolio optimization and diversification.

7 Appendix

7.1 Descriptive statistics for key variables: instability index and investments in SRI and conventional assets

Table 9: Descriptive statistics for professional and student samples. Instability index by treatment and portfolio type.

Professionals							
Treatment	**Portfolio type**	**Mean**	**Median**	**St dev**	**Min**	**Max**	**N of obs**
	Green	0.21	0.06	0.43	0.00	2.16	38
	Brown	0.45	0.22	0.61	0.00	2.87	24
Baseline	*Neutral*	0.83	0.46	1.24	0.08	5.24	19
	Optimal	0.11	0.03	0.20	0.00	0.59	8
	Total	**0.40**	**0.16**	**0.75**	**0.00**	**5.24**	**89**
	Green	0.48	0.10	0.90	0.00	4.14	41
	Brown	0.90	0.83	0.77	0.00	1.99	8
Ranking	*Neutral*	0.42	0.22	0.69	0.00	2.22	9
	Optimal	0.65	0.05	1.10	0.00	2.73	6
	Total	**0.54**	**0.16**	**0.87**	**0.00**	**4.14**	**64**
	Green	0.35	0.08	0.72	0.00	4.14	79
	Brown	0.56	0.26	0.67	0.00	2.87	32
Total	*Neutral*	0.70	0.38	1.10	0.00	5.24	28
	Optimal	0.34	0.03	0.75	0.00	2.73	14
	Total	**0.46**	**0.16**	**0.80**	**0.00**	**5.24**	**153**
Students							
Treatment	**Portfolio type**	**Mean**	**Median**	**St dev**	**Min**	**Max**	**N of obs**
	Green	0.36	0.06	0.98	0.00	5.05	27
	Brown	1.12	0.30	2.08	0.00	12.60	60
Baseline	*Neutral*	0.79	0.20	1.22	0.00	5.23	27
	Optimal	0.35	0.00	1.21	0.00	4.70	15
	Total	**0.80**	**0.17**	**1.66**	**0.00**	**12.60**	**129**
	Green	1.04	0.22	1.47	0.00	5.16	51
	Brown	0.89	0.25	1.50	0.00	6.13	30
Ranking	*Neutral*	1.40	0.73	1.46	0.05	4.70	13
	Optimal	0.17	0.00	0.41	0.00	1.30	10
	Total	**0.96**	**0.24**	**1.42**	**0.00**	**6.13**	**104**
	Green	0.80	0.13	1.35	0.00	5.16	78
	Brown	1.04	0.28	1.90	0.00	12.60	90
Total	*Neutral*	0.99	0.37	1.31	0.00	5.23	40
	Optimal	0.28	0.00	0.96	0.00	4.70	25
	Total	**0.87**	**0.20**	**1.56**	**0.00**	**12.60**	**233**

Table 10: Descriptive statistics for professional and student samples. Investments in assets in relative (%) and absolute (euros) terms.

Professionals								
Treatment	**Investments in**	**Assets**	**Mean**	**Median**	**St dev**	**Min**	**Max**	**N of obs**
Baseline	%	*Green*	39.85	40.00	23.14	0.00	100.00	89
		Brown	28.16	20.00	23.20	0.00	100.00	89
		Neutral	31.99	27.00	19.59	0.00	100.00	89
	euros	*Green*	24.77	25.46	15.96	0.00	93.78	89
		Brown	18.35	12.70	18.15	0.00	109.47	89
		Neutral	21.34	16.63	16.57	0.00	101.85	89
Ranking	%	*Green*	49.45	50.00	24.17	0.00	100.00	64
		Brown	22.63	18.00	21.84	0.00	100.00	64
		Neutral	27.92	27.00	17.85	0.00	100.00	64
	euros	*Green*	30.00	30.00	16.78	0.00	95.26	64
		Brown	13.76	10.00	14.06	0.00	81.75	64
		Neutral	17.49	15.00	13.84	0.00	101.57	64
Total	%	*Green*	43.87	50.00	24.04	0.00	100.00	153
		Brown	25.85	20.00	22.80	0.00	100.00	153
		Neutral	30.29	27.00	18.98	0.00	100.00	153
	euros	*Green*	26.96	27.50	16.51	0.00	95.26	153
		Brown	16.43	11.73	16.71	0.00	109.47	153
		Neutral	19.73	15.09	15.60	0.00	101.85	153
Students								
Treatment	**Investments in**	**Assets**	**Mean**	**Median**	**St dev**	**Min**	**Max**	**N of obs**
Baseline	%	*Green*	29.47	25.70	19.56	0.00	92.50	129
		Brown	38.08	36.50	23.59	0.00	100.00	129
		Neutral	32.45	29.70	17.38	0.00	96.00	129
	euros	*Green*	15.56	13.27	11.02	0.00	46.25	129
		Brown	21.96	19.05	17.77	0.00	94.96	129
		Neutral	18.37	15.25	12.52	0.00	81.02	129
Ranking	%	*Green*	41.42	43.20	19.68	0.00	77.50	104
		Brown	30.13	24.00	21.85	0.00	100.00	104
		Neutral	28.45	26.25	13.38	0.00	98.50	104
	euros	*Green*	22.49	22.40	11.88	0.00	47.44	104
		Brown	17.02	12.34	14.66	0.00	76.20	104
		Neutral	16.24	13.63	10.84	0.00	83.09	104
Total	%	*Green*	34.80	32.80	20.45	0.00	92.50	233
		Brown	34.53	28.50	23.12	0.00	100.00	233
		Neutral	30.67	28.00	15.81	0.00	98.50	233
	euros	*Green*	18.66	17.00	11.90	0.00	47.44	233
		Brown	19.76	14.25	16.60	0.00	94.96	233
		Neutral	17.42	14.60	11.82	0.00	83.09	233

7.2 Descriptive statistics and tests on control variables

Table 11: Descriptive statistics for professional and student samples. Control variables.

