Do Investors Compensate for Unsustainable Consumption Using Sustainable Assets?*

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April 13, 2023

Abstract

To understand retail investor demand for sustainable assets, I estimate carbon footprints for 6,151 investors by linking their administrative consumption data to product-level carbon intensities. I show that compensation motives drive investments in low-emission assets and formally rule out alternative explanations. A survey with 3,646 participants reveals that investors who believe they have above-average footprints choose sustainable investing specifically as a form of compensation and significantly more often than others. I provide further evidence that portfolio sustainability is related to religious beliefs which are historically tied to offsetting and that income or sample selection effects are not driving my results.

Keywords: Sustainable investment, trading motives, retail investors, carbon footprints, administrative data.

JEL classification: G40, G50, G11, Q54, Q56.

*I thank Steven Ongena (discussant), Paul Smeets, Loriana Pelizzon, Francesco D'Acunto, Tobin Hanspal, Andreas Hackethal, Christine Laudenbach, Alexander Hillert, Marco Bellifemine, Philip Schnorpfeil, Sabine Bernard, Anna Pestova, and participants of the 16th International Conference on Computational and Financial Econometrics (CFE 2022, King's College, London) and the 2022 Tri-City Day-Ahead Workshop on the Future of Financial Intermediation (Frankfurt School of Finance and Management, Frankfurt) for their invaluable comments. I also wish to express my gratitude to Marvin Dransfeld, Eric Reifer, and Felix Kuntz for their excellent research assistantship, as well as to my partners at a bank for their supportive collaboration and granting me the data necessary to conduct this research.
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1 Introduction

Socially responsible investment (SRI) has experienced rapid growth over the past years, with total global sustainable investment volumes reaching an aggregate of USD 35.3 trillion across four major world regions, marking an increase of 55% over four years between 2016 and 2020.[1] Of the total value of managed assets in these regions, SRI make up 35.9% in 2020 (GSIR, 2020). Globally, SRI is expected to account for 21.5% of total assets under management by 2026 (PwC, 2022).

Despite these massive flows into SRI, the drivers of investor demand for sustainable assets are not yet clear. Especially for retail investors, considerations beyond beliefs of outperformance or lower risk profiles for sustainable investments are likely to play a crucial role. For instance, it is possible that investors choose sustainable assets altruistically in order to make an impact. However, it is also conceivable that investor sentiment for sustainable assets is higher than for conventional alternatives (Lei and Zhang, 2020). In addition, investors may invest sustainably because they are motivated by feelings of warm glow (Andreoni, 1995; Taufik et al., 2015; Van der Linden, 2018), to compensate for their carbon footprints, or to adhere to a social norm (e.g., Kormos et al., 2015). The motivation underlying sustainable investing is therefore unobservable in administrative (trading) data. One solution to this issue is to conduct surveys and (incentivized) experiments. Since sustainable behavior is socially desirable, the results offered by such studies may however be biased to suggest impacts as the main driver of SRI. If "talk is cheap" when it comes to sustainability-related actions (e.g., List and Gallet, 2001; Carrington et al., 2010; FeldmanHall et al., 2012), analyzing actual behavior in addition to surveyed preferences is crucial to understand the predictors of sustainable investing.

In this paper, I show that carbon compensation behavior is a strong driver of retail investor demand for sustainable assets. Specifically, I find that investors with high carbon footprints from consumption hold more sustainable portfolios in terms of emission ratings. To this end, I leverage administrative transaction-level data on portfolios, trades, and consumption to relate the individual carbon footprints of 6,151 investors to multiple indicators for sustainable portfolio characteristics. I compute these footprints by combining categorized consumption

[1] GSIR (2020). The regions covered in this report were Europe, North America, Australia, and Asia.

with product-by-product greenhouse gas (GHG) emission intensities. In analyzing this objective data, I am able to avoid potential biases of prior studies based on survey data and to add to the understanding of investor preferences for sustainable investing and consumption.

Based on cross-sectional regressions of environmental, social, and governance (ESG) investment activity and intensity on consumption sustainability, I find that investors with high carbon footprints from consumption invest significantly more sustainably at the extensive and intensive margins. This negative relation between the sustainability of consumption and investments is both sizable and highly significant: Investors with high carbon footprints from consumption are 8.7% more likely to hold assets ranking in the top 20% of sustainability ratings, hold 5.311% (0.436%) higher portfolio shares (asset shares) in such assets, have 7.039% higher overall portfolio sustainability scores, and are 4.9% more likely to rank in the top quintile of portfolio sustainability scores compared to investors with low carbon footprints. In line with the notion that investors aim to offset their footprints from consumption by investing more sustainably, I find this compensation effect only for ESG ratings which explicitly measure the emissions and air quality profiles of the rated securities. For general environmental, social, or governance profiles, I do not find unambiguously significant relations to carbon footprints from consumption. 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.

In further analyses, I investigate whether my findings of a negative relation between portfolio and consumption sustainability are driven by plausible alternatives. Sustainability preferences may be heterogeneous across consumption-driven footprints. If unsustainable consumers have a higher preference for impact investing for other reasons than compensation, the uncovered relations would be spurious and would disappear upon controlling for sustainability preferences. If, on the other hand, financial motives, driven by higher investor sentiment for SRI, were better predictors of portfolio sustainability than compensation considerations, the effects would disappear after controlling for return-chasing proxies. While sustainability proxies exhibit occasional significant and positive relations to overall portfolio sustainability, the size of these effects amounts to about 5% to 10% of those found for compensation behavior. Therefore, the economic impact of compensation as a driver for sustainable investments is magnitudes larger.

The predictive power of financial-motive proxies alternates in sign, magnitude, and significance, failing to provide an unambiguous explanation for portfolio sustainability. None of the included proxies therefore explain sustainable investing to a larger extent than carbon compensation.

In addition, I conduct a survey with 3,646 clients of the same bank whose data I analyze in my main analyses. The majority of survey participants underestimate their carbon footprints, and the degree of misestimation increases systematically in the size of observed footprints. In addition, males, married individuals, and managers significantly underestimate their own carbon footprints. Despite the inability of investors to adequately estimate their emissions from consumption, further survey analyses reveal that the mechanisms uncovered in the baseline analyses indeed follow from an awareness for one's own footprint *in relation to those of one's peers* and a conscious choice to choose sustainable investments as a means of compensation: Specifically, I show that participants (i) who believe that their own carbon footprints exceed those of their peers and (ii) those whose observed footprints are above the median more frequently state that they have chosen sustainable investing as a means of compensating for their carbon footprints before, exceeding the prevalence of those with below-median estimates by a statistically significant extensive (intensive) margin of 4.71% (5.32%).

I assess the robustness of my findings by addressing three concerns associated with my study: First, I rule out that income effects drive my results. To this end, I repeat the baseline analysis for two definitions of carbon intensity. Carbon intensities scale footprints by income (consumption) and therefore capture (un-)sustainable consumption irrespectively of the investors' total income and consumption levels. The main findings for GHG emission ratings remain robust to this adjustment.

Second, by relating socio-cultural factors at the regional level to portfolio sustainability, I provide additional suggestive evidence that my findings are indeed driven by compensation considerations. Since Catholics have a cultural heritage of atoning for their sins *financially*, a dominance of Catholics at the investors' five-digit zip code level should only be related to portfolio sustainability if offsetting attempts are driving sustainable investments. Indeed, I find that investor exposure to a higher representation of Catholics is positively and significantly related to higher portfolio sustainability even after controlling for regional socio-economic status.

Third, I test the robustness of my findings to different investor sampling restrictions. The majority of my baseline results remains robust to these adjustments, indicating that the findings are not driven by sample selection or small-sample properties, but by compensation as a significant motivation to invest sustainably.

Finally, I provide back-of-the-envelope calculations of the maximum compensation benefit associated with the more sustainable investment behavior of high-footprint investors. In doing so, I show that the more favorable portfolio sustainability in terms of emissions observed for this group cannot adequately offset their carbon footprints from consumption. The highest-possible offsetting potential these calculations reveal is 2.1 metric tonnes of CO_2 (henceforth tCO_2), which leaves a considerable portion of emissions for high-footprint investors of about 19 tCO_2 unaccounted for after factoring in potential compensation benefits.

My findings challenge the notion that SRI can be a viable tool to help compensate for carbon footprints. In fact, ESG investments might even lead to net negative effects on the climate if investors feel morally licensed to retain their consumption behavior – whose carbon footprints they systematically underestimate. It is conceivable that this issue extends beyond the realm of retail investors, thereby highlighting the need to reduce carbon emissions in the first place instead of attempting to offset them later with the help of sustainable investments or otherwise.

This study contributes to several strands of the (behavioral) finance literature. To the best of my knowledge, my analysis is the first to provide evidence that compensation considerations are a significant motive for sustainable investing, while addressing common issues of the prior, primarily survey-based literature. I therefore predominantly contribute to a relatively new strand of the literature which studies retail investor trading motives and demand for sustainable investments. Riedl and Smeets (2017) analyze motives for sustainable investments based on survey and experimental data and find that retail investors are driven by sustainability motives and are willing to forgo returns for a higher sustainability impact. Gutsche and Ziegler (2019) find that environmental consciousness is one significant determinant of sustainable investing. Barber et al. (2021) show that the willingness to pay for sustainable impacts is especially strongly pronounced for investor groups with incentives to achieve impacts which go beyond pure return considerations, such as development financial institutions. Along similar lines, I find that sustainability preference proxies carry additional explanatory power for investments in ESG assets targeted specifically at lowering GHG emissions. Importantly, however, I suggest that attempted compensation for emissions outside of the investment domain is a previously undocumented additional driver of sustainable investing.

Second, I identify and aim to close a considerable gap in the financial literature regarding spillovers of sustainable behavior between consumption and investments. Specifically, whether (un-)sustainable consumption exhibits a positive or negative relationship with sustainable investments as captured by administrative and objective data on transactions and portfolio holdings. Within consumption categories, the prior literature suggests positive sustainability spillovers (Thomas and Sharp, 2013; Truelove et al., 2014; Penz et al., 2019; Hakenes and Schliephake, 2021). Regarding spillovers across domains of financial activity, however, the prior literature suggests that stated actions do not necessarily carry over to actual behavior, i.e., talk is cheap (e.g., List and Gallet, 2001; Carrington et al., 2010; FeldmanHall et al., 2012). Examples from the prior literature that specifically analyze spillovers of sustainability-oriented behavior between investment and consumption are scarce, and I am not aware of any paper that employs administrative data to study this question. Palacios-González and Chamorro-Mera (2018) utilize a survey conducted with 415 bank clients and find a positive relation between consumption and investment choices. However, behaving environmentally friendly is socially desirable, which means that participants tend to overestimate the sustainability of their choices, or understate their detrimental impacts (Grimm, 2010; Juvan and Dolnicar, 2016; Ried et al., 2022). Therefore, I have reason to assume that (incentivized) surveys and experiments might fall victim to well-documented survey biases (e.g., selection bias), or biases from participants under-reporting "brown" or over-reporting "green" activities.

Brunen (2019) and Brunen and Laubach (2022) present the only comparable studies to this paper. Brunen and Laubach (2022) study the relation of consumption choices and socially responsible investments (SRI) observed through robo advisor holdings for 448 investors. The main measure of consumption the authors use in their study is based on a financially incentivized choice. While this improves on previous, purely survey-based approaches, the authors do not observe consumption objectively and outside of the laboratory, i.e., from real account transactions. In addition, Brunen and Laubach (2022) base their finding of a positive spillover between sustainable consumption and investments on a sample of investors who have zero or negligible prior experience with sustainable investing, which leaves out a considerable portion of the potential relation that might be negative (Khan and Dhar, 2006; Lacasse, 2016), and further depletes the already-low sample size to 115 individuals. Therefore, their results might be driven by small-sample properties such as multicollinearity or outliers, as the authors themselves concede. Furthermore, Brunen and Laubach (2022) consider SRI in general, whereas I offer analyses that target more specifically the climate-relevant question whether investors aim to offset their emissions from consumption with investments, leaving out social and governance considerations.

Compared to Brunen (2019), Brunen and Laubach (2022), and Palacios-González and Chamorro-Mera (2018), I offer evidence based on a much larger sample of 6,151 investors. The sample is drawn from the client universe of a large German retail bank, is representative of the bank's customer base, and analyzes all investors within this representative sample. Since the bank offers universal services across the country, the results are therefore more generalizable to the wider German public compared to Brunen and Laubach (2022) or Palacios-González and Chamorro-Mera (2018). Moreover, I measure the sustainability of both consumption and investments objectively at a more granular level as compared to, e.g., (binary) classifications, or lottery vouchers/expenditure for specific consumption categories (Brunen, 2019; Brunen and Laubach, 2022). The granularity of the transaction data, which is sorted into more than 100 categories, enables category-by-category linkages of consumption to product-specific GHG emissions from the EXIOBASE 3 Multiregional Input-Output (MRIO) database. In addition, I observe trading behavior (portfolio holdings) at the transaction (monthly) level, and am able to match to each security four different ESG scores, two of which specifically target GHG emissions and air quality. By using specific scores, I reduce the influence of commonly-observed noise in ESG ratings (Berg et al., 2022), and am able to identify spillovers between sustainable consumption and investment choices specifically for GHG emissions, which is arguably the most relevant category of E, S, and G factors in slowing down climate change.

Third, I add to the understanding of spillovers between different domains of (financial) behavior. The notion that a compensation motive drives investor preferences for sustainable assets is in line with previous accounts from neighboring disciplines which explain negative spillovers between behaviors perceived as more "positive" (in this case: environmentally sustainable) and those viewed as more "negative" (environmentally unsustainable) with guilt reduction and moral licensing (Khan and Dhar, 2006 and Lacasse, 2016, for environmentally (un-)sustainable choices, specifically). Heeb et al. (2022) similarly posit that the positive emotion induced by investing sustainably does not necessarily follow from the investments' impact, suggesting that sustainability and impact goals need not be driving investor demand for sustainable assets. Similar in general setup to my study, Brunen (2019) analyzes the relation of investing in sustainable funds and consuming sustainably, finding a negative relation consistent with moral licensing. The analysis is based on a small sample of 287 investors and measures the sustainability of consumption based on purchases at organic stores, small independent bookstores, and donations. This study may suffer from small-sample issues, and the analyzed variables might have to be evaluated more critically: The EU regulation on organic produce labeling lacks transparent and unified standards (BUND Bund für Umwelt und Naturschutz Deutschland, 2021), does not rule out factory farming, and requires only 95% of products' ingredients to be of organic origin (BUND Bund für Umwelt und Naturschutz Deutschland, 2021; Ökologische Wissens Akademie, 2021). The "real" sustainability profile of the sustainable-consumption proxies used by Brunen (2019) is therefore not unambiguous.

