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# Do Investors Use Sustainable Assets as Carbon Offsets?

SAFE Working Paper No. 431 | September 2024

# Leibniz Institute for Financial Research SAFE Sustainable Architecture for Finance in Europe

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# Do Investors Use Sustainable Assets as Carbon Offsets?\*

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#### Abstract

We present novel evidence that retail investors attempt offsetting their carbon footprints by investing sustainably. Using highly granular transaction data from bank clients, we find that higher footprints are linked to greener portfolios. In an experiment with clients from the same bank, we show that an exogenous shock to the participants' salience of their emissions causally shifts sustainable asset allocations upward. Finally, we identify a substitution effect between offsetting through donations and sustainable assets. Our findings add to an understanding of the behavioral drivers of sustainable investing, which is crucial to design effective policies aligning financial markets with environmental goals.

Keywords: sustainable investing, carbon footprints, green portfolios, retail investors, experimental finance.

#### JEL classification: G40, G41, G11, D14, C93.

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## 1 Introduction

In this paper, we investigate whether retail investors try to offset their carbon emissions from consumption with sustainable investments. Based on a detailed panel of 6,151 bank clients' transaction-level data, which provides granular information on consumption, trading, and portfolio holdings, and a large-scale survey experiment with 4,249 clients of the same bank, we provide comprehensive empirical and experimental evidence that one reason why retail investors choose sustainable investments is that they try to compensate for their emission-driven environmental impact. We first show empirically that investors with high carbon footprints from consumption hold more sustainable portfolios in terms of emission ratings than investors with lower footprints. We provide additional causal evidence in favor of a negative relation between sustainable investing and unsustainable (high-emission) consumption based on experimental evidence.

The rise of socially responsible investment (SRI) has experienced rapid growth over the past years: From 2016 to 2020, global sustainable investment volumes surged by 55%, reaching a total of USD 35.3 trillion across Europe, North America, Australia, and Asia. In 2020, SRI constituted 35.9% of the total managed assets in these regions (PwC, 2022; GSIR, 2020). This growth has been followed by significant regulatory changes aimed at fostering SRI, such as the Sustainable Europe Investment Plan (SEIP) and MiFID II's integration of sustainability preferences.<sup>1,2</sup>

Despite this massive shift towards SRI, the underlying drivers of retail investor demand for sustainable assets need to be understood in order to design effective policies. The prior literature has shown that factors such as altruism, warm glow, social norms, and investor sentiment are related to sustainable investing.<sup>3</sup> Nevertheless, the behavioral responses they trigger are complex and multifaceted. Therefore, it is crucial to not only understand *whether* and *why* investors choose sustainable assets, but also how other financial decisions they make influence this preference: In 2022, about one quarter of total GHG emissions

<sup>&</sup>lt;sup>1</sup> "European Commission Delegated Regulation (EU) 2021/1253 of 21 April 2021 amending Delegated Regulation (EU) 2017/565 as regards the integration of sustainability factors, risks, and preferences into certain organisational requirements and operating conditions for investment firms", Official Journal of the European Union, L 277 pp. 1-5 (2 August 2022).

<sup>&</sup>lt;sup>2</sup>For detailed information on the SEIP see: https://eur-lex.europa.eu/legal-content/EN/TXT/ ?uri=CELEX:52020DC0021

<sup>&</sup>lt;sup>3</sup>See Andreoni (1995); Kormos et al. (2015); Taufik et al. (2015); Riedl and Smeets (2017); Van der Linden (2018); Hartzmark and Sussman (2019); Lei and Zhang (2020); Bauer et al. (2021); Heeb et al. (2023a).

in Germany was emitted directly by households through heating, hot water supply, and private transport (Jacksohn et al., 2023). Recent work suggests that a share as high as 60% of total GHG emissions in Europe are driven by households' economic activity when taking into account indirect impacts, e.g., through goods and services purchased Ivanova et al. (2016). In addition, investors may view sustainable investments as substitutes for direct carbon offsets, which could potentially lead to unintended consequences if they feel morally licensed to retain high consumption levels due to their more sustainable investments. This concern is highlighted by instances where financial institutions have been accused of falsely marketing investments as carbon offsets.<sup>4</sup>

Figure 1 presents initial evidence in support of this exact link based on a large bank-client survey conducted in October 2022. Of 3,646 participants, 2,702 (74.11%) indicate that they currently attempt or have attempted compensating for their individual carbon emissions in one way or another. Among these, 414 (15.32%) choose sustainable investments to help offset their footprints from consumption.

We show more formally that investors choose green investments due to attempted carbon offsetting by estimating and relating the individual carbon footprints of 6,151 clients of a large German bank to multiple indicators for sustainable investing. In doing so, we find that investors with high carbon footprints from consumption invest more sustainably at the extensive and intensive margins: Compared to investors with low carbon footprints from consumption, high-footprint investors are 8.7 percentage points (pp) more likely to hold assets with high sustainability ratings (top 20%), have 5.3pp (0.44%) higher sustainable portfolio (asset) shares, hold portfolios whose composite sustainability scores are 7.0pp higher than those of their lower-emission peers, and are 4.9pp more likely to hold portfolios ranking in the top 20% of portfolio sustainability scores. In line with a compensation explanation, we find this effect only for sustainable assets in terms of emissions and air quality ratings.

We run a series of tests to rule out concerns associated with our analyses: Specifically, we show that neither heterogeneous sustainability preferences nor return expectations for green assets or general income and consumption levels drive our findings.

<sup>&</sup>lt;sup>4</sup>In a related lawsuit, the German consumer protection bureau sued DekaBank over allegations of false advertising. For further details, refer to the following web articles: https://www.responsible-investor.com/dekabank-sued-over-misleading-fund-impact-calculator/ and https://www.responsible-investor.com/dekabank-drops-impact-calculator-for-sustainability-funds-to-avoid-lawsuit-over-greenwashing-claims/ (last accessed on March 8<sup>th</sup>, 2024).



*Note.* The above figure displays results from a survey conducted in October 2022 with 3,646 clients of the same bank whose data we analyze in this paper. The bars with annotated numbers depicted above indicate the number of survey participants who state that they have or have not used one or more of the indicated means to compensate their carbon footprints in the past. Bar labels list the possible answers provided by default to the survey participants. The main option of interest, *Sustainable investments*, is listed roughly in the middle of all possible answers to prevent anchoring of the respondents. Of the surveyed bank clients, 2,702 (74.11%) indicate that they have used any method of compensating for their consumption-driven footprints in the past or are actively doing so. *Other* is a free-text field and comprises all answers not listed in the pre-defined list, whereas *No offset* denotes the option which participants may choose if they do not employ any means of offsetting their consumption-driven footprints nor did so in the past.

#### Figure 1 Compensating emissions from consumption

Based on a randomized control trial (RCT) with 4,249 clients, we provide validating causal evidence in favor of this link: By estimating and presenting participants with their carbon footprints and how they compare to those of their peers in terms of age and income, we create an exogenous sustainability signal. We are able to confirm that participants who receive a negative signal, i.e., whose footprint is higher than that of their peers, allocate 6.380pp higher funds to sustainable funds (significant at the 1% level). Importantly, however, echoing earlier work on the relation between sustainable investments and impact beliefs,<sup>5</sup> we only find this effect for participants who have moderate beliefs of the effectiveness of sustainable investments (significant at the 1% level).<sup>6</sup> For those with more extreme (higher or lower) prior beliefs and the aggregate participant pool, we do not find statistically significant treatment effects and they keep their invested share on the initial (high or low) level.

The design of our RCT also enables investigating whether investors view direct offsets

 $<sup>{}^{5}</sup>$ See, e.g., Siemroth and Hornuf (2023); Luz et al. (2024).

<sup>&</sup>lt;sup>6</sup>This variable is based on one question in our experiment which prompts participants to indicate to what extent they believe that sustainable assets can carry actionable impact in aiding the green transition.

through donations and indirect offsets through sustainable investments as substitutes: We find that, if the investment exercise is preceded by a more direct offsetting option through donations, the negative sustainability shock is not associated with more sustainable fund allocations.

Our findings can be aligned with either moral licensing or moral cleansing, both of which have been documented in several domains (e.g., Khan and Dhar, 2006; Sachdeva et al., 2009; Merritt et al., 2010; Lacasse, 2016). In the case of moral *licensing*, investors use an initial action considered as moral, such as investing sustainably, to liberate themselves from the perceived immorality of subsequent actions, like engaging in unsustainable consumption behaviors. Conversely, under moral *cleansing*, investors engage in moral actions, such as purchasing direct offsets, after previous immoral (in the present case unsustainable) behaviors.

We contribute to several strands of the literature, primarily to a relatively new strand which studies retail investor demand for sustainable investments. First, we add to the literature which finds that investors choose sustainable assets for reasons beyond pure return considerations (e.g., Gutsche and Ziegler, 2019; Barber et al., 2021), even to an extent that they are willing to forgo returns for a higher sustainability impact (Riedl and Smeets, 2017; Bauer et al., 2021). The substitution effect between direct donation-based offsets and indirect offsets with SRI adds to the literature on the substitution between different social and sustainable financial activities (Brodback et al., 2021; An et al., 2023; Meyer, 2023). In a similar vein, we also contribute to the multi-disciplinary literature on spillovers between the sustainability of different domains of (financial) behavior (Thomas and Sharp, 2013; Anderson and Robinson, 2022; Truelove et al., 2014; Penz et al., 2019; Hakenes and Schliephake, 2021; Chen et al., 2023; Heeb et al., 2023b). Examples from the prior literature specifically analyzing the relation of investment and consumption sustainability are scarce, primarily because of a lack of adequate data sources, which can inevitably lead to issues with sample size and selection (Palacios-González and Chamorro-Mera, 2018; Brunen, 2019; Brunen and Laubach, 2022). We also contribute to the closely related stream of the literature which studies cheap talk, i.e., whether stated actions carry over to actual behavior or not (List and Gallet, 2001; Carrington et al., 2010; FeldmanHall et al., 2012).

By combining an RCT with empirical observations, our study design can address both issues of (self-)selection biases in surveys as well as the shortcomings of purely empirical studies (including our own). With this, we also contribute to the growing stream of the literature which draws causal conclusions from behavior observed in RCTs. Within this stream of the literature, information-provision experiments and nudging studies are most prevalent (Milkman et al., 2014; Beshears et al., 2015, 2021; Andre et al., 2022; DellaVigna and Linos, 2022; Heim and Huber, 2022; Schnorpfeil et al., 2023). Similar to such studies, we bring consumption-driven carbon footprints and compensation methods to the attention of the participants in our RCT. In addition to pure information-provision experiments, however, we present participants with information that is directly tied to their individual choices and preferences: By confronting the participants with how their carbon footprints elicited within the survey compare to those of their peers, we provide a more direct and credible exogenous shock to their belief of how sustainably they consume – which in turn we can subsequently relate to the sustainability of their investment choices.

Finally, we contribute more broadly to the large and growing literature on household finance and individual investor portfolio choice. Previous work has shown that retail investors trade for reasons beyond return maximization, such as trend or sensation seeking, which tends to lead to overtrading (e.g., Barber and Odean, 2000, 2008, 2013; Grinblatt and Keloharju, 2009), social norms and identification (Hong and Kacperczyk, 2009; Kormos et al., 2015; Bauer and Smeets, 2015; Gamel et al., 2017; Ried et al., 2022), or peer effects (Kuchler and Stroebel, 2021; Knüpfer et al., 2021; Balakina et al., 2022; Balakina, 2022). Individual investors have also been shown to prefer assets based on local preferences (French and Poterba, 1991; Seasholes and Zhu, 2010), high expected dividends (Graham and Kumar, 2006; Hartzmark and Solomon, 2019; Bräuer et al., 2022), or their names or order of appearance (Green and Jame, 2013; Itzkowitz et al., 2015). In the domain of socially responsible investments, prior studies suggest that sustainable investing preferences are related to sensation-seeking and risk/return expectations (e.g., Barber et al., 2021; Stroebel and Wurgler, 2021), feelings of warm glow (Andreoni, 1995; Taufik et al., 2015; Van der Linden, 2018; Andersen et al., 2023; Heeb et al., 2023a; Gutsche et al., 2023), a preference for social causes (e.g., Riedl and Smeets, 2017; Gutsche and Ziegler, 2019; Siemroth and Hornuf, 2023; Andersen et al., 2023; Gutsche et al., 2023), and individual characteristics such as age, gender, sustainable finance literacy, or socioeconomic status (Gutsche and Ziegler, 2019; Faradynawati and Söderberg, 2022; Andersen et al., 2023; Olumekor and Oke, 2024; Filippini et al., 2024). We contribute to this broad literature by providing empirical and experimental (causal) evidence that one motivating factor for investors to choose sustainable assets is trying to compensate for carbon emissions.

# 2 Data

We analyze fully anonymized administrative data from a large German bank that offers comprehensive retail services and has several million customers in Germany. The data set is highly granular and contains information on demographics, checking and savings account transactions, transaction-level investments, as well as end-of-month portfolio and asset holdings. To estimate carbon footprints from consumption, we utilize categorized checking account transactions recorded by an in-house personal financial management tool (PFM) that the bank offers to its clients. The PFM tool is comparable to other PFM tools such as MINT, You Need a Budget, or Spendee, and categorizes the clients' account inflows and outflows into more than 100 spending and income categories. Clients can activate and access the PFM tool directly through the bank's online banking service using an online browser or mobile phone application.<sup>7</sup>

This administrative data set allows for individual-level estimation of spillovers between the consumption and trading domain in that we observe not only consumption, but also securities trades and portfolio holdings for investments with the in-house brokerage. As the partner bank is a universal bank, the portfolio holdings and trades at our disposal include transactions from managed, unmanaged, and dedicated online-brokerage accounts.

We construct our main sample as representatively as possible for a typical German stock market participant. This aim entails two main criteria: Firstly, we select only investors. Secondly, each investor needs to have sufficient observations to enable an estimate for carbon footprints which is as unbiased as possible. Appendix A details how we restrict the sample to achieve this objective. We also show that the imposed sample restrictions generally do not affect our main results in Appendix E.3.

To provide evidence for the potential motives driving investments in ESG assets, we estimate total annual consumption-driven GHG emissions and compare one more sustainable consumer group to one less sustainable one.<sup>8</sup> Specifically, we split the sample at the

<sup>&</sup>lt;sup>7</sup>For more detailed information on the PFM tool and bank-client data, please refer to Bräuer et al. (2022).

 $<sup>^{8} \</sup>rm Our$  method of estimating individual carbon footprints from consumption is outlined in more detail in Appendix B.

median of carbon footprints. Unsustainable (sustainable) consumers are defined as individuals with average annual carbon footprints above (below) the median. We present descriptives for the overall sample and the (un-)sustainable consumer groups in Appendix C.

As footprints are strongly and positively related to income levels, we need to control for income in all regressions. Analyzing within-investor differences already limits the extent to which income effects might be driving results, as investors tend to have higher income than non-investors (e.g., Guiso and Jappelli, 2005; Balloch et al., 2014). Nevertheless, we show that income and consumption levels are not confounding our results by repeating our main analyses for carbon intensities which abstract from these factors (Appendix E.2). Our results are robust to this adjustment.

# 3 Empirical analysis

#### 3.1 Methodology

Figure 1 shows that, among other things, investors state to choose sustainable assets specifically in order to decrease their total emissions. In order to validate this finding more formally, we first analyze the cross-sectional relation between unsustainable consumption (in terms of individual emissions) and sustainable investments. To this end, we need to construct measures which adequately capture portfolio (PF) sustainability. Appendix D.1 describes the literary foundation and construction of our main outcomes of interest in more detail. Since there is no unambiguous ground truth, i.e., definitive measure of PF sustainability, we will need to establish whether our results also hold in an experimental setting (results presented in Section 4). These experimental results will aid our understanding whether compensation considerations are, in fact, able to shift sustainable investing rates causally.

We use five sustainability outcomes, namely, (1) whether investors hold any assets ranked in the top quintile (20%) of TruValue Labs (TVL) ESG scores, the portfolio and asset shares devoted to these assets (2 and 3), (4) investors' value-weighted PF ESG scores, and (5) whether their score ranks in the top 20% of all scores in the sample.<sup>9</sup> Appendix D demonstrates that more sustainable PF outcomes are generally more prevalent among

<sup>&</sup>lt;sup>9</sup>The ESG ratings used in this study are based on (social) media coverage and therefore mimic the information retrieval process of retail investors more closely and at higher (daily) frequency than private ESG ratings.

investors with higher consumption-driven carbon footprints.

It is striking that a positive relation between unsustainable consumption and sustainable PF outcomes seems to exist primarily for GHG emissions: If investors chose sustainable assets for any reason other than attempting to compensate their own emissions, e.g., because of a general investor sentiment/hype around green assets, sustainability preferences, or beliefs of higher performance for ESG assets, the positive relation between sustainability scores would present itself not only for GHG emission ratings, but also for air quality, environmental, and ecological scores. As Tables D.1 and D.2 in Appendix D demonstrate, this is not the case.

We formally test whether attempted compensation motivates drive retail investors to choose sustainable assets by running cross-sectional OLS and logistic regressions of PF sustainability on unsustainable consumption in terms of emissions. Specifically, we regress each metric defined in Appendix D on a binary indicator which is equal to one for investors with above-median total annual carbon footprints from consumption and zero otherwise.<sup>10</sup> This means that negative spillovers between investment and consumption sustainability would be reflected by *positive* coefficient estimates. To this end, we estimate OLS regressions as follows:

$$V_{\text{ESG},i} = \beta_0 + \beta_1 \cdot D_i + \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k} + \varepsilon_i, \qquad (1)$$

and logistic regressions are based on the following form:

$$\Pr(\mathcal{V}_{\mathrm{ESG},i} = 1 \mid D_i, X_i) = \beta_0 + \beta_1 \cdot D_i + \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k} + \varepsilon_i, \qquad (2)$$

where  $V_{\text{ESG},i}$  stands for the outcome variable of interest for investor *i* as described in Appendix D.1 (1: Holds top-rated asset, 2: % PF top rated, 3: % AS top rated, 4: PF ESG score, or 5: Top-quintile PF ESG score),  $D_i$  is the main dummy variable which is equal to one for investors with above-median footprints from consumption and zero for below-median-footprint investors, and  $X_{i,k}$  is a vector of control variables for all controls k = 1 through K. Since footprints are related to income levels (see Figure B.1

 $<sup>^{10}\</sup>mathrm{We}$  aggregate the sample period to a cross-section by choosing averages for each individual in our sample.

in Appendix B or Ivanova and Wood, 2020), average net annual income is a crucial part of the control vector  $X_{i,k}$ . The remaining control variables include investor age, gender, marital status, profession, trading risk class as elicited by the bank upon opening an in-house securities account, and dichotomous variables equal to one if the investor owns a credit card, savings account, or online brokerage account with the bank, has a property loan, or uses the account jointly, e.g., with a spouse, respectively, and equal to zero otherwise.

#### 3.2 Results

Table 1 presents the results from 20 separate regressions following equations 1 and 2. The table reports only estimates for the main coefficient of interest (COI),  $\beta_1$ , along with *p*-values based on heteroskedasticity-robust standard errors. In Table 1, each column corresponds to one outcome for PF sustainability, as defined in Appendix D.1 and described above, while rows indicate the TVL rating category which is chosen to compute these outcomes to obtain the respective presented COI.