Professionals

Treatment	**Variable**	**Mean**	**Median**	**St dev**	**Min**	**Max**	**N of obs**
	Initial portfolio	0.69	0	0.78	0	2	89
	Gender	0.52	1	0.50	0	1	89
Baseline	*Birth year*	1975	1975	9	1950	1994	89
	BRET	32.53	30	25.44	0	100	89
	NEP	57.53	58	6.59	40	74	89
	Initial portfolio	0.69	0.50	0.77	0	2	64
	Gender	0.58	1	0.50	0	1	64
Ranking	*Birth year*	1976	1977	10	1951	1994	64
	BRET	36.52	30	26.25	0	100	64
	NEP	58.88	59	5.53	47	69	64
	Initial portfolio	0.69	0	0.77	0	2	153
	Gender	0.54	1	0.50	0	1	153
Total	*Birth year*	1975	1976	10	1950	1994	153
	BRET	34.20	30	25.77	0	100	153
	NEP	58.09	59	6.19	40	74	153

Students

Treatment	**Variable**	**Mean**	**Median**	**St dev**	**Min**	**Max**	**N of obs**
Baseline	*Initial portfolio*	0.86	1	0.90	0	2	129
	Gender	0.44	0	0.50	0	1	129
	Birth year	1996	1997	4	1972	2003	129
	BRET	42.83	45	21.97	1	100	129
	NEP	40.84	41	5.04	21	65	129
Ranking	*Initial portfolio*	0.85	1	0.83	0	2	104
	Gender	0.50	0.50	0.50	0	1	104
	Birth year	1996	1997	6	1951	2002	104
	BRET	36.11	40	20.05	0	90	104
	NEP	40.95	41	4.44	26	53	104
Total	*Initial portfolio*	0.85	1	0.87	0	2	233
	Gender	0.47	0	0.50	0	1	233
	Birth year	1996	1997	5	1951	2003	233
	BRET	39.83	40	21.36	0	100	233
	NEP	40.89	41	4.78	21	65	233

Table 12 presents the p-values of control variables obtained in several tests. With the help of Shapiro-Wilk normality test we observe gaussian distribution only in the Birth year and the NEP score variables (overall result for 2 treatments, the result is the same if variables are tested separately by treatment), the other control variables are not normally distributed. The Birth year and NEP score variables are tested with the Welch Two Sample t-test which shows no significant difference in means between two treatments. The control variables with non-gaussian distribution are tested with Mann-Whitney test (as t-test is not applicable in this case) which states no significant difference in medians between the treatments (except the BRET score in the student sample). Anova test confirms that the variances of all control variables between two treatments are not significantly different (except the BRET score in the student sample).

Table 12: Tests results for the comparison between the baseline and the ranking treatments (p-values).

Tests	Shapiro-Wilk		T-test		Mann-Whitney		Anova	
Variables	Prof	Stud	Prof	Stud	Prof	Stud	Prof	Stud
Initial portfolio choice	0.000	0.000	-	-	0.976	0.992	0.987	0.692
Gender	0.000	0.000	-	-	0.456	0.378	0.456	0.379
Birth year	0.167	0.000	0.705	-	-	0.474	0.700	0.284
BRET score	0.000	0.001	-	-	0.329	0.022	0.347	0.017
NEP score	0.091	0.000	0.173	-	-	0.868	0.185	0.856

7.3 Tobit regressions for the instability index

Table 13 and Table 14 show β-coefficients of tobit models with robust standard errors in parentheses which describe the changes of latent variables (while AME for tobit models previously presented in the article work on the observed variables). The tobit regressions confirm the results shown in Table 4 and Table 5 with AME. SRI portfolios provide lower instability than brown portfolios (for professionals) (models (1,2) in Table 13), but higher instability than optimal portfolios (for students) (models (1-3) in Table 14). Instability is lower in case of initial choice of brown portfolios (model (2) in Table 13). Finally, portfolios have higher instability if participants are risk-loving (models (2,3) in Table 13) and if they are younger (model (3) in Table 13).

Table 13: Portfolio instability. Tobit models. Professionals.

	Dependent variable:		
	Instability index		
	(1)	(2)	(3)
Brown portfolio	0.371*	0.337*	0.278
	(0.155)	(0.146)	(0.145)
Neutral portfolio	0.432	0.389	0.343
	(0.250)	(0.222)	(0.221)
Optimal portfolio	−0.249	−0.153	−0.137
	(0.301)	(0.264)	(0.255)
Initial choice of green portfolio	−0.128	−0.129	−0.137
	(0.169)	(0.157)	(0.154)
Initial choice of brown portfolio	−0.313	−0.321*	−0.296
	(0.172)	(0.161)	(0.154)
Ranking	0.226	0.202	0.174
	(0.144)	(0.140)	(0.136)
BRET score		0.011**	0.010**
		(0.004)	(0.004)
NEP score		−0.015	−0.015
		(0.011)	(0.011)
Birth year			0.018**
			(0.006)
Gender			0.118
			(0.134)
Observations	153	153	153

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 13 shows tobit models on instability index with robust standard errors in parentheses for professional sample. Lower instability index implies lower portfolio instability. Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for female and 0 for male gender. Finally, Ranking is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 153.

Table 14: Portfolio instability. Tobit models. Students.

	Dependent variable:		
	Instability index		
	(1)	(2)	(3)
Brown portfolio	0.650	0.648	0.664
	(0.381)	(0.372)	(0.381)
Neutral portfolio	0.514	0.469	0.488
	(0.294)	(0.297)	(0.301)
Optimal portfolio	-1.593^{**}	-1.576^{**}	-1.578^{**}
	(0.520)	(0.515)	(0.518)
Initial choice of green portfolio	−0.120	−0.104	−0.062
	(0.313)	(0.315)	(0.319)
Initial choice of brown portfolio	−0.689	−0.670	−0.689
	(0.393)	(0.416)	(0.406)
Ranking	0.341	0.320	0.329
	(0.230)	(0.233)	(0.230)
BRET score		−0.003	−0.003
		(0.007)	(0.007)
NEP score		0.021	0.023
		(0.024)	(0.025)
Birth year			0.027
			(0.020)
Gender			0.082
			(0.263)
Observations	233	233	233

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 14 shows tobit models on instability index with robust standard errors in parentheses for student sample. Lower instability index implies lower portfolio instability. Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for male and 0 for female gender. Finally, Ranking is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 233.

7.4 OLS regressions for the instability index

OLS models in Table 15 and Table 16 do not show significant ($p < 0.05$) results related to instability difference between SRI and conventional portfolios. However, we observe the significant coefficient at the BRET score indicating higher instability in the portfolios of risk-loving professionals (models (2,3) in Table 15). As well, the coefficient of the birth year indicates that younger people own less stable portfolios (model (3) in Table 15).

Table 15: Portfolio instability OLS models. Professionals.

	Dependent variable:		
	Instability index		
	(1)	(2)	(3)
Brown portfolio	0.318	0.286	0.239
	(0.181)	(0.171)	(0.170)
Neutral portfolio	0.351	0.307	0.276
	(0.186)	(0.176)	(0.175)
Optimal portfolio	−0.060	0.034	0.044
	(0.235)	(0.224)	(0.221)
Initial choice of green portfolio	−0.128	−0.131	−0.138
	(0.155)	(0.147)	(0.145)
Initial choice of brown portfolio	−0.280	−0.292	−0.275
	(0.183)	(0.173)	(0.171)
Ranking	0.213	0.180	0.156
	(0.134)	(0.127)	(0.126)
BRET score		0.011**	0.010**
		(0.002)	(0.002)
NEP score		−0.013	−0.012
		(0.010)	(0.010)
Birth year			0.013*
			(0.006)
Gender			0.138
			(0.122)
Constant	0.337*	0.742	−25.351*
	(0.140)	(0.590)	(12.436)
Observations	153	153	153
R^2	0.062	0.173	0.207
Adjusted R^2	0.024	0.127	0.151
Residual Std. Error	0.791 (df = 146)	0.748 (df = 144)	0.738 (df = 142)
F Statistic	1.615 (df = 6; 146)	3.768** (df = 8; 144)	3.696** (df = 10; 142)

*p<0.05; **p<0.01

Notes: Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for female and 0 for male gender. Finally, Ranking is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 153.