In addition, the analysis proposed by Brunen (2019) does not enable the estimation of carbon footprints from consumption. Footprints as used in this manuscript measure the complete climate-relevant activity of investors more directly since they consider all aspects of consumption. This is important if, e.g., sustainability is a luxury good, and the measures used in Brunen (2019) are more prevalent among higher-income but not necessarily more sustainable consumers.[2] Nevertheless, it is reassuring that the results presented by Brunen (2019) point in a similar direction as those presented in this study.

[2]Consider this example: It is conceivable that especially wealthy consumers with large sports cars or multiple cars, who fly frequently, and often purchase fast fashion also exhibit a higher demand for organic produce, books purchased at independent bookstores, or donate more frequently. Such individuals would be considered as sustainable in Brunen (2019). However, in totality, their behavior would not be sustainable. In fact, I argue that such cases are quite likely.

2 Data

2.1 Investor and transaction data

I 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, I leverage categorized bank 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' checking 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.[3]

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

I condition on investors in order to limit the influence of heterogeneous market participation, which might be driven by, e.g., income or wealth effects. In order to ensure that I estimate climate-relevant consumption and investing patterns for investors who use their main accounts, I impose three further selection criteria. These steps are crucial so as not to capture investor behavior based on checking accounts dedicated to savings, vacation, or shopping. I 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 1 presents the

[3]For more detailed information on the PFM tool, please refer to Bräuer et al. (2022).

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. Nevertheless, I repeat the baseline analysis for each of the subsamples to ensure the robustness of my results to the sampling restrictions in Section 4.4.

[Table 1 about here]

For the estimation of carbon footprints, aggregating total consumption to the annual level is sufficient. Annual aggregates also enable merging the investor sample directly to the EXIOBASE MRIO database, which offers information on 200 product-by-product GHG emission intensities at the annual level. I aggregate all income, consumption, and wealth records for each investor to the annual level. Income tax is directly withheld by the employer, leading to observed income data at net levels, while gross consumption is recorded inclusive of value-added tax (VAT). Therefore, I need to adjust consumption for VAT rates. Table A.1 in the Appendix displays all tax rates that deviate from the standard rate of 19% in Germany. I 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 roughly 100 categories. Since I estimate consumption-based emissions, I only consider outflow transactions for the purpose of this analysis. Further, I exclude financial transaction categories from the analysis, such as investments, savings, retirement plans, or private insurance (health insurance is deducted directly by the employer in Germany). Such transactions should predominantly have close to a neutral impact on emissions. Finally, I exclude business trips and business expenses from the scope of my 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 categorization of consumption categories cannot unambiguously assign a category to a transaction, it assigns the category label "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 in fact consumption transactions which 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 carbon footprints.

2.2 Carbon footprint estimation

In order to estimate CO_2 footprints of individual consumption, I 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 word 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.

I use those satellite accounts to derive product-level carbon intensities, which I calculate using the Global Warming Potential Standard 100 (GWP100). This standard describes the amount of climate relevant emissions (CO_2, CH_4, N_2O from combustion and non-combustion, and SF_6) as kgCO_2-equivalents per year (IPCC, 2007; Ivanova and Wood, 2020). I follow Ivanova and Wood (2020) in mapping consumption categories to the 200 EXIOBASE product categories. For instance, I match the PFM tool's transaction category 'Food / beverages' to the EXIOBASE categories 'Food products nec' (85%) and 'Beverages' (15%). For weighting, I follow Ivanova, Barrett, Wiedenhofer, Macura, Callaghan, and Creutzig (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, I assume an average basket of goods, which I base on 20 EXIOBASE categories. The exact weighting is recorded in a harmonization spreadsheet which can be made available upon request.

Before I can multiply the categorized expenditures with carbon intensities in gCO_2/EUR, I 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, arguably, electricity and refueling.[4] 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, I 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.[5,6] However, German renters usually do not pay sewage directly but through an annual payment to their landlords. As 58% of Germans are renters, I cut the average sewage cost by this rate, i.e., to 118 EUR.[7] This implies 85% electricity cost and 15% sewage cost 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. I therefore use this tax rate to net refueling consumption.[8]

[4]All products *not* taxed at the standard rate of 19% are recorded in Table A.1 of the Table Appendix.

[5]https://www.blitzrechner.de/wasserkosten/#wasserkosten-berechnen, accessed in March 2022.

[6]https://www.gasag.de/magazin/neudenken/stromverbrauch-ein-personen-haushalt#showResults, accessed in March 2022.

[7]https://de.statista.com/statistik/daten/studie/237719/umfrage/verteilung-der-haushalte-in-deutschland-nach-miete-und-eigentum/

[8]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/).

I 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. I 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 in order to provide respective end-products and/or services, which implies linearly increasing emissions. The prior literature offers robustness tests of this implicit assumption, and find 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 true for other financial transactions such as savings plans, most insurance contracts, etc. I 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, etc. They may, however, enable consumption, which is covered by the respective account transactions.

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, I aggregate all sub-categories to 16 main categories excluding uncategorized consumption. Next, I 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, I aggregate total annual carbon emissions as the sum of emissions from all individual consumption categories excluding financial transactions.

Figure 1 displays total average consumption-based carbon footprints of individuals by income percentiles. On average, individuals emit 14.2 tCO_2 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_2 p.a.[9] The exclusion of uncategorized consumption may bias estimates of carbon footprints downward. However, another effect may balance out this deviation: The average income of individuals in the analyzed sample is roughly 51,800 EUR (net) p.a. (see Table 2), while it is roughly 24,000 EUR p.a., on average, in Germany in 2018 and 2019, i.e., the recorded sample is much wealthier and has higher corresponding consumption levels than the German average.[10] There is a strong link

[9]https://www.umweltbundesamt.de/klimaneutral-leben-persoenliche-CO2-bilanz-im-blick

[10]Based on data from the Federal Statistical Office of Germany, see this link.

between income and consumption-based emissions (compare Figure 1). Between the omission of uncategorized expenses and the higher-than-average income levels observed, I expect these two potential sources of bias to cancel out to a certain extent.

Another important factor contributes to the fact that I have higher average footprint estimates than provided by the German Federal Environment Agency. I study a restricted sample of investors to rule out income effects which might lead to heterogeneous stock market participation. Since participants in financial markets tend to be wealthier and earn higher income than non-participants (Guiso and Jappelli, 2005), this sampling restriction leads to higher overall income and consumption levels. Higher consumption increases footprints from consumption mechanically. In the unrestricted sample, the average footprint is therefore even closer to the official estimate at 10.6 tCO_2 (not depicted). The estimated carbon footprints of 14.2 tCO_2 are, however, in line with the estimate for Norwegian households of 22.3 tCO_2 p.a. in 2012 (Steen-Olsen et al., 2016). For individual consumers, the number should be half this size or less. Across the EU, Ivanova et al. (2016) find average footprints of 8.2 tCO_2 p.a./cap. Importantly, all of these footprint estimates by far exceed the target amount between 2.5 and 3.3 tCO_2 p.a./cap that would be required to limit emissions sufficiently to achieve a global warming goal of 1.5°C by 2030 (Ivanova and Wood, 2020). This fact highlights the importance of studying whether investments can help offset consumption-driven emissions.

To provide evidence for the potential motives driving investments in ESG assets, I use my estimate of total annual consumption-driven GHG emissions to compare one more and one less sustainable consumer sub-group. Specifically, I split the sample at the median of carbon footprints. Unsustainable (sustainable) consumers are defined as individuals with average annual carbon footprints above (below) the median. As footprints are strongly and positively related to income levels, I need to control for income in all regressions. However, as outlined previously, analyzing within-investor differences limits the extent to which income effects might be driving results.

[Figure 1 about here]

2.3 Sample descriptives

Table 2 displays socio-demographic summary statistics for the investor sample. 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 invest more than women. High-footprint investors are slightly more male than 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 in line with the fact that, e.g., retirees tend to have lower emissions, and managers might conceivably drive a larger car and use it more often.

[Table 2 about here]

As mentioned above, 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 31,900 EUR (net), which translates to emissions from consumption of about 14.16 tCO_2 on average. Unsurprisingly, 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, it will be crucial to not only control for income in regressions, but also to test more formally whether sustainable portfolios can be aligned with sustainability and/or financial motives.

Next, Table 3 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 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 dense 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. Lottery stocks based on Kumar (2009) are less frequently held, with participation rates of 0.08% and 0.93%, respectively.

[Table 3 about here]

The observed participation rates translate 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%), 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 3 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 in 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 trade risk 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 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.

3 Sustainability metrics and indicators for investment motives

3.1 Measures for sustainable investments

I construct five individual-level indicators to measure sustainable investments which will subsequently be related to the sustainability of consumption using the median split described above. All indicators (outcome variables in the regressions) are based on Factset Truvalue Labs (TVL) scores, which I 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 Sustainability Accounting Standards Board's 26 categories across 5 areas and cover more than 120,000 companies.[11] Daily scores are calculated based on publicly available data from more than 100,000 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 subcategories 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), since specific sub-category scores are not based on a plethora of inputs pertaining to all three E, S, and G factors.

In the main regressions, I 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

[11] https://go.factset.com/marketplace/catalog/product/sasb-scores-datafeed

financial motives. To this end, I 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, I compute five ESG investment 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 granular 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 ranks in the top quintile of scores at the end of 2019.

Table 4 presents summary statistics for each of the overall, GHG emissions, ecological, and air quality scores. This table provides first indicative evidence that the choice of ESG rating category matters, and that high-footprint consumers hold significantly higher-ranked securities. For variables based on GHG emissions scores, I find the largest values and prevalences, suggesting that investors irrespective of their consumption-driven footprints have a preference for these assets: 48.11% of the overall sample hold one or more top-ranked securities, and the share for high-emissions investors is significantly higher by 9.09% than that of their low-emissions counterparts (significant at the 1% level). For the overall, ecological, and air quality variables, values range from 23.73% to 35.70%, and differences between low- and high-footprint consumers are statistically significant at the 1% level. Amongst TVL rating categories, results for the remaining four outcome variables follow an analogous pattern, and are more prevalent for high-ranking securities and portfolios based on GHG emissions scores.

Portfolio shares held in top-ranked assets are much higher than asset shares. This suggests that the high-ranking assets held by investors in this sample have relatively high values compared to lower-ranking assets. One exception to the highest prevalence of high-ESG investors for the GHG emissions scores is the number of investors whose value-weighted portfolio scores rank in the top quintile of scores: The share of investors whose portfolio achieves this ranking is highest for the overall ratings (12.60%), followed by the ecological ratings (12.03%). For GHG emissions assets, only 10.49% of investors achieve a top-quintile portfolio score – the difference between low- and high-emissions investors is, again, rather high at 3.09% and statistically significant (1% level). The variations between overall, GHG emissions, ecological, and air quality indicators highlight that rating categories matter and category-specific analyses are required to draw meaningful conclusions.

[Table 4 about here]

Generally, portfolio-level ESG metrics across TVL rating categories are higher for unsustainable consumers. In eleven out of 20 cases, these differences are statistically significant at the 1% or 5%. The statistics presented in Table 4 suggest negative spillover effects, which I test in a more formal setting in Section 4.

3.2 Proxies for sustainability motives

This study aims to uncover spillovers of sustainability preferences, or offsetting behavior, between consumption and investing. I want to investigate this link, and formally contrast competing explanations for the negative relation between both financial domains which Table 4 hints at. These explanations are compensation behavior, heterogeneous sustainability preferences, and financial motives. 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 study 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, rather than compensation behavior. If sustainability preferences aside from offsetting footprints from consumption were driving results, the main result would be a statistical artifact. If this were the case, I expect the coefficients to lose explanatory power upon including proxies for sustainability preferences.

To investigate whether heterogeneous sustainability preferences explain ESG investments as well as or better than high footprints from consumption, I use three proxies based on the prior literature on ESG investment. First, I leverage the high frequency of TVL ratings that enable constructing measures for a strong ESG preference based on changes in these ratings at the daily level. If investors pay attention to the sustainability impact transported via sustainability ratings, they might trade in the direction of said change, 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 is important to investors. Both studies demonstrate that the introduction of sustainability ratings by Morningstar resulted in a substantial inflow of funds into mutual funds with high ESG ratings, while mutual funds with poor ESG ratings experienced substantial outflows. Bialkowski and Starks (2016) provide additional evidence that (retail) investors trade securities based on ESG ratings. I follow this literature and construct two measures for sustainability motives based on rating changes. After removing (bank) holidays and weekends from the TVL sample, I 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. I 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 2 and 3 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 below- and above-median footprint consumers separately. To estimate MPTs, I adapt the methodology to estimate MPCs from dividends outlined in Bräuer et al. (2022) to my 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 equal to the construction of PCBR and NCSR as outlined above, since I cannot estimate MPTs at the individual-ISIN level due to small sample sizes. Nonetheless, it is conceivable that investors buy (sell) any high-ranking asset after a rating change if they generally reevaluate their holdings after such events. 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.

[Figures 2 and 3 about here]

There is no clear pattern as to the MPT after rating changes in overall TVL scores (Figure 2). 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, I 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 3). Nevertheless, the 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 2), and (ii) significant MPTs for changes in GHG-emissions scores (Figure 3) 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, I 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, I construct a measure for ESG home bias as follows (ESG home-bias ratio, EHBR_i):

$$\text{EHBR}_i = \frac{\frac{N_{i,\text{ESG}\cup\text{home}}}{N_{i,\text{ESG}}}}{\frac{N_{i,\text{home}}}{N_i}}, \tag{1}$$

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.[12,13] 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 I am interested in relative differences between sustainable securities and unsustainable securities, I refrain from calculating model- or data-based benchmark portfolios, but relate the share of local high-ESG assets over total ESG assets to all local assets over all total assets held by each investor.