Importantly, we find a clear demarcation of results between outcomes based on TVL ratings targeted at GHG emissions and air quality on the one hand, and overall and ecological outcome variables on the other. High-emission investors have significantly higher likelihoods and portfolio scores based on GHG emissions ratings, with most effects being significant at the 1% level: They are 8.7pp more likely to hold securities ranking in the top quintile of TVL emissions scores (column 1), have 5.311pp higher portfolio weights allocated to such securities (column 2), and have significantly higher composite GHG emissions portfolio scores (7.039, column 4, all significant at the 1% level). Investors with high footprints from consumption also have significantly higher portfolio asset shares devoted to the top quintile of low-emissions assets (column 3, 0.436pp, significant at the 10% level) and are 4.9pp more likely to hold portfolios which rank in the top quintile of all investors' emissions-based PF ESG scores (column 5, significant at the 5% level).

Similarly, albeit less strongly pronounced in terms of magnitude and statistical significance, we find that high-emission investors are more likely to hold top-rating assets concerning air quality scores (column 1, 2.6pp, significant at the 5% level), have significantly higher portfolio shares in top-rated air quality assets (column 2, 0.587pp, 10% level), higher composite air-quality portfolio scores (column 4, 3.912pp, 5% level), and are 1.6pp more likely to hold a portfolio ranking in the top quintile of air quality ratings (column 5,

	(1) Holds top rated	(2) % PF top rated	(3) % AS top rated	(4) PF ESG score	(5) Top PF ESG score
	Marg. effect	Coef.	Coef.	Coef.	Marg. effect
Overall	$0.020^{**}$	0.126	0.193	$5.499^{***}$	0.011
	(0.036)	(0.703)	(0.102)	(0.000)	(0.221)
GHG emissions	$0.087^{***}$	$5.311^{***}$	$0.436^{**}$	$7.039^{***}$	$0.049^{***}$
	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)
Ecological	$0.021^{*}$	0.410	0.033	$5.524^{***}$	0.011
	(0.050)	(0.243)	(0.643)	(0.000)	(0.227)
Air quality	$0.026^{***}$	$0.587^{**}$	0.058	$3.912^{***}$	$0.016^{**}$
	(0.006)	(0.012)	(0.394)	(0.000)	(0.045)
Observations	6,151	6,151	6,151	6,151	6,151

#### Table 1 ESG investment regressions: Cross-domain offsetting behavior

Note. The above table displays results from eight logistic (columns 1 and 5) and twelve OLS regressions (columns 2, 3, and 4) of the sustainability indicators constructed from asset- and portfolio-level TVL ratings as described in Section D.1. All models are estimated separately for the TruValueLabs (TVL) Overall, GHG emissions, Ecological, and Air quality ratings as indicated by the row labels of the above table. Specifically, the dependent variables used in all 20 regressions are Holds top rated, which is equal to one if an investor holds at least one security which ranks in the top 20% of ratings (column 1), % PF top rated (column 2) and % AS top rated (column 3), which measure the portfolio and asset shares devoted to these top-rated assets, respectively, PF ESG score, which is equal to one for investors whose portfolio ESG score rank in the top 20%) of all investors' scores, and zero otherwise (column 5). The coefficient estimates and p-values presented above capture the difference between investors with an above-median footprint from consumption and those with below-median consumption-driven emissions. All regressions control for investors' profession, age, gender, marital status, joint account usage, median annual net income, trading risk classes elicited by the bank, and financial product ownership. p-values based on robust standard errors are presented underneath coefficients in parentheses. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

significant at the 10% level).

For sustainable PF outcomes in terms of overall and ecological ratings, we find only occasionally significant relations to high footprints: Investors with high emissions from consumption are more likely to hold top-quintile assets (2.0pp for overall and 2.1pp for ecological ratings, significant at the 5% and 10% levels, respectively, column 1), have higher PF ESG scores (5.499pp and 5.524pp, significant at the 1% level, column 4).

Our results are in line with the self-reported evidence shown in Figure 1, and thus the notion that not only are unsustainable consumers aware of their environmental impact from consumption, but also do they try offsetting it by investing in more sustainable assets specifically in terms of emissions and air quality, but not in terms of overall or ecological factors.

One major concern associated with the results presented in Table 1 might be that

individual carbon emissions are driven by consumption levels, which themselves are driven by income. To rule out this concern, we control for income in all regressions. This might not, however, rule out an income effect confounding our results. Therefore, we repeat the analysis for carbon intensities as an alternative definition of unsustainable consumption. Specifically, we derive carbon intensities of income and consumption and repeat the baseline analyses for all TVL rating categories, where the main COI now captures the effect for investors who have an above-median carbon *intensity* of consumption or income, respectively. The results for GHG emission ratings are presented in Table 2. Appendix E.2 lists further details on the methodology for this carbon intensity specification and presents the full set of results for all four TVL rating categories (Table E.2.1).

	(1) Holds top rated	(2) % PF top rated	$\begin{array}{c} (3) \\ \% \text{ AS top} \\ \text{rated} \end{array}$	(4) PF ESG score	(5) Top PF ESG score
	Marg. effect	Coef.	Coef.	Coef.	Marg. effect
Above-median CI of consumption	$0.038^{***}$ (0.001)	3.294*** (0.000)	0.141 (0.322)	$2.811^{***}$ (0.001)	$0.041^{***}$ (0.000)
Above-median CI of income	$0.030^{**}$ (0.011)	$3.052^{***}$ (0.000)	$0.319^{**}$ (0.030)	1.389 (0.111)	$0.030^{***}$ (0.000)
Observations	6,151	6,151	6,151	6,151	6,151

Table 2 Robustness analysis: Carbon-intensity specification

Note. The above table displays results from logistic (columns 1 and 5) and OLS regressions (columns 2, 3, and 4) of sustainability indicators computed as described in Appendix D.1. All models are estimated separately for TruValueLabs (TVL) *GHG emissions* ratings. Specifically, the dependent variables used in the are *Holds top rated*, which is equal to one if an investor holds any securities ranking in the top 20% of ratings (column 1), % *PF top rated* (column 2) and % *AS top rated* (column 3), which measure the portfolio and asset shares devoted to these top-rated assets, respectively, *PF ESG score*, which measures the value-weighted composite ESG score for each portfolio (column 4), and *Top PF ESG score*, which is equal to one for investors with portfolio scores ranking in the top quintile (20%) of all investors' scores, and zero otherwise (column 5). Estimates capture the difference between investors with above-median carbon intensities and those with below-median intensities. Appendix E.2 describes in more detail how carbon intensities are calculated, and presents results for the full set of TVL rating categories. All regressions control for investors' profession, age, gender, marital status, joint account usage, median annual net income, trading risk classes elicited by the bank, and financial product ownership. *p*-values are based on robust standard errors and presented underneath coefficients in parentheses. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

Since carbon intensities abstract from general income and consumption levels, the positive relation between high footprints or intensities from consumption and sustainable investments presented in Tables 1 and 2 would not be present if income or consumption *per se* were driving our main results.<sup>11</sup> Instead, Table 2 emphasizes that, irrespective of their financial means or intrinsic spending patterns, investors with a less sustainable *lifestyle* choose

<sup>&</sup>lt;sup>11</sup>The analysis would not be able to rule out the concern of an income or consumption channel driving our findings if carbon intensities were proportionally increasing with footprints. In an untabulated analysis, whose results we omit for the sake of brevity here, we show that this is not the case.

lower-emission assets:<sup>12</sup> Closely mirroring the results presented for carbon footprints (Table 1), investors with emission-intensive consumption hold statistically significantly more sustainable portfolios in terms of GHG emission ratings for four out of five outcomes in both the income and consumption-intensity specifications. In Appendix E.2, we describe the underlying rationale and construction of the two measures for carbon intensity in more detail and present results for PF sustainability outcomes across the four different TVL rating categories (Table E.2.1). The results show that the offsetting pattern is not prevalent for other rating categories than GHG emissions, thus lending further support to the notion that investors actively seek out low-emission assets to help offset their unsustainable consumption behavior.

We provide further evidence in favor of this hypothesis in several robustness tests and additional analyses. Specifically, we show that our results are not driven by sustainability preferences or return expectations for green assets, which might both be heterogeneous across low- and high-emission investor groups (Appendix E.1), and rule out potential sample selection issues (Appendix E.3). In Internet Appendix F.4, we present results from an alternative specification based on regional socio-cultural factors, which underscores the offsetting interpretation by showing that Catholicism is related to more sustainable PF outcomes.

# 4 Experimental evidence from RCT

#### 4.1 Study design

To conduct an online experiment with randomized treatment and control groups, we again cooperated with the same German retail bank as we did for the empirical part of this study. The invitation to participate in our experiment was extended to a sample of 343,447 retail banking clients. Within three weeks, 8,332 clients initiated the experiment,

<sup>&</sup>lt;sup>12</sup>Intensities can be interpreted as capturing the sustainability of consumers' lifestyles. The following example illustrates this idea: If households A and B both have annual emissions of 12 metric tonnes of  $CO_2$  (henceforth  $tCO_2$ ), but an annual income of EUR 60,000 and 30,000, respectively, they have corresponding carbon intensities of 2.5 and 5.0. The much higher carbon intensity observed for B cannot be explained by their income, which means that this household leads a much more unsustainable lifestyle, for instance by flying more frequently or using transportation based on fossil fuels more often, even though both households have the same carbon footprint. Conversely, two households might have the same income but different carbon intensities because their emissions differ; in this case, intensities also help disentangle which household consumes more (un-)sustainably while abstracting from effects driven by a potential income channel.

of which 4,249 fully completed the experiment, constituting our final sample.

A graphical overview of the experimental setup is presented in Figure 2. At the beginning of the experiment, participants are randomly assigned to a control group or one of two treatment groups. The experiment commences with a set of questions on financial literacy, financial market participation, and preferences, as well as environmental beliefs and prior beliefs of sustainable investments, such as perceptions of the impact of such assets. Next, we estimate the participants' carbon footprints with a survey-based procedure, following the guidelines of the German Federal Environmental Agency (Umweltbundesamt). Here all participants have to answer 13 questions.<sup>13,14</sup> In the *footprint treatment*, participants are subsequently presented with a graphical comparison (bar chart) contrasting their carbon footprint as calculated in the previous questionnaire with the average of their peers in terms of income and age. Peer footprints are calculated before the experiment using the administrative data described in Appendix B. Depending on their answers during the footprint estimation questionnaire, participants are confronted with the corresponding peer footprint. Participants in the *full treatment* group are subsequently presented with an allocation decision: They are given a hypothetical budget of 250 EUR and are asked to distribute it between themselves and  $atmosfair^{15}$ , an environmental organization that compensates for carbon emissions by investing in decarbonization projects.<sup>16</sup>

After the treatment, all participants are faced with an investment decision. The participants are asked to allocate a hypothetical investment budget of 12,500 EUR between two funds. They are provided with brief information on the sustainability profile of the two global

<sup>&</sup>lt;sup>13</sup>See the carbon calculator at https://uba.co2-rechner.de/en\_GB/.

<sup>&</sup>lt;sup>14</sup>In this estimation, we deviate from the footprint calculation described in Appendix B. This is due to the fact that the analogous estimation to our empirical analysis would require participants to accurately estimate their monthly or annual spending in dozens of categories. Based on previous work on the budgeting fallacy, i.e., consumers' inability to estimate their spending, we deem this approach infeasible for a survey: Sussman and Alter (2012), for instance, provide relatively recent insights on the subject while presenting a comprehensive overview of earlier work on mental accounting, specifically in terms of discrepancies in households' backward-looking evaluations of their spending. In following the Environmental Agency's guidelines, we assume to obtain an adequate estimation of participants' footprints.

<sup>&</sup>lt;sup>15</sup>Please see https://www.atmosfair.de for more information on *atmosfair* and their projects.

<sup>&</sup>lt;sup>16</sup>In a third treatment (*donation treatment*), we provide participants with the donation decision only, without the visualization of the footprint. As the analysis of this treatment does not yield additional results, we exclude it from this manuscript in the interest of brevity. Detailed information on the treatment is available upon request.



*Note.* The above figure depicts the study design of the field experiment. The participants are split into three groups (one control, two treatments). All participants initially fill out a survey to calculate their carbon footprint and finally are presented with the same investment decision between a sustainable and a conventional fund. However, (a) both treatment groups are confronted with their carbon footprint in relation to their peers and (b) the second treatment group is additionally given the opportunity to offset their footprint through a donation.

#### Figure 2 Experimental design

funds: one conventional equity fund and one dedicated sustainable equity fund.<sup>17,18</sup>

In both allocation decisions, we use a probabilistic incentivization scheme to incentivize the participants to make realistic choices reflective of their behavior outside of the experiment: For the donation allocation to *atmosfair*, we realize the choice for ten randomly drawn participants. The investment decision is realized for one randomly drawn participant in that we invest the funds according to their decision and pay out the return after an investment period of six months. The participants are informed of the potential to participate in these lotteries before receiving the respective treatments or tasks. We conclude the experiment with a set of socio-demographic questions, including participants' age, education, profession, and living situation (co-habiting, singles, families).<sup>19</sup> The experiment was conducted in July 2023 and programmed using LimeSurvey.<sup>20</sup> For more information regarding the selection of bank clients invited to participate as well as a description of the final participant sample, please see Appendix C.

Following the experiment, we also ask the participants who received a footprint sustainability

 $<sup>^{17}\</sup>mathrm{The}$  fund names cannot be disclosed here to protect the privacy of our cooperating bank partner and its clients.

<sup>&</sup>lt;sup>18</sup>To exclude biases stemming from prior knowledge of the specific funds or the names, names are not communicated to the participants prior to the investment decision. The participants can, however, at this point in the survey opt in to receive more detailed information on the funds at the end of the survey.

<sup>&</sup>lt;sup>19</sup>We decided not to query socio-demographics in the beginning of the survey in order to limit early drop-outs from survey fatigue.

<sup>&</sup>lt;sup>20</sup>LimeSurvey refers to the LimeSurvey GmbH, situated in Hamburg, Germany, which provides an open-source survey tool. More information can be accessed at http://www.limesurvey.org

signal whether they believe their footprint was calculated accurately: 61.7% would have believed their footprint to be in a similar range, whereas 27.0% and 11.2% thought their actual footprints to be smaller and higher than calculated, respectively.

#### 4.2 Results

Using the experimental setting described in Section 4.1, we test our empirical findings from Section 3 in a controlled environment, allowing for causal inferences.

Shock to sustainability perception First, we evaluate whether participants shift their investment allocation when confronted with an exogenous shock to the salience of their above- or below-average carbon footprints compared to their peers. Participants receive a positive sustainability signal if their carbon footprint is lower than their peers' average. Conversely, they receive a negative shock if their footprint is higher. The corresponding results are presented in Table 3.

	Baseline		Low Impact		Medium Impact		High Impact	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FP Treatment	0.217	0.385	-0.253	0.345	0.841	1.052	1.164	1.531
	(1.350)	(1.327)	(3.367)	(3.210)	(1.630)	(1.616)	(2.358)	(2.397)
Above Peer FP	-5.422***	-0.151	-7.750*	0.531	-5.597***	-1.714	-4.345	0.653
	(1.813)	(2.306)	(4.650)	(6.056)	(2.127)	(2.754)	(3.102)	(3.950)
FP Treatment	2.552	2.145	5.304	4.426	5.557*	5.213*	-3.979	-4.841
x Above Peer	(2.482)	(2.414)	(6.436)	(6.172)	(2.922)	(2.894)	(4.332)	(4.392)
Constant	54.713***	63.079***	36.070***	65.802***	53.268***	53.114***	67.921***	67.894***
	(0.975)	(3.509)	(2.555)	(8.858)	(1.167)	(4.263)	(1.753)	(6.078)
Total marg. effect	2.770	2.530	5.050	4.771	6.398***	$6.265^{***}$	-2.816	-3.309
(FP + Above Peer)	(2.083)	(2.011)	(5.485)	(5.229)	(2.426)	(2.381)	(3.633)	(3.652)
Observations	2,230	2,230	365	365	1,267	1,267	598	598
Controls	No	Yes	No	Yes	No	Yes	No	Yes
$R^2$	0.006	0.054	0.009	0.120	0.007	0.034	0.014	0.050

 Table 3 Effects of Footprint treatment

Note. The above table describes the results from several OLS regressions. The indicator variable *FP Treatment* captures the effect of the footprint treatment compared to the *Control group*. The additional treatment is the visualization of participants' own carbon footprint relative to the footprint of their peers. Above Peer FP is a dummy variable, taking on the value 1 if the individual's footprint is higher than the footprint of their peers (peers are defined as individuals in a similar age and income bracket). Column (1) and (2) show the baseline regression with all participants. In column (3) - (8) participants are split along their beliefs of sustainable investment impacts (into a group with low, medium and high impact beliefs). Participants are considered to have "Low Impact Beliefs" if they answer the question "How high do you expect the impact of sustainable investments to be?" on a Likert scale from 1-7 with 2 or less, "Medium Impact Beliefs" with values 3-5 and "High Impact Beliefs" otherwise. In each regression, only the contrasted groups remain in the sample. Asterisks denote statistical significance at the 10% (\*), 5% (\*\*), and 1% levels (\*\*\*), respectively. Robust standard errors are reported underneath coefficients in parentheses. Regressions control for age, gender, income, education, parents, employment and individual carbon footprints.

The average *Footprint treatment* effect shows that individuals in this group do not significantly change their investment allocation (the sustainable asset share increases by 0.217%, see Table 3). To understand whether the salience of investors' individual footprints compared to their peers causally shifts sustainable asset allocations, we need to inspect the total treatment effect of (i) having received *any* sustainability signal (*FP treatment* coefficients in Table 3), be it positive or negative, and (ii) having an above-peer footprint, i.e., having received a negative shock to emission salience. The corresponding estimates are denoted by *Total marg. effect* in Tables 3 and 4. The treated participants who also find their footprint is higher, i.e., receive a negative sustainability shock, increase their allocation by 2.770pp, albeit not statistically significantly (compare columns 1 and 2 of Table 3). These results capture the differences between the treatment and control groups irrespective of any potentially important levels of heterogeneity.

Levels of heterogeneity One influential variable to capture heterogeneous treatment effects for the sustainable asset allocation exercise might be the degree of participants' prior knowledge. However, Heeren et al. (2016) find that knowledge is not a significant driver of sustainable behavior when controlling for attitudes and social norms, which are both captured in the present setting. Another important heterogeneity level might be participants' beliefs about the sustainability impact of green investments (see, e.g., Siemroth and Hornuf, 2023; Luz et al., 2024 for previous evidence of the importance of impact beliefs). We argue that individuals who believe sustainable investments have significant impacts might prefer such assets precisely because of this belief, and might therefore react differently than those who doubt the non-pecuniary benefits of green investments.<sup>21</sup>

To elicit impact beliefs, we prompted participants as follows: "How high do you expect the impact of sustainable investments to be?", which they had to answer by choosing a value between one (1) and seven (7) on a Likert scale. We classified those choosing one (1) or two (2) as having "low impact" beliefs, values between three (3) and five (5) as "medium impact" beliefs, and the highest values six (6) and seven (7) as "high impact" beliefs.

Splitting participants by their impact beliefs, the total treatment effect of being in

<sup>&</sup>lt;sup>21</sup>We preregistered this level of heterogeneity at the AEA registry as one of the main dimensions along which we expected significantly different treatment effects. Please refer to https://www.socialscienceregistry.org/trials/11792 for preregistration details.

the footprint treatment group and receiving a negative sustainability signal induces participants with medium impact beliefs to increase their sustainable fund allocation by 6.398pp (6.265pp after including controls, both significant at the 1% level; see columns 5 and 6 of Table 3). The effects are not statistically significant for participants with low (high) impact beliefs (columns 3, 4, 7, and 8). Figure 4.2 visually demonstrates these effects.