Table 16: Portfolio instability OLS models. Students.

	Dependent variable:		
	Instability index		
	(1)	(2)	(3)
Brown portfolio	0.574	0.574	0.567
	(0.293)	(0.294)	(0.297)
Neutral portfolio	0.342	0.327	0.322
	(0.314)	(0.319)	(0.322)
Optimal portfolio	−0.500	−0.493	−0.503
	(0.366)	(0.368)	(0.370)
Initial choice of green portfolio	−0.011	−0.007	0.013
	(0.266)	(0.267)	(0.271)
Initial choice of brown portfolio	−0.462	−0.451	−0.469
	(0.280)	(0.283)	(0.286)
Ranking	0.246	0.235	0.226
	(0.215)	(0.218)	(0.221)
BRET score		−0.001	−0.002
		(0.005)	(0.005)
NEP score		0.006	0.007
		(0.022)	(0.022)
Birth year			0.009
			(0.021)
Gender			0.111
			(0.214)
Constant	0.682**	0.499	−18.168
	(0.245)	(0.925)	(41.138)
Observations	233	233	233
R^2	0.039	0.040	0.042
Adjusted R^2	0.014	0.005	-0.002
Residual Std. Error	1.549 (df = 226)	1.555 (df = 224)	1.561 (df = 222)
F Statistic	1.530 (df = 6; 226)	1.156 (df = 8; 224)	0.964 (df = 10; 222)

*p<0.05; **p<0.01

Notes: Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for male and 0 for female gender. Finally, Ranking is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 233.

7.5 Calculations of the optimal, green and brown portfolios.

Let's state N as the number of risky assets, each of them has expected return $E(r_i)$. The variable R is the column vector of assets' expected return:

$$R = \begin{bmatrix} E(r_1) \\ E(r_2) \\ \vdots \\ E(r_N)) \end{bmatrix}$$

$\sigma_{i,j}$ is the covariance between the assets i and j. The variance-covariance matrix, S, is defined as:

$$S = \begin{bmatrix} \sigma_{1,1} & \sigma_{2,1} & \dots & \sigma_{N,1} \\ \sigma_{1,2} & \sigma_{2,2} & \dots & \sigma_{N,2} \\ \vdots & & & \\ \sigma_{1,N} & \sigma_{2,N} & \dots & \sigma_{N,N}) \end{bmatrix}$$

The column vector x denoted the proportions of each asset i in the portfolio:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$$

Then, the portfolio return $E(r_x)$ is given by the product of x and R: $E(r_x) = x \times R$. The variance of the portfolio is equal to: $\sigma_x^2 = x^T Sx$, where x^T is the transposition of matrix x, while the standard deviation of the portfolio is $\sigma_x = \sqrt{\sigma_x^2}$.

In the presence of a risk free asset, returning r_f, the optimization program consists of finding the proportions x maximizing the following ratio:

$$\frac{E(r_x) - r_f}{\sigma_x^2}$$

Under the constraint: $\sum_{i=1}^{N} x_i = 1$.

The asset proportions for the optimal portfolio are implemented by using Black's (1972) zero-beta CAPM. This method allows us to draw an analytical solution to the portfolio optimization program. Considering c as a constant, the vector column $R - c$ is noted as follows:

$$R - c = \begin{bmatrix} E(r_1) - c \\ E(r_2) - c \\ \vdots \\ E(r_N) - c \end{bmatrix}$$

The portfolio optimization program consists of finding the vector z that solves the system of simultaneous linear equations $R - c = Sz$. The solution for the vector z satisfies the following condition:

$$z = S^{-1}\{R - c\}$$

The proportions $x = \{x_1, \dots, x_N\}$ for each asset i are obtained as follows:

$$x_i = \frac{z_i}{\sum_{j=1}^{N} z_j}$$

We solve this optimization problem for the three assets characterized by the following returns and standard deviation:

Table 17: Assets characteristics

Asset type	**Return (μ)**	**Risk (σ)**
Green (SRI)	2%	1%
Brown (anti-SRI)	6%	3%
Neutral	4%	2%

The covariances between the assets are zero since their distributions are independent. For simplicity, we attribute zero to the constant c. We obtain the following proportions for each of the three assets:

Table 18: Optimal portfolio asset allocation

Asset type	**Asset shares**
Green (SRI)	55%
Brown (anti-SRI)	18%
Neutral	27%

Following the above formula we calculate the return, the standard deviation and the sharpe ratio for a three asset portfolio, in particular, the optimal, green (SRI) and brown (anti-SRI) portfolios used in the experiment. Table 19 summarizes the characteristics of portfolios.

Table 19: Portfolios characteristics

Portfolio type	**Return (μ)**	**Risk (σ)**	**Sharpe ratio**
Optimal	3,273%	0,945%	3,464
Green (SRI)	3,200%	0,938%	3,411
Brown (anti-SRI)	4,800%	1,855%	2,588

7.6 Multinomial logistic regressions for the choice of the initial portfolio.

Table 20 and Table 21 show the multinomial logistic regression for the three initial portfolio choices: optimal, green and brown, in professional and student samples, respectively. The initial choice of the green or brown portfolios is not affected by participants' risk tolerance as the BRET score coefficient is not significant in both samples. Additionally, in Table 21 we find that male students are more likely to choose the initial brown portfolio than females if compared to the initial choice of the optimal portfolio.

Table 20: Multinomial logistic regression for the portfolio initial choice. Professionals.

	Initial portfolio choice
Green initial portfolio	
Ranking treatment	0.043
	(0.380)
BRET score	-0.000
	(0.007)
NEP score	-0.010
	(0.031)
Birth year	-0.008
	(0.019)
Gender	0.272
	(0.377)
Constant	16.691
	(38.384)
Brown initial portfolio	
Ranking treatment	-0.003
	(0.449)
BRET score	0.004
	(0.009)
NEP score	-0.024
	(0.036)
Birth year	-0.012
	(0.023)
Gender	0.302
	(0.447)
Constant	24.301
	(45.536)
Observations	153

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Green and brown initial portfolios are dummy variables with the optimal portfolio type as the reference category. Gender is a dummy equal to 1 (0) for female (male) gender. Ranking treatment is a dummy that is equal to 1 (0) for the ranking treatment (baseline). Sample size N for each test is 153.

Table 21: Multinomial logistic regression for portfolio initial choice. Students.