[Table 5 about here]

Panel A of Table 5 displays summary statistics of sustainability-motive proxies for the analyzed sample. Similar to sustainability metrics (Table 4), I 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

[12] I 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.

[13] For the EHBR, I choose the same snapshot time as for the ESG outcome variables.

the 1% level. Again, the results presented in Panel A of Table 5 suggest a negative relation of consumption-driven emissions and the sustainability of investments.

3.3 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) as the study closest to mine 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, I construct several further measures at the individual investor level.

One proxy for financial motives may be high (trading) activity. The propensity of populations 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), or investors' perceptions of their own competence (Graham et al., 2009). I 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, I leverage the sample average of monthly online banking logins as a proxy for general financial activity.[14] Finally, I 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), I compute this difference, or $\Delta\,(\text{PGR}\,,\,\text{PLR})$, based on the following computations of PGR and PLR:

[14] 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.

$$\text{PGR} = \frac{\text{no. of realized gains}}{\text{no. of realized gains + paper gains}} \tag{2}$$

and

$$\text{PLR} = \frac{\text{no. of realized losses}}{\text{no. of realized losses + paper losses}} \tag{3}$$

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 5 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 5, 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. Since these differences between groups can somewhat be likened to those found for the sustainability proxies, they again stress the importance of a formal analysis of the relation of sustainability- and financial-motive proxies to the ESG profiles of individual-investor portfolios.

4 Results

4.1 Cross-domain offsetting of carbon footprints

This section studies the relationship between carbon footprints from consumption and investment in securities with high sustainability ratings. Figure 4 shows the relationship between deciles of the carbon footprint distribution and the five sustainable investment metrics described in Section 3.1 graphically. Each of the five plots display average values of the respective ESG investment outcome based on the four different TVL score categories overall (blue), GHG emissions (red), ecological (green), and air quality (orange) across footprint deciles.

For the overall, ecological, and air quality variables, the distribution of ESG investments is somewhat similar between the lower and upper footprint deciles. Analogously to the statistics presented in Tables 4 and 5, results are highly dependent on the choice of TVL rating category: A positive relationship between carbon footprints and sustainable investment metrics based on GHG emissions ratings can generally be observed for the share of investors holding securities ranked in the top quintile of ratings (Panel A), portfolio and asset shares held in the top quintile of ratings (Panel B and Panel C), and, to a lesser extent, the percentage of investors in the top quintile of composite portfolio ratings (Panel E).

Across these four plots, the increase is strongest for GHG emissions ratings. The percentage of investors who hold securities ranked in the top 20% increases from roughly 42% for the lowest carbon footprint decile to about 59% for the highest decile. The share of top-ranked securities increases from about 6% to over 11% (portfolio share) and from about 0.4% to roughly 1.1% (asset share) between the first and tenth decile. There is almost no difference in average composite portfolio GHG emission scores (from 61 to about 62), which is consistent with the remaining TVL rating categories. In Panel A, there is a similar pattern for air quality and ecological metrics as for GHG emission ones, albeit at a generally lower prevalence across deciles. For the propensity of investor portfolio scores to rank in the top quintile of scores, overall and ecological prevalences are higher than investor shares based on GHG emissions for the first through sixth as well as the eighth decile of emissions from consumption.

[Figure 4 about here]

Along similar lines as for the descriptive findings presented in Tables 4 and 5, Figure 4 provides additional indicative evidence that (A) investors invest more actively in securities ranking high based on GHG emissions ratings than on other rating categories, and (B) that there seems to be a negative relationship between sustainable consumption behavior and sustainable investment behavior (even irrespective of the rating category chosen, however less strongly pronounced). Additionally, it is possible that investors disregard S and G criteria, and perceive the E part of ESG as the only relevant metric, which would mean that the GHG emissions score should be perceived as most important. Such an investor perception would lead to an overweighting of high-ranking GHG emissions assets relative to other ESG ratings, which would be especially strongly pronounced if consumer-investors aim to compensate their GHG emissions from consumption with investments. The indicative findings presented in Tables 4 and 5 and Figure 4 match this offsetting pattern well.

Nevertheless, I formally test competing explanations for the increased prevalence of sustainable investments among higher-emission consumers. To this end, I run cross-sectional OLS (logistic) regressions for the continuous (dichotomous) metrics of high investment sustainability. I regress each metric on a binary indicator of consumption sustainability which is equal to one if the investor has above-median average carbon footprints from consumption over the sample period and zero otherwise. This means that negative spillovers would be reflected by *positive* coefficient estimates. I estimate OLS regressions as follows:

$$\mathrm{V}_{\mathrm{ESG},i} = \beta_0 + \beta_1 \cdot D_i + \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k} + \varepsilon_i, \tag{4}$$

and logistic regressions are based on the following form:

$$\Pr(\mathrm{V}_{\mathrm{ESG},i} = 1 \mid D_i\,,\, X_i) = \beta_0 + \beta_1 \cdot D_i + \sum_{k=1}^{K} \beta_{i,k} \cdot X_{i,k} + \varepsilon_i, \tag{5}$$

where $\mathrm{V}_{\mathrm{ESG},i}$ stands for the outcome variable of interest as described in Section 3.1 (*Holds top rated*, *% PF top rated*, *% AS top rated*, *PF ESG score*, or *Top-quintile PF ESG score*), D_i is the main dummy variable taking on the value one for above-median consumption footprint investors and zero for below-median investors, and $X_{i,k}$ is a vector of control variables for all controls $k = 1$ through K. Since footprints are highly dependent on income levels (see Figure 1 or Ivanova and Wood, 2020), average net annual income is a crucial part of 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.

Table 6 presents the results from 20 separate regressions following equations 4 and 5. The table reports only estimates for the main coefficient of interest, β_1, along with p-values based on heteroskedasticity-robust standard errors. Importantly, I 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. Across outcomes, 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 8.7% more likely to hold securities ranking in the top quintile of TVL emissions scores (column 1), have 5.311% higher portfolio weights allocated to top-20% 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 20% of low-emissions assets (column 3: 0.436%, significant at the 10% level) and are 4.9% more likely to hold portfolios which rank in the top quintile of all investors' emissions-based ESG scores (column 5, significant at the 5% level). Similarly, albeit less strongly pronounced in terms of magnitude and statistical significance, I find that high-emission investors are more likely to hold top-rating assets with respect to air quality scores (column 1, 2.6%, significant at the 5% level), have significantly higher portfolio shares in top-rated air quality assets (column 2, 0.587%, 10% level), higher composite air-quality portfolio scores (column 4, 3.912, 5% level), and are 1.6% more likely to hold a portfolio ranking in the top quintile of air quality ratings (column 5, significant at the 10% level). In line with the hypothesis that investors aim to compensate for their high emissions from consumption by investing specifically in low-emissions assets, there is no similarly unambiguous pattern of a significant difference in portfolio sustainability between high- and low-footprint investors for overall and ecological scores. The occasionally significant estimates, however, are positive, supporting the notion of a negative relation of the sustainability of consumption and investing.

[Table 6 about here]

My results can best be aligned with the explanation that unsustainable consumers are aware of and understand their environmental impact from consumption, and that they seek to offset it through investments in securities with positive sustainability characteristics specifically targeted at emissions and air quality. While it is possible that other motives than aiming to offset footprints from consumption drive these results, those other motives are unlikely to yield significant results predominantly for outcomes based on GHG emissions and air quality scores, and to a much lesser extent for overall or ecological scores. Rather, if high-emission households were following heterogeneous and income-driven sustainability, return-chasing, gambling, or sensation-seeking motives by investing in such assets, effects for all indicators should be similarly unambiguous. Therefore, it is more likely that investors aim to offset their negative environmental impact by investing specifically in assets that promise a positive carbon impact.

Such offsetting behavior across the consumption and investment domains is a new, previously undocumented finding that is not in line with the prior, albeit limited, literature that finds a positive relation of sustainability preferences between consumption and investing (Brunen and Laubach, 2022; Palacios-González and Chamorro-Mera, 2018). It is important to note the key differences in the proposed methodological and data setup compared to prior studies: Contrary to subjective survey or experimental measures, the external validity of which might be limited, I analyze actual consumption at a granular transaction level. I also compute and use measures for sustainable investments based on real trades and portfolio holdings, and are able to harness the heterogeneity in sustainability preferences by analyzing different rating categories. Therefore, the presented analyses are able to capture spillover effects between investment and consumption in a more objective and differentiated manner than previous attempts. Nevertheless, I want to formally establish whether the results presented in Table 6 can indeed be aligned with offsetting or compensation behavior, or whether they follow from other motives.

4.2 Motives for sustainable investment

One primary concern with the findings presented in Table 6 might be that higher-income investors have higher footprints from consumption by design (see Figure 1, Table 2 and Ivanova et al., 2020). If sustainability is a luxury good, and therefore more attractive to high-income investors, results would be biased towards estimating negative spillovers. Therefore, I not only control for annual income in all regressions, but also test whether heterogeneous sustainability preferences or financial motives can explain cross-sectional variation in the sustainability of investor portfolios better than high carbon emissions from consumption. To this end, I include each of the proxies for sustainability preferences and financial motives presented in Sections 3.2 and 3.3 sequentially in the regressions outlined in equations 4 and 5. Estimates are based on the following extension of the previous regression models:

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

and

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

where the new coefficient, β_2, measures the influence of the financial or sustainability-motive proxy P_i for investor i on ESG investment outcomes. If heterogeneous sustainability preferences explain high ESG investments better than compensation behavior, I expect the coefficient of interest in equations 4 and 5, β_1, to lose statistical significance, and the effect of the respective sustainability proxy, β_2, to have a statistically significant impact on ESG investment outcomes. If financial motives are driving the findings presented in Table 6, I expect β_1 to lose significance upon including financial motive-proxies, and β_2 to have a statistically significant influence. If β_1 retains significance in either case, compensation behavior is either as significant or more significant than the included proxy to explain high-sustainability outcomes. The schematic presented in Figure 5 outlines the rationale behind the proposed analyses graphically.

[Figure 5 about here]

Since Table 6 exhibits the most consistent evidence of offsetting behavior for outcomes based on GHG emissions ratings, I present results for sustainability and financial motives for the same outcome indicators based on GHG-emission scores in Table 7. Analogously to Table 6, I present estimates and corresponding p-values for the coefficient of interest (COI) on above-median carbon footprints after inclusion of each proxy, β_1, as well as estimates for the proxy, β_2.

As outlined in Sections 3.2 and 3.3, I 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.

[Table 7 here.]

Sustainability-preference proxies 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 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. In addition, the results for financial-motive proxies are more ambiguous than the relation between unsustainable consumption and sustainable portfolio measures. This ambiguity is unlikely if financial motives were driving the sustainability of investments.

Financial-motive proxies Return-chasing proxies offer mixed results with respect to the direction of effects as well as the statistical significance. The propensity to hold high-ranking GHG emissions assets is influenced positively by the monthly number of trades and online banking logins, but negatively by portfolio turnovers (column 1, all significant at the 1% level). For portfolio and asset shares held in top-rated assets, the influence of monthly trades and portfolio turnovers exhibits the opposite sign as for propensities to hold top-rated assets, with levels of statistical significance ranging from 1% to 10% (columns 2 and 3). Higher portfolio turnovers and the disposition effect are also significantly and positively related to the propensity of investor portfolios to rank in the top quintile of composite portfolio ESG scores (column 5, significant at the 1% and 5% levels, respectively), and the disposition effect is additionally positively related to portfolio shares held in top-rated assets (column 2).

While there is some evidence that financial motives influence the sustainability of investor portfolios with respect to GHG emissions, the direction of effects alternates between positive and negative, and the coefficient on high emissions from consumption retains its level of statistical significance and, generally, its magnitude. If financial-motive proxies that measure behavioral biases such as excessive trading, overconfidence, or sensation-seeking were driving portfolio selection with respect to sustainability scores based on GHG-emissions, the sign of coefficients should be positive throughout. In fact, the significance of the positive relation between unsustainable consumption behavior as measured by carbon footprints and sustainable investments occasionally even increases after including almost all of the aforementioned financial-motive indicators compared to the baseline model (Table 6). This means that the potential compensation behavior documented in Table 6 for high-emission investors cannot be explained by financial-motive proxies, and that the finding of a negative relation between unsustainable consumption and sustainable investments cannot be aligned with an alternative explanation that high-footprint investors chase returns by investing in ESG assets.

It is possible that high-emission investors *both* aim to compensate for their consumption-based carbon footprints by investing in ESG assets *and* exhibit well-studied behavioral biases associated with financial motives such as overconfidence, excessive trading, or sensation-seeking. Importantly, however, none of those biases explain high-sustainability investments with respect to GHG emissions to a larger extent than having high emissions from consumption. It is also important to note that coefficients on financial-motive and sustainability-motive proxies are generally smaller than those on the COI, again emphasizing that unsustainable consumption can explain investment sustainability better than the tested alternatives. I therefore interpret the results of Tables 6 and 7 together as evidence that investors with especially high footprints from consumption are aware of the environmental impact of their consumption behavior, and aim to offset those impacts by investing more intensively in assets targeted specifically at reducing carbon emissions.

4.3 Survey evidence

In this Section, I 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, I 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, I survey the participants' estimates, opinions and prior experience with key aspects of my 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 Section 2.2. I ask participants to provide this estimate in $kgCO_2$ per capita and annum so as not to bias results upwards by suggesting values in metric tons. 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 (higher) footprint than their peers'. Finally, I query whether the participants have used certain compensation methods in the past. For this question, I offer a free-entry field in addition to several pre-set options, among them sustainable investing. I take care to list sustainable investing as one of the middle options so as not to anchor the participants in choosing this option. Figure 8 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 Table A.2 in the Appendix).

Table 8 presents the estimated and actual carbon footprints for the 2,383 survey participants for whom I observe consumption data. Actual footprints are computed following the description in Section 2.2. Generally, survey participants tend to over-estimate their carbon footprints on average, however, this finding might be driven by outliers, i.e., very high estimates.[15] On average, participants estimate an annual footprint of 9.48 tCO_2, which is reasonably close to the official estimate of 11.6 tCO_2.[16] 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_2 p.a. (compare Table 2). 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_2 p.a., respectively.

[Table 8 about here]

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 tCO_2 – a result that might seem to counter my 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 8 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 6, 7.A, 7.B, and 7.C). In addition, participants do not know other participants' answers, which is why I additionally segment the likelihood to choose 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 9.