*Note.* This figure shows the allocation into the sustainable fund (%) for participants receiving a negative signal (FP>Peer) or positive signal (FP<Peer) of their sustainability and sustainable behavior. On the left, participants with a low belief in the impact of sustainable investments are shown. The middle shows individuals with moderate beliefs in the impact and the right bars show individuals with a high belief into the impact of sustainable investments. While the control group is not informed about their own carbon footprint, the *FP Treatment* receives information on their own carbon footprint and it is set into relation to the footprint of their peers. Individuals with medium impact beliefs significantly increase their allocation after the negative signal to their own sustainability.

#### Figure 3 Sustainable fund allocation (%) by sustainability signal and impact beliefs

These results mirror our empirical results presented in Section 3: Investors in the observed data and experiment seem to specifically choose sustainable assets significantly to compensate for their consumption-driven environmental impacts in terms of carbon emissions. The experiment not only shows that this is a causal link, but also that investors do this only if they do not have extreme beliefs in the real environmental impacts of green assets. The effect size in this experiment is similar to the effects of our empirical study.

Our findings hold noteworthy implications for policy design and marketing of sustainable assets: If policymakers aim to increase retail investment in sustainable assets, they might consider leveraging the link between investors' perception of their consumption and investment sustainability. Importantly, however, it is possible that this leads to net-negative effects on the climate if investors feel morally licensed to retain high levels of emission-intensive consumption. This concern can be mediated to a certain extent by the fact that investors who (do not) prefer sustainable assets seem to have more robust preferences for such instruments. Based on their prior impact beliefs, at least, they will not choose green investments to compensate for their emissions from consumption even when confronted with a negative signal such as the one provided in our experiment. Instead, it is likely that such investors (do not) have a preference for sustainable investments based on other factors.

Notably, the participant groups with extremely high or low impact beliefs are much smaller than the medium-impact group at 598 and 365 vs 1,267 participants, respectively. This means that, if our experimental results translate to the field, as is supported by the results presented in Section 3, the vast majority of investors might choose sustainable assets at least in part because of individual compensation motives.

**Direct vs indirect carbon offsets** Next, we examine whether a negative shock to participants' awareness of their consumption sustainability induces a permanent shift in the demand for sustainable investments. To this end, we compare participants in the *Control* and *Full treatment* groups (see Table 4). In addition to confronting individuals with their carbon footprint relative to their peers, we also ask participants to allocate EUR 250 between themselves and a carbon offsetting organization (*atmosfair*). This additional treatment step takes place before the investment allocation choice between the conventional and sustainable fund, and provides participants with an alternative channel to address the sustainability signal received. Results for the *Full treatment* group can thereby shed light on whether investments perceive direct offsets, e.g., by donating to carbon offsetting organizations like *atmosfair*, and indirect offsets with sustainable investments differently.

We again examine overall (baseline) treatment effects as well as effects based on impact beliefs. Compared to the control group, participants who receive the negative footprint signal and the option to donate directly do not significantly adjust their sustainable fund shares compared to the control group (columns 1 and 2 of Table 4). While there are some differences in the signs and directions of effects, none are statistically significant even when separating participants by prior impact beliefs (columns 3 through 8).

The results from the *Full treatment* presented in Table 4 are largely analogous to those

	Baseline		Low Impact		Medium Impact		High Impact	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full Treatment	2.145	2.278	-4.387	-4.981	3.922**	3.956**	2.236	3.218
	(1.435)	(1.420)	(3.735)	(3.537)	(1.731)	(1.724)	(2.390)	(2.433)
Above Peer FP	-5.422***	-2.460	-7.750*	-2.806	-5.597***	-3.605	-4.345	-0.831
	(1.813)	(2.405)	(4.652)	(6.418)	(2.127)	(2.939)	(3.102)	(3.872)
Full Treatment	-1.778	-2.072	5.554	5.323	-0.584	-0.614	-3.744	-4.643
x Above Peer	(2.605)	(2.555)	(6.246)	(6.014)	(3.187)	(3.156)	(4.316)	(4.319)
Constant	54.713***	63.227***	36.070***	78.236***	53.268***	51.802***	67.921***	65.313***
	(0.975)	(3.634)	(2.557)	(8.403)	(1.167)	(4.521)	(1.753)	(6.007)
Total marg. effect	0.367	0.206	1.167	0.342	3.338	3.342	-1.508	-1.426
(Full + Above Peer)	(2.174)	(2.115)	(5.006)	(4.793)	(2.676)	(2.625)	(3.594)	(3.585)
Observations	2,087	2,087	329	329	1,184	1,184	574	574
Controls	No	Yes	No	Yes	No	Yes	No	Yes
$R^2$	0.012	0.059	0.012	0.145	0.016	0.050	0.016	0.055

Table 4 Effects of Full treatment

Note. The above table describes the results from several OLS regressions. The indicator variable *Full Treatment* captures the effect of the footprint treatment compared to the *Control group*. The additional treatment is the visualization of participants' own carbon footprint relative to the footprint of their peers. Above Peer FP is a dummy variable, taking on the value 1 if the individual's footprint is higher than the footprint of their peers (peers are defined as individuals in a similar age and income bracket). Column (1) and (2) show the baseline regression with all participants. In column (3) - (8) participants are split along their beliefs of sustainable investment impacts (into a group with low, medium and high impact beliefs). Participants are considered to have "Low Impact Beliefs" if they answer the question "How high do you expect the impact of sustainable investments to be?" on a Likert scale from 1-7 with 2 or less, "Medium Impact Beliefs" with values 3-5 and "High Impact Beliefs" otherwise. In each regression, only the contrasted groups remain in the sample. For the marginal effects, the treatment dummy and interaction term have to be added. Asterisks denote statistical significance at the 10% (\*), 5% (\*\*), and 1% levels (\*\*\*), respectively. Robust standard errors are reported underneath coefficients in parentheses. Regressions control for age, gender, income, education, parents, employment and individual carbon footprints.

of the *Footprint treatment* of Table 3 for all specifications except for the medium-impact group (columns 5 and 6). Here, the additional intervention of the *Full treatment*, which is otherwise analogous to the *Footprint treatment*, seems to have reversed its effect on the sustainable fund allocation: Treated participants do not increase their sustainable fund share significantly when they receive the option to donate directly after a negative sustainability signal and before the investment exercise. This suggests a substitution mechanism between direct carbon offsets through donations and indirect carbon offsets through sustainable investments. The additional option to allocate money into carbon offsets, makes the significantly positive effect of the negative sustainability shock disappear.

# 5 Conclusion

This study examines the relationship between the sustainability of individual consumption and retail investing. We find evidence that high-emission consumers tend to invest more sustainably, suggesting a compensatory behavior. Our analyses, using unique transaction-level data, show that these consumers prefer investments with favorable environmental ratings. Additional evidence from a survey with the same bank whose data we analyze supports that this is a conscious choice.

We address several associated concerns in a series of robustness analyses, providing evidence that this behavior is not driven by income or consumption levels, financial motives, or heterogeneous sustainability preferences.

Furthermore, we conduct a randomized control trial showing causally that individuals are more likely to choose sustainable investments after learning about their high carbon footprints. This behavior diminishes when direct carbon offsets are an option, indicating that sustainable investments and direct offsets are viewed as substitutes.

A back-of-the-envelope computation of the offset potential borne by the sustainable assets in our sample shows that while sustainable investments can aid the green transition, they are less efficient in reducing emissions than direct offsets. This can lead to a cycle of high emissions if consumers rely on investments to offset their carbon footprints without reducing their actual emissions from consumption.

Our secondary analyses provide mixed evidence that behavioral biases might be more prevalent among sustainable investors than unsustainable investors, which, if increasing participation in sustainable investments is desired, would leave this important investor group vulnerable to financial mistakes leading to sub-optimal outcomes. Future research should explore this avenue further. In addition, we propose that a more in-depth examination of the interplay and relative dominance of various motives for sustainable investing, such as warm glow, sustainability preferences, altruism, or compensation as covered by this manuscript, is important to understand sustainable investor behavior better and design effective policies. Furthermore, investigating whether sustainable investing leads to higher levels of unsustainable consumption could provide valuable insights for policy design and investor education. Finally, while our results can be aligned with moral cleansing, gaining a deeper understanding of how moral licensing, moral cleansing, and warm glow effects factor into one another will also be crucial for comprehending (sustainable) investor behavior.

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# Appendices

# A Sample requirements

To ensure that we estimate climate-relevant consumption and investing patterns for investors who use their primary accounts, we impose three selection criteria. These steps are crucial so as not to capture investor behavior based on checking accounts dedicated to savings, vacation, or shopping. We restrict the sample to investors who have (i) non-missing income data, (ii) non-missing wealth information, and (iii) receive a minimum of EUR 10,000 of net annual permanent income from salaries and wages for at least 75% of the recorded months, i.e., are income receivers. Table A.1 presents the breakdown of investor samples following each additional sampling criterion. The final sample comprises 6,151 consumers who have portfolio holdings, invest, and are most likely primary account users. As a robustness check, we repeat the baseline analysis for each of the subsamples to ensure the robustness of our results to the sampling restrictions in Appendix E.3.

Restriction	No. of investors
Unrestricted sample	19,929
Non-missing income and wealth data	19,011
Permanent net annual income $\geq$ EUR 10,000	17,989
Regular income receivers	9,901
Main sample	6,151

Table A.1 Sample selection and restriction criteria

*Note.* The above table shows the size of subsamples selected according to the criteria described in Section 2. We impose minimum requirements to data availability for wealth and income. Further restrictions select only those investors who receive income from salaries, wages, and pensions in their checking accounts for at least 75% of all recorded sample months. The main sample therefore consists of investors who likely use their checking and securities accounts as main accounts. The robustness of our baseline findings to these sample restrictions is tested in Table E.3.1 of Appendix E.3.

For the estimation of carbon footprints, we aggregate total consumption to the annual level, which also allows us to merge the investor sample directly to the EXIOBASE MRIO database. This database offers information on 200 product-by-product GHG emission intensities at the annual level. Next to consumption, we also aggregate all income and wealth records for each investor to the annual level, e.g., to compute carbon intensities (cp. Section 3 and Appendix E.2).

Notably, income tax is directly withheld by the employer, which means that we observe

income data at net levels, while gross consumption is recorded inclusive of value-added tax (VAT). Therefore, we need to adjust consumption for VAT rates. Table F.1.1 in the Internet Appendix F.1 displays all tax rates that deviate from the standard rate of 19% in Germany. Finally, we winsorize all consumption, income, portfolio, and wealth variables at the 0.1% level.

The consumption data includes the date and amount as well as the category of each checking account transaction, whereby inflows and outflows are categorized into over 100 categories.<sup>22</sup> Since we estimate consumption-based emissions, we only consider outflow transactions for this analysis. Further, we exclude financial transaction categories from the analysis, such as investments, savings, retirement plans, or private insurance.<sup>23</sup>. Such transactions should predominantly have close to a neutral impact on emissions if we disregard indirect downstream emissions of the vendor or financial institution. Finally, we exclude business trips and business expenses from the scope of our analysis. Although transactions in this category presumably represent a significant share of individual carbon footprints, individuals cannot adjust their decisions in this domain based on personal preferences, since business trips tend to be mandated by employers.

If the classification algorithm underlying the PFM tool's classification of consumption categories cannot unambiguously assign a category to a transaction, transactions are labeled "Uncategorized". In most cases, uncategorized transactions are wire transfers or payments to unknown parties or small businesses that are not recognized by the PFM tool. While clients can categorize those transactions manually ex-post, they rarely do so. Bräuer et al. (2022), whose study builds on a similar data set, find that about 25% of uncategorized outflow transactions are wire transfers while 71% are consumption transactions that cannot be categorized. Importantly, however, major stores, businesses, and online retailers are all recognized by the PFM tool. Uncategorized consumption is not likely to be a main driver for this analysis, since wire transfers, payments for manual labor, or purchases at smaller shops can be expected to be of limited relevance to investors' carbon footprints.

<sup>&</sup>lt;sup>22</sup>To protect the identity of our cooperating bank and its customers, we are not at liberty to disclose the exact number of categories or the category labels.

<sup>&</sup>lt;sup>23</sup>Public health insurance fees are deducted directly by employers in Germany. Under specific circumstances, employees can opt out of public insurance and choose private insurance coverage, which will be reflected by corresponding checking account transactions in our sample.

### **B** Carbon footprint estimation

In order to estimate the CO<sub>2</sub> footprints of investors' consumption patterns, we combine individual-level consumption with carbon intensities from the EXIOBASE 3.8.2 MRIO database (see Stadler et al., 2018; Ivanova et al., 2016; Steen-Olsen et al., 2016; Ivanova et al., 2017, for further information on the EXIOBASE database and its use in estimating individual GHG emissions). MRIO models describe the interdependent relationships between countries' economic sectors providing goods and services to final demand. EXIOBASE provides data for 28 EU member countries, 16 major economies, and five rest of world regions, the latter of which summarize the remainder of countries in Europe, Asia, Africa, America, and the Middle East. The data is available from 1995 to 2022 and, in addition to the more general MRIO calculations, provides a broad range of environmental and social satellite accounts for 200 product categories.<sup>24</sup>

We use those satellite accounts to derive product-level carbon intensities, which we calculate using the Global Warming Potential Standard 100 (GWP100). This standard describes the amount of climate relevant emissions (CO<sub>2</sub>, CH<sub>4</sub>, N<sub>2</sub>O from combustion and non-combustion, and SF<sub>6</sub>) as kgCO<sub>2</sub>-equivalents per year (IPCC, 2007; Ivanova and Wood, 2020). We follow Ivanova and Wood (2020) in mapping consumption categories to the 200 EXIOBASE product categories. For instance, we match the PFM tool's transaction category 'Food / beverages' to the EXIOBASE categories 'Food products nec' (85%) and 'Beverages' (15%). For weighting, we follow Ivanova et al. (2020) and consult official correspondences for statistics reporting of the UN (2022). Within some categories, such as cash or credit card expenses, it is not unambiguous how customers allocate funds. For such aggregate categories, we assume an average basket of goods, which we base on 20 EXIOBASE categories. The exact weighting is recorded in a harmonization spreadsheet which can be made available upon request.

Before we can multiply the categorized expenditures with carbon intensities in  $gCO_2/EUR$ , we need to consider tax rates, as the bank account transaction data includes value-added tax, whereas EXIOBASE records net prices. While most products and services in Germany are taxed at 0% (mainly financial services), 7% (mainly basic consumer staples such as food), or 19% (standard VAT rate), exemptions exist. The most relevant exemptions for this study are electricity and refueling. Details on the approximation of average tax rates

 $<sup>^{24} {\</sup>rm In}$  this context, satellite accounts mean accounts which add to the standard MRIO tables, i.e., they "hover above" the standard tables, so to speak.
for these exemptions can be found in the Internet Appendix  $F.1.^{25}$ 

We assume that emissions increase proportionally with expenditure within each category. For instance, a refueling bill of 50 EUR is associated with emissions twice as high as a refueling bill of 25 EUR. We consider this implicit assumption as an adequate approximation for most consumption categories, since the majority of purchases require the use of physical goods as inputs to provide respective final products and/or services, which implies linearly increasing emissions. The prior literature offers robustness tests of this implicit assumption and finds it to be adequate (Ivanova and Wood, 2020).

However, financial transactions follow a different logic. For instance, a wire transfer of 10,000 Euro does not generate 100 times the emissions of a 100 Euro transfer. The same holds for other financial transactions such as savings plans, most insurance contracts, etc. We generally exclude financial transactions from all footprint analyses since financial transactions do not generate carbon emissions beyond negligible impacts related to factors such as server capacities.

Consumption expenditure and carbon footprints are computed at the individual level and by year for all sub-categories following the adjustments outlined above. After linking the EXIOBASE carbon intensity data, we aggregate all sub-categories to 16 main categories excluding uncategorized consumption. Next, we compute the total carbon footprint for each of these main categories as the sum of footprints across the respective sub-categories at the individual-year level. For each individual, we aggregate total annual carbon emissions as the sum of emissions from all individual consumption categories excluding financial transactions.

Figure B.1 displays total average consumption-based carbon footprints of individuals by income percentiles. On average, individuals emit 14.2 tCO<sub>2</sub> p.a. from categorized consumption only. As a comparison, the German Federal Environment Agency finds an average carbon footprint of German single-person households of 11.6 tCO<sub>2</sub> p.a.<sup>26</sup> The exclusion of uncategorized consumption may bias estimates of carbon footprints downward. However, another effect may balance out this deviation: The average net income of individuals in the analyzed sample, after taxes and other deductions at source, such as, e.g., public healthcare premia, is roughly 51,800 EUR p.a. (compare Table C.1

 $<sup>^{25}\</sup>mathrm{All}$  products not taxed at the standard rate of 19% are recorded in Table F.1.1 of the Internet Appendix F.1.

<sup>&</sup>lt;sup>26</sup>https://www.umweltbundesamt.de/klimaneutral-leben-persoenliche-CO2-bilanz-im-blick



Note. The above figure depicts the sample average of annual consumption-based emissions in  $tCO_2$  by percentile of annual net income. The red vertical line indicates the sample average of annual carbon footprints from consumption (14.16  $tCO_2$ ). Consumption-driven emissions are calculated at the individual-investor level by combining the EXIOBASE 3 database on household-level carbon intensities with administrative data of the studied investors' consumption expenses.

#### Figure B.1 Total carbon emissions by income percentile

of Appendix C), while net household income was roughly 30,308 EUR p.a., on average, in Germany in 2023.<sup>27</sup> Thus, our sample earns higher income than the German average, which presumably carries over to higher corresponding consumption levels.<sup>28</sup> There is a strong link between income and consumption-based emissions (compare Figure B.1). Between the omission of uncategorized expenses and the higher-than-average income levels observed, we expect these two potential sources of bias to cancel out to the largest extent.

<sup>&</sup>lt;sup>27</sup>Based on data from the European Union Statistics on Income and Living Conditions – EU-SILC survey as presented by the Federal Statistical Office of Germany (DESTATIS), see https: //www.destatis.de/EN/Themes/Society-Environment/Income-Consumption-Living-Conditions/ Living-Conditions-Risk-Poverty/Tables/income-distribution-mz-silc.html.

 $<sup>^{28}</sup>$ In addition, the averages presented in Table C.1 of Appendix C can capture either single or household income if the observed individual is the primary earner. We assume that the rate at which individual and household income concur and are observed for one single person/household head is roughly equal for our sample and the German average, and thereby reflected also by the figures published by DESTATIS.

# C Sample descriptives

### C.1 Cross-sectional data

Table C.1 displays socio-demographic summary statistics (sample averages) for the investor sample used in Section 3 to draw conclusions from correlational (empirical) evidence. Men are slightly over-represented in the sample with 55.65% of total sample size, which is in line with the well-documented finding that men are more likely to participate in the stock market than women (e.g., Barber and Odean, 2001). High-footprint investors are slightly more likely to be males than their low-footprint counterparts, but the difference is statistically insignificant. Investors are, on average, 52 years old, with high-footprint investors being significantly older than low-footprint ones by roughly 5 years. The most frequent occupation of the analyzed investors are regular employees, followed by retirees, industrial workers, and students (46.33%, 9.98%, 4.05%, and 2.98%, respectively). The prevalence of civil servants, managers, and unemployed individuals range from 2.34% to 0.81%. The remainder of the sample (not depicted), either work as homemakers or employment information is not available. Importantly, low- and high-footprint groups have a significantly different distribution of employment status, which is intuitive seen as, e.g., retirees should arguably have lower emissions, and managers might conceivably drive a larger car and use it more often.