	Initial portfoio choice
Green initial portfolio	
Ranking treatment	0.589
	(0.349)
BRET score	0.001
	(0.008)
NEP score	-0.040
	(0.039)
Birth year	-0.057
	(0.034)
Gender	-0.300
	(0.359)
Constant	115.217
	(68.098)
Brown initial portfolio	
Ranking treatment	-0.078
	(0.323)
BRET score	0.014
	(0.008)
NEP score	-0.009
	(0.032)
Birth year	-0.012
	(0.037)
Gender	0.818*
	(0.319)
Constant	23.112
	(74.855)
Observations	233

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Green and brown initial portfolios are dummy variables with the optimal portfolio type as the reference category. Gender is a dummy equal to 1 (0) for male (female) gender. Ranking treatment is a dummy that is equal to 1 (0) for the ranking treatment (baseline). Sample size N for each test is 233.

7.7 Robustness check for the results on portfolio instability

To ensure the robustness of our results, we conducted two additional analyses.
First, we performed a sensitivity analysis based on the following alternate definition of an SRI portfolio. We categorize a portfolio as an SRI (or green) portfolio, noted SRI^{*}, if it contains at least 50% of green assets, over the 10 periods on average. Similarly, a portfolio is categorized as brown (neutral) if it contains at least 50% of brown (neutral) assets, over the 10 periods on average. We categorize as "mixed portfolios", portfolios that are neither green, brown or neutral. We refer to the alternate instability index by noting it *Instability**.
The AME for tobit regressions, in tables Table 22 and Table 23 below, are in line with the results obtained with the original definition of an SRI portfolio (see Table 4 and Table 5). In the professional sample the instability of SRI portfolios is lower than that of brown and neutral portfolios. In the student sample the instability of SRI portfolios is higher than that of optimal portfolios. Note also that mixed portfolios are always more unstable than any other portfolio category.
Second, we divided the investment game in two parts comprising periods 1-5 and 6-10. Table 24 and Table 25 show the AME for tobit regressions on instability index in periods 1-5 and 6-10 for the professional sample, and Table 26 and Table 27 report the AME for tobit regressions on instability index in periods 1-5 and 6-10 for the student sample. The results of two sub-games confirm the results obtained in the original investment game: in both samples SRI portfolios provide lower instability if compared to brown and neutral portfolios, but still higher instability than optimal portfolios (see Table 4 and Table 5).

Table 22: Portfolio instability with SRI^* - Professionals (AME, Tobit estimates)

	Dependent variable:		
	*Instability**		
	(1)	(2)	(3)
Brown portfolio	0.300*	0.265*	0.270*
	(0.141)	(0.132)	(0.130)
Neutral portfolio	0.466*	0.444*	0.420*
	(0.200)	(0.190)	(0.186)
Optimal portfolio	−0.038	0.022	0.030
	(0.151)	(0.147)	(0.145)
Mixed portfolio	0.307**	0.309**	0.277**
	(0.114)	(0.109)	(0.106)
Initial choice of green portfolio	−0.085	−0.076	−0.081
	(0.107)	(0.101)	(0.098)
Initial choice of brown portfolio	−0.183	−0.180	−0.179
	(0.103)	(0.100)	(0.098)
Ranking treatment	0.150	0.132	0.119
	(0.104)	(0.100)	(0.096)
BRET score		0.007**	0.007**
		(0.003)	(0.003)
NEP score		−0.007	−0.007
		(0.008)	(0.008)
Birth year			0.011**
			(0.004)
Gender			0.099
			(0.085)
Observations	153	153	153

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 22 shows AME for tobit models for the *Instability** index with robust standard errors in parentheses for the professional sample. Brown, neutral, optimal, and mixed portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 (0) for female (male) gender. Finally, Ranking treatment is a dummy that is equal to 1 (0) for the ranking treatment (the baseline). Sample size N for each test is 153.

Table 23: Portfolio instability with SRI^* - Students (AME, Tobit estimates)

	Dependent variable:		
	*Instability**		
	(1)	(2)	(3)
Brown portfolio	0.294	0.276	0.238
	(0.265)	(0.273)	(0.262)
Neutral portfolio	0.265	0.237	0.218
	(0.218)	(0.217)	(0.210)
Optimal portfolio	-0.495^{**}	-0.487^{**}	-0.495^{**}
	(0.169)	(0.172)	(0.174)
Mixed portfolio	0.732^{**}	0.736^{**}	0.752^{**}
	(0.197)	(0.198)	(0.202)
Initial choice of green portfolio	0.058	0.073	0.109
	(0.198)	(0.200)	(0.204)
Initial choice of brown portfolio	−0.177	−0.152	−0.143
	(0.225)	(0.235)	(0.232)
Ranking treatment	0.170	0.155	0.148
	(0.153)	(0.150)	(0.144)
BRET score		−0.002	−0.002
		(0.004)	(0.005)
NEP score		0.017	0.019
		(0.015)	(0.015)
Birth year			0.019
			(0.013)
Gender			0.096
			(0.153)
Observations	233	233	233

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 23 shows AME for tobit models on the *Instability** index with robust standard errors in parentheses for the student sample. Brown, neutral, optimal, and mixed portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 (0) for male (female) gender. Finally, Ranking treatment is a dummy that is equal to 1 (0) for the ranking treatment (the baseline). Sample size N for each test is 233.

Table 24: Portfolio instability in P1P5 - Professionals (AME, Tobit estimates).

	Dependent variable:		
	Instability		
	(1)	(2)	(3)
Brown portfolio	0.196^{*}	0.186^{*}	0.172^{*}
	(0.086)	(0.078)	(0.077)
Neutral portfolio	0.209^{*}	0.201^{*}	0.185^{*}
	(0.094)	(0.090)	(0.092)
Optimal portfolio	-0.137^{**}	-0.132^{**}	-0.136^{**}
	(0.043)	(0.042)	(0.043)
Initial choice of green portfolio	−0.003	−0.004	−0.005
	(0.065)	(0.063)	(0.062)
Initial choice of brown portfolio	−0.104	−0.106	−0.101
	(0.061)	(0.060)	(0.058)
Ranking treatment	0.020	0.018	0.013
	(0.042)	(0.041)	(0.040)
BRET score		0.002	0.002
		(0.001)	(0.001)
NEP score		−0.005	−0.005
		(0.006)	(0.006)
Birth year			0.005^{*}
			(0.002)
Gender			−0.004
			(0.051)
Observations	153	153	153

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 24 shows AME for tobit models on instability index in periods 1-5 with robust standard errors in parentheses for professional sample. Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for female and 0 for male gender. Finally, Ranking treatment is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 153.

Table 25: Portfolio instability in P6P10 - Professionals (AME, Tobit estimates).