Figure 6 shows the frequency and degree of under- and overestimated carbon footprints. Specifically, I compute the deviation of estimated and actual carbon footprints at the individual

[15] I winsorize all footprint estimates at the 5% level to limit the influence of outliers. I choose this comparably 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_2.

[16] https://www.umweltbundesamt.de/klimaneutral-leben-persoenliche-CO2-bilanz-im-blick

level such that negative (positive) values indicate underestimations (overestimations). The top panel of Figure 6 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 8 suggest otherwise. Still, the difference between estimated and actual footprints is sizable in both directions at roughly 7.5 tCO_2 (underestimated) and more than 20 tCO_2 (overestimated), respectively, suggesting that both effects cancel out in the general mean-sample analysis of Table 8. The lower panel of Figure 6 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.[17] At the seventh septile of actual footprints, 316 (24) participants underestimate (overestimate) their own footprints by about 23 tCO_2 (over 70 tCO_2).

Next, I inspect the drivers of the deviation of real and estimated consumption-driven carbon footprints. To this end, I 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 7.A, 7.B, and 7.C 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 7.A shows that, analogous to the sample-mean analyses of Figure 6, 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,

[17]The seven sub-figures in the lower panel of Figure 6 show positive and negative deviations of the participants' estimated from their actual footprints split by septiles of actual footprints. I choose septiles to mimic the Likert scale on which participants are asked to rank their own footprints in a later part of the survey.

whereas overestimated emissions are only significantly driven by actual footprints in the sixth and seventh septile.

[Figure 6 about here]

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 7.B and 7.C 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_2. Specifically, Figure 7.B shows that males, married individuals, managers, blue-collar workers, homemakers, and students exhibit significantly higher degrees of underestimating their carbon footprints than others, whereas – among all over-estimators – only managers significantly overstimate their carbon footprints than other populations. The lower panel of Figure 7.B shows that securities account, consumer loan, property loan, and savings account owners additionally exhibit significantly higher degrees of footprint underestimation, whereas, among over-estimators, 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 7.C).

[Figures 7.A, 7.B, and 7.C about here]

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 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.[18] This is strong

[18]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.

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 my analyses. Figure 8 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 seventh most frequently chosen. Since *No offset* remains in Figure 8, sustainable investing is actually the sixth most popular answer at the intensive margin.

[Figure 8 about here]

The results presented in Table 8 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_2). As a more formal assessment of whether individuals who believe that their emissions are higher than their peers', Table 9 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. I code all answers larger than five as assessments of above-median footprints for the purpose of validating my 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 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 A.2 in the Appendix.

[Table 9 about here.]

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 6 and 7 can indeed be traced back to investors attempting to compensate for their consumption-driven emissions by investing more sustainably.

4.4 Robustness analyses

The previous sections presented evidence for negative spillovers between the sustainability of individual-investor consumption and investments consistent with offsetting emissions from consumption by sustainable investing. Nevertheless, in order to really pin down the mechanism behind the presented findings, I offer additional robustness analyses in the following.

Income effects The analysis of whether financial motives explain portfolio sustainability better than high consumption-driven footprints addresses the primary concern of potentially income-driven baseline results. However, financial motives need not be present only among higher-income individuals. Therefore, the fact that the variation in portfolio sustainability is not explained better by financial motives than unsustainable consumption does not fully rule out income effects.

To address this concern in a more straightforward manner, I offer alternative specifications of unsustainable consumption that are independent of income in Table 10. Specifically, I 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, e.g. earnings or sustainability reports.

[Table 10 about here]

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 6 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 6 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.

Socio-cultural factors The prior literature has found that the regional composition of religious faiths at the aggregate can aid the identification of important behavioral patterns, e.g., for Catholics and Protestants in the domain of gambling preferences (Kumar, 2009). In a similar vein, I leverage religious information at the aggregate level to pin down the offsetting mechanism behind the baseline results presented in Table 6 above.

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.

I leverage this cultural heterogeneity to pin down more specifically whether the results presented above 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, I resort to German census data from 2011 at the (aggregate) 5-digit zip code level.[19] 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. I merge these variables to each investors at the 5-digit zip code level. Table 11 presents the decomposition of religious faiths across the overall, low-, and high-footprint sample.

[Table 11 about here]

Census data on religious faiths is available for the zip codes of 5,732 investors (Table 11). 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% 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. I test the relation of Catholicism and portfolio sustainability by repeating the baseline specifications of equations 4 and 5, presented in Table 6. Instead of the above-median footprint variable, however, I use the share of Catholics in investors' zip code area (in percentage points). I 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. I add both variables to disentangle the effect of exposure to religious beliefs from socio-economic factors.

[Table 12 about here]

Compared to the baseline presented in Table 6, 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

[19]The query of religious beliefs has since been discontinued.

quantitatively similar. A higher share of Catholics is also associated with significantly higher overall and ecological portfolio 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 6 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 12, the relation between ecological activity and religion is more strongly pronounced for Catholics than Protestants (Gutsche, 2019).

The results presented in Table 12 provide additional evidence that there are negative spillovers between sustainable consumption and investing. Adding to earlier analyses, they also suggest that these spillovers are indeed consistent with unsustainable consumers' aim to offset their emissions from consumption with more sustainable investments. The fact that the corresponding relation of Catholics to portfolio sustainability metrics can only conclusively and unambiguously be found for securities with favorable GHG emissions and air quality ratings further supports this interpretation.

Investor sample definition Tables 10 and 12 support that the estimated negative spillovers between the sustainability of consumption and investing are not driven by income-driven consumption patterns. Rather, the presented findings suggest that investors with less sustainable consumption patterns indeed attempt to offset the resulting emissions. As outlined in Section 2.1, however, I imposed several sample restrictions in order to estimate the baseline cross-domain spillovers for main and income account users. I now assess the robustness of the baseline findings presented in Table 6 to different investor sample definitions. To this end, I repeat the main analysis for the unrestricted sample, investors with non-missing income and wealth data, investors with total annual income from salaries, wages, and pensions of at least EUR 10,000, and regular income receivers. The latter are defined as investors who receive regular, permanent income for at least 75% of the months over the sample period (see Table 1 for the full sample breakdown).

Table 13 presents the corresponding results. The results are largely equivalent to this robustness analysis. However, the robustness of the baseline findings presented in Table 6 is highly dependent on the outcome variable. Specifically, the findings for composite portfolio ESG scores (column 4), significant across TVL rating categories in the baseline, remain significant irrespective of the analyzed investor sample. In fact, coefficients are even larger in terms of magnitude for less restrictive samples. For the asset share devoted to assets ranking in the top 20% of TVL ratings (column 3), the baseline finding of statistical significance only for GHG emission ratings remains significant across all investor sample definitions except for the income-receiver specification. In fact, the level of statistical significance even increases to 1% for all 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) is statistically significant across TVL rating categories and sample definitions. The baseline result is therefore robust to the sampling choice, and potential offsetting might be present even for other rating categories than emission or air quality profiles. 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), however, are ambiguous, indicating that the baseline results are not robust to the extension of the investor sample.

[Table 13 about here]

Importantly, however, the results presented in Table 13 should be interpreted with caution, especially in the case of investor likelihoods to invest in any top-ranking asset. Without the restrictions imposed on the baseline analysis, estimates might capture effects for investors who do not use their checking or trading accounts frequently, use them for either one of both activities but not the other, or use them to consume and invest specifically, e.g., only for savings, retirement investments, or travel expenses. Adding to this the fact that holding any top-ranking asset (column 1) is a rather lenient measure of portfolio sustainability, the main takeaway remains unchanged by the ambiguous findings for this specific outcome. The remainder of the results presented in Table 13, while not equivalent to the baseline in every respect, are sufficiently close to the main findings to lend further support to the notion that investors with especially unsustainable consumption patterns aim to offset their carbon footprints from consumption using sustainable investments.

5 Compensation efficiency

The evidence presented thus far points to an investor belief that consumption-driven emissions can be offset by investing more sustainably. This ultimately begs the question whether such a compensation method is actually efficient, i.e., more sustainable investing is "enough" to compensate for individual-investor emissions. In contrast to a direct offset through a specific platform or service, such as *atmosfair*, the compensation benefit of investing sustainably is not only more indirect, but also inherently complex to calculate.[20] Therefore, I offer two rough back-of-the-envelope calculations of the compensation efficiency. It is important note that both are specific to the studied investor sample and can only offer a crude estimate of whether compensating with SRI can even come close to offsetting consumption-driven emissions.

According to Ivanova et al. (2016), households are responsible for 60% of EU emissions, and household-level footprints would have to be between 2.5 and 3.3 tCO_2 to adhere to the 1.5°C goal by 2030. According to *atmosfair*, emissions per capita would have to be 1.5 tCO_2 p.a.[21] Comparing these figures to the average emissions associated with consumption in the studied sample, sustainable investing as the only method of compensation would have to be associated with over 10 tCO_2 lower emissions for the average investor, and close to 20 tCO_2 for high-footprint investors (compare Table 2). The first back-of-the-envelope calculation of offseting efficiency focuses on the average carbon footprints associated with the portfolios of high- vs. low-footprint investors in our sample. If the actual portfolio emissions of high-footprint investors are lower than those of their lower-footprint counterparts, the difference would be the compensation benefit associated with the more sustainable investment practices observed for the former. The second calculation leverages the difference in likelihoods and portfolio outcomes presented in Section 4 (Table 6), addressing the shortcomings of the first approach.

Table 14 presents average total direct and indirect emissions by scopes 1, 2, and 3.[22] Specifically,

[20] *Atmosfair* is the leading platform for carbon offsets in Germany. More information on the organization can be found at https://www.atmosfair.de/en/.

[21] The emissions calculation and offsetting platform also assumes a goal of limiting global warming to 1.5°C, and divides the IPCC budget of 420 billion tCO_2 by 2050 over an average global population of 8.8 billion people. Source: https://www.atmosfair.de/de/kompensieren/.

[22] 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).

it displays average emissions by category of consumption-driven footprints (high, low) as defined in Section 2.2. Next to average footprints from consumption, I also compute emissions associated with investments. To this end, I obtain GHG emissions and scope classifications at the ISIN level for each stock held at some point during the sample period from Refinitiv. I subsequently 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. It is important to note that this calculation is a rough approximation in two aspects: First, the assessment of emissions and classification of emission scopes is only mandatory for stocks, which means that Refinitiv does not offer this information for other asset classes than equity. The results presented in this Section can therefore not be expected to adequately capture emission profiles of full investor portfolios, but only of the included equity shares. Second, scope 2 and 3 emissions (indirect emissions) are notoriously difficult to assess. Therefore, Table 14 presents statistics across several definitions of total portfolio emissions, namely, separately by scopes 1, 2, and 3, as well as two estimates of total portfolio emissions. The first one subsumes all direct scope 1 and indirect scope 2 emissions, whereas the second one captures all scope 1, 2, and 3 emissions.

[Table 14 about here]

Despite the fact that high-footprint investors hold more sustainable portfolios overall with respect to their emission ratings, their portfolios are associated with higher overall emissions than those of their lower-footprint counterparts: Depending on the emission scope, differentials between high- and low-footprint investors are *positive* (meaning that there is no compensation benefit) and range from 0.401 to 3.194 tCO_2. This figure adds to the much higher emissions of the studied investors of 21.1 tCO_2 p.a. compared to the low-footprint average of 7.22 tCO_2. This finding is likely driven by the fact that high-footprint investors also hold much higher-value portfolios, leading to overall higher emissions (the difference between high- and low-footprint investors of about 83,840 EUR is sizable in economic terms and statistically significant at the 1% level, see Table 3). Scaled by total portfolio values, the average asset-level emissions of this group's portfolios are likely to be lower than those of investors with lower emissions from consumption. Nevertheless, high-footprint investors factually hold portfolios at these high values, which means that their real investment behavior in the equity space where I can estimate total emissions is – at least on average – not associated with lower emissions despite their more favorable portfolio emission ratings.

To offer an alternative assessment of the offset potential offered by investing in more sustainable assets while addressing the shortcomings of the approach presented in Table 14, I provide an additional option to evaluate the offsetting efficiency. This method is based on the baseline regression results of Table 6: To assess the highest-possible offset potential associated with highly sustainable investment practices, I compute the emission differential for the top and bottom quintile of stock-level emissions, i.e., the average scope 1, 2, 3, and total GHG emissions associated with investing in the highest and lowest 20% of stocks based ranked by their emission profiles. The benefit (negative differential) associated with investing in the top 20% of emissions (the 20% of stocks which have the lowest emissions) is the resulting estimate of the highest-possible compensation from investing in these stocks. I then multiply the resulting compensation benefit by each of the coefficients from Table 6, which indicate the difference in holdings or likelihoods between high- and low-footprint investors. The obtained average emissions capture the compensation effect that is associated with the investment (portfolio) sustainability of high-footprint investors compared to their low-footprint counterparts, and thereby offers an estimate of the maximum extent to which the investment behavior of high-footprint investors can help compensate for their consumption-driven emissions.

The results for this additional approach of evaluating the efficiency of investment-driven offsets are presented in Table 15. In this Table, the respective baseline regression specification that the offsetting benefit estimates are based on is provided in the column headed *Baseline specification*, where the number corresponds to the respective column of Table 6. Columns titled *Offset potential* and *Emissions after offset* present the maximum compensation benefit associated with investing in the top 20% of emissions compared to the bottom 20%, calculated as described above, and the average total consumption-driven emissions of high-footprint investors after subtracting this compensation benefit, respectively. Finally, I add an *"Exchange rate"*, which captures what percentage of consumption-driven emissions can be offset by investing in these low-emission stocks at the intensity or likelihood estimated in Table 6.

[Table 15 about here]

Table 15 shows that the difference in emissions of top- and bottom-ranking stocks weighted by the coefficients from baseline specifications 1, 2, or 3 are associated with offset potentials between 0 and at most 2.1 tCO_2. These compensation benefits yield average total emissions for high-footprint investors ranging from 19 tCO_2 to the full 21.1 tCO_2 that cannot be compensated even if they chose only the top 20% assets with respect to emissions. These figures are still a magnitude larger than the target rate between 1.5 and 3.3 tCO_2. Overall, despite the perceived investor belief that sustainable investments can help offset carbon emissions from consumption, the back-of-the-envelope calculations presented in this Section demonstrate that investing more sustainably alone does not come close to offsetting these emissions in full.