The analyzed sample earns relatively high income compared to the German average at 51,800 EUR net p.a. These high income levels are reflected by high consumption levels of about 31,990 EUR (net), which translates to emissions from consumption of about 14.16 tCO<sub>2</sub> on average. Per default, income and consumption levels are higher for individuals with high carbon footprints, with the differences being statistically significant at the 1% level. These high income levels for high-footprint individuals may translate to them following financial (e.g., return-chasing) motives more than low-footprint investors. Therefore, we not only control for income in regressions (compare Tables 1 and 2 in Section 3), but also test more formally whether sustainable portfolios can be aligned with heterogeneous sustainability and/or financial motives (see Appendix E.1).

Next, Table C.2 presents portfolio statistics for these investors. The table shows asset class participation rates, portfolio weights, and trading statistics. In line with the high income levels of the analyzed sample, the average of investor median portfolio values is

Demographics	Sample	Low	High	$\operatorname{High}-\operatorname{Low}$
Male (%)	55.65	55.07	56.23	1.16
Age	51.57	49.14	54.00	$4.85^{***}$
Married (%)	39.33	34.95	43.71	8.76***
Employee (%)	46.33	53.38	39.28	-14.10***
Industr. worker $(\%)$	4.05	4.75	3.35	-1.40***
Civil servant (%)	2.34	2.83	1.85	-0.97**
Manager (%)	2.10	0.88	3.32	$2.44^{***}$
Student (%)	2.98	5.10	0.85	-4.26***
Retired (%)	9.98	10.86	9.11	-1.75**
Unemployed (%)	0.81	1.14	0.49	-0.65***
Micro status	7.06	6.67	7.46	0.79***
Income and consumption	Sample	Low	High	$\operatorname{High}-\operatorname{Low}$
Net income (k€ p.a.)	51.80	35.26	68.35	33.09***
Consumption (k€ p.a.)	31.99	18.85	45.13	$26.27^{***}$
Footprint from consumption (tCO2 p.a.)	14.16	7.22	21.10	13.88***
Observations	6,151	3,076	3,075	6,151

### Table C.1 Socio-demographics

Note. The above table presents summary statistics for demographic variables across the overall, low-, and high-footprint samples. All Euro variables are winsorized at the 0.1% level. Profession is captured by seven dichotomous variables equal to one if an investor is employed regularly, works in an industrial profession (i.e., blue-collar worker), as a civil servant, manager, studies, or is retired, respectively, and zero otherwise. Micro status is a proxy for regional socio-economic status based on an investor's area of residence elicited by the bank, with values ranging from 0 to 9. Columns with header *Sample* show averages for the whole sample, whereas columns titled Low and High distinguish between below- and above-median footprints from consumption, respectively. Columns titled High – Low report differences between the high- and low-footprint averages including their level of statistical significance using Welch's unequal variances t-test. Asterisks denote statistical significance of this difference at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

roughly 103,720 Euro, with a considerable and statistically significant (1%) difference between high- and low-footprint investors of about 83,840 Euro. Participation rates per asset class are driven by German market structures and the partnering bank's clientele as well: 59.37% of all investors hold equities, and 73.30% hold funds. As the bank is a universal bank with a network of branches and an advisory-based coverage model, participation rates are much higher for active funds (48.95%) than for passive funds (18.54%). Within passive products, ETFs (18.41%) are held much more frequently than index certificates (2.05%) and index funds (0.29%). This is in line with average German market structures. Kumar (2009) lottery stocks are less frequently held, with participation rates of 0.08% and 0.93%, respectively.

The observed participation rates translate roughly to portfolio weights: Investors hold average weights in equities and funds of 36.46% and 54.10%, respectively. Analogously to participation rates, active funds are allocated higher weights than passive funds (48.95% and 5.06%, respectively), and ETFs account for the majority of portfolio shares devoted to passive products (5.01%). The shares of bonds (1.22%), index certificates (0.10%),

	S	L	Н	$\mathrm{H}-\mathrm{L}$
$PF \ value \ (median, \ k \mathcal{C})$	103.72	61.81	145.65	83.84***
Participation rates	S	L	Н	$\mathrm{H}-\mathrm{L}$
Equity	59.37	51.24	67.50	16.27***
ETFs	18.41	14.66	22.15	7.49***
Bonds	8.00	5.82	10.18	$4.36^{***}$
Funds	73.30	75.62	70.98	-4.64***
Active funds	66.93	69.54	64.31	-5.22***
Passive funds	18.54	14.73	22.35	7.62***
Index funds	0.29	0.16	0.42	$0.26^{*}$
Index certificates	2.05	0.94	3.16	$2.21^{***}$
Kumar (2009) lottery stocks	0.93	0.72	1.14	$0.42^{*}$
Portfolio weights	S	L	Н	$\mathrm{H}-\mathrm{L}$
Equity	36.46	32.25	40.68	8.42***
ETFs	5.01	4.73	5.30	0.57
Bonds	1.22	1.11	1.33	0.22
Funds	54.10	60.21	48.00	-12.21***
Active funds	48.95	55.39	42.50	-12.88***
Passive funds	5.06	4.74	5.39	0.65
Index funds	0.05	0.01	0.10	0.09**
Index certificates	0.10	0.06	0.13	0.07
Kumar (2009) lottery stocks	0.07	0.07	0.08	0.02
Trading statistics	S	L	Н	$\mathrm{H}-\mathrm{L}$
Avg. trade risk	3.51	3.43	3.59	0.16***
Securities (median)	7.05	5.42	8.68	$3.25^{***}$
PF HHI	0.26	0.25	0.28	$0.03^{***}$
Equity HHI	0.36	0.33	0.38	$0.05^{***}$
PF home share $(\%)$	28.78	26.55	31.01	4.46***
Equity home share $(\%)$	69.67	72.34	67.63	-4.71***
Observations	6,150	3,076	3,074	6,150

### Table C.2 Portfolio statistics

Note. The above table presents portfolio statistics for the overall, low-, and high footprint samples. All value-based variables are winsorized at the 0.1% level. Kumar (2009) lottery stocks are computed following Kumar (2009), i.e., stocks with below-median price, above-median idiosyncratic skewness, and above-median idiosyncratic volatility. We use a ten-year estimation period from June 2012 to June 2022 to estimate average prices, skewness, and volatility. *PF HHI* stands for the portfolio-level Herfindahl-Hirschman-Index measuring portfolio concentration, i.e., under-diversification. *Equity HHI* captures the same for equity holdings only. Columns with header S show averages for the whole sample, whereas columns titled L and H distinguish between below- and above-median footprint strong consumption, respectively. The column titled H - L reports differences between the high- and low-footprint averages including its statistical significance based on paired t-tests. Asterisks denote statistical significance of this difference at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

and lottery stocks (0.07%) are negligible in terms of portfolio weights.

Comparing sustainable and unsustainable consumers, the participation rates and portfolio weights presented in Table C.2 indicate higher risk-taking by unsustainable consumers, which is in line with their socio-demographic characteristics outlined previously. Unsustainable consumers are more likely to hold equities, which subsequently make up a higher share of portfolios (both statistically significant at the 1% level). On the other hand, they are less likely to hold funds in general and active funds specifically, which translates to lower

portfolio weights for both asset classes (all statistically significant at the 1% level). The same relation is reflected by trading statistics: The average trading risk class as elicited by the bank is 3.51 for the total sample and significantly higher for unsustainable consumers than for their more sustainable counterparts. The same holds true for sample averages of the investor-level median of securities held, for portfolio and equity share concentration (measured by the Herfindahl-Hirschman-Index, HHI), and the portfolio home share. Only the equity home share is significantly lower for high-footprint investors. All results are statistically significant at the 1% level. These findings emphasize the importance of analyzing investor motives for sustainable investments.

## C.2 RCT participants

We ran our experiment with the clients of a major German retail bank, the same bank that provided the data used in the empirical part of this study. We limit our target group along two criteria: First, clients need to have regular account inflows. This ensures that participants in our experiment are active bank clients, increasing the chances that their consumption and investment responses are reflective of their complete financial behavior profiles. Second, clients need to have a trading account or an affinity to trading.<sup>29</sup> This ensures that the investment decisions in our experiment are backed by real-world trading experience or a high likeliness to start trading sometime in the near future.

Table C.3 shows socio-demographic summary statistics for our full sample as well as the individual control and treatment groups. The sample size of the three groups is comparably balanced at 1,161 for the *Footprint (FP) treatment*, 1,069 for the *Control*, and 1,018 for the *Full treatment* group.<sup>30</sup> The samples exhibit a similar distribution of socio-demographic attributes. Minor, but statistically significant differences between the groups only exist for age, the share of students and retirees (all between the control and the footprint group) as well as the share of participants with academic degrees (between the footprint and full treatment groups). Since we control for these factors in our analyses, these differences should not cause major concern.

<sup>&</sup>lt;sup>29</sup>The bank estimates trading affinity in-house as part of their private banking activities. They use a proprietary calculation algorithm to identify clients who are likely to open a trading account.

 $<sup>^{30}</sup>$ Throughout this paper, we refer to a number of 4,249 total participants. This includes the *Donation* treatment group, which does not receive the negative or positive footprint shock, but is directed to the donation decision and investment exercise directly after completing the emission-estimation questionnaire. Because there are no noteworthy results for this treatment group that speak in favor or against our key takeaways, we exclude the results from our discussion for the sake of brevity. The results for this group can be made available upon request.

Demographics	Full sample	Control group	Footprint treatment	Full treatment	Control vs FP	FP vs Full
Male (%)	69.18	68.76	68.91	69.94	-0.15	-1.03
Age	48.25	47.39	48.81	48.51	-1.43**	0.30
Married (%)	52.00	52.10	51.08	52.95	1.03	-1.87
Children (%)	32.02	32.74	31.09	32.32	1.65	-1.22
Academic degree $(\%)$	48.86	49.11	52.11	44.89	-3.00	7.22***
Employee (%)	54.09	52.95	53.23	56.29	-0.28	-3.06
Unemployed (%)	4.22	4.12	3.96	4.62	0.15	-0.65
Income (k€ p.m.)	3,821.20	3,797.94	3,867.36	3,792.98	-69.41*	74.3793*
Personal Carbon Footprint (t)	10.5489	10.5122	10.6574	10.4636	-0.1452	0.1938
Observations	3,248	1,069	1,161	1,018	2,230	2,179

Table C.3 Socio-demographics of the field experiment

Note. The above table presents summary statistics for demographic variables across the overall sample as well as individual treatment groups of the survey experiment. Married, Children, and Academic degree are dichotomous variables equal to one if an investor is married, has at least one child, and has an academic university degree, respectively, and zero otherwise. The profession is captured by five dichotomous variables equal to one if an investor is a student, regularly employed, self-employed, employed as a civil servant, unemployed, respectively, and zero otherwise. Income is coded as the midpoint in of three income brackets. Personal Carbon Footprint is based on the questionnaire version to determine carbon footprints from the experiment (results in tons of carbon). Column headers indicate sample averages for the full sample, control, footprint treatment and full treatment groups. Statistics for the donation treatment group are omitted here, as we did not find substantial variation for this group. For information on the donation treatment please contact the authors. Columns titled Control vs FP and FP vs Full report differences between the respective group averages. Asterisks denote statistical significance of these differences based on two-sample t-tests at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

Overall, male participants are over-represented in our sample with 69.2% of the total sample size, which is not surprising given the historical over-representation of males in stock market participation and tendency to be the financial household head (e.g., Barber and Odean, 2001). On average, our participants are 48 years old. Roughly 52.0% of our participants are married, and 32.0% have at least one child. Moreover, our sample is balanced between academics and non-academics with 48.9% of participants indicating to have an academic degree. At 54.1%, the majority of our participants are employees. In the experimental data regressions, we control for the characteristics displayed in Table C.3.

Figure 1 is based on an earlier survey with 3,646 clients of the same bank. 8.7% of the participants in our RCT also participated in the first survey. While it had a different focus than our RCT, an associated concern might be that the participation in the survey conducted in October 2022 affects response rates or treatment effects of our RCT conducted in July and August 2023. In untabulated findings, we are able to rule out this concern: Controlling for participation in the first survey does not change our results.<sup>31</sup>

<sup>&</sup>lt;sup>31</sup>The corresponding findings can be made available upon request.

## D Portfolio sustainability and investment motives

In the empirical analysis of administrative trading data, we need to construct proxies for sustainable investment outcomes as well as potential drivers of the positive or negative relation between footprint estimates and these outcomes. In the following, we describe the construction and literary foundation of these proxies. To address the shortcomings of using these proxies for behaviors and preferences, the RCT results presented in Section 4 are instrumental. They provide evidence of whether compensation considerations are able to shift sustainable investing causally.

## D.1 Outcomes: measures for sustainable investments

**Construction of PF outcomes** We construct five individual-level indicators to measure sustainable investments which will subsequently be related to the sustainability of consumption. All indicators (outcome variables in the regressions) are based on Factset Truvalue Labs (TVL) scores, which we match to the portfolio holdings of each investor at the ISIN level. These scores are calculated by mass processing of (social) media articles using artificial intelligence (AI), and therefore allow for high-frequency updating of sustainability scores at the daily level. TVL sustainability scores are based on 26 Sustainability Accounting Standards Board categories (SASB) across 5 areas and cover more than 267,000 companies.<sup>32</sup> Daily scores are calculated based on publicly available data from more than 150,000 sources including news, publications and social media content. Companies are ranked in percentiles compared to industry peers and classified in tiers from "leaders" to "laggards", with values ranging from 0 to 100. Peers are chosen for environmental and social considerations based on their industries and the country of incorporation is used to benchmark governance standards. Besides overall sustainability ratings pertaining to E, S, and G factors, scores are available for a range of sub-categories specifically targeted at, for instance, employee management, wastewater, or GHG emissions of companies. Since the primary goal is to analyze whether investors attempt to compensate for their consumption behavior by sustainable investments, the GHG emissions, ecological, and air quality scores are of particular interest. An added benefit of using specific sub-scores is that the common issue of ESG rating noise might be mitigated (see, for instance Berg et al., 2022).

<sup>&</sup>lt;sup>32</sup>For further information, visit the Factset documentation at https://go.factset.com/ marketplace/catalog/product/sasb-scores-datafeed.

In the main regressions, we evaluate whether and to what extent above-median carbon footprints as a measure of unsustainable consumption can explain the cross-sectional variation of these five indicators, and whether this explanatory power is affected by proxies for sustainability and financial motives. To this end, we use end-of-year portfolio holdings in 2019 so as not to bias results by potential COVID-19 or intra-year effects. Based on daily TVL scores, we compute five portfolio sustainability indicators for each rating category of interest (overall, GHG emissions, ecological, and air quality). Together, these metrics paint a holistic picture of how sustainably individuals invest.

The first measure is dichotomous and takes on the value one for investors who hold assets whose average ranking over the sample period ranks in the top quintile of the respective TVL score (referred to as *Holds top rated* in the regressions). Arguably, it is the least indicative, or restrictive, of all outcome variables. The second and third outcomes measure portfolio value (asset) shares held in this top quintile of rankings based the value (number) of assets that rank in the top 20% of ratings (referred to as % of PF top rated and % AS top rated in the tables). Both variables rank from 0% to 100% and differ only in their weighting scheme of constituent assets, which is based on the number of top-ranking assets divided by the number of total assets (asset share) and the portfolio weight devoted to top-ranking assets (portfolio share), respectively. The fourth measure is the investor-level, value-weighted TVL portfolio score for each respective rating category (overall, GHG emissions, ecological, or air quality), and ranges from 0 to 100 (referred to as *PF ESG score* in tables). The fifth and final measure is again dichotomous and equal to one if the investor's portfolio ESG score itself ranks in the top quintile of scores at the end of 2019.

Summary statistics along high- and low-emission investor groups Table D.1 presents summary statistics for overall, GHG emissions, ecological, and air quality scores, showing that the choice of ESG rating category is important and that high-footprint consumers hold higher-ranked securities. For GHG emissions scores, the largest values and prevalences are found, with 48.11% of the overall sample holding top-ranked securities. High-emissions investors have a significantly higher share by 9.09% compared to low-emissions counterparts (significant at the 1% level). For overall, ecological, and air quality variables, values range from 23.73% to 35.70%, with differences between low- and high-footprint consumers also significant at the 1% level. Other TVL rating categories follow a similar pattern, with higher prevalence for high-ranking securities and portfolios based on GHG

emissions scores. Portfolio shares in top-ranked assets are much higher than asset shares, indicating that high-ranking assets held by these investors have relatively high values.

An exception is the number of investors whose value-weighted portfolio scores rank in the top quintile: the highest share is for overall ratings (12.60%), followed by ecological ratings (12.03%). For GHG emissions assets, only 10.49% of investors achieve a top-quintile portfolio score, with a significant difference of 3.09% between low- and high-emissions investors (1% level). These variations emphasize the importance of rating categories and the need for category-specific analyses to draw meaningful conclusions.

TVL overall	S	L	Н	H - L
Holds top rated (%)	26.14	22.45	28.83	6.38***
% PF top rated (%)	2.30	2.16	2.44	0.29
% AS top rated (%)	0.13	0.07	0.18	0.11
PF ESG score $[0,100]$	52.05	51.74	52.27	0.54
Top PF ESG score	12.60	10.96	14.24	$3.29^{***}$
TVL GHG emissions	S	$\mathbf{L}$	Н	$\mathrm{H}-\mathrm{L}$
Holds top rated (%)	48.11	42.86	51.95	9.09***
% PF top rated (%)	8.66	7.34	9.91	$2.57^{***}$
% AS top rated (%)	0.56	0.50	0.61	0.11
PF ESG score $[0,100]$	63.04	62.80	63.21	0.41
Top PF ESG score	10.49	8.94	12.03	$3.09^{***}$
TVL ecological	S	L	Н	$\mathrm{H}-\mathrm{L}$
Holds top rated (%)	35.70	31.95	38.44	6.50***
% PF top rated (%)	3.17	2.78	3.53	$0.74^{**}$
% AS top rated (%)	0.16	0.15	0.17	0.02
PF ESG score $[0,100]$	54.67	54.46	54.83	0.37
Top PF ESG score $(\%)$	12.03	10.34	13.72	$3.39^{***}$
TVL air quality	S	L	Н	$\mathrm{H}-\mathrm{L}$
Holds top rated (%)	23.73	19.54	26.77	7.23***
% PF top rated (%)	1.59	1.33	1.83	$0.50^{**}$
% AS top rated (%)	0.10	0.08	0.12	0.04
PF ESG score $[0,100]$	34.63	34.53	34.70	0.17
Top PF ESG score $(\%)$	8.73	7.93	9.53	$1.60^{**}$
Observations	6,151	3,076	3,075	6,151

Table D.1 Outcomes: Sustainable investment indicators

Note. The above table presents sample averages for the sustainable investment measures we use as outcome variables in the trading-motive regressions. We compute each measure separately for the TVL overall, GHG emissions, ecological, and air quality ratings as described in Section D.1. Holds top rated is an indicator equal to one if an investor holds at least one security which ranks in the top 20% of ratings, whereas % PF top rated and % AS top rated measure the portfolio and asset shares devoted to these top-ranking assets, respectively and in percentage points. The PF ESG score and the Top PF ESG score variables measure the composite value-weighted ESG score for each investor's portfolio and the share of investors whose portfolio rank in the top quintile (top 20%) of the distribution of all PF ESG scores, respectively. Columns with header S show averages for the whole sample, whereas columns titled L and H distinguish between below- and above-median footprints from consumption, respectively. Columns titled H - L report differences between the high- and low-footprint averages including their level of statistical significance using Welch's unequal variances t-test. Asterisks denote statistical significance of this difference at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

Generally, portfolio-level ESG metrics across TVL rating categories are higher for unsustainable

consumers, with eleven out of 20 cases showing statistically significant differences at the 1% or 5% levels. The statistics in Table D.1 suggest negative spillover effects, which are tested more formally throughout this manuscript.