	Dependent variable:		
	Instability		
	(1)	(2)	(3)
Brown portfolio	0.051	0.042	0.017
	(0.065)	(0.064)	(0.063)
Neutral portfolio	0.159	0.139	0.120
	(0.088)	(0.077)	(0.074)
Optimal portfolio	0.051	0.090	0.098
	(0.140)	(0.139)	(0.137)
Initial choice of green portfolio	−0.018	−0.016	−0.024
	(0.065)	(0.062)	(0.062)
Initial choice of brown portfolio	−0.060	−0.064	−0.059
	(0.065)	(0.064)	(0.061)
Ranking treatment	0.140*	0.127	0.116
	(0.067)	(0.065)	(0.062)
BRET score		0.004**	0.004**
		(0.001)	(0.001)
NEP score		−0.004	−0.004
		(0.005)	(0.004)
Birth year			0.007*
			(0.003)
Gender			0.073
			(0.048)
Observations	153	153	153

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 25 shows AME for tobit models on instability index in periods 6-10 with robust standard errors in parentheses for professional sample. Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for female and 0 for male gender. Finally, Ranking treatment is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 153.

Table 26: Portfolio instability in P1P5 - Students (AME, Tobit estimates).

	Dependent variable:		
	Instability		
	(1)	(2)	(3)
Brown portfolio	0.054	0.056	0.060
	(0.116)	(0.115)	(0.113)
Neutral portfolio	0.506^{**}	0.503^{**}	0.508^{**}
	(0.179)	(0.185)	(0.186)
Optimal portfolio	-0.200^{**}	-0.199^{**}	-0.199^{**}
	(0.066)	(0.064)	(0.063)
Initial choice of green portfolio	−0.026	−0.025	−0.019
	(0.088)	(0.088)	(0.090)
Initial choice of brown portfolio	−0.105	−0.103	−0.102
	(0.116)	(0.121)	(0.122)
Ranking treatment	0.039	0.036	0.042
	(0.071)	(0.071)	(0.069)
BRET score		−0.000	−0.001
		(0.002)	(0.002)
NEP score		0.001	0.002
		(0.008)	(0.008)
Birth year			0.005
			(0.006)
Gender			−0.017
			(0.073)
Observations	233	233	233

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 26 shows AME for tobit models on instability index in periods 1-5 with robust standard errors in parentheses for student sample. Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for male and 0 for female gender. Finally, Ranking treatment is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 233.

Table 27: Portfolio instability in P6P10 - Students (AME, Tobit estimates).

	Dependent variable:		
	Instability		
	(1)	(2)	(3)
Brown portfolio	0.234	0.243^{*}	0.240^{*}
	(0.125)	(0.121)	(0.121)
Neutral portfolio	0.176	0.177	0.167
	(0.114)	(0.114)	(0.114)
Optimal portfolio	-0.290^{**}	-0.287^{**}	-0.294^{**}
	(0.106)	(0.107)	(0.105)
Initial choice of green portfolio	−0.099	−0.099	−0.080
	(0.119)	(0.121)	(0.123)
Initial choice of brown portfolio	-0.280^{*}	-0.275^{*}	-0.271^{*}
	(0.110)	(0.113)	(0.110)
Ranking treatment	0.163	0.159	0.165^{*}
	(0.085)	(0.084)	(0.084)
BRET score		−0.001	−0.002
		(0.002)	(0.002)
NEP score		−0.001	0.000
		(0.008)	(0.008)
Birth year			0.014
			(0.008)
Gender			−0.001
			(0.087)
Observations	233	233	233

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 27 shows AME for tobit models on instability index in periods 6-10 with robust standard errors in parentheses for student sample. Brown, neutral, and optimal portfolios are dummy variables for different portfolio types with the green portfolio type as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for male and 0 for female gender. Finally, Ranking treatment is a dummy that is equal to one for the ranking treatment and equal to zero for the baseline. Sample size N for each test is 233.

7.8 Fractional probit regressions for investments in assets

Table 28 and Table 29 below provide the results of fractional probit regressions on investments in assets in relative terms. The obtained results are in line with original findings reported in the article (Table 7 and Table 8). The ranking feedback significantly impacted the professionals' and students' investment behavior. In particular, professionals and students invested more in green assets in the ranking treatment than in the baseline. Besides, students diminished their investment in brown and neutral assets after the ranking feedback.

Table 28: Investments in assets - Professionals (fractional probit models).

	Inv in green	Inv in brown	Inv in neutral
Lag diff on B and G returns	0.102**	-0.030	-0.081*
	(0.036)	(0.045)	(0.034)
Lag diff on N and G returns	-0.148*	0.086	0.086
	(0.058)	(0.071)	(0.056)
Treatment	0.239**	-0.163	-0.118
	(0.074)	(0.092)	(0.066)
Initial choice of green portfolio	0.251**	0.023	-0.309**
	(0.082)	(0.102)	(0.067)
Initial choice of brown portfolio	-0.270*	0.407**	-0.109
	(0.114)	(0.124)	(0.114)
BRET score	-0.002	0.002	-0.000
	(0.002)	(0.002)	(0.001)
NEP score	0.009	-0.012	0.001
	(0.006)	(0.008)	(0.006)
Gender	0.008	0.013	-0.014
	(0.076)	(0.092)	(0.068)
Birth year	-0.004	0.003	0.002
	(0.004)	(0.005)	(0.004)
Constant	6.447	-6.499	-3.683
	(8.578)	(9.416)	(6.961)
Observations	153	153	153

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 28 shows fractional probit models on investments in assets with robust standard errors in parentheses for student sample. The Hausman test favored a random effect model. Investments in green, brown, and neutral assets denote the respective investment weights in percent of the total portfolio weight. Lag diff of B and G returns and Lag diff of N and G returns represent the difference perceived by professionals between lagged returns on brown and green or neutral and green assets which might change their investment decisions. Treatment is a dummy for the ranking treatment with the baseline as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 0 for male and 1 for female. Sample size N for each test is 153.

Table 29: Investments in assets - Students (fractional probit models).

	Inv in green	Inv in brown	Inv in neutral
Lag diff on B and G returns	0.029	-0.068*	0.038
	(0.031)	(0.034)	(0.031)
Lag diff on N and G returns	-0.040	0.038	0.002
	(0.053)	(0.054)	(0.043)
Treatment	0.294**	-0.177**	-0.119*
	(0.062)	(0.068)	(0.058)
Initial choice of green portfolio	0.051	0.072	-0.137
	(0.078)	(0.080)	(0.070)
Initial choice of brown portfolio	-0.647**	0.802**	-0.256**
	(0.076)	(0.081)	(0.073)
BRET score	-0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)
NEP score	-0.010	-0.000	0.009
	(0.006)	(0.007)	(0.005)
Gender	-0.159*	0.162*	-0.011
	(0.062)	(0.067)	(0.055)
Birth year	-0.003	0.001	0.002
	(0.004)	(0.004)	(0.004)
Constant	6.981	-3.508	-4.411
	(8.387)	(7.909)	(7.934)
Observations	233	233	233

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$

Notes: Table 29 shows fractional probit models on investments in assets with robust standard errors in parentheses for student sample. Investments in green, brown, and neutral assets denote the respective investment weights in percent of the total portfolio weight. Lag diff of B and G returns and Lag diff of N and G returns represent the difference perceived by students between lagged returns on brown and green or neutral and green assets which might change their investment decisions. Treatment is a dummy for the ranking treatment with the baseline as the reference category. Initial choice of green and brown portfolios are dummies for initially chosen portfolios with the optimal portfolio as the reference category. Gender is a dummy equal to 1 for male and 0 for female. Sample size N for each test is 233.

