Skill, Scale, and Value Creation in Sustainable Funds

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This thesis is submitted to complete the degree

Master's degree in Economics

University of Bergen, Department of Economics

June 2024

Preface

This thesis is a part of my master´s degree in Economics at the University of Bergen, marking the end of my time as a student in the Department of Economics. I would like to extend gratitude to my supervisor, Anantha Divakaruni, for valuable input early in the process.

Additionally, I would like to thank my family for their endless support and guidance throughout this process. To my friends, both old and new, I thank you for making my time in Bergen special.

Jørgen Wattø Sjuve

Bergen, May 31, 2024

ABSTRACT

Sustainability has become a central focus point in most matters in recent years, and it is especially important to a growing number of investors. According to a recent Bloomberg article, global ESG assets exceeded 30 USDtn in 2022, and is predicted to reach 40 USDtn by 2030, thus accounting for 25% of worldwide assets under management. Therefore, many mutual funds have adopted and incorporated sustainability, or ESG considerations, into their investment approach. The impact on portfolio performance from incorporating such considerations into portfolio choice is a heavily debated topic where academics and practitioners disagree.

The focus of this debate has thus far largely been concerned with differences between expected and realized *returns*. The crux of the debate lies in that finance theory states that expected returns from sustainability should be lower, whereas the empirical literature has found evidence of sustainability outperforming. Inspired by the empirical findings, I want to investigate whether this also means that sustainable funds *extract* more value from capital markets than conventional mutual funds without an explicit sustainability focus. As such, I focus on the funds' value creation, i.e., the dollar amounts that the they are able to extract from capital markets. The question that I aim to answer is:

Are sustainable funds able to extract more value than conventional mutual funds?

Central to understanding a fund's ability to extract value are its skill (ability to find and profitable investment opportunities) and scalability (how hard it is to scale up and investment idea as the fund grows in size). Therefore, I also ask whether

ESG funds are less skilled than conventional funds?

And whether

ESG funds have higher scale constraints than conventional funds?

Using the literature's most up-to-date estimation techniques, I estimate the cross-sectional distributions of value added, skill, and scale for a global sample of 14,114 mutual funds. My findings show that sustainable funds create *less* value than conventional funds. The main driver for this is that even though sustainable funds are *equally* skilled as conventional funds, they are *more* sensitive to diseconomies of scale. This dynamic has evolved over time, with sustainable funds adding less value due to a combination of an insignificant differential increase in skill and a significant differential increase in diseconomies of scale. Comparing the fund groups across different investment strategies, I find that the overall findings reverses for small cap funds, where sustainable funds add significantly *more* value.

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1 Introduction

Interest in, and demand for, sustainability has grown rapidly in recent years. In response, a number of mutual funds have incorporated sustainability considerations into their investment approach. Consequently, capital has increasingly been redirected to these funds. According to Bloomberg, global ESG assets exceeded 30 USDtn in 2022 and are predicted to reach 40 USDtn by 2030, accounting for 25% of worldwide assets under management. Moreover, according to the Investment Company Institute (ICI), the number of U.S. funds that invest according to ESG criteria has increased 1.9 times from 2019 to the end of 2023, with assets under management growing on average by 18.3% over the same period, from 278 to 532 USDbn.[1] Despite the enormous growth in the ESG investment industry, academics and practitioners hold opposing views on the impact of sustainable investing on performance.

The current theoretical thinking is that investors who have a taste for sustainability gain additional utility from holding these investments. This additional utility is then offset by lower expected returns because these investors' demand for sustainable companies pushes up their prices, making future expected returns lower. In other words, you cannot "have your cake and eat it too" when it comes to doing good while doing well. On the other hand, the empirical literature has found that realized performance has been strong, creating a gap between what is expected and what is realized.

This debate largely focuses on the differences between expected and realized *returns*. Given this disconnect, and considering that the literature has mainly focused on returns (which is prevalent in the mutual fund literature) rather than value, I focus on differences in value creation between funds with and without an explicit sustainability focus. Our understanding of whether mutual funds are able to earn economic rent through their investment decisions is less developed and to the best of my knowledge not well-studied within the literature on the impact of sustainability on performance. My main research question is therefore:

> ***Are sustainable funds able to extract more value than conventional mutual funds?***

Overall, active mutual funds create value by timing factors or picking stocks (usually based on superior information), or when they provide liquidity to the market (Gârleanu and Pedersen, 2018). Central to understanding a fund's ability to extract value are its skill (ability to find and profitable investment opportunities) and scalability (how hard it is to scale up and investment

[1]See , ICI p.39 for details.

idea as the fund grows in size). This follows from the central work on value added by Berk and Van Binsbergen (2015), and the decomposition of value added into skill and scalability by Barras et al. (2022*a*).

Despite the rapid growth in sustainable investing, the average conventional mutual fund is still larger than the average sustainable fund with 144 USDm more in assets under management.[2] Following the predictions of Lucas (1978) and the empirical results on the cross-sectional distribution of managerial talent in Berk and Van Binsbergen (2015), I also ask whether

Sustainable funds are less skilled than conventional funds?

The literature on the impact of scale on returns has largely focused on fund-level returns to scale and industry-level returns to scale. In both cases, the rationale is liquidity constraints. Funds that grow in size impact prices to a larger extent, and when the overall industry becomes larger, more capital is chasing the same opportunities, increasing the scarcity of the profitable opportunities. Therefore, since sustainable investing is a subset of the overall market, as more capital is allocated to that subset, the profitable opportunities should become more scarce, and individual funds will impact prices more as they grow. This is also in line with the findings in Van der beck (2021), who shows that the recent high realized returns from sustainable investing is largely caused by the price impact that flows into sustainable funds have had on asset prices. My third, and last question is therefore whether

Sustainable funds have higher scale constraints than conventional funds?

To investigate this, I first document the extent to which these groups of funds create or destroy value. Second, I document differences and similarities between sustainable and conventional funds with respect to skill and scalability. Third, I investigate the importance of investment strategy, by analyzing differences between the fund groups within sample sub-sets based on investment style and trading frequency. Finally, I discuss who the most valuable funds are.

The premise for my analyses is the same as that put forth in Barras et al. (2022*a*), namely that the amount of value a fund can create is mainly a function of its ability to identify profitable investments and its exposure to scale constraints. My analyses utilize a global sample of actively managed mutual funds spanning the period from 2010 through the end of 2023. In total, my sample consists of 14,114 mutual funds located in 32 different countries. To identify sustainable mutual funds, I use a combination of ESG indicators provided by Morningstar, as well as matching fund names against a list of keywords capturing sustainability.

[2]See Table 2

Following Barras et al. (2022*a*), I estimate fund-level skill and scale parameters, as well as their value added. The empirical approach also allows me to obtain the full cross-sectional distributions of these parameters. Given the challenge inherent in specifying skill, scale, and value-added, this approach is non-parametric, which helps alleviate the risk of misspecification. Also, to infer the distributions, I rely on the estimated values. The estimation approach corrects for the bias that this causes (Shanken, 1992). The cross-sectional correlation between skill and scale for the full sample of funds is 0.81, indicating that profitable investments are hard to scale.[3]

In modeling gross alpha, I use the linear model by Berk and Green (2004), where $\alpha_{i,t} = a_i - b_i q_{i,t-1}$. Skill is captured by