6 Conclusion

Sustainable behavior has been and is gaining interest from regulators, asset managers, financial institutions, and retail investors. A growing body of literature investigates the sustainability of individual consumption and investment decisions. Literature on specific spillovers between both domains based on objective data, however, is scarce. The work that has been done on the subject is based on experiments or survey data and utilizes relatively small samples. Such approaches might produce biased estimates inherent to their unavoidable shortcomings, for instance if participants under-report their "brown" and overstate their "green behavior", or if the method of incentivization or choice of survey platform bias sample selection (online vs. paper-/lab-based). Nevertheless, the prior literature points towards a positive relation between individual investors' sustainability in the consumption and investment domains. Contrary to this finding, I present evidence of negative spillovers consistent with a pattern of offsetting unsustainable consumption behavior by investing more sustainably based on individual-investor administrative data. This analysis thereby adds to an understanding of the relationship between the sustainability of consumption and investments while addressing common shortfalls of prior studies, leveraging the unique combination of transaction-level investment and trading data, and providing novel insights into motives for sustainable investment behavior.

This study can offer a holistic assessment of spillovers between the sustainability of consumption and investments. Across various measures for sustainable investment, high-footprint consumers seem to understand the environmental impacts of their consumption patterns, and aim to offset them by investing specifically in securities which have extremely low-emission profiles. I present additional evidence that investors use only these specific securities to offset their carbon-based emissions, whereas portfolios with high general ESG ratings do not exhibit such a relation to unsustainable consumption. I provide further support for the notion that unsustainable consumers seek offsetting opportunities using GHG-sustainable investments by testing the prevalence of two different investment motives, i.e., heterogeneous sustainability preferences and financial motives. The main result of carbon offsetting behavior between consumption and investments is robust to the inclusion of proxies for alternative motives. Nonetheless, I find some (mixed) evidence (i) that investors have sustainability motives beyond compensating for their consumption-driven emissions and (ii) that common behavioral biases related to overtrading, under-diversification, or disposition effects might be more prevalent among sustainable investors others. However, these effects cannot explain sustainable investments better than having high footprints from consumption.

To pin down the mechanism driving my results, I test alternative explanations for my findings. First, I rule out that income effects drive my results by testing alternative definitions of unsustainable consumption based on carbon intensities. The adjustment does not change the main result. Second, I show that Catholicism, historically tied to financial offsetting practices through the 15^th and 16^th-century letters of indulgence, is significantly and positively related to the sustainability profile of retail investor portfolios. In terms of statistical significance, the results match those of the baseline exactly. Similar to the baseline findings of negative spillovers between the sustainability of consumption and investing, this relation is especially strongly pronounced for assets with favorable GHG emissions and air quality ratings. Finally, I conduct a survey with 3,646 clients of the same bank that provided the administrative data analyzed in this paper, finding that the majority of investors underestimate their own carbon footprints from consumption. This underestimation increases systematically in the size of the survey participants' real footprints and is more pronounced for certain demographics and financial-product users. Nevertheless, further survey analyses additionally reveal that (i) participants with higher observed footprints from consumption and (ii) those who believe their own footprints are higher than those of their peers are significantly more likely to try to offset their emissions by investing more sustainably, thereby confirming that the mechanisms studied in this paper follow from an awareness for investors' own footprints – even though the actual size is misestimated – and a conscious choice to choose sustainable investments as a means to offset them.

I identify several intriguing areas for future research. First, future research may provide additional insights on trading motives for sustainable investments. While I show that offsetting is a significant driver of sustainable investment among retail investors, the analysis is far from complete. Second, future research might shed further light on sustainable investors' trading behavior. The provided evidence suggests that some well-studied trading biases may be more prevalent among sustainable investors. For instance, I find sustainable portfolios to be associated with excessive trading activity and higher degrees of under-diversification. Since sustainable retail investors are a vital pillar to achieve climate goals and the transition to green finance, it would be unfortunate if this essential group fell victim to certain biases more often than others. This could induce investors to refrain from (additional) investments and, subsequently, a decrease in aggregate funds allocated to sustainable investments. Future studies may analyze whether sustainable investors are in more need of financial education or policies targeted at increasing their financial literacy than others. Such studies may aim to provide additional evidence of the connection between behavioral biases and sustainable investments by employing methods such as transaction-based measurements of behavioral biases, the application of mental accounting explanations to sustainability, or through the use of surveys and experiments.

While the rapidly increasing investor demand for SRI in recent years aids the transition to a greener economy, global greenhouse gas emissions are increasing at an even faster pace: According to Our World in Data, GHG emissions increased by about 25 percentage points over roughly the same period from 2015 to 2019, to 49.76 billion tCO_2.[23] In Europe, households account for 60% of total GHG emissions (Ivanova et al., 2016). To reach the 1.5° Celsius target which is required to prevent cataclysmic climate events, the household-level footprint would

[23] https://ourworldindata.org/greenhouse-gas-emissions, accessed on November 17, 2022.

need to be closer to 2.5 tCO_2 per annum (p.a.). The average individual living in Germany thereby emits 11.6 tCO_2 p.a., leaving a gap of over 9 tCO_2. For the investors studied in this sample, this gap is even higher at about 12 tCO_2.

This paper demonstrates that investors consciously choose sustainable investing in an attempt to compensate for their carbon emissions, especially if they believe that their footprints are higher than their peers'. My findings can be aligned with the notion that sustainable investing might lead to net negative effects on the climate in terms of emissions if investors feel morally licensed to retain their unsustainable, high carbon footprint behavior because of their sustainable investment choices. These negative effects would be especially concerning if investors systematically underestimate their own carbon footprints, which they seem to do based on the survey conducted in this paper. This effect might reverse the intended positive effect of sustainable investment choices and even lead to the opposite result, in that consumers' carbon emissions remain high when a reduction of carbon footprints on all levels of the economy is required. In this light, regularly ascertaining and evaluating the accuracy of ESG classifications is crucial, as investors seem to choose sustainable assets according to their certified degree of sustainability. At the same time, it is imperative to educate and inform consumers and investors of the veracity and overall effectiveness of their choices in order to prevent this outlined potential net negative effect of sustainable investing on individuals' total carbon emissions.

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Figures

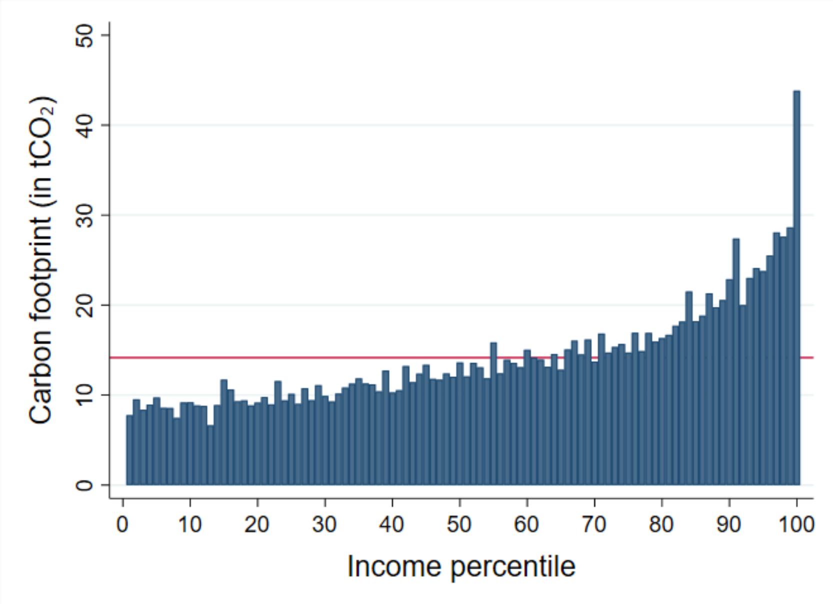
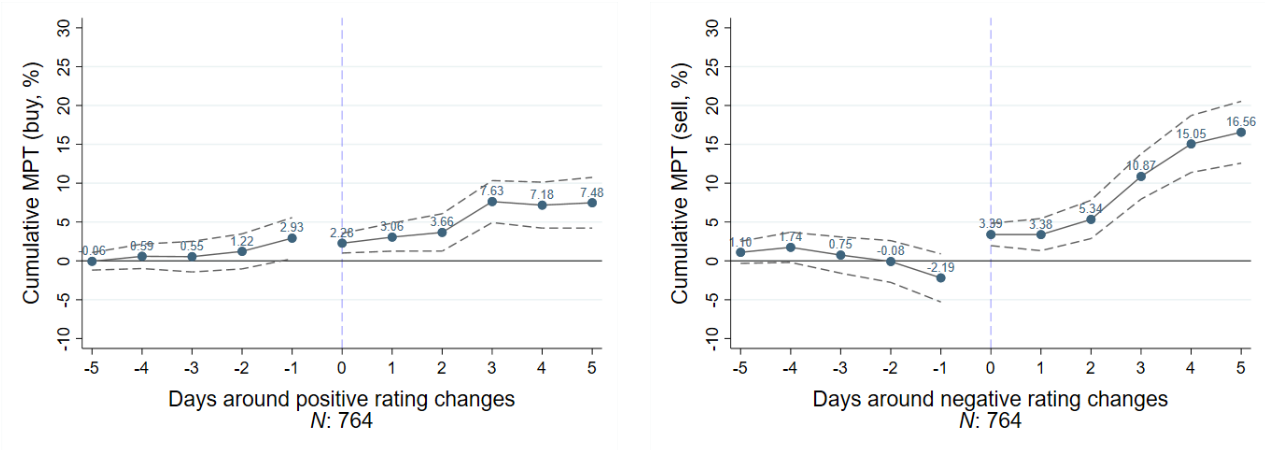


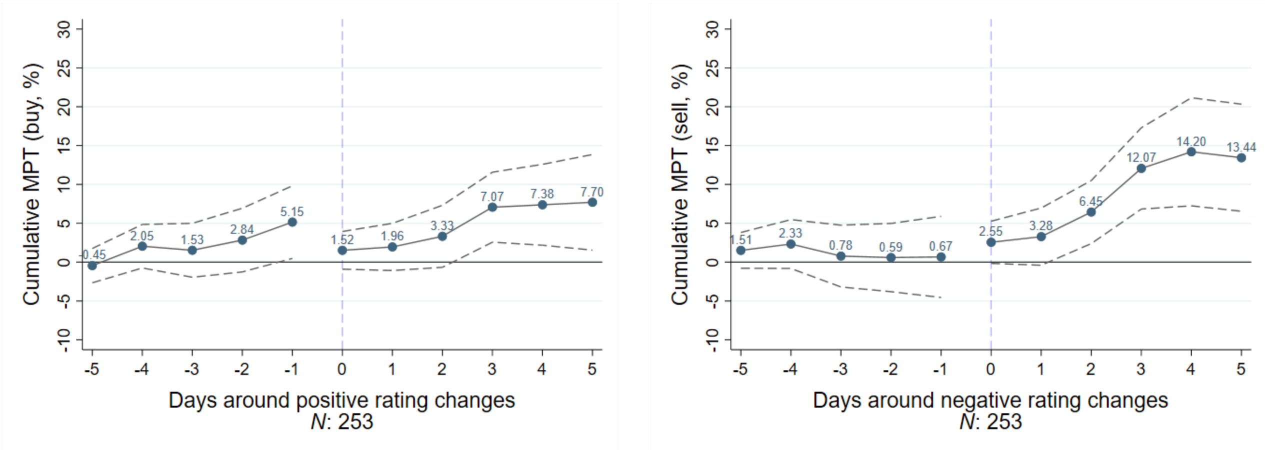
Figure 1 Total carbon emissions by income percentile

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 as described in Section 2.2.

Panel A: Sample



Panel B: Low footprint



Panel C: High footprint

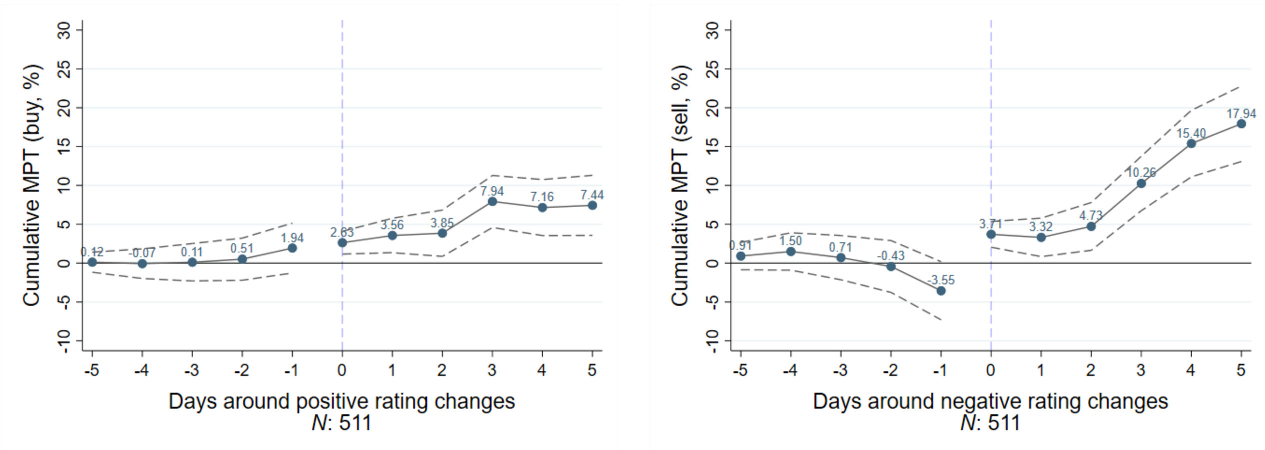


Figure 2 MPT around overall rating changes

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, I 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.