7.9 Distribution of professionals' job functions and employers

Table 30: Professionals' job functions

	Job function	Frequency	Weight
1	Prop Trader	0	0%
2	Sales Trader	26	17%
3	Sales	0	0%
4	Market Maker	13	8%
5	Asset/Portfolio Manager	5	3%
6	Financial Analyst (buy/sell side)	2	1%
7	Risk analyst	5	3%
8	Private equity Manager	0	0%
9	Other	102	67%
	Total	**153**	**100%**
	Job function "Other"	**Frequency**	**Weight**
1	Not specified	69	45%
2	Acheteur	1	1%
3	Amélioration continue	1	1%
4	Analyste crédit	1	1%
5	Analyste risque de credits	1	1%
6	Assistant	1	1%
7	Assistante de Direction	1	1%
8	Audit	1	1%
9	Auditeur	2	1%
10	Banquier prive	1	1%
11	Broker	2	1%
12	Bts	1	1%
13	Business Developer	1	1%
14	Cadresup banque	1	1%
15	Chargé d affaire promotion immobilière	1	1%
16	Chargé d'Affaires Entreprise s Innovantes	1	1%
17	Chargée de RH	1	1%
18	Chef de oprojet	1	1%
19	Chef de produit	2	1%
20	Chef de projet	4	3%
21	Chief Investment Officer	1	1%
22	Communication	1	1%
23	CONSEILLÉ COMMERCIAL	1	1%
24	Consultant	4	3%
25	Consultant Asset Management	1	1%
26	Consultant en organisation et management en gestion d'actifs	1	1%
27	Consultant Gestion d'Actifs	1	1%
28	Consultant Senior Asset Management	1	1%
29	Contrôle de gestion	2	1%
30	Contrôle permanent et analyste financier	1	1%
31	Contrôleur de gestion	5	3%
32	Crédits	1	1%
33	Directeur	1	1%
34	Directrice Marché Particulier s	1	1%

Table 30: Professionals' job functions (continued)

	Job function "Other"	**Frequency**	**Weight**
35	Évent un finance	1	1%
36	Executive Director	1	1%
37	Financial services production developer	1	1%
38	Gérant portefeuilles	1	1%
39	Head of istitutional	1	1%
40	Immobilier	1	1%
41	Internal audit manger	1	1%
42	It financial support	1	1%
43	Journalist	2	1%
44	Juriste	1	1%
45	Légal & public affairs	1	1%
46	Logistique	1	1%
47	Manager	2	1%
48	Marketing	1	1%
49	MD	1	1%
50	Moyens de paiement	1	1%
51	Opérations manager	1	1%
52	Organisateur	2	1%
53	Pmo deploy	1	1%
54	Production specialist	1	1%
55	Project Manager	1	1%
56	Public sector	1	1%
57	Responsable de service	1	1%
58	Responsable prevention	1	1%
59	Responsable projets	1	1%
60	Responsable rh	1	1%
61	Responsable rse	1	1%
62	Responsable service successions	1	1%
63	Reviseur	1	1%
64	Senior Business Analyst	1	1%
65	Senior Consultant - Asset Management	1	1%
66	Treasurer	1	1%
67	Treasuret	1	1%
68	Trustee	1	1%
	Total	**153**	**100%**

Table 31: Professionals' employers

	Employer	Frequency	Weight
1	Bank	82	54%
2	Asset management company	25	16%
3	Trading company	0	0%
4	Broker	3	2%
5	Hedge fund	1	1%
6	Insurance company	6	4%
7	Work for your own	1	1%
8	Private equity company	0	0%
9	Other	35	23%
	Total	**153**	**100%**
	Employer "Other"	**Frequency**	**Weight**
1	Not specified	114	75%
2	Advisory firm	1	1%
3	Alpha fmc	1	1%
4	Alpha FMC	1	1%
5	Asset servicer	1	1%
6	Association	1	1%
7	Banque populaire mediterranee	1	1%
8	Bpmed	2	1%
9	BPMED	3	2%
10	Cabinet de conseil	3	2%
11	Chef de produit	1	1%
12	Consultancy firm	2	1%
13	consulting	1	1%
14	Consulting	1	1%
15	Consulting Firm	1	1%
16	Consulting Group	1	1%
17	Corporate	2	1%
18	Crédit agricole	1	1%
19	Européen investors	1	1%
20	Family office	1	1%
21	France	1	1%
22	Media	2	1%
23	Pension fund	1	1%
24	Professionnal association	1	1%
25	Public sector	1	1%
26	Responsable	1	1%
27	Rewable energy	1	1%
28	Royal Dutch Airline Klm	1	1%
29	Self employed	1	1%
30	société deconseil	1	1%
31	Software	1	1%
32	Trade association	1	1%
	Total	**153**	**100%**

7.10 Instructions

Instructions to the baseline treatment (translation from French)

Welcome

LEEM

LABORATORY FOR EXPERIMENTAL ECONOMICS - MONTPELLIER

Thank you for your participation in this experiment.

The experiment lasts approximately thirty minutes and includes three games and two questionnaires.

At the end of the experiment one participant out of ten will be chosen for payment. If you are selected, your gain in the experiment will be equal to the sum of your gain in part 3 and your gain in either part 1 or part 2. Each of two parts has the same chance to be selected (one chance out of two).
You can earn up to 350,00 € if you are selected.

Next

Instructions - Part 2

This part includes 10 periods. The periods are interconnected.

This part consists in choosing an initial portfolio of assets and changing its composition during 10 periods.

Three initial portfolios will be proposed to you: portfolio X, portfolio Y, and portfolio Z. Each of these three portfolios is composed of 50.00 € in assets and 20.00 € in cash. There exist three types of assets, called asset A, asset B, and asset C. Three portfolios differ only by allocation of these three assets. The initial value of three portfolios is the same whatever is their composition, it is equal to 70.00 €.

Having selected your initial portfolio, you will have the possibility to modify it after learning new information communicated to you in each period. This information concerns the realized return of each asset in each period.

To change the composition of your portfolio, you can : (i) modify the cash amount and (ii) modify the share of each asset in your portfolio. The sum of three asset shares should always be 100%.

Assets

The assets differ by three criteria: their return, their risk and their impact on a third party. The returns of three assets and their risks are independent. Each period the program will choose an asset specific return. As for the assets entailing the payment to a third party, the experimenter is obliged to transfer the amount corresponding to your decisions to the stated third party. The following instructions will explain you how this amount is determined.