## D.2 Proxies for sustainability motives

This study aims to uncover spillovers of sustainability preferences, or offsetting behavior, between consumption and investing. Intuitively, one might expect compensation behavior to be driven by sustainability motives. While this may be the case and cannot be ruled out in the proposed setting, it is important to rule out that the results are driven by heterogeneous demand for sustainable assets, which itself might be driven by income levels also related to footprint size, rather than compensation behavior. If sustainability preferences and not offsetting considerations were driving results, the main result would be a statistical artifact. If this were the case, we expect the coefficients to lose explanatory power upon including proxies for sustainability preferences. This reasoning is in line with Degryse et al. (2023), who find that one distinct group of sustainable investors is motivated by financial motives, while another is motivated by pure sustainability motives.

To investigate whether heterogeneous sustainability preferences explain sustainable investments as well as or better than high footprints from consumption, we use three proxies based on the prior literature on sustainable investing. First, we leverage the high frequency of TVL ratings that enable measuring sustainability preferences at the daily level. If investors pay attention to the sustainability impact transported via sustainability ratings, they might trade in the direction of changes covered by the news which feed into TVL ratings, i.e., buy a security after it experiences a positive change, and sell after a negative rating change.

A growing body of literature studies the relevance of sustainability ratings for retail investors' portfolio choices. In the domain of mutual fund flows, Ammann et al. (2019) and Hartzmark and Sussman (2019) show that sustainability ratings are important to mutual fund flows. Bialkowski and Starks (2016) provide additional evidence that (retail) investors trade securities based on ESG ratings. We follow this literature and construct two measures for sustainability motives based on rating changes. After removing (bank) holidays and weekends from the TVL sample, we compute daily changes in ratings for each ISIN by aggregating the total sum of buys (sells) over the five days following each positive (negative) rating change by ISIN and investor separately for the overall, GHG emissions, ecological, or air quality scores. We then divide the total number of buys (sells) after positive (negative) changes by the total number of buys (sells) over the sample period to obtain the positive-change-buy-rate for each investor (negative-change-sell-rate), abbreviated as PCBR (NCSR) in the following. The resulting rates are multiplied by 100 to reflect percentages of buys (sells) that follow rating changes.

Figures D.1 and D.2 present marginal propensities to trade (MPT) around rating changes for overall and GHG emissions scores, respectively. Left-hand plots show the marginal propensity to buy (MPB), whereas plots on the right-hand side present marginal propensities to sell (MPS) following positive and negative changes, respectively. Panel A shows results for the overall sample, whereas Panel B and C estimate MPTs for the belowand above-median footprint consumers separately. To estimate MPTs, we adapt the methodology to estimate MPCs from dividends outlined in Bräuer et al. (2022) to our setting by running panel regressions of indicator variables equal to one if investors buy (sell) any asset ranked in the specific TVL sub-category score on five leads and lags of positive (negative) rating changes. This methodology is not entirely analogous to the construction of PCBR and NCSR in this setting, since we cannot estimate MPTs at the individual-ISIN level due to small sample sizes. Nonetheless, we propose that investors may buy (sell) any high-ranking asset after any of their holdings experience a rating change if the rating change triggers a general reshuffling or reevaluation of their PF holdings. However, these results can only be interpreted as indicative of general ESG trading behavior in the analyzed sample, and do not pinpoint spillovers between consumption and investment exactly.

There is no clear pattern as to the MPT after rating changes in overall TVL scores (Figure D.1). For the overall and high-footprint samples, there is a non-zero, significant MPB after positive changes, but the increase has commenced before the change, and a significant jump in MPBs cannot be found here. Around negative changes, however, the overall and high-footprint samples exhibit a significant decrease in the MPS before and increase after rating changes. Since TVL scores are based on publicly available information, it is possible that the pre-change decreases are caused by information leakage ahead of rating changes.

Around GHG emissions rating changes, we find clear jumps and statistically significant MPBs on the day of and over the five days following positive rating changes for the overall and high-emission, but not for the low-emission samples (Figure D.2). Nevertheless, the



*Note.* The above figures show estimates for the marginal propensity to trade (MPT) after TVL overall rating changes. Left-hand plots show the marginal propensity to buy (MPB) after positive changes, and plots on the right-hand side show marginal propensities to sell (MPS) after negative changes. For each estimate, we select one of the overall (Panel A), below-median carbon footprint (Panel B), and above-median carbon footprint samples (Panel C). Estimates are obtained by running panel linear probability models (LPM) at daily level, where dichotomous variables equal to one for buys (sells) are regressed on five leads and lags of rating changes. All LPMs control for (bank) holidays and use HAC-robust standard errors. The sample of traded ISINs in each model only comprises those that have a TVL overall rating.

### Figure D.1 MPT around overall rating changes

fact that both the MPB and MPS estimates show non-zero changes within five days after overall and GHG-emission rating changes validates the use of the PCBR and NCSR as proxies for sustainability preferences. Furthermore, it is intriguing that both (i) increased MPS after negative overall-score changes (Figure D.1), and (ii) significant MPTs for



*Note.* The above figures show estimates for the marginal propensity to trade (MPT) after TVL GHG emissions rating changes. Left-hand plots show the marginal propensity to buy (MPB) after positive changes, and plots on the right-hand side show marginal propensities to sell (MPS) after negative changes. For each estimate, we select one of the overall (Panel A), below-median carbon footprint (Panel B), and above-median carbon footprint samples (Panel C). Estimates are obtained by running panel linear probability models (LPM) at daily level, where dichotomous variables equal to one for buys (sells) are regressed on five leads and lags of rating changes. All LPMs control for (bank) holidays and use HAC-robust standard errors. The sample of traded ISINs in each model only comprises those that have a TVL GHG emissions rating.

### Figure D.2 MPT around GHG emission rating changes

changes in GHG-emissions scores (Figure D.2) are present only for the high-footprint and overall sample (likely driven by high-footprint investors). This might suggest that high-emission investors have a particularly strong preference to trade on ESG information.

As an additional metric for sustainability preferences, we construct a measure for home

bias specific to ESG asset holdings. In seminal work on the subject, French and Poterba (1991) argue that holding a disproportionate share of wealth in domestic assets is the result of individual preferences and not driven by market frictions. More recently, Groen-Xu and Zeume (2021) find that market reactions to sustainability-related incidents are more strongly pronounced for national events. In light of these findings, we construct a measure for ESG home bias as follows (ESG home-bias ratio, EHBR<sub>i</sub>):

$$EHBR_{i} = \frac{\frac{N_{i,ESG\cuphome}}{N_{i,ESG}}}{\frac{N_{i,home}}{N_{i}}},$$
(3)

where  $N_{i,\text{ESG}\cap\text{home}}$  is the number of German assets held by investor *i* that rank in the top quintile of TVL overall ratings,  $N_{i,\text{ESG}}$  is the total number of assets held that rank in the top quintile of the rating distribution,  $N_{i,\text{home}}$  is the number of German securities held by investor *i*, and  $N_i$  is the total number of assets held by the respective investor in December 2019.<sup>33,34</sup> If investors seek sustainability impact and perceive that they have an information advantage about sustainability-relevant events, their portfolio home bias may be more pronounced for sustainable investments compared to other investments. As we are interested in relative differences between sustainable and unsustainable securities, we refrain from calculating model- or data-based benchmark portfolios, but relate the share of local sustainable assets over the number of total sustainable assets to all local over all total assets held by each investor.

Panel A of Table D.2 displays summary statistics of sustainability-motive proxies for the analyzed sample. Similar to sustainability metrics (Table D.1), we find values for sustainability-motive proxies to differ strongly between TVL rating categories, with PCBR and NCSR values ranging from 11.48% and 13.80% for overall sustainability ratings to 0.69% and 0.95% for air quality ratings. For all rating categories, the NCSR is larger than the PCBR. The ESG home-bias ratio is 0.19% for the total sample. While there is no significant difference between sustainable and unsustainable consumers for the ESG home-bias ratio, PCBR and NCSR are higher for unsustainable consumers across rating categories. All differences are statistically significant at the 1% level. Again, the results presented in Panel A of Table D.2 suggest a negative relation of consumption-driven

<sup>&</sup>lt;sup>33</sup>We do not compute the EHBR separately for the overall, GHG emissions, ecological, and air quality ratings since there are not enough observations to compute the measure for all individual investors.

 $<sup>^{34}</sup>$ For the EHBR, we choose the same snapshot time as for the ESG outcome variables.

	Panel A: Sustainability-motive proxies					
TVL overall	S	L	Н	$\mathrm{H}-\mathrm{L}$		
PCBR NCSR	11.48 13.80	$8.75 \\ 11.56$	$14.19 \\ 15.67$	5.45*** 4.11***		
TVL GHG emissions	S	$\mathbf{L}$	Н	$\mathrm{H}-\mathrm{L}$		
PCBR NCSR	$\begin{array}{c} 3.94 \\ 6.05 \end{array}$	$2.82 \\ 5.24$	$5.04 \\ 6.72$	$2.22^{***}$ $1.48^{***}$		
TVL ecological	S	$\mathbf{L}$	Н	$\mathrm{H}-\mathrm{L}$		
PCBR NCSR	$\begin{array}{c} 1.65 \\ 2.01 \end{array}$	$1.20 \\ 1.38$	$2.10 \\ 2.54$	$0.90^{***}$ $1.16^{***}$		
TVL air quality	S	$\mathbf{L}$	Н	$\mathrm{H}-\mathrm{L}$		
PCBR NCSR	$0.69 \\ 0.95$	$0.53 \\ 0.67$	$0.84 \\ 1.19$	0.31*** 0.52***		
ESG home-bias ratio	S	$\mathbf{L}$	Н	$\mathrm{H}-\mathrm{L}$		
	0.19	0.24	0.15	-0.08		
Observations	6,151	3,076	3,075	6,151		
		Panel B: Financi	al-motive proxies	3		
	S	L	Н	$\mathrm{H}-\mathrm{L}$		
Avg. monthly number of trades PF turnover (%) Avg. monthly logins Disposition effect $\Delta$ (PGR, PLR)	$1.39 \\ 17.32 \\ 14.36 \\ 0.07$	$     1.12 \\     18.25 \\     12.49 \\     0.08 $	$1.67 \\ 16.41 \\ 16.20 \\ 0.07$	0.55*** -1.84** 3.72*** -0.01		
Observations	6,102	3,041	3,061	6,102		

#### Table D.2 Sustainability-motive and financial-motive proxies

Note. The above table presents sample averages for the sustainability-motive (Panel A) and financial-motive (Panel B) proxies. PCBR and NCSR stand for positive-change-buy-rate and negative-change-sell-rate, respectively, and divide the total number of buys (sells) after positive (negative) changes by the number of total buys (sells) over the sample period. The ESG home-bias ratio (referred to as EHBR throughout the paper) is the proportion of German assets which rank in the top quintile of TVL overall ratings over all top quintile rated assets divided by the number of German assets over the number of all assets at year-end of 2019. The average number of monthly trades and logins are measured over the sample period. Portfolio turnovers are computed following Dorn and Sengmueller (2009), and the disposition effect measures the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR), which we compute following Barberis and Xiong (2009). Columns with header S show averages for the whole sample, whereas columns titled L and H distinguish between below- and above-median footprints from consumption, respectively. Columns titled H - L report differences between the high- and low-footprint averages including their level of statistical significance using Welch's unequal variances t-test. Asterisks denote statistical significance of this difference at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

emissions and the sustainability of investments.

## D.3 Proxies for financial motives

Alternatively to offsetting behavior or heterogeneous sustainability preferences driving a potential relation of (un-)sustainable consumption and sustainable investments, it is possible that more (less) sustainable consumers invest more intensively in ESG assets in search for high returns or other financial motives. For instance, Brunen and Laubach (2022) find that ESG investing is aided by high expected returns. To contrast the explanatory power of potential compensation behaviors to financial motives, i.e., mainly behaviors that follow from a search for returns, we construct several further measures at the individual investor level.

One proxy for financial motives may be high (trading) activity. A retail investor propensity to overtrade and the detrimental impacts of excessive trading are well-studied (see, for instance, Barber and Odean, 2000, as a seminal example). Several drivers have been linked to excessive trading, among them overconfidence (Odean, 1998b; Barber and Odean, 2001), past returns and gambling motives (Grinblatt and Keloharju, 2001; Dorn and Sengmueller, 2009; Grinblatt and Keloharju, 2009; Kormanyos et al., 2023), or investors' perceptions of their own competence (Graham et al., 2009). We measure high trading activity by the sample average of monthly trades and portfolio turnovers following Dorn and Sengmueller (2009). To measure investors' attention to their finances, we leverage the sample average of monthly online banking logins as a proxy for general financial activity.<sup>35</sup> Finally, we construct a measure for the disposition effect as the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) to proxy for return-chasing motives as another well-studied behavioral trading bias (Shefrin and Statman, 1985; Odean, 1998a; Frazzini, 2006; Barberis and Xiong, 2009). Following Barberis and Xiong (2009), we compute this difference, or  $\Delta$  (PGR, PLR), based on the following computations of PGR and PLR:

$$PGR = \frac{\text{no. of realized gains}}{\text{no. of realized gains + paper gains}}$$
(4)

and

$$PLR = \frac{\text{no. of realized losses}}{\text{no. of realized losses} + \text{paper losses}}$$
(5)

 $<sup>^{35}</sup>$ Campbell and Frei (2010) analyze the relationship between bank performance and the availability of online banking services. They find that the provision of online banking services lead to a significant increase of transaction volumes. Xue et al. (2011) find that online banking usage is associated with higher trading activity at the individual level.

Barberis and Xiong (2009) document that the difference between the PGR and PLR is empirically positive and significant, constituting the disposition effect.

Panel B of Table D.2 displays summary statistics of the four financial-motive proxies across investors. On average, investors in the studied sample execute 1.39 trades per month, exhibit a monthly portfolio turnover of 17.32%, and log into their online banking 14.36 times per month. The disposition effect measure is 0.07 for the overall sample. Analogously to the sustainability proxies presented in Panel A of Table D.2, high-footprint consumers have a significantly higher number of monthly trades and logins than their low-emission counterparts (significant at the 1% level), but significantly lower portfolio turnovers. The disposition effect is not significantly different between groups.

## **E** Robustness analyses

## E.1 Alternative explanations

One primary concern with the findings presented in Table 1 of Section 3 is that higher-income investors have higher footprints from consumption by design (see Figure B.1 in Appendix B, Table C.1 in Appendix C, and Ivanova et al., 2020). If sustainability is a luxury good (e.g., Andersen et al., 2023), and therefore more attractive or attainable to high-income investors, results would be biased towards estimating negative spillovers. Therefore, we not only control for annual income in all regressions, but also test whether heterogeneous sustainability of investor portfolios better than high carbon emissions from consumption. To this end, we include each of the proxies for sustainability preferences and financial motives in the baseline regressions of Section 3 (equations 1 and 2).<sup>36</sup> Estimates are based on the following extension of the previous regression models:

$$\mathbf{V}_{\mathrm{ESG},i} = \beta_0 + \beta_1 \cdot D_i + \beta_2 \cdot P_i + \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k} + \varepsilon_i$$
(6)

and

$$\Pr(\mathcal{V}_{\text{ESG},i} = 1 \mid D_i, X_i) = \beta_0 + \beta_1 \cdot D_i + \beta_2 \cdot P_i + \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k} + \varepsilon_i, \quad (7)$$

where the new coefficient,  $\beta_2$ , measures the influence of the financial or sustainability-motive proxy  $P_i$  for investor *i* on sustainable portfolio outcomes. If heterogeneous sustainability preferences explain sustainable investments better than compensation behavior, we expect the coefficient of interest in equations 1 and 2,  $\beta_1$ , to lose statistical significance, and the effect of the respective sustainability proxy,  $\beta_2$ , to have a statistically significant impact on sustainability outcomes. If financial motives are driving the findings presented in Table 1, we expect  $\beta_1$  to lose significance upon including financial motive-proxies, and  $\beta_2$  to have a statistically significant influence. If  $\beta_1$  retains significance in either case, compensation behavior is either as significant or more significant than the included proxy to explain

 $<sup>^{36}</sup>$ For a detailed breakdown of the calculation of the proxies used, please see Appendix D.2 and D.3.