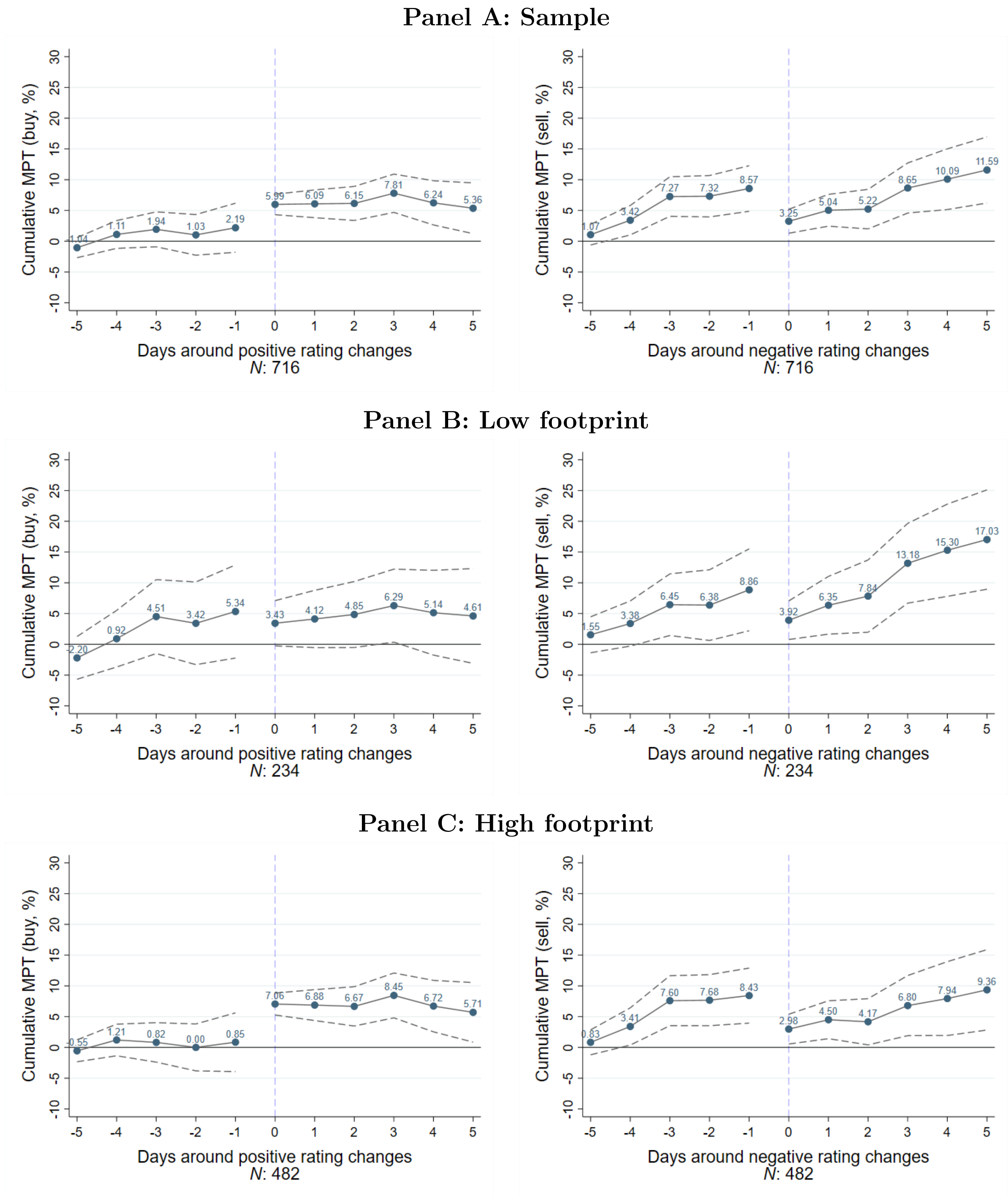


Figure 3 MPT around GHG emission rating changes

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, I 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.

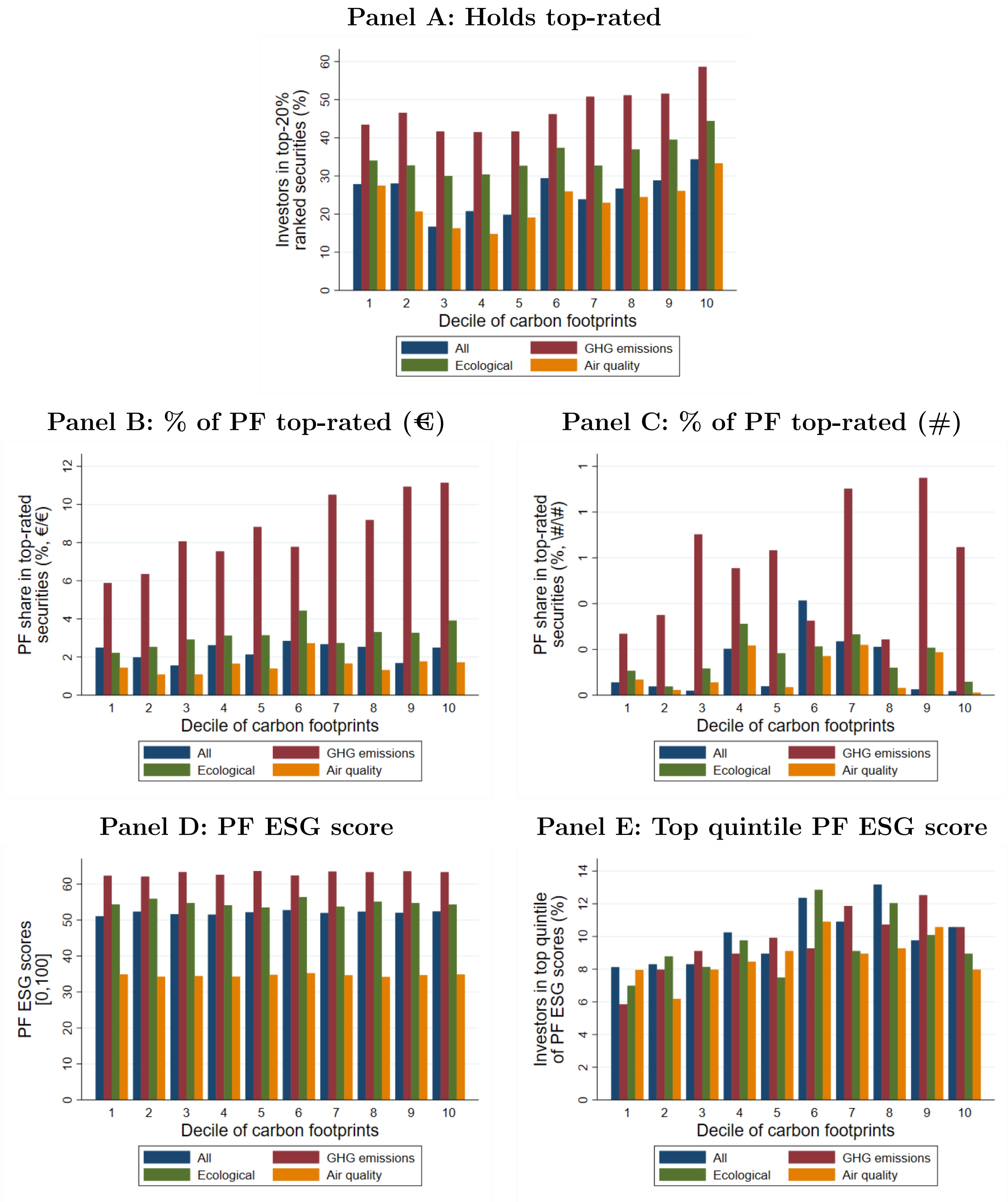


Figure 4 Distribution of ESG investment indicators across deciles of carbon footprints

Note. The above figures show the distribution of the five main sustainable investment outcome variables used in the analysis across deciles of consumption-based carbon footprints. Panel A shows the percentage of investors in each decile who hold assets that rank in the top 20% of TVL overall, GHG emissions, ecological, or air quality ratings. Panels B and C display analogous figures for portfolio shares (weights) and asset shares, respectively, that investors devote to assets which rank in the top 20% of TVL scores. Panel D shows the distribution of composite portfolio ESG scores at the individual-investor level by footprint decile, whereas Panel E displays the percentage of investors in each decile of consumption-driven emissions who rank in the top quintile of portfolio ESG scores.

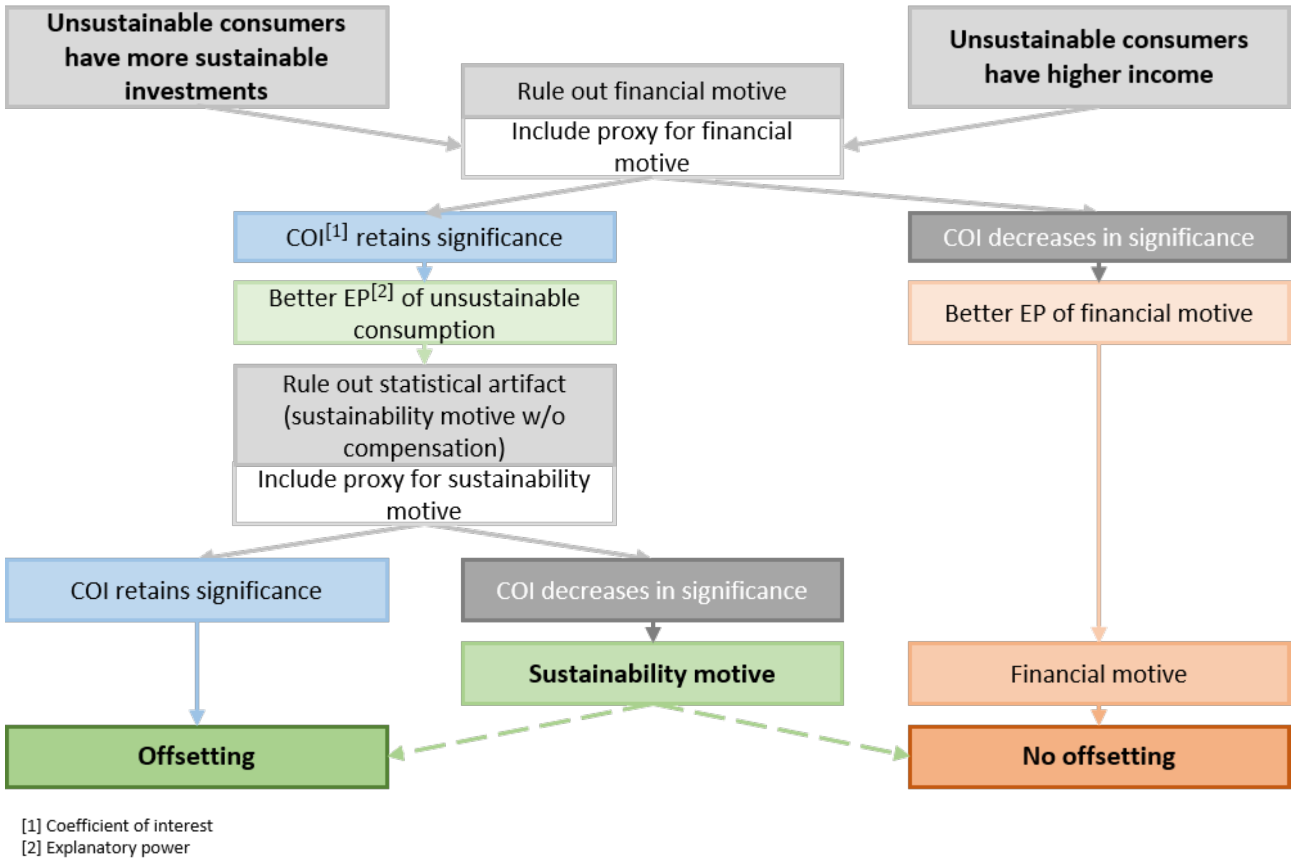
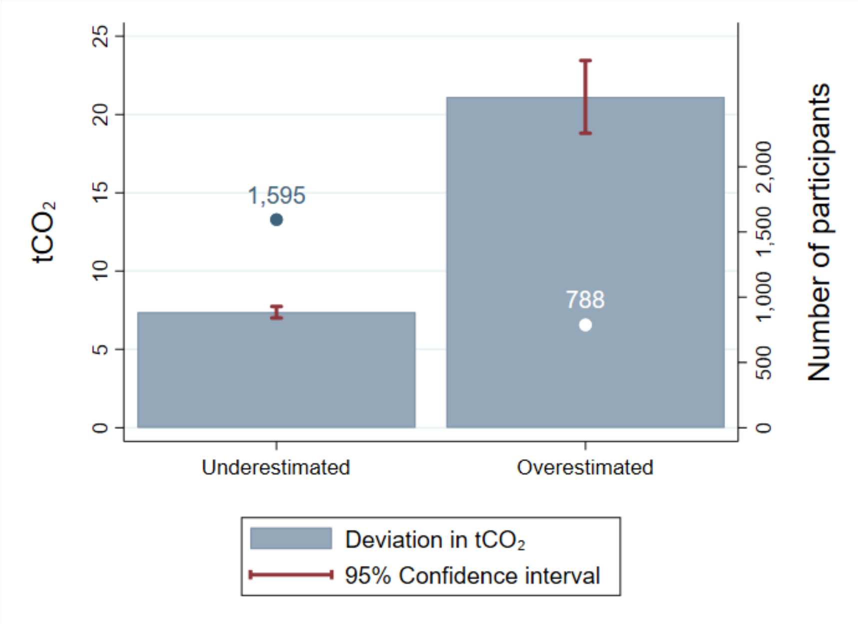


Figure 5 Schematic of the methodological study setup

Note. The above figures presents a schematic of how compensation behavior, heterogeneous sustainability preferences, or financial motives might drive the main finding of negative spillovers between the sustainability of consumption and investments. Both income and compensation effects might drive the main result. To rule out alternatives, I sequentially include proxies for sustainability and financial motives. If the coefficient of interest (COI) on unsustainable consumption retains statistical significance, offsetting cannot be ruled out by the respective included proxy. Conversely, if it decreases in significance, the new proxy offers better explanatory power (EP) than the potential offsetting mechanism. Heterogeneous sustainability preferences do not point to either the *offsetting* or *no offsetting* explanation unambiguously. Therefore, financial motives and sustainability proxies need to be tested against the high-footprint variable individually.