Asset A

This asset brings the gain to you only. Its expected return is 4% and its standard deviation is 2%.

Asset B

This asset brings the gain both to you and to XXX association (*).
Its expected return is 2% and its standard deviation is 1%.

The gain of XXX : 20% of the average capital that you will invest in this asset during 10 periods will be paid to XXX.

(*) XXX association allows individuals and companies directly contribute to reforestation in France and in the world.

Asset C

This asset brings the gain both to you and to YYY association (*).
Its expected return is 6% and its standard deviation is 3%.

The gain of YYY: 20% of the average capital that you will invest in this asset during 10 periods will be paid to YYY.

(*) YYY association is an international company of oil and gas producers, which technical expertise includes extraction of shale gas.

Note: Portfolio X is the optimal portfolio according to the portfolio theory proposed by Markowitz. The optimal portfolio is a portfolio with the lowest risk for a given level of expected return.

Practical procedures

You can modify the composition of your portfolio in each period by changing the cash amount and proportions of each asset in your portfolio.

When you finished to modify your portfolio, or you don't want to change it, click on the button «next». Then, the screen with the realized returns of each asset and the value of your portfolio will appear.

At the end of each period, your gain of the period is calculated as follows:

Gain of the period = cash available
+ share of asset A × total value of assets in portfolio x (1 + return of asset A for the period)
+ share of asset B × total value of assets in portfolio x (1 + return of asset B for the period)
+ share of asset C × total value of assets in portfolio x (1 + return of asset C for the period)

The realized returns of risky assets in your portfolio will be paid in the form of dividends (i.e. in cash) and will be added to your cash in portfolio. If the realized returns are negative, they will be deducted from your cash.

Gain

Your gain in this part is equal to your gain in period 10, that corresponds to your portfolio value (cash + assets) at the end of period 10.

Next

Choice of the initial portfolio

Review the instructions

Please, find below three initially suggested portfolios. For each portfolio you have the expected return, the standard deviation and the shares of three assets that it comprises.

Portfolio	Value	Composition		Asset allocation and characteristiques								
		Cash	Assets	Asset A			Asset B			Asset C		
				Expected dividend	Standard deviation	Share	Expected dividend	Standard deviation	Share	Expected dividend	Standard deviation	Share
X	70,00 €	20,00 €	50,00 €	4%	2%	**27%**	2%	1%	**55%**	6%	3%	**18%**
Y	70,00 €	20,00 €	50,00 €	4%	2%	**20%**	2%	1%	**60%**	6%	3%	**20%**
Z	70,00 €	20,00 €	50,00 €	4%	2%	**20%**	2%	1%	**20%**	6%	3%	**60%**

Please, choose your initial portfolio:

Next

Period 1 / 10

Review the instructions

Your portfolio at the beginning of period 1 contains 70.00 €: 20.00 € in cash and 50.00 € in assets. Its asset allocation is as follows: 27% of Asset A, 55% of Asset B and 18% of Asset C.
You can modify the composition of your portfolio by changing the amount of cash and proportions of each asset.

Cash	Assets
20	50

Asset allocation in the portfolio

Asset A Expected dividend 4%, standard deviation 2%	27
Asset B Expected dividend 2%, standard deviation 1% 20% of the mean capital invested in this asset during 10 periods will be transferred to XXX	55
Asset C Expected dividend 6%, standard deviation 3% 20% of the mean capital invested in this asset during 10 periods will be transferred to YYY	18

Next

Period results 1/10

Review the instructions

Your portfolio at the beginning of the period was as follows:

Cash = 20.00 € and assets = 50.00 €, with the allocation: Asset A = 27%, Asset B = 55% and Asset C = 18%.

Your portfolio at the end of the period is:

Cash = 20.00 € and assets = 50.00 €, with the allocation: Asset A = 27%, Asset B = 55% and Asset C = 18%.

The realised returns are: Asset A : 4.12%, Asset B : 1.41%, and Asset C : 3.66%.

Your portfolio value at the end of period 1 is 71.27 € : 21.27 € in cash and 50.00 € in assets.

Next

Historic information on previous periods is below

Period	Cash	Assets	Portfolio composition			Realised returns			Portfolio value
			Asset A	Asset B	Asset C	Asset A	Asset B	Asset C	
1	20,00 €	50,00 €	27%	55%	18%	4,12%	1,41%	3,66%	71,27 €

Part 2 is finished

Your portfolio value at the end of period 10 is 84.80 €. Thus, if you are selected for the payment and this part is randomly chosen, your gain in the experiment will be equal to 84.80 €.

On average, you have invested 27.50 € in asset B, so if you are selected for the payment and this part is randomly chosen, we are to pay 5.50 € to XXX.

On average, you have invested 9.00 € in asset C, so if you are selected for the payment and this part is randomly chosen, we are to pay 1.80 € to YYY.

Next

Instructions - Part 3

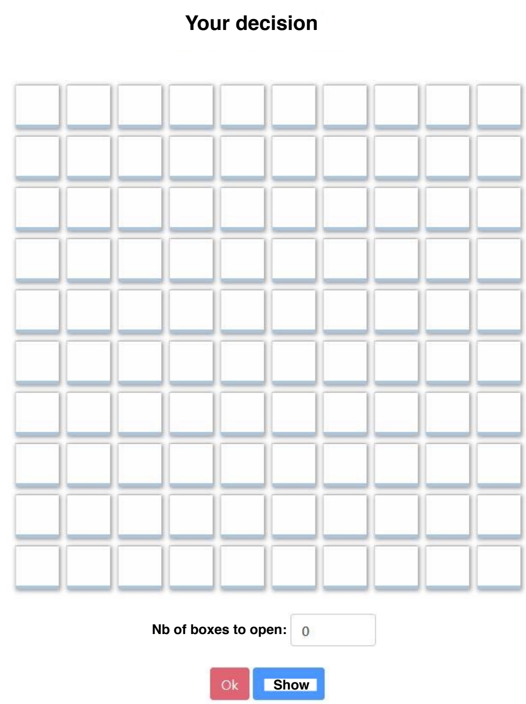
In this part you will see on the screen a 10x10 matrix containing 100 boxes. Behind one of these boxes hides a mine that destroys all the open boxes. The rest 99 boxes cost 0.50 € each.

You do not know where the mine lies. You only know that the mine can be behind any box with equal probability.

You should choose the number of boxes you would like to open. If you open the box with a bomb, it exploses and you earn zero. Otherwise, you earn 0.50 € for each open box.

After having made your choice, click the button «Show», it will open the chosen number of boxes and thus you can see if the bomb is behind one of these boxes or not.

Next


Your decision
Nb of boxes to open:
0
Ok
Show


Your decision
Nb of boxes to open:
50
Next

Part 3 is finished

You have opened 50 boxes out of 100. The bomb was located in line 6 and column 10.