### sustainable PF outcomes.

	(1) Holds top rated	(2) % PF top rated	(3) % AS top rated	(4) PF ESG score	(5) Top PF ESG score				
	Marg. effect	Coef.	Coef.	Coef.	Marg. effect				
	Coefficient of interest (COI) before inclusion								
Above-median	0.087***	5.311***	0.436**	7.039***	0.049***				
carbon footprint	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)				
	Panel A: sustainability-motive proxies								
PCBR	0.006***	0.137***	0.001	0.518***	0.000				
	(0.000)	(0.000)	(0.744)	(0.000)	(0.985)				
COI	$0.065^{\diamond\diamond\diamond}$	$2.419^{\diamond\diamond\diamond}$	$0.212^{\diamond}$	$5.611^{\diamond\diamond\diamond}$	$0.026^{\diamond\diamond\diamond}$				
	(0.000)	(0.000)	(0.053)	(0.000)	(0.006)				
NCSR	0.004***	$0.139^{***}$	0.002	0.327***	0.000				
	(0.000)	(0.000)	(0.195)	(0.000)	(0.229)				
COI	$0.095^{\diamond \diamond \diamond}$	$3.689^{\circ \circ \circ}$	$0.175^{\diamond}$	6.807***	0.040***				
	(0.000)	(0.000)	(0.058)	(0.000)	(0.000)				
EHBR	0.005***	0.007	0.001	0.229***					
	(0.000)	(0.799)	(0.693)	(0.002)					
COI	0.088	$5.312^{\circ \circ \circ}$	$0.436^{\diamond \diamond}$	$7.074^{\circ \circ \circ}$	$0.049^{\diamond\diamond\diamond}$				
	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)				
	Panel B: financial-motive proxies								
Monthly trades	0.019***	-0.106	-0.018**	1.028***	-0.003				
	(0.000)	(0.123)	(0.013)	(0.000)	(0.116)				
COI	$0.078^{\diamond\diamond\diamond}$	$3.725^{\diamond\diamond\diamond}$	$0.239^{\diamond\diamond}$	$6.949^{\circ \circ \circ}$	$0.037^{\diamond\diamond\diamond}$				
	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)				
PF turnover (%)	-0.175***	7.883***	0.274***	-3.825*	0.051***				
	(0.000)	(0.000)	(0.001)	(0.065)	(0.000)				
COI	$0.083^{\diamond\diamond\diamond}$	$3.409^{\diamond\diamond\diamond}$	$0.231^{\diamond\diamond}$	$7.068^{\diamond\diamond\diamond}$	$0.033^{\diamond\diamond\diamond}$				
	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)				
Monthly logins	0.001***	0.002	-0.001	0.027	-0.000*				
	(0.001)	(0.912)	(0.823)	(0.316)	(0.083)				
COI	0.083***	$5.174^{\circ \circ \circ}$	$0.437^{\diamond \diamond}$	6.912	0.050***				
	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)				
Disp. effect	0.020	$4.495^{*}$	0.122*	-1.240	0.045***				
$(\Delta PGR - PLR)$	(0.456)	(0.011)	(0.063)	(0.536)	(0.007)				
COI	0.113***	5.143***	0.108***	$7.267^{\diamond \diamond \diamond}$	0.045***				
	(0.000)	(0.000)	(0.006)	(0.000)	(0.006)				

Table E.1.1 Sustainable investments and trading-motive proxies

Since Table 1 in Section 3 exhibits the most consistent evidence of offsetting behavior for outcomes based on GHG emission ratings and these are arguably the most relevant to investors seeking to offset their footprints, we present only the results for PF sustainability outcomes based on emission ratings in Table E.1.1. Analogously to Table 1, we present

Note. The above table displays results from several logistic (columns 1 and 5) and OLS regressions (columns 2, 3, and 4) of the sustainability indicators constructed from asset- and portfolio-level TVL ratings as described in Section D.1. All models are estimated separately for the TruValueLabs (TVL) Overall, GHG emissions, Ecological, and Air quality ratings as indicated by the row labels of the above table. Specifically, the dependent variables used in all regressions are Holds top rated, which is equal to one if an investor holds at least one security which ranks in the top 20% of ratings (column 1), % PF top rated (column 2) and % AS top rated (column 3), which measure the portfolio and asset shares devoted to these top-rated assets, respectively, PF ESG score, which measures the value-weighted composite ESG score for each investor's portfolio (column 4), and Top PF ESG score, which is equal to one for investors whose portfolio ESG scores rank in the top quintile (top 20%) of all investors' scores, and zero otherwise (column 5). Regressions follow the baseline specifications from Table 1. Each regression model, however, adds one proxy for heterogeneous sustainability preferences or financial (return-chasing) motives as defined in Sections D.2 and D.3. The reported coefficients show the estimated change in the main COI (coefficient of interest, i.e., the above-median footprint dummy), statistical significance is indicated by diamonds at the 1% ( $^{\circ\circ}$ ), 5% ( $^{\circ}$ ), and 10% ( $^{\circ}$ ) levels, respectively. All regressions control for investors' profession, age, gender, marital status, joint account usage, median annual net income, trading risk classes elicited by the bank, and product ownership.

estimates and corresponding *p*-values for the coefficient of interest (COI) on above-median carbon footprints after inclusion of each proxy,  $\beta_1$ , as well as estimates for the proxy,  $\beta_2$ . As outlined in Appendices D.2 and D.3, we use the PCBR, NCSR, and EHBR to proxy for sustainability-preference motives, and average monthly trades, logins, portfolio turnovers, and the disposition effect measure as financial-motive proxies.

### E.1.1 Sustainability motives

Both the PCBR and NCSR significantly and positively influence investors' probabilities to hold high-ranking assets (column 1), portfolio shares devoted to assets ranking in the top 20% of GHG emissions scores (column 2), and composite portfolio ESG scores (column 4, all significant at the 1% level). For asset shares held in top-ranking securities and the likelihood to rank in the top 20% of portfolio ESG scores, the PCBR and NCSR do not offer additional explanatory power beyond that of unsustainable consumption. The ESG home bias ratio offers additional explanatory power for the likelihood of holding top-ranking assets (column 1, significant at the 1% level) and for the composite ESG score (column 4, 5% level). Again, the COI remains unchanged. The COI on unsustainable consumption does not decrease in significance and only marginally changes in magnitude after including the PCBR, NCSR, or EHBR, suggesting that financial motives offer *additional* explanatory power, but are unable to explain sustainable investments to a larger extent than unsustainable consumption. For the remainder of the outcomes, the PCBR, NCSR, and EHBR are not statistically significant.

Overall, both sustainability preferences and offsetting behavior are conceivable drivers of sustainable investments targeted at lowering GHG emissions, jointly influencing the sustainability of portfolio outcomes. However, heterogeneous sustainability preferences, and thereby the potential influence of income in driving this demand heterogeneity, are not *more* influential than the proposed offsetting mechanism.

### E.1.2 Financial motives

Return-chasing proxies show mixed results for direction and statistical significance. The propensity to hold high-ranking GHG emissions assets is positively influenced by monthly trades and online banking logins, but negatively by portfolio turnovers (column 1, all significant at 1%). For portfolio and asset shares in top-rated assets, monthly trades and portfolio turnovers show opposite effects, with significance ranging from 1% to 10%

(columns 2 and 3). Higher portfolio turnovers and the disposition effect are positively related to the likelihood of portfolios ranking in the top quintile of composite portfolio ESG scores (column 5, significant at 1% and 5%, respectively). The disposition effect is also positively related to portfolio shares in top-rated assets (column 2).

Financial motives do influence the sustainability of investor portfolios regarding GHG emissions, but the effects vary. The coefficient on high emissions from consumption remains significant and generally maintains its magnitude. If behavioral biases like excessive trading, overconfidence, or sensation-seeking were driving the sustainability of investor portfolios, the coefficients should consistently be positive. However, the significance of the positive relation between unsustainable consumption behavior (measured by carbon footprints) and sustainable investments sometimes increases when financial-motive indicators are included, compared to the baseline model (Table 1). This suggests that compensation behavior for high-emission investors cannot be fully explained by financial-motive proxies, and high-footprint investors are not merely chasing returns by investing in ESG assets.

High-emission investors may try to compensate for their carbon footprints by investing in ESG assets while also exhibiting behavioral biases related to financial motives. However, these biases do not explain sustainable investments concerning GHG emissions more than high emissions from consumption. Coefficients on financial-motive and sustainability-motive proxies are generally smaller than those on the COI, emphasizing that unsustainable consumption better explains investment sustainability than tested alternatives. The results of Table E.1.1 support our main findings from Section 3 that high-footprint investors (i) are aware of their consumption's environmental impact and (ii) aim to offset these impacts by investing more in assets targeting carbon emission reduction.

## E.2 Carbon intensity specification

One major concern beyond the potentially heterogeneous preference for sustainable assets based on return-chasing or sustainability motives addressed in Appendix E.1, (Section 3) might be that high-income investors have higher carbon footprints by design, i.e., because consumption tends to increase with income, and consumption itself is positively related to footprints from consumption.

To address this concern in a more straightforward manner, we offer alternative specifications

of unsustainable consumption that are independent of income in Table 2 of Section 3. In Table E.2.1 of this Appendix, we present results for the full set of TVL ratings-based PF sustainability outcomes. Specifically, we divide total emissions from consumption by total consumption (income) to obtain income-independent measures of carbon intensity, subsequently referred to as the carbon intensity of consumption (carbon intensity of income). Since they abstract from issues where emissions increase mechanically with the measured activity, carbon intensities enable objective comparisons of climatically relevant activities in various settings, and are therefore prominently used in official sustainability reports.

The adjustment yields largely similar results as the baseline specification: Investors with an above-median carbon intensity of consumption (income) are significantly more likely to hold top-rated securities, have significantly higher portfolio and asset shares devoted to high-ranking securities, exhibit higher composite portfolio ESG scores, and are significantly more likely to rank in the top quintile of PF ESG scores compared to all low-intensity investors with respect to GHG emissions and air quality ratings. This finding rules out that the baseline findings presented in Table 1 are driven by income effects.

The magnitude and significance for the carbon intensity of consumption (Panel A) are close to the baseline results. For the carbon intensity of income (Panel B), results are marginally less strongly pronounced. Importantly, however, based on carbon intensities, the positive relation of unsustainable consumption and sustainable investing presented in Table 1 can only be confirmed for GHG emissions and air quality ratings. This fact offers additional support for the hypothesis that investors consider only assets which promise lowering GHG emissions and improved air quality as viable offsetting instruments.

## E.3 Investor sample definition

Table E.2.1 in Appendix E.2 supports our key findings, showing that negative spillovers between unsustainable consumption and sustainable investments are not driven by general income or consumption levels. As detailed in Section 2 and Appendix A, several sample restrictions were imposed to estimate the baseline cross-domain spillovers for main and income account users.

We now assess the robustness of the baseline findings in Table 1 using different investor

	(1) Holds top			(4)	(5) Top PF ESG				
	rated	rated	rated	PF ESG score	score				
	Panel A: Carbon intensity of consumption								
Overall	-0.004 (0.644)	$0.048 \\ (0.866)$	-0.091 (0.184)	$2.293^{***}$ (0.001)	-0.006 (0.489)				
GHG emissions	$0.038^{***}$ (0.001)	$3.294^{***}$ (0.000)	$0.141 \\ (0.322)$	$2.811^{***} \\ (0.001)$	$0.041^{***}$ (0.000)				
Ecological	-0.005 (0.629)	$0.668^{**}$ (0.035)	-0.052 (0.392)	$1.751^{**}$ (0.019)	$0.002 \\ (0.777)$				
Air quality	$0.000 \\ (0.978)$	$\begin{array}{c} 0.333 \\ (0.138) \end{array}$	-0.064 (0.237)	$1.324^{**}$ (0.010)	-0.010 (0.184)				
Controls	Yes	Yes	Yes	Yes	Yes				
Observations	6,151	6,151	6,151	6,151	6,151				
		Panel B: C	Carbon intensit	y of income					
Overall	$-0.016^{*}$ (0.070)	-0.175 (0.519)	$0.043 \\ (0.607)$	$0.845 \\ (0.238)$	-0.009 (0.288)				
GHG emissions	$0.030^{**}$ (0.011)	$3.052^{***}$ (0.000)	$0.319^{**}$ (0.030)	$1.389 \\ (0.111)$	$0.030^{***}$ (0.000)				
Ecological	-0.004 (0.665)	$0.103 \\ (0.745)$	$0.029 \\ (0.681)$	$0.762 \\ (0.320)$	-0.009 (0.271)				
Air quality	-0.006 (0.479)	$0.187 \\ (0.391)$	$0.014 \\ (0.831)$	$1.104^{**}$ (0.037)	-0.005 (0.515)				
Controls	Yes	Yes	Yes	Yes	Yes				
Observations	6,151	6,151	6,151	6,151	6,151				

#### Table E.2.1 Robustness analysis: Carbon-intensity specification

Note. The above table displays results from eight logistic (columns 1 and 5) and twelve OLS regressions (columns 2, 3, and 4) of the sustainability indicators constructed from asset- and portfolio-level TVL ratings as described in Section D.1. All models are estimated separately for the TruValueLabs (TVL) Overall, GHG emissions, Ecological, and Air quality ratings as indicated by the row labels of the above table. Specifically, the dependent variables used in all 20 regressions are Holds top rated, which is equal to one if an investor holds at least one security which ranks in the top 20% of ratings (column 1), % PF top rated (column 2) and % AS top rated (column 3), which measure the portfolio and asset shares devoted to these top-rated assets, respectively, PF ESG score, which is equal to one for investors whose portfolio ESG scores rank in the top 20% of all investors's cores, and zero otherwise (column 5). The coefficient estimates and p-values presented above capture the difference between investors with an above-median carbon intensity of consumption (Panel A) or carbon intensity of income (Panel B) and those with below-median annual net income, trading risk classes elicited by the bank, and financial product ownership. p-values based on robust standard errors are presented underneath coefficients in parentheses. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

sample definitions. The main analysis is repeated, sequentially adding restrictions, for the unrestricted sample, investors with complete income and wealth data, those with an annual income of at least EUR 10,000 from salaries, wages, and pensions, and regular income receivers (defined as investors receiving permanent income for at least 75% of the sample period months). Please refer to Table A.1 in Appendix A for the full sample breakdown.

Unrestricted sample	(1) Holds top rated	(2) % PF top rated	(3) % AS top rated	(4) PF ESG score	(5) Top PF ESG score				
Overall	-0.041***	-0.586***	0.031	8.951***	0.131***				
GHG emissions	-0.047*** (0.000)	(0.002) -0.049 (0.892)	(0.370) 0.230*** (0.001)	(0.000) 10.603*** (0.000)	(0.000) $0.167^{***}$ (0.000)				
Ecological	-0.041***	-0.099	0.080**	(0.000) 8.890*** (0.000)	0.130***				
Air quality	-0.031*** (0.000)	(0.003) $-0.348^{**}$ (0.021)	(0.032) 0.003 (0.922)	(0.000) $5.591^{***}$ (0.000)	(0.000) $0.148^{***}$ (0.000)				
Observations	19,929	19,929	19,929	19,929	19,929				
Non-missing income	and wealth data								
Overall	-0.041***	-0.654***	0.030	9.430***	0.138***				
GHG emissions	-0.045***	-0.032	(0.404) 0.195***	(0.000)	0.175***				
Ecological	(0.000) -0.040***	(0.929) -0.072	(0.003) $0.083^{**}$	(0.000) $9.365^{***}$	(0.000) $0.137^{***}$				
Air quality	(0.000) - $0.030^{***}$ (0.000)	(0.714) - $0.353^{**}$ (0.021)	$(0.034) \\ 0.002 \\ (0.949)$	$(0.000) \\ 5.889^{***} \\ (0.000)$	$(0.000) \\ 0.156^{***} \\ (0.000)$				
Observations	19,011	19,011	19,011	19,011	19,011				
Permanent net annua	Permanent net annual income $\geq EUR \ 10,000$								
Overall	-0.041***	-0.558***	0.029	10.030***	0.142***				
GHG emissions	-0.054***	-0.256	(0.476) 0.259***	(0.000) 11.867***	(0.000) 0.181***				
Ecological	(0.000) -0.045***	(0.520) -0.209	(0.000) $0.061^*$	(0.000) $9.975^{***}$	(0.000) $0.141^{***}$				
Air quality	(0.000) - $0.035^{***}$ (0.000)	$(0.302) \\ -0.396^{**} \\ (0.018)$	(0.099) -0.003 (0.942)	(0.000) $6.259^{***}$ (0.000)	$(0.000) \\ 0.161^{***} \\ (0.000)$				
Observations	17,989	17,989	17,989	17,989	17,989				
Regular income receiv	vers								
Overall	-0.016	-1.228**	0.055	13.199***	$0.134^{***}$				
GHG emissions	(0.212) -0.022 (0.178)	(0.035) -1.557 (0.126)	(0.173) 0.144 (0.445)	(0.000) 15.940*** (0.000)	(0.000) 0.219*** (0.000)				
Ecological	-0.016	(0.130) 0.043 (0.024)	(0.443) $0.065^{*}$ (0.088)	13.210***	0.138***				
Air quality	(0.287) -0.018 (0.151)	(0.924) -0.529 (0.228)	(0.088) 0.024 (0.200)	(0.000) $8.454^{***}$ (0.000)	(0.000) $0.184^{***}$ (0.000)				
Observations	9,901	9,901	9,901	9,901	9,901				

Table E.3.1 Robustness analysis: Investor sample

Note. The above table displays results from eight logistic (columns 1 and 5) and twelve OLS regressions (columns 2, 3, and 4) of the sustainability indicators constructed from asset- and portfolio-level TVL ratings as described in Section D.1. All models are estimated separately for the TruValueLabs (TVL) Overall, GHG emissions, Ecological, and Air quality ratings as indicated by the row labels of the above table. Specifically, the dependent variables used in all 20 regressions are Holds top rated, which is equal to one if an investor holds at least one security which ranks in the top 20% of ratings (column 1), % PF top rated (column 2) and % AS top rated (column 3), which measure the portfolio and asset shares devoted to these top-rated assets, respectively, PF ESG score, which is equal to one for investors whose portfolio ESG scores rank in the top 20% of all investors' scores, and zero otherwise (column 5). Each set of regressions displays results for a different choice of sampling restriction based on the descriptions in Section 2 (see also Table A.1). The coefficient of interest presented above captures the difference between above- and below-median footprint investors. Regressions control for socio-demographics and financial product ownership. p-values based on robust standard errors are presented underneath coefficients in parentheses. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

Table E.3.1 presents the results. The robustness of the baseline findings varies by outcome variable. The findings for composite portfolio ESG scores (column 4) remain significant across TVL rating categories and are even more prominent for less restrictive samples. The asset share devoted to top 20% TVL ratings (column 3) retains statistical significance for GHG emission ratings across all investor sample definitions except for the

income-receiver specification, with increased significance for other sample definitions. The likelihood of investors with above-median carbon footprints from consumption to rank in the top quintile of portfolio ESG scores (column 5) remains statistically significant across TVL rating categories and sample definitions, indicating robustness to sampling choice and potential offsetting for other rating categories besides emission or air quality profiles.

However, estimates for the propensity of unsustainable consumers to hold any top-ranking asset (column 1) and the portfolio share devoted to such assets (column 2) are ambiguous. These results should be interpreted with caution, especially for the likelihood of investing in any top-ranking asset: Without the baseline restrictions, estimates may capture effects for infrequent account users or those using accounts for specific purposes such as savings, retirement, or travel expenses. Given that holding any top-ranking asset (column 1) is a weak measure of portfolio sustainability compared to the other PF sustainability outcomes, the ambiguous findings for this specific outcome do not change the main takeaway. Overall, the results in Table E.3.1 are sufficiently close to the main findings to suggest that our results are not driven by sample selection.

# **F** Internet Appendix

## F.1 Value-added tax rates used for carbon footprint estimation

Consumption (sub-)category	Applicable tax rate in Germany	Consumption (sub-)category	Applicable tax rate in Germany
Food / beverages	7%	Tuition fees	0%
Further education	0%	Retirement provision	0%
Building savings	0%	Savings account & call money	0%
Investment in securities	0%	Savings plan	0%
Rent / utilities	35%	Personal liability insurance	19%
Health insurance	0%	Life insurance	0%
Pension insurance	0%	Construction financing	0%
Books / music / movies / apps	7%	Car loan	0%
Installment loan	0%	Other loans	0%
Donations	0%	Public transport	7%
Cash deposits	0%	Special payments / bonuses	0%
Refueling	45%	Rental income	0%
Pension / annuity	0%	Medical treatment Interest / dividends /	0%
Government benefits	0%	distributions	0%
Hospital	0%	Child benefit	0%
Reimbursements	0%	Public funds / tax	0%
Child support	0%		

Table F.1.1 Tax rates in Germany (2022)

*Note.* The above table displays applicable tax rates for VAT as of March 2022 only where they deviate from the standard 19%. To comply with the data privacy of our partnering bank, we cannot list all available consumption categories. In Germany, the VAT is included in retail prices and therefore not directly visible to consumers. The shown consumption categories include all categories known to the classification algorithm which our partnering bank uses to categorize checking account bookings. For uncategorized, other, and cash consumption, we assume the standard tax rate of 19%, since goods that cannot be categorized by the bank, do not fall within any of the other categories, and cash consumption are most likely subject to this standard rate.