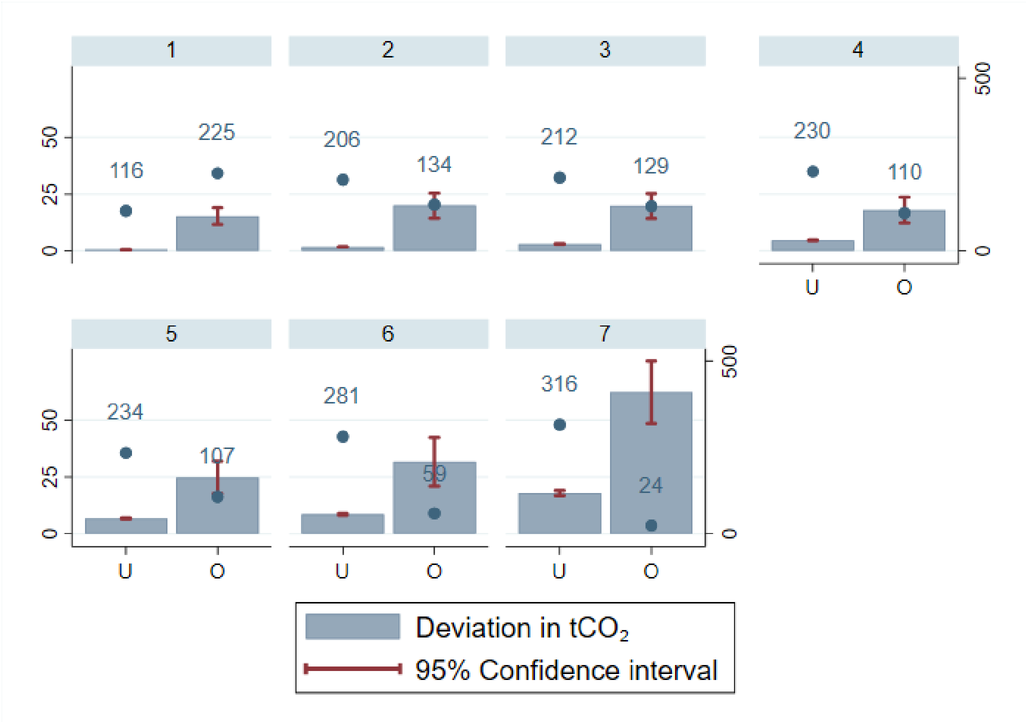
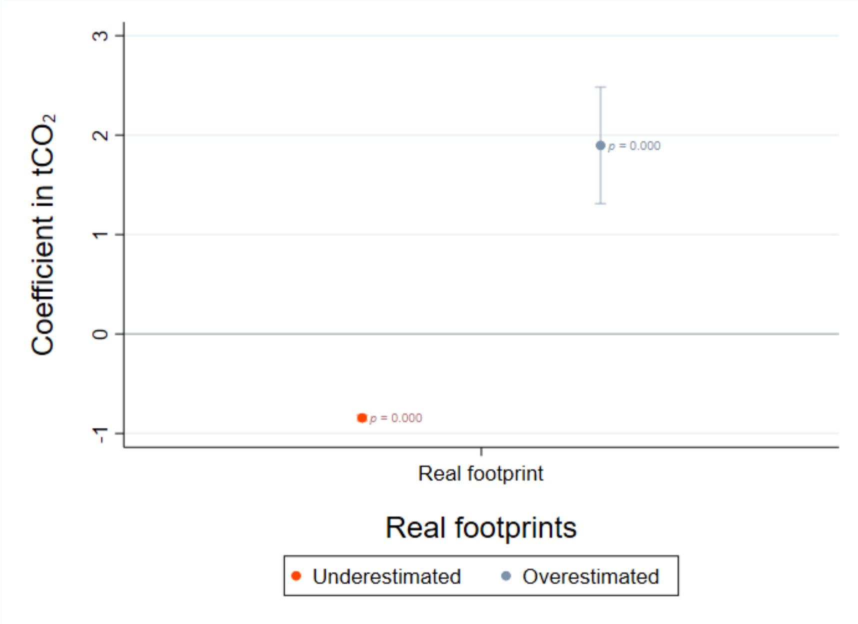


Figure 6 Survey: Differences between estimated and observed carbon footprints

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 Section 2.2. 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. I 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".



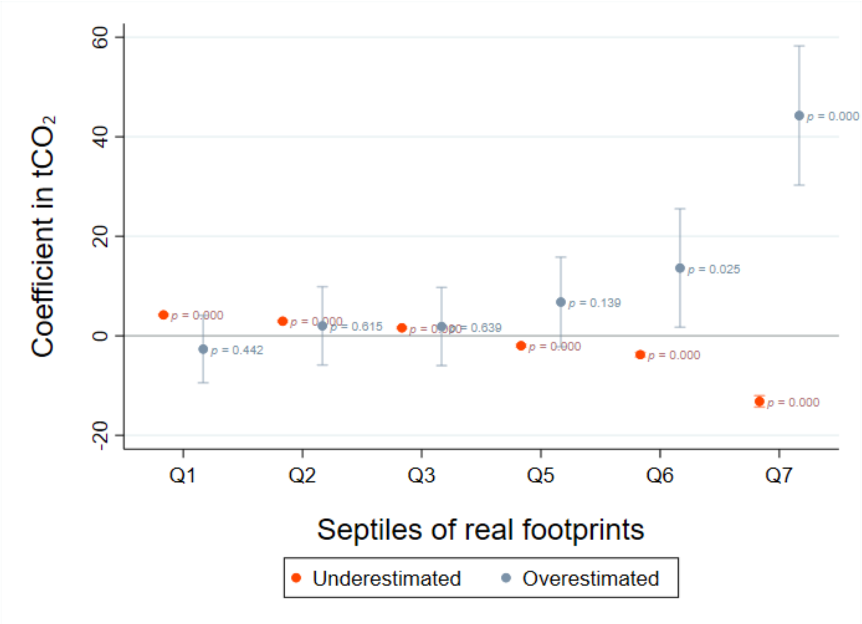


Figure 7.A Survey: Heterogeneity of footprint misestimation (I)

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. I 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 Section 2.2. 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.

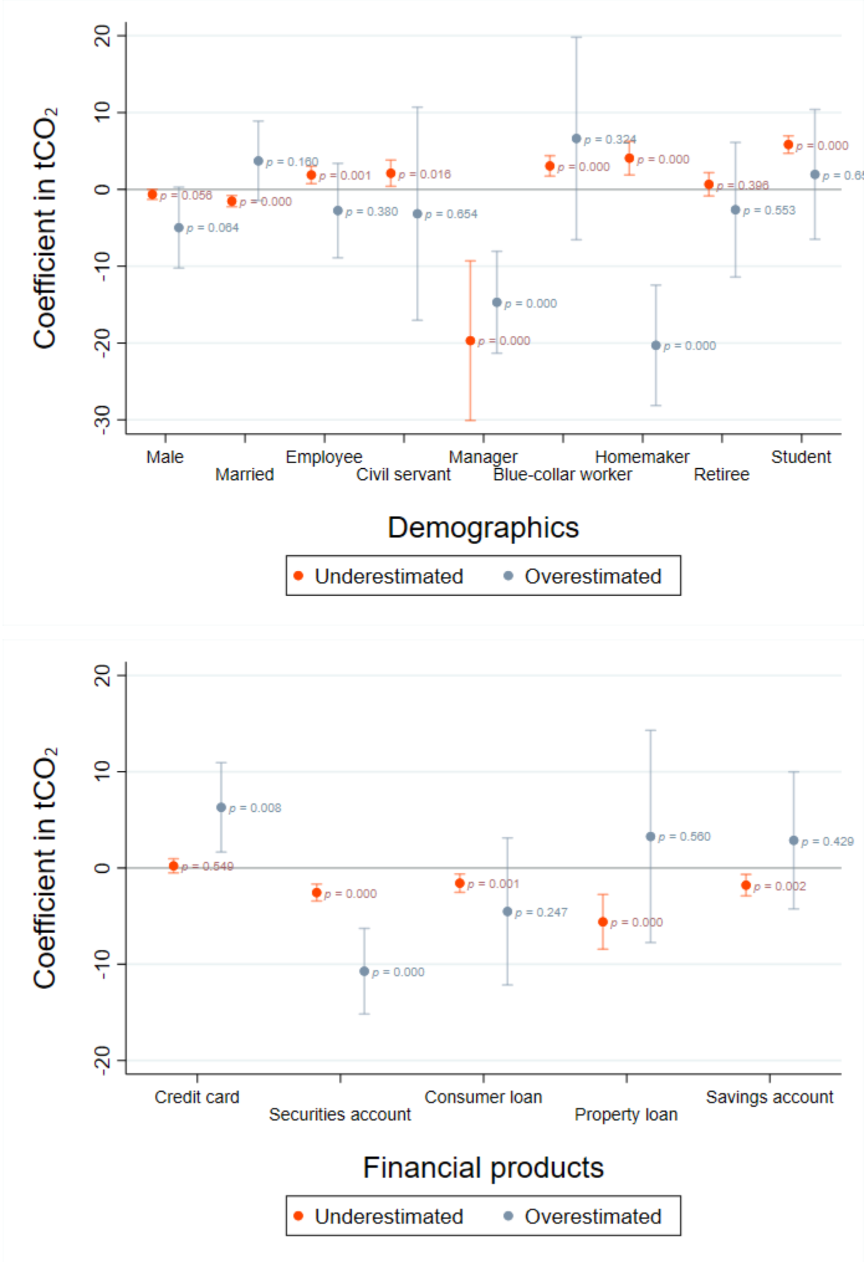


Figure 7.B Survey: Heterogeneity of footprint misestimation (II)

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 Section 2.2. 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.

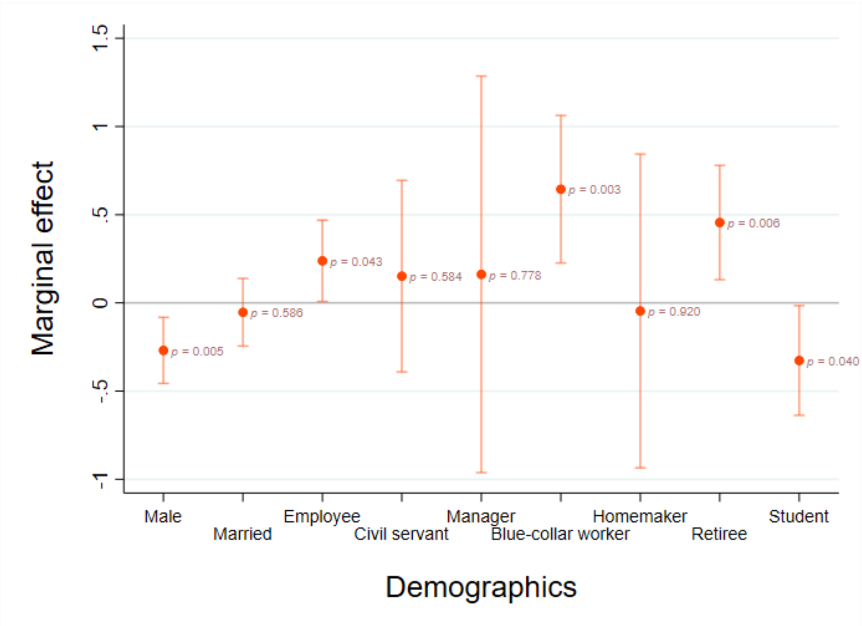


Figure 7.C Survey: Heterogeneity of footprint misestimation (III)

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 Section 2.2. 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.

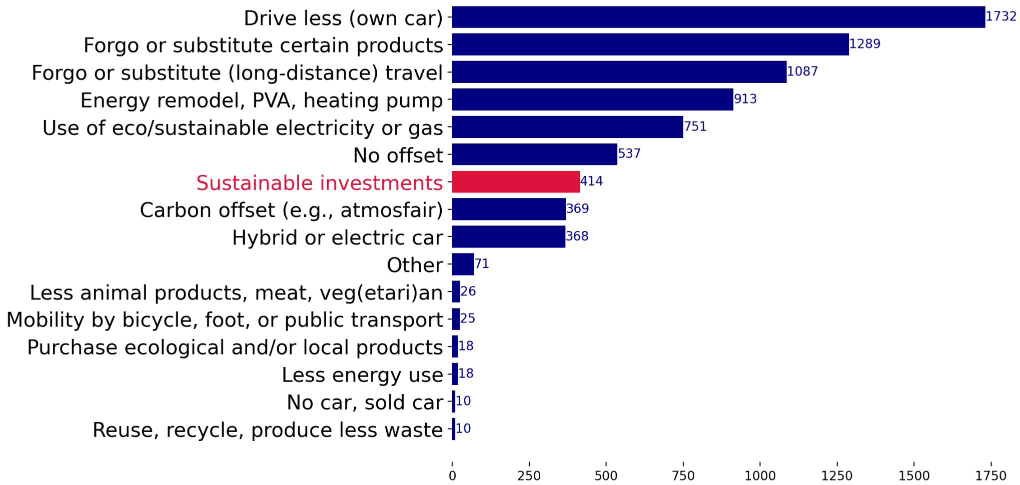


Figure 8 Survey: Methods of compensating for emissions from consumption

Note. The above figure displays results from a survey conducted in October 2022 with 3,646 clients of the same bank whose data I 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.

Tables

Table 1 Sample selection and restriction criteria

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***

Note. The above table shows the size of subsamples selected according to the criteria described in Section 2.1. I 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 my baseline findings to these sample restrictions is tested in Table 13.

Table 2 Socio-demographics

Demographics	Sample	Low	High	High – 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	High – 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

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.

Table 3 Portfolio statistics

	Sample	Low footprint	High footprint	High – low footprint
PF value (median, k€)	103.72	61.81	145.65	83.84***
Participation rates	Sample	Low footprint	High footprint	High – low footprint
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	Sample	Low footprint	High footprint	High – low footprint
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	Sample	Low footprint	High footprint	High – low footprint
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

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 *Sample* show averages for the whole sample, whereas columns titled *Low footprint* and *High footprint* distinguish between below- and above-median footprints from consumption, respectively. The column titled *High – low footprint* 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.

Table 4 ESG investment indicators

TVL overall	Sample	Low	High	High – Low
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	Sample	Low	High	High – Low
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	Sample	Low	High	High – Low
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	Sample	Low	High	High – Low
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

Note. The above table presents sample averages for the sustainable-investment measures I use as outcome variables in the trading-motive regressions. I compute each measure separately for the TVL overall, GHG emissions, ecological, and air quality ratings as described in Section 3.1. *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 *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.