The bomb was in one of the open boxes.
That is why all your accumulated earnings are lost and your gain is 0.00 €.

Thus, if you are selected for the payment, your gain for this part will be 0.00 €.

Next

Below you will find the sentences concerning relationship between human beings and the environment. For each sentence, state if you strongly agree - agree - disagree - strongly disagree - you do not know - by choosing your answer.

We are approaching the limit of the number of people the earth can support.	---------
Humans have the right to modify the natural environment to suit their needs.	---------
When humans interfere with nature it often produces disastrous consequences.	---------
Human ingenuity will insure that we do NOT make the earth unlivable.	---------
Humans are severely abusing the environment.	---------
The earth has plenty of natural resources if we just learn how to develop them.	---------
Plants and animals have as much right as humans to exist.	---------
The balance of nature is strong enough to cope with impacts of modern industrial nations.	---------
Despite our special abilities humans are still subject to the laws of nature.	---------
The so-called "ecological crisis" facing humankind has been greatly exaggerated.	---------
The earth is like a spaceship with very limited room and resources.	---------
Humans were meant to rule over the rest of nature.	---------
The balance of nature is very delicate and easily upset.	---------
Humans will eventually learn enough about how nature works to be able to control it.	---------
If things continue on their present course, we will soon experience a major ecological catastrophe.	---------

Next

Questionnaire

Thank you for filling in the questionnaire below

How old are you?	
What is your gender?	---------
What is your final academic degree?	--------- Other:
What is your current job?	--------- Other:
Who is your employer ?	--------- Other:
In which country do you work?	--------- Other:
How long have you been working on Financial Markets?	
What is your annual income?	---------

What is your annual income over the last 5 years? ----------

What is the main strategy you employ to trade assets? ----------

Other:

Next

End of the experiment

The experiment is finished, thank you for your participation.

In the first part you have earned 58.00 €, in the second part 84.80 € and in the third part 0.00 €.

You have not been selected for payout.

Instructions to the ranking treatment (translation from French) include only screens different from the baseline.

Instructions - Part 2

This part includes 10 periods. The periods are interconnected.

This part consists in choosing an initial portfolio of assets and changing its composition during 10 periods.

Three initial portfolios will be proposed to you: portfolio X, portfolio Y, and portfolio Z. Each of these three portfolios is composed of 50.00 € in assets and 20.00 € in cash. There exist three types of assets, called asset A, asset B, and asset C. Three portfolios differ only by allocation of these three assets. The initial value of three portfolios is the same whatever is their composition, it is equal to 70.00 €.

Having selected your initial portfolio, you will have the possibility to modify it after learning new information communicated to you in each period. This information concerns the realized return of each asset in each period.

To change the composition of your portfolio, you can : (i) modify the cash amount and (ii) modify the share of each asset in your portfolio. The sum of three asset shares should always be 100%.

Assets

The assets differ by three criteria: their return, their risk and their impact on a third party. The returns of three assets and their risks are independent. Each period the program will choose an asset specific return. As for the assets entailing the payment to a third party, the experimenter is obliged to transfer the amount corresponding to your decisions to the stated third party. The following instructions will explain you how this amount is determined.

Asset A

This asset brings the gain to you only. Its expected return is 4% and its standard deviation is 2%.

Asset B

This asset brings the gain both to you and to XXX association (*).
Its expected return is 2% and its standard deviation is 1%.

The gain of XXX : 20% of the average capital that you will invest in this asset during 10 periods will be paid to XXX.

(*) XXX association allows individuals and companies directly contribute to reforestation in France and in the world.

Asset C

This asset brings the gain both to you and to YYY association (*).
Its expected return is 6% and its standard deviation is 3%.

The gain of YYY: 20% of the average capital that you will invest in this asset during 10 periods will be paid to YYY.

(*) YYY association is an international company of oil and gas producers, which technical expertise includes extraction of shale gas.

Before starting you should choose one the following portfolios : X, Y or Z.

- Portfolio X : 27% of asset A + 18% of asset B + 55% of asset C + 20.00 € in cash
- Portfolio Y : 20% of asset A + 20% of asset B + 60% of asset C + 20.00 € in cash
- Portfolio Z : 20% of asset A + 60% of asset B + 20% of asset C + 20.00 € in cash

Note: Portfolio X is the optimal portfolio according to the portfolio theory proposed by Markowitz.

The optimal portfolio is a portfolio with the lowest risk for a given level of expected return.

Practical procedures

You can modify the composition of your portfolio in each period by changing the cash amount and proportions of each asset in your portfolio.

When you finished to modify your portfolio, or you don't want to change it, click on the button «next». Then, the screen with the realized returns of each asset and the value of your portfolio will appear.

At the end of each period, your gain of the period is calculated as follows:

Gain of the period = cash available
+ share of asset A × total value of assets in portfolio x (1 + return of asset A for the period)
+ share of asset B × total value of assets in portfolio x (1 + return of asset B for the period)
+ share of asset C × total value of assets in portfolio x (1 + return of asset C for the period)

The realized returns of risky assets in your portfolio will be paid in the form of dividends (i.e. in cash) and will be added to your cash in portfolio. If the realized returns are negative, they will be deducted from your cash.

Environmental performance of your portfolio

This part of the experiment has been already held with a sample of 30 participants. For each portfolio allocation that you choose you will be ranked in terms of environmental performance compared to this sample of 30 participants. The environmental performance in the period only depends on the share of Asset C which you hold in your portfolio in the relevant period.

Example: among 30 participants in the sample 12 chose the share of Asset C superior or equal to 60. If you choose the share of 59, your ranking will be 13 out of 31.

Gain

Your gain in this part is equal to your gain in period 10, that corresponds to your portfolio value (cash + assets) at the end of period 10.

Next

Period results 1/10

Review the instrcutions

Your portfolio at the beginning of the period was as follows:

Cash = 20.00 € and assets = 50.00 €, with the allocation: Asset A = 27%, Asset B = 55% and Asset C = 18%.

Your portfolio at the end of the period is:

Cash = 20.00 € and assets = 50.00 €, with the allocation: Asset A = 27%, Asset B = 55% and Asset C = 18%.

The realised returns are: Asset A: 3.74%, Asset B : 7.84%, and Asset C : 0.52%.

Your portfolio value at the end of period 1 is 71.35 € : 21.35 € in cash and 50.00 € in assets.

Compared to 30 first persons having participated in this experience, you are ranked **number 6** according to the share of asset C in your portfolio in this period.

Next

Historic information on previous periods is below

Period	Cash	Assets	Portfolio composition			Realised returns			Portfolio value	Ranking
			Asset A	Asset B	Asset C	Asset A	Asset B	Asset C		
1	20,00 €	50,00 €	27%	18%	55%	3,74%	7,84%	0,52%	71,35 €	6

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