Approximation of tax rates for electricity and fueling While most products and services in Germany are taxed at 0% (mainly financial services), 7% (mainly basic consumer staples such as food) or 19% (standard VAT rate), electricity and fueling present two notable exemptions. These two consumption categories are ambiguous in the sense that there is not a fixed and/or unique tax rate per Euro spent. First, electricity and sewage are combined in the analyzed sample. While electricity is taxed at 41% total tax (incl. surcharges), sewage is taxed at 19%. Therefore, we compute an average tax rate based on shares of the respective cost based on an average German single-person household. While sewage cost accounts for an average of 280 EUR per annum based on data for Germany's largest state (North-Rhine Westphalia), electricity accounts for 690 EUR on average.<sup>37,38</sup> However, German renters usually do not pay sewage directly but through an annual payment to their landlords. As 58% of Germans are renters, we cut the average sewage cost by this rate, i.e., to 118 EUR.<sup>39</sup> This implies 85% electricity cost and 15% sewage cost, which is equivalent to an average tax rate of 35%. Second, taxation of refueling requires attention as there is no fixed tax rate as a percentage of total cost. Some cost components are fixed in absolute terms. Due to the high volatility of refueling cost, the implied total tax rate (incl. surcharges) varies significantly. Based on data from the German Federal Office for Motor Traffic and Germany's largest automobile association ADAC, taxes and surcharges account for 45% of refueling cost on average. We therefore use this tax rate to net refueling consumption.<sup>40</sup>

## F.2 Additional survey evidence

In this Appendix, we provide additional survey-based evidence to support that compensating consumption-based carbon emissions is one significant driver of the demand for sustainable investments. To this end, we conduct a survey with 3,646 clients of the same bank that provided the investor data for this paper. In addition to questions on socio-demographics, financial literacy, stock market participation, and risk preferences, we survey the participants' estimates, opinions and prior experience with key aspects of our baseline findings. Specifically, participants provide an estimate of their own carbon footprint from consumption, defined as total emissions from the relevant consumption categories and as described in Appendix B. We ask participants to provide this estimate in kgCO<sub>2</sub> per capita and annum so as not to bias results upwards by suggesting values in metric tonnes. Participants are then asked to rank their own footprints compared to their peers with respect to age, profession, and income on a Likert scale from 1 to 7, where 1 (7) indicates a much lower

<sup>&</sup>lt;sup>37</sup>https://www.blitzrechner.de/wasserkosten/#wasserkosten-berechnen, accessed in March 2022.

<sup>&</sup>lt;sup>38</sup>https://www.gasag.de/magazin/neudenken/stromverbrauch-ein-personen-haushalt# showResults, accessed in March 2022.

<sup>&</sup>lt;sup>39</sup>https://de.statista.com/statistik/daten/studie/237719/umfrage/ verteilung-der-haushalte-in-deutschland-nach-miete-und-eigentum/

<sup>&</sup>lt;sup>40</sup>Please refer to the ADAC home page for more information (https://www.adac.de/ verkehr/tanken-kraftstoff-antrieb/tipps-zum-tanken/7-fragen-zum-benzinpreis/), and to the resources from the Federal Office for Motor Traffic (https://de.statista.com/statistik/daten/ studie/4270/umfrage/pkw-bestand-in-deutschland-nach-kraftstoffarten/).

(higher) footprint than their peers'. Finally, we query whether the participants have used certain compensation methods in the past. For this question, we offer a free-entry field in addition to several pre-set options, among them sustainable investing. We take care to list sustainable investing as one of the middle options so as not to anchor the participants in choosing this option. Figure 1 shows all pre-set options as well as the frequency with which participants selected them (all answers including *t*-tests for sample means are also listed in full in Table F.2.3 at the end of this Appendix).

Table F.2.1 presents the estimated and actual carbon footprints for the 2,383 survey participants for whom we observe consumption data. Actual footprints are computed following the description in Appendix B. Generally, survey participants tend to overestimate their carbon footprints on average, however, this finding might be driven by outliers, i.e., very high estimates.<sup>41</sup> On average, participants estimate an annual footprint of 9.48 tCO<sub>2</sub>, which is reasonably close to the official estimate of 11.6 tCO<sub>2</sub>.<sup>42</sup> Importantly, however, participants have much *lower* overall *actual* footprints than the average investor in the main set of analyses presented in this paper, with values ranging from 7.34 to 7.98 tCO<sub>2</sub> p.a. (compare Table C.1). At such values, they are closer to the below-median footprint sample than the average investor sample analyzed in the baseline analyses, who exhibit average footprints of 7.22 and 14.16 tCO<sub>2</sub> p.a., respectively.

This generally lower level of consumption-driven emissions for the surveyed individuals might explain the fact that survey participants who state that they have compensated their carbon emissions with sustainable investments in the past provide an even lower footprint estimate at  $7.34 \text{ tCO}_2$  – a result that might seem to counter our key findings at first sight. Conversely, however, it is also possible that these individuals already factored in their compensation efforts, and thus provide generally lower estimates after subtracting the perceived benefit of investing sustainably or using other offsetting methods. It is additionally important to note that Table F.2.1 does not distinguish between over- and underestimated footprints, which is why a more detailed inspection by the direction of misestimation is required to grasp how individuals estimate their own footprints (Figures F.2.1, F.2.2, F.2.3, and F.2.4). In addition, participants do not know other participants' answers, which is why we additionally segment the likelihood to choose

 $<sup>^{41}</sup>$ We winsorize all footprint estimates at the 5% level to limit the influence of outliers. We choose this relatively high level of winsorization since there are quite a few extreme outliers. The value at which winsorization occurs is a carbon footprint of 100 tCO<sub>2</sub>.

<sup>&</sup>lt;sup>42</sup>https://www.umweltbundesamt.de/klimaneutral-leben-persoenliche-CO2-bilanz-im-blick

	Mean	Min.	P5	P25	P50	P75	P95	Max.
			All	survey	partici	pants		
Estimated	9.48	0	0	1	10	100	22.84	2,383
Actual	7.43	0	2	5	10	74	7.55	2,383
	Compensate with SRI: Yes							
Estimated	8.00	0	0	3	10	100	17.01	311
Actual	7.98	0	2	5	11	63	8.62	311
			Com	pensate	with S	RI: No		
Estimated	9.70	0	0	1	10	100	23.58	2,072
Actual	7.34	0	3	5	10	74	7.37	2,072

Table F.2.1 Survey: Footprint estimates

Note. The above table presents estimated and actual carbon footprints for participants in the survey. Observed, or actual, footprints are calculated at the individual level as described in Section B. Survey participants are asked to estimate their total carbon footprint from consumption in kgCO<sub>2</sub> following the same calculation logic used to estimate actual footprints, i.e., by subsuming consumption across the analogous categories. Statistics titled *All survey participants* present overall descriptives, whereas results titled *Compensate with SRI: Yes (Compensate with SRI: No)* select only those survey participants who stated (did not state) that they have consciously attempted to compensate their consumption-driven emissions by investing more sustainably in the past or are (not) actively doing so. All numbers are based on a survey conducted in October 2022 with 3,646 clients of the same bank that provided the administrative data analyzed in the main part of this paper. Since administrative consumption data is not available for all survey participants, the sample underlying the above figures comprises 2,383 individuals.

sustainable investing as a means to offset carbon footprints by the provided assessment of participants' footprints in relation to their peers. Arguably, this variable is a more direct measure of high and low carbon footprints in the survey setting. The respective results are presented below in Table F.2.2.

Figure F.2.1 shows the frequency and degree of under- and overestimated carbon footprints. Specifically, we compute the deviation of estimated and actual carbon footprints at the individual level such that negative (positive) values indicate underestimations (overestimations). The top panel of Figure F.2.1 shows that, while individuals who underestimate their footprints generally exhibit lower deviations from their actual footprints, the vast majority of participants provides estimates that are too low (1,595 vs. 788 participants). This validates the need to inspect misestimations in more detail, as the average numbers presented above in Table F.2.1 suggest otherwise. Still, the difference between estimated and actual footprints is sizable in both directions at roughly 7.5 tCO<sub>2</sub> (underestimated) and more than 20 tCO<sub>2</sub> (overestimated), respectively, suggesting that both effects cancel out in the general mean-sample analysis of Table F.2.1. The lower panel of Figure F.2.1 shows that, in addition to the general finding that most individuals under-estimate their footprints, the degree of misestimation in both directions increases dramatically with the size of the participants' *actual* footprints.<sup>43</sup> At the seventh septile of actual footprints, 316 (24) participants underestimate (overestimate) their own footprints by about 23 tCO<sub>2</sub> (over 70 tCO<sub>2</sub>).

Next, we inspect the drivers of the deviation of real and estimated consumption-driven carbon footprints. To this end, we run separate regressions of the difference between estimated and actual footprints by the direction of misestimation, i.e., separately for positive (overestimation) and negative (underestimation) deviations on five sets of independent variables. Figures F.2.2, F.2.3, and F.2.4 depict the coefficient estimates from these regressions. All cross-sectional regressions use standard errors clustered at the individual level. In each Figure, orange dots and confidence intervals indicate estimated coefficients for individuals who underestimated their carbon footprints, whereas blue dots and confidence bars denote analogous estimates for those who overestimated them. Figure F.2.2 shows that, analogous to the sample-mean analyses of Figure F.2.1, the degree of misestimation is positively related to the direction in which participants' estimates deviate from their actual footprints, i.e., actual footprints are significantly negatively related to the difference between actual and estimated footprints for individuals who provide underestimations, whereas the opposite holds for overestimations. This is unsurprising. however, when split by the septile of actual footprints, the magnitude of observed emissions significantly influences the degree of misestimation only for underestimated carbon footprints, whereas overestimated emissions are only significantly driven by actual footprints in the sixth and seventh septile.

Of particular interest is whether certain variables for demographic and behavioral characteristics drive the extent and likelihood of misestimating carbon footprints. To this end, Figures F.2.3 and F.2.4 present coefficient estimates for the difference between estimated and observed footprints by the direction of misestimation for demographic information on gender, marital status, professions, and financial product ownership. Therein, all coefficients show the deviation in estimated and observed emissions in tCO<sub>2</sub>. Specifically, Figure F.2.3 shows that males, married individuals, managers, blue-collar workers, homemakers, and students exhibit significantly higher degrees of underestimating their carbon footprints

 $<sup>^{43}</sup>$ The seven sub-figures in the lower panel of Figure F.2.1 show positive and negative deviations of the participants' estimated from their actual footprints split by septiles of actual footprints. We choose septiles to mimic the Likert scale on which participants are asked to rank their own footprints in a later part of the survey.



Figure F.2.1 Survey: Differences between estimated and observed carbon footprints

Note. The above figures depict the extent to which survey participants under- or overestimate their own carbon footprints from consumption. All bars show the average deviation between estimated and observed carbon footprints, and red lines indicate the corresponding 95% confidence intervals. The unit of the values on the primary y-axis (left) is  $tCO_2$ , whereas the secondary y-axis (right) shows the total number of survey participants. On this secondary axis, the depicted dots with annotations indicate the number of survey participants who under- or overestimated their carbon footprint to the extent indicated by the height of the blue bars. Values on the x-axis titled "Underestimated" (U in lower panel) capture individuals for whom the observed footprint exceeds their estimate (negative deviation). The opposite holds for bars titled "Overestimated" (O in lower panel). Observed footprints are calculated at the individual level and as described in Appendix B. Since administrative consumption data is not available for all survey participants, the sample underlying the above figures comprises 2,383 individuals. The top panel of the above figure shows overall averages and distributions, whereas the bottom panel shows analogous numbers separated by septiles of actual carbon footprints. We choose septiles since participants are asked to provide an assessment of how they believe their footprint ranks compared to their peers with respect to age, income, and profession on a Likert scale from 1 to 7, where 1 stands for "much lower" and 7 for "much higher".

than others, whereas – among all overestimators – only managers significantly overstimate their carbon footprints than other populations. The lower panel of Figure F.2.3 shows that securities account, consumer loan, property loan, and savings account owners additionally exhibit significantly higher degrees of footprint underestimation, whereas, among overestimators, only securities account owners have statistically significant positive differences. Finally, inspecting marginal effects of the *likelihood* to underestimate one's carbon footprints across demographic characteristics reveals that regular employees, retirees and blue-collar workers (males and students) are significantly more (less) likely to underestimate their emissions compared to other demographic groups (Figure F.2.4).

Central to the survey analysis is the inspection of whether choosing sustainable investing as a means to offset carbon footprints is more prevalent among participants with above-median



Figure F.2.2 Survey: Heterogeneity of footprint misestimation (I)

*Note.* The above figures show the relation of observed footprints and differences between actual footprints and estimates provided by the survey participants. The upper panel shows how actual footprints in  $tCO_2$ influence over- or underestimations, whereas the bottom panel shows estimates for septiles of actual footprints, where the fourth septile is the base category. We choose septiles since participants are asked to provide an assessment of how they believe their footprint ranks compared to their peers with respect to age, income, and profession on a Likert scale from 1 to 7, where 1 stands for "much lower" and 7 for "much higher". Underestimated footprints capture negative differences between observed and estimated footprints, that is, individuals for whom the observed footprint exceeds their estimate, whereas overestimated footprints originate from a positive deviation. Observed footprints are calculated at the individual level and as described in Appendix B. Since administrative consumption data is not available for all survey participants, the sample underlying the above figures comprises 2,383 individuals. All coefficients and confidence intervals are based on two separate regressions split by the direction of misestimation. In each figure, orange dots and confidence bars present estimated coefficients for individuals who underestimated their carbon footprints, whereas blue dots and confidence intervals denote analogous estimates for those who overestimated them. Each coefficient estimate is annotated by its respective p-value obtained in these regressions. The unit of coefficients and confidence intervals is  $tCO_2$ . Standard errors are clustered at the individual level.

consumption-driven footprints. Based on the survey participants' answers and actual observed footprints, this question can be tackled both from the angle of perceived and observed footprints. Among all 3,646 survey participants, 2,702 (74.11%) state that they have used any form of compensation to help offset their carbon footprints from consumption.<sup>44</sup> This is strong indicative evidence that investors believe they can make up for perceived wrongdoings in one domain by doing better in another. Therein, the survey answers in line with interpretations of moral licensing and guilt reduction as well as the main results of our analyses. Figure 1 presents the frequency with which the survey participants stated that they have used one or more method to help compensate for their consumption-driven emissions. Among all provided answers, sustainable investing is the

<sup>&</sup>lt;sup>44</sup>This figure is based on the number of all participants who selected any of the provided answers or entered valid options in the free-entry field.



Figure F.2.3 Survey: Heterogeneity of footprint misestimation (II)

Note. The above figures show the relation of demographic characteristics (upper panel) and financial-product ownership (lower panel) to differences between actual footprints and estimates provided by the survey participants. Underestimated footprints capture negative differences between observed and estimated footprints, that is, individuals for whom the observed footprint exceeds their estimate, whereas overestimated footprints originate from a positive deviation. Observed footprints are calculated at the individual level and as described in Appendix B. Since administrative consumption data is not available for all survey participants, the sample underlying the above figures comprises 2,383 individuals. All coefficients and confidence intervals are based on two separate regressions split by the direction of misestimation. In each figure, orange dots and confidence bars present estimated coefficients for individuals who underestimated their carbon footprints, whereas blue dots and confidence intervals denote analogous estimates for those who overestimated them. Each coefficient estimate is annotated by its respective p-value obtained in these regressions. The unit of coefficients and confidence intervals is tCO<sub>2</sub>. Standard errors are clustered at the individual level.

seventh most frequently chosen. Since *No offset* remains in Figure 1, sustainable investing is actually the sixth most popular answer at the intensive margin.

The results presented in Table F.2.1 above suggest that participants who choose sustainable investing to offset, on average, provide lower estimates of their carbon footprints, which might be due to them factoring in their perceived compensation benefits. Importantly, however, the *actual* footprints of those individuals are higher than those of participants who do not use sustainable investments as a means of compensation (7.97 vs. 7.34 tCO<sub>2</sub>). As a more formal assessment of whether individuals who believe that their emissions are higher than their peers', Table F.2.2 presents the prevalence of choosing sustainable investing as a compensation method split by the participants' assessments of how their footprints rank compared to their peers. We code all answers larger than five as assessments of above-median footprints for the purpose of validating our empirical findings. Indeed, participants who believe that they have above-median footprints are 4.71% more likely to compensate with sustainable investments than others (difference statistically significant



Figure F.2.4 Survey: Heterogeneity of footprint misestimation (III)

Note. The above figure marginal effects obtained from a logistic regression of the survey participants' likelihood to underestimate their carbon footprints on demographic characteristics. The dependent variable is equal to one for survey participants who underestimated their carbon footprints, that is, individuals for whom the observed footprint exceeds their estimate, and conversely equal to zero for those who overestimated them. Observed footprints are calculated at the individual level and as described in Appendix B. Since administrative consumption data is not available for all survey participants, the sample underlying the above figures comprises 2,383 individuals. Each coefficient estimate is annotated by its respective p-value obtained in this regression. Standard errors are clustered at the individual level.

 Table F.2.2 Survey: Compensation with sustainable investments

	Sample	Low	High	High – Low
Unconditional	13.17 (3,646)	12.54 (3,165)	$17.26 \\ (481)$	
Conditional	15.44 (3,051)	14.73 (2,647)	20.05 (404)	$5.32^{**}$ (3,051)

Note. This table presents the average share of survey participants who stated that they have previously used or are currently using sustainable investments to help compensate their carbon emissions from consumption in percentage points. Unconditional estimates present sample averages for all participants, whereas Conditional numbers show only those who selected one or more of the compensation methods provided. The full list of provided compensation methods, as well as some frequently-provided answers entered in the free-entry field, are presented in Figure 1 and Table F.2.3 in the Appendix. The column with header Sample shows averages for the whole sample, whereas columns titled Low and High distinguish between participants who believe that their carbon footprints are below or above those of their peers with respect to age, income, and profession. This assessment is provided on a Likert scale ranging from 1 to 7, where 1 represents "much lower" and 7 corresponds to "much higher" footprints. The column titled High – Low reports differences between the high- and low-footprint averages including its level of statistical significance using Welch's unequal variances t-test. Asterisks denote statistical significance of this difference at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively. All numbers are based on a survey conducted in October 2022 with 3,646 clients of the same bank that provided the administrative data analyzed in the main part of this paper.

at the 1% level). Conditional on choosing any compensation method, this difference is exacerbated (5.32% higher likelihood, significant at the 1% level). Both findings support the notion that investors aim to offset their carbon footprints from consumption using sustainable investments. Results for the full set of potential compensation methods are presented in Table F.2.3 at the end of this Appendix.