Table 5 Sustainability-motive and financial-motive proxies

Panel A: *Sustainability-motive proxies*	Sample	Low	High	High – Low
PCBR overall	11.48	8.75	14.19	5.45***
NCSR overall	13.80	11.56	15.67	4.11***
PCBR GHG emissions	3.94	2.82	5.04	2.22***
NCSR GHG emissions	6.05	5.24	6.72	1.48***
PCBR ecological	1.65	1.20	2.10	0.90***
NCSR ecological	2.01	1.38	2.54	1.16***
PCBR air quality	0.69	0.53	0.84	0.31***
NCSR air quality	0.95	0.67	1.19	0.52***
ESG home-bias ratio	0.19	0.24	0.15	-0.08
Observations	6,151	3,076	3,075	6,151
Panel B: *Financial-motive proxies*	Sample	Low	High	High – Low
Avg. monthly number of trades	1.39	1.12	1.67	0.55***
PF turnover (%)	17.32	18.25	16.41	-1.84**
Avg. monthly logins	14.36	12.49	16.20	3.72***
Disposition effect (Δ (PGR , PLR))	0.07	0.08	0.07	-0.01
Observations	6,102	3,041	3,061	6,102

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. Porfolio 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 I compute following Barberis and Xiong (2009). 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.

Table 6 ESG investment regressions: Cross-domain offsetting behavior

	(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
Controls	Yes	Yes	Yes	Yes	Yes

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 3.1. 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 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.

Table 7 ESG investment regressions: Trading motives

	(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 carbon footprint	0.087***	5.311***	0.436*	7.039***	0.049***
	(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	$5.611^{\diamond\diamond\diamond}$	$0.026^{\diamond\diamond}$
	(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	$0.095^{\diamond\diamond\diamond}$	$3.689^{\diamond\diamond\diamond}$	0.175	$6.807^{\diamond\diamond\diamond}$	$0.040^{\diamond\diamond\diamond}$
	(0.000)	(0.000)	(0.058)	(0.000)	(0.000)
ESG home-bias ratio	0.005***	0.007	0.001	0.229**	
	(0.000)	(0.799)	(0.693)	(0.002)	
COI	$0.088^{\diamond\diamond\diamond}$	$5.312^{\diamond\diamond\diamond}$	0.436*	$7.074^{\diamond\diamond\diamond}$	$0.049^{\diamond\diamond\diamond}$
	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)
	Panel B: financial-motive proxies				
Average monthly trades	0.019***	-0.106	-0.018*	1.028***	-0.003
	(0.000)	(0.123)	(0.013)	(0.000)	(0.116)
COI	$0.078^{\diamond\diamond\diamond}$	$3.725^{\diamond\diamond\diamond}$	$0.239^{\diamond}$	$6.949^{\diamond\diamond\diamond}$	$0.037^{\diamond\diamond\diamond}$
	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)
Average PF turnover (%)	-0.175***	7.883***	0.274***	-3.825	0.051***
	(0.000)	(0.000)	(0.001)	(0.065)	(0.000)
COI	$0.083^{\diamond\diamond\diamond}$	$3.409^{\diamond\diamond\diamond}$	$0.231^{\diamond}$	$7.068^{\diamond\diamond\diamond}$	$0.033^{\diamond\diamond\diamond}$
	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)
Average monthly logins	0.001***	0.002	-0.001	0.027	-0.000
	(0.001)	(0.912)	(0.823)	(0.316)	(0.083)
COI	$0.083^{\diamond\diamond\diamond}$	$5.174^{\diamond\diamond\diamond}$	$0.437^{\diamond}$	$6.912^{\diamond\diamond\diamond}$	$0.050^{\diamond\diamond\diamond}$
	(0.000)	(0.000)	(0.013)	(0.000)	(0.000)
Disposition effect	0.020	4.495*	0.122	-1.240	0.045**
(Δ PGR – PLR)	(0.456)	(0.011)	(0.063)	(0.536)	(0.007)
COI	$0.113^{\diamond\diamond\diamond}$	$5.143^{\diamond\diamond\diamond}$	$0.108^{\diamond\diamond}$	$7.267^{\diamond\diamond\diamond}$	$0.045^{\diamond\diamond}$
	(0.000)	(0.000)	(0.006)	(0.000)	(0.006)

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 3.1. 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 6. Each regression model, however, adds one proxy for heterogeneous sustainability preferences or financial (return-chasing) motives as defined in Sections 3.2 and 3.3. The reported coefficients show the estimated change in the outcome variable (marginal effect for logistic regressions) if the respective sustainability- or financial-motive proxy increases by one unit. Asterisks denote statistical significance of each included proxy at the 1% (***), 5% (**), and 10% (*) levels, respectively. For the main *COI* (coefficient of interest, i.e., the above-median footprint dummy), statistical significance is indicated by diamonds at the 1% ($^{\diamond\diamond\diamond}$), 5% ($^{\diamond\diamond}$), and 10% ($^{\diamond}$) 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.

Table 8 Survey: Footprint estimates

	Mean	Min.	P5	P25	P50	P75	P95	Max.
	All survey participants							
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
	Compensate with SRI: 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

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 2.2. Survey participants are asked to estimate their total carbon footprint from consumption in $kgCO_2$ 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.

Table 9 Survey: Compensation with sustainable investments

	Sample	Low	High	High – Low
Unconditional	13.17	12.54	17.26	4.71***
	(3,646)	(3,165)	(481)	(3,646)
Conditional	15.44	14.73	20.05	5.32**
	(3,051)	(2,647)	(404)	(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 8 and Table A.2 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.

Table 10 Robustness analysis: Carbon-intensity specification

	(1) Holds top rated	(2) % PF top rated	(3) % AS top rated	(4) PF ESG score	(5) Top PF ESG score
	Panel A: Carbon intensity of consumption				
Overall	-0.004	0.048	-0.091	2.293**	-0.006
	(0.644)	(0.866)	(0.184)	(0.001)	(0.489)
GHG emissions	0.038***	3.294***	0.141	2.811***	0.041***
	(0.001)	(0.000)	(0.322)	(0.001)	(0.000)
Ecological	-0.005	0.668*	-0.052	1.751*	0.002
	(0.629)	(0.035)	(0.392)	(0.019)	(0.777)
Air quality	0.000	0.333	-0.064	1.324*	-0.010
	(0.978)	(0.138)	(0.237)	(0.010)	(0.184)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	6,151	6,151	6,151	6,151	6,151
	Panel B: Carbon intensity of income				
Overall	-0.016	-0.175	0.043	0.845	-0.009
	(0.070)	(0.519)	(0.607)	(0.238)	(0.288)
GHG emissions	0.030*	3.052***	0.319*	1.389	0.030***
	(0.011)	(0.000)	(0.030)	(0.111)	(0.000)
Ecological	-0.004	0.103	0.029	0.762	-0.009
	(0.665)	(0.745)	(0.681)	(0.320)	(0.271)
Air quality	-0.006	0.187	0.014	1.104*	-0.005
	(0.479)	(0.391)	(0.831)	(0.037)	(0.515)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	6,151	6,151	6,151	6,151	6,151

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 3.1. 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 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 intensities. 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.

Table 11 Religious affiliation

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 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.

Table 12 Robustness analysis: Exposure to religious beliefs

	(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	0.009	-0.003	0.071***	0.000*
	(0.339)	(0.244)	(0.209)	(0.000)	(0.028)
GHG emissions	0.001**	0.036*	0.002	0.107***	0.000*
	(0.001)	(0.016)	(0.513)	(0.000)	(0.029)
Ecological	0.000	0.003	0.003	0.065**	0.000
	(0.381)	(0.679)	(0.466)	(0.002)	(0.116)
Air quality	0.001*	0.020**	0.004	0.055***	0.001**
	(0.017)	(0.004)	(0.230)	(0.000)	(0.005)
Observations	5,732	5,732	5,732	5,732	5,732
Investor-level controls	Yes	Yes	Yes	Yes	Yes
Micro status	Yes	Yes	Yes	Yes	Yes
Population	Yes	Yes	Yes	Yes	Yes

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 3.1. 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, I 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 and proxies for socio-economic status of investors' surrounding area. 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.

Table 13 Robustness analysis: Investor sample

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***
	(0.000)	(0.002)	(0.370)	(0.000)	(0.000)
GHG emissions	-0.047***	-0.049	0.230***	10.603***	0.167***
	(0.000)	(0.892)	(0.001)	(0.000)	(0.000)
Ecological	-0.041***	-0.099	0.080*	8.890***	0.130***
	(0.000)	(0.605)	(0.032)	(0.000)	(0.000)
Air quality	-0.031***	-0.348*	0.003	5.591***	0.148***
	(0.000)	(0.021)	(0.922)	(0.000)	(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***
	(0.000)	(0.000)	(0.404)	(0.000)	(0.000)
GHG emissions	-0.045***	-0.032	0.195**	11.172***	0.175***
	(0.000)	(0.929)	(0.003)	(0.000)	(0.000)
Ecological	-0.040***	-0.072	0.083*	9.365***	0.137***
	(0.000)	(0.714)	(0.034)	(0.000)	(0.000)
Air quality	-0.030***	-0.353*	0.002	5.889***	0.156***
	(0.000)	(0.021)	(0.949)	(0.000)	(0.000)
Observations	19,011	19,011	19,011	19,011	19,011
Permanent net annual income ≥ EUR 10,000					
Overall	-0.041***	-0.558**	0.029	10.030***	0.142***
	(0.000)	(0.006)	(0.476)	(0.000)	(0.000)
GHG emissions	-0.054***	-0.256	0.259***	11.867***	0.181***
	(0.000)	(0.520)	(0.000)	(0.000)	(0.000)
Ecological	-0.045***	-0.209	0.061	9.975***	0.141***
	(0.000)	(0.302)	(0.099)	(0.000)	(0.000)
Air quality	-0.035***	-0.396*	-0.003	6.259***	0.161***
	(0.000)	(0.018)	(0.942)	(0.000)	(0.000)
Observations	17,989	17,989	17,989	17,989	17,989
Regular income receivers					
Overall	-0.016	-1.228*	0.055	13.199***	0.134***
	(0.212)	(0.035)	(0.173)	(0.000)	(0.000)
GHG emissions	-0.022	-1.557	0.144	15.940***	0.219***
	(0.178)	(0.136)	(0.445)	(0.000)	(0.000)
Ecological	-0.016	0.043	0.065	13.210***	0.138***
	(0.287)	(0.924)	(0.088)	(0.000)	(0.000)
Air quality	-0.018	-0.529	0.024	8.454***	0.184***
	(0.151)	(0.228)	(0.200)	(0.000)	(0.000)
Observations	9,901	9,901	9,901	9,901	9,901

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 3.1. 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). Each set of regressions displays results for a different choice of sampling restriction based on the descriptions in Section 2.1 (see also Table 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 14 Emissions from consumption and investments

Emissions scope	Footprint	Avg. emissions from Investments	Δ PF	Consumption	Δ Consumption	Δ Emissions not offset
Direct 1	Low	2.155		7.22		
Direct 1	High	2.562	**0.407**	21.1	**13.88**	**14.287**
Indirect 2	Low	0.478		7.22		
Indirect 2	High	0.654	**0.176**	21.1	**13.88**	**14.056**
Indirect 3	Low	11.844		7.22		
Indirect 3	High	14.454	**2.610**	21.1	**13.88**	**16.490**
Total 1 + 2	Low	2.633		7.22		
Total 1 + 2	High	3.217	**0.584**	21.1	**13.88**	**14.464**
Total 1 + 2 + 3	Low	14.477		7.22		
Total 1 + 2 + 3	High	17.671	**3.194**	21.1	**13.88**	**17.074**

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 + 3* 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). I 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 Δ *Emissions not offset* captures the sum of the difference in total emissions of the average high- and low-footprint investors' equity holdings (Δ *PF*) and the analogous difference in consumption-driven carbon emissions p.a. (Δ *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 Section 2.2 based on investor-level consumption and data on carbon intensities from the EXIOBASE 3 database.

Table 15 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	High	1	0.087	-2.100	21.1	19.000	9.95%
Direct 1	High	2	0.053	-1.282	21.1	19.818	6.08%
Direct 1	High	3	0.004	-0.105	21.1	20.995	0.50%
Indirect 2	High	1	0.087	-0.002	21.1	21.098	0.01%
Indirect 2	High	2	0.053	-0.001	21.1	21.099	0.00%
Indirect 2	High	3	0.004	0.000	21.1	21.100	0.00%
Total 1 + 2	High	1	0.087	-1.191	21.1	19.909	5.64%
Total 1 + 2	High	2	0.053	-0.727	21.1	20.373	3.45%
Total 1 + 2	High	3	0.004	-0.060	21.1	21.040	0.28%

Note. The above table presents the maximum offset potential associated with a counterfactual investment strategy that selects only the top-rated quintile (20%) of stocks with respect to emission ratings. The maximum compensation benefit is derived by computing the difference between average emissions for the top and bottom quintile of emissions scores. The resulting differential is weighted by each of the coefficients estimated in the baseline regression specifications 1, 2, and 3 (see Table 6 in Section 4), which capture the extent to which investors with above-median footprints from consumption are more likely to hold these top-rated assets (specification 1) or to hold higher relative portfolio weights (asset shares) in such assets (specifications 2 and 3, respectively). The resulting compensation benefit is an approximation of which portion of consumption-driven emissions the high-footprint investors in my sample could realistically offset by investing more sustainably. The column headed *Emissions after offset* shows that the estimated compensation benefit is far from sufficient to offset the high levels of annual emissions observed for these investors. 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). Since scope 3 emissions are notoriously difficult to assess, they are omitted from this table. ISIN-level emissions data is obtained from Refinitiv, GHG emission ratings from TruValueLabs, and total annual footprints from consumption are estimated as described in Section 2.2 based on investor-level consumption and data on carbon intensities from the EXIOBASE 3 database.

Appendix

Table A.1 Tax rates in Germany (2022)

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	0%
Government benefits	0%	Interest / dividends / distributions	0%
Hospital	0%	Child benefit	0%
Reimbursements	0%	Public funds / tax	0%
Child support	0%		

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, I 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, I 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.

Table A.2 Survey: Compensation methods

	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

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.