Taking together all of the results presented in this Section, the survey analysis provides strong additional evidence that the patterns found in the baseline and investment-motive regressions presented in Tables 1 and E.1.1 can indeed be traced back to investors attempting to compensate for their consumption-driven emissions by investing more sustainably.
	Unconditional				Conditional				
	Sample	Low	High	H - L	Sample	Low	High	H - L	
Invest sustainably	13.17	12.54	17.26	4.71***	15.44	14.73	20.05	5.32**	
Purchase carbon offset	11.74	11.37	14.14	2.76	13.73	13.30	16.58	3.29*	
Substitute or forgo certain products	40.92	40.66	42.62	1.96	48.12	47.90	49.50	1.60	
Substitute (long-distance) travel	34.61	35.10	31.39	-3.71	40.74	41.44	36.14	-5.30**	
Energy remodel, PVA, heating pump	23.97	23.51	27.03	3.52	28.12	27.58	31.68	4.10*	
Ecological gas or electricity	28.36	27.71	32.64	4.93**	33.30	32.68	37.38	4.70*	
Less energy use	0.52	0.54	0.42	-0.12	0.62	0.64	0.50	-0.15	
Less meat, animal products, veg(etari)an	0.82	0.85	0.62	-0.23	0.95	0.98	0.74	-0.24	
Purchase regional/ecological products	0.52	0.54	0.42	-0.12	0.62	0.64	0.50	-0.15	
Reuse, recycle, produce less waste	0.33	0.35	0.21	-0.14	0.39	0.42	0.25	-0.17	
Low-emission transportation	0.91	0.92	0.83	-0.08	1.08	1.10	0.99	-0.11	
Sold car/no car	0.36	0.38	0.21	-0.17	0.39	0.42	0.25	-0.17	
Electric or hybrid car	11.08	10.27	16.42	6.16***	12.95	12.13	18.32	6.19***	
Drive less	55.05	55.64	51.14	-4.50*	64.67	65.47	59.41	-6.06**	
Other	2.36	2.40	2.08	-0.32	2.62	2.68	2.23	-0.45	
No offset	16.32	16.37	16.01	-0.36	0.00	0.00	0.00	0.00	
Observations	3,646	3,165	481	3,646	3,051	2,647	404	3,051	

Table F.2.3 Survey: Compensation methods

*Note.* This table presents the average share of survey participants who stated that they have previously used or are currently using one or more of the listed methods to help compensate their carbon emissions from consumption in percentage points. Unconditional estimates present sample averages for all participants, whereas *Conditional* numbers show only those who selected one or more of the compensation methods provided. Some of the listed options subsume several answers in a single compensation method. This is the case for, e.g., Energy remodel, PVS, heating pump, which comprises any means of compensation related to energetic remodels of residential real estate or the installation of photovoltaic systems (PVS) and/or heating pumps. Similarly, Low-emission transportation comprises any use of low-emission transportation modes such as bicycles, electronic bicycles, by foot, or public transportation. The column with header Sample shows averages for the whole sample, whereas columns titled Low and High distinguish between participants who believe that their carbon footprints are below or above those of their peers with respect to age, income, and profession. This assessment is provided on a Likert scale ranging from 1 to 7, where 1 corresponds to "much lower" and 7 to "much higher" footprints. Columns with header Sample show averages for the whole sample, whereas columns titled Low and High distinguish between below- and above-median footprints from consumption, respectively. Columns titled H - L report differences between the high- and low-footprint averages including their level of statistical significance using Welch's unequal variances t-test. Asterisks denote statistical significance of this difference at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively. All numbers are based on a survey conducted in October 2022 with 3,646 clients of the same bank that provided the administrative data analyzed in the main part of this paper.

## F.3 Compensation efficiency

The evidence in this paper indicates that investors believe consumption-driven emissions can be offset by investing more sustainably. This raises the question of whether such a compensation method is effective. Unlike direct offsets through platforms like *atmosfair*, the benefits of sustainable investing are indirect and complex to calculate.<sup>45</sup> We provide two rough estimates of compensation efficiency, specific to our sample, to gauge whether SRI can offset consumption-driven emissions.

Households account for 60% of EU emissions, requiring footprints of 2.5 to 3.3 tCO<sub>2</sub> per household to meet the  $1.5^{\circ}$ C goal by 2030 (Ivanova et al., 2016). Atmosfair suggests emissions must be  $1.5 \text{ tCO}_2$  per capita annually.<sup>46</sup> In our sample, sustainable investing would need to offset over 10 tCO<sub>2</sub> for average investors and nearly 20 tCO<sub>2</sub> for high-footprint investors (see Table C.1). The first estimate compares average carbon footprints of highand low-footprint investors' portfolios. If high-footprint investors' portfolio emissions are lower, the difference represents the compensation benefit of sustainable investing. The second estimate uses differences in likelihoods and portfolio outcomes from Section 3 (Table 1).

Table F.3.1 shows average direct and indirect emissions by scopes 1, 2, and 3.<sup>47</sup> It displays average emissions by consumption-driven footprints (high, low) as detailed in Appendix B, along with investment-related emissions. GHG emissions and scope classifications at the ISIN level for each stock during the sample period were obtained from Refinitiv. Portfolio-level emissions are approximated with value-weighted averages, considering only the equity share of portfolios. Note that emissions and scope classifications are mandatory only for stocks, and indirect emissions (scopes 2 and 3) are difficult to assess. Therefore, Table F.3.1 presents statistics by scopes 1, 2, and 3, as well as total portfolio emissions for scopes 1 and 2, and for scopes 1, 2, and 3.

Despite high-footprint investors having more sustainable portfolios by emission ratings, their overall emissions are higher than those of low-footprint investors. Differences range

 $<sup>^{45}</sup>Atmosfair$  is a leading platform for carbon offsets in Germany. More information can be found at https://www.atmosfair.de/en/.

<sup>&</sup>lt;sup>46</sup>Source: https://www.atmosfair.de/de/kompensieren/.

<sup>&</sup>lt;sup>47</sup>Scope 1, 2, and 3 emissions are defined in the Greenhouse Gas Protocol of 2001. Scope 1 includes direct emissions from production, Scope 2 covers emissions from energy used in production, and Scope 3 includes all other indirect emissions (Deloitte UK, 2023).

		Avg. emissions from				
Emissions scope	Footprint	Investments	$\Delta$ PF	Consumption	$\Delta$ Consumption	$\Delta$ Emissions not offset
Direct 1 Direct 1	Low High	$2.155 \\ 2.562$	0.407	$7.22 \\ 21.1$	13.88	14.287
Indirect 2 Indirect 2	Low High	$\begin{array}{c} 0.478 \\ 0.654 \end{array}$	0.176	$7.22 \\ 21.1$	13.88	14.056
Indirect 3 Indirect 3	Low High	$\frac{11.844}{14.454}$	2.610	$7.22 \\ 21.1$	13.88	16.490
Total $1+2$ Total $1+2$	Low High	$2.633 \\ 3.217$	0.584	$7.22 \\ 21.1$	13.88	14.464
Total $1 + 2 + 3$ Total $1 + 2 + 3$	Low High	$\frac{14.477}{17.671}$	3.194	$7.22 \\ 21.1$	13.88	17.074

Table F.3.1 Emissions from consumption and investments

Note. The above table presents average direct scope 1, indirect scope 2, and indirect scope 3 emissions for average investor portfolios of high- vs. low-footprint investors. Total 1 + 2 and Total 1 + 2 + 2 $\beta$  emissions subsume direct and indirect scope 1 and 2, or direct scope 1 and indirect scope 2 and 3 emissions to capture total portfolio emissions. Scope 1, 2, and 3 emissions are first defined in the Greenhouse Gas Protocol of 2001. Specifically, scope 1 emissions cover direct emissions from production, whereas scopes 2 and 3 are defined as indirect emissions in that scope 2 captures all emissions from producing goods which are used in all production, sales, research, and development activities, such as the energy or electricity used for production. Scope 3 comprises all emissions which are indirectly associated with the company's economic activity (Deloitte UK, 2023). We approximate portfolio-level emissions with a value-weighted average, where the weights are the investor's portfolio weights of each stock, considering only the equity share of investors' portfolios. The column titled *Investments* shows the resulting average portfolio emissions. The column headed  $\Delta$  Emissions not offset captures the sum of the difference in total emissions of the average high- and low-footprint investors' equity holdings ( $\Delta PF$ ) and the analogous difference in consumption-driven carbon emissions p.a. ( $\Delta$  Consumption). Since the portfolios of investors with high footprints from consumption are, on average, not associated with lower emissions than those of their low-footprint counterparts, this sum of differences is larger than the total consumption-driven emissions before considering potential compensation benefits. ISIN-level emissions data is obtained from Refinitiv, GHG emission ratings from TruValueLabs, and total annual footprints from consumption are estimated as described in Appendix B based on investor-level consumption and data on carbon intensities from the EXIOBASE 3 database.

from 0.401 to  $3.194 \text{ tCO}_2$ , adding to higher total emissions of  $21.1 \text{ tCO}_2$  p.a. compared to  $7.22 \text{ tCO}_2$  for low-footprint investors. This is likely due to high-footprint investors holding higher-value portfolios. When scaled by portfolio values, the asset-level emissions are lower, but high-footprint investors' real investment behavior does not result in lower emissions despite better emission ratings.

To address shortcomings in Table F.3.1, we provide another estimate using the baseline regression results in Table 1. We compute the emission differential for the top and bottom quintile of stock-level emissions, weighted by coefficients from Table 1. This estimates the maximum compensation benefit of investing in low-emission stocks. The emissions

after offset and the percentage of consumption-driven emissions that can be offset are shown in Table F.3.2.

 Table F.3.2 Counterfactual portfolio emissions: Investments in top-ranked assets only

Emissions scope	Footprint	Baseline specification	Coefficient	Offset potential	Total emissions	Emissions after offset	"Exchange rate" (%)
Direct 1 Direct 1 Direct 1	High High High	$\begin{array}{c} 1\\ 2\\ 3\end{array}$	$0.087 \\ 0.053 \\ 0.004$	-2.100 -1.282 -0.105	$21.1 \\ 21.1 \\ 21.1$	$\begin{array}{c} 19.000 \\ 19.818 \\ 20.995 \end{array}$	$9.95\%\ 6.08\%\ 0.50\%$
Indirect 2 Indirect 2 Indirect 2	High High High	$\begin{array}{c} 1\\ 2\\ 3\end{array}$	$0.087 \\ 0.053 \\ 0.004$	-0.002 -0.001 0.000	$21.1 \\ 21.1 \\ 21.1$	$21.098 \\ 21.099 \\ 21.100$	$\begin{array}{c} 0.01\% \\ 0.00\% \\ 0.00\% \end{array}$
$\begin{array}{l} \text{Total } 1+2\\ \text{Total } 1+2\\ \text{Total } 1+2 \end{array}$	High High High	$\begin{array}{c} 1 \\ 2 \\ 3 \end{array}$	$0.087 \\ 0.053 \\ 0.004$	-1.191 -0.727 -0.060	$21.1 \\ 21.1 \\ 21.1$	$19.909 \\ 20.373 \\ 21.040$	$5.64\%\ 3.45\%\ 0.28\%$

*Note.* The table above shows the maximum offset potential for a counterfactual investment strategy that selects the top-rated quintile (20%) of stocks based on emission ratings. This potential is calculated by the difference in average emissions between the top and bottom quintiles, weighted by coefficients from baseline regression specifications 1, 2, and 3 (see Table 1 in Section 3). These coefficients reflect how likely investors with above-median consumption footprints are to hold these top-rated assets (specification 1) or have higher portfolio weights in such assets (specifications 2 and 3). This compensation benefit approximates the portion of consumption-driven emissions that high-footprint investors could offset by investing sustainably. The column *Emissions after offset* shows that the estimated benefit is insufficient to offset the high annual emissions of these investors. Scope 1, 2, and 3 emissions, as defined in the Greenhouse Gas Protocol (2001), are addressed: Scope 1 includes direct emissions from production, Scope 2 covers indirect emissions from energy used in production, and Scope 3 involves all other indirect emissions related to the company's economic activities. Due to the difficulty in assessing Scope 3 emissions, they are excluded from this table. ISIN-level emissions data is sourced from Refinitiv, GHG emission ratings from TruValueLabs, and total annual footprints from consumption are estimated using investor-level consumption data and carbon intensities from the EXIOBASE 3 database, as detailed in Appendix B.

Table F.3.2 shows offset potentials between 0 and 2.1 tCO<sub>2</sub>, yielding average emissions for high-footprint investors from 19 tCO<sub>2</sub> to 21.1 tCO<sub>2</sub>, far above the target rate of 1.5 to 3.3 tCO<sub>2</sub>. Thus, despite what investors might hope, sustainable investing alone does not significantly offset consumption-driven emissions – at least based on these rough approximations.

## F.4 Socio-cultural factors

The prior literature has found that regional socio-cultural factors affect patterns of financial behavior, e.g., for Catholics and Protestants in the domain of gambling preferences (Kumar, 2009), or for cultural heritage and trading behavior (e.g., Laudenbach et al., 2023; Schnorpfeil and Johanning, 2021; D'Acunto et al., 2022). In a similar vein, we leverage religious information at the aggregate level to pin down the offsetting mechanism behind the baseline results presented in Section 3.

Catholicism is historically tied to offsetting in that believers in the  $15^{th}$  and  $16^{th}$  centuries could compensate for their perceived sins by purchasing letters of indulgence that granted them the right to forgiveness of their sins or those of their deceased relatives. In a simplified comparison of the markets for carbon offsets and letters of indulgence, offsetting has even been referred to as 'carbon indulgence' (see Dalsgaard, 2022, for a linguistic review). The condemnation of this practice by Martin Luther was one of the reasons for the reformation of the Catholic church which ultimately led to the inception of the Protestant denomination. Therefore, Catholics likely have a different relationship to compensating "sinful" behavior than Protestants.

We leverage this cultural heterogeneity to pin down more specifically whether our results follow from offsetting. If investors with higher exposure to Catholic beliefs are more likely to invest sustainably, the analysis would speak to offsetting as an important predictor of the sustainability profiles of retail investor portfolios. The bank data does not survey information on religious affiliations at the individual level. To analyze the relation between religious faiths and portfolio sustainability, we resort to German census data from 2011 at the (aggregate) 5-digit zip code level.<sup>48</sup> The census lists the share of Catholics, Protestants, and other religions and people without religious affiliations (referred to as 'others' in the census) at the zip code level. We merge these variables to each investors at the 5-digit zip code level. Table F.4.1 presents the decomposition of religious faiths across the overall, low-, and high-footprint sample.

Census data on religious faiths is available for the zip codes of 5,732 investors (Table F.4.1). On average, investors live in cities where 26.32% of the population are Catholic, 26.74% are Protestant, and 46.95% are neither. In 43.16% of the zip code areas where the analyzed investors live, Catholics are more prevalent than protestants, and in 11.11%

<sup>&</sup>lt;sup>48</sup>The query of religious beliefs has since been discontinued.

Variable	Sample	Low	High	High - low
Catholic	26.32	25.29	27.32	2.03***
Protestant	26.74	26.34	27.13	0.78**
No affiliation or other	46.95	48.36	45.55	-2.81***
Catholic share larger than protestant share	43.16	41.11	45.18	4.07***
Catholic share over $50\%$	11.11	10.51	11.71	1.21
Observations	5,732	2,846	2,886	5,732

Note. The above table presents summary statistics for census information on religious decomposition at the regional level across the investor sample. Each investor is assigned the share of each religious denomination at the aggregate 5-digit zip-code level. Data on religious composition at the 5-digit zip code level is obtained from the 2011 German census, the last year during which the census included information on religious affiliations. Columns with header Sample show averages for the whole sample, whereas columns titled Low and High distinguish between below- and above-median footprints from consumption, respectively. The column with header Sample shows averages for the whole sample, whereas columns titled Low and High distinguish between below- and above-median footprints from consumption, respectively. The column with header Sample shows averages for the whole sample, whereas columns titled High – Low reports differences between the high- and low-footprint averages including its level of statistical significance using Welch's unequal variances t-test. Asterisks denote statistical significance of this difference at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

they are the largest group among Catholics, Protestants, and others. High-footprint investors seem to be slightly more prevalent in Catholic-leaning areas. The differences are, however, rather small in economic terms.

We test the relation of Catholicism and portfolio sustainability by repeating the baseline specifications of equations 1 and 2, presented in Table 1 of Section 3. Instead of the above-median footprint variable, however, we use the share of Catholics in investors' zip code area (in percentage points). We additionally control for population at the 5-digit zip code level and *micro status*, a variable elicited by the bank that ranks several indicators for socio-economic status at the zip-code level on a scale from 0 to 9. We add both variables to disentangle the effect of exposure to religious beliefs from socio-economic factors which also present at the regional level.

Table F.4.2 presents the results of this analysis. Compared to the baseline results, the results using the percentage of Catholics are qualitatively unchanged: For GHG emissions scores, a one percentage point higher share of Catholics is associated with a 0.1% higher likelihood to hold top-rating securities, 0.045% higher portfolio shares held in such assets, 0.123 higher portfolio ESG scores, and a 0.1% higher likelihood to rank in the top 20% of all investors' ESG scores (significant at the 1%, 5%, 1%, and 5% level, respectively). For air quality ratings, the results are qualitatively and quantitatively similar. A higher share of Catholics is also associated with significantly higher overall and ecological portfolio

	(1) Holds top rated	(2) % PF top rated	(3) % AS top rated	(4) PF ESG score	(5) Top PF ESG score
	Marg. effect	Coef.	Coef.	Coef.	Marg. effect
Overall	$0.000 \\ (0.339)$	$0.009 \\ (0.244)$	-0.003 (0.209)	$0.071^{***}$ (0.000)	$0.000^{**}$ (0.028)
GHG emissions	$0.001^{**}$ (0.001)	$0.036^{**}$ (0.016)	$0.002 \\ (0.513)$	$0.107^{***}$ (0.000)	$0.000^{**}$ (0.029)
Ecological	$0.000 \\ (0.381)$	$0.003 \\ (0.679)$	$0.003 \\ (0.466)$	$0.065^{***}$ (0.002)	$0.000 \\ (0.116)$
Air quality	$0.001^{**}$ (0.017)	$0.020^{***}$ (0.004)	$0.004 \\ (0.230)$	$0.055^{***}$ (0.000)	$0.001^{***}$ (0.005)
Observations	5,732	5,732	5,732	5,732	5,732
Investor-level controls Micro status Population	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes

Table <b>F.4.2</b>	Robustness	analysis:	Exposure	to	religious	beliefs
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Note. The above table displays results from eight logistic (columns 1 and 5) and twelve OLS regressions (columns 2, 3, and 4) of the sustainability indicators constructed from asset- and portfolio-level TVL ratings as described in Section D.1. All models are estimated separately for the TruValueLabs (TVL) Overall, GHG emissions, Ecological, and Air quality ratings as indicated by the row labels of the above table. Specifically, the dependent variables used in all 20 regressions are Holds top rated, which is equal to one if an investor holds at least one security which ranks in the top 20% of ratings (column 1), % PF top rated (column 2) and % AS top rated (column 3), which measure the portfolio and asset shares devoted to these top-rated assets, respectively, PF ESG score, which measures the value-weighted composite ESG score for each investor's portfolio (column 4), and Top PF ESG score, which is equal to one for investors whose portfolio ESG scores rank in the top quintile (top 20%) of all investors' scores, and zero otherwise (column 5). The coefficient estimates and p-values presented above capture the relation of each outcome variable to the share of Catholics in each investor's 5-digit zip code area. Data on religious composition at the 5-digit zip code level is obtained from the 2011 German census, the last year during which the census included information on religious affiliations. In this set of regressions, we additionally control for population size and micro status at the 5-digit zip code level. Information on population size is obtained from the 2011 census, and micro status is computed by the bank as a proxy for investors' regional socio-economic status. All regressions control for investors' profession, age, gender, marital status, joint account usage, median annual net income, trading risk classes elicited by the bank, and financial product ownership. p-values based on robust standard errors are presented underneath coefficients in parentheses. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), and 10% (\*) levels, respectively.

ESG scores, as well as a higher likelihood to rank in the top quintile of overall scores (significant at the 1%, 1%, and 1% levels, respectively). The magnitude of coefficients is much smaller than in Table 1 (Section 3) due to the different scaling of the variables (the main COI measures the effect for an indicator that is equal to one or zero, whereas the share of Catholics should be expressed in percentage points ranging from zero to 100). Along similar lines, Gutsche (2019) find that, irrespective of which Catholic denomination is analyzed, Catholicism is related to self-reported ecological, social, and ethical activities. Comparable to the findings presented in Table F.4.2, the relation between ecological activity and religion is more strongly pronounced for Catholics than Protestants (Gutsche, 2019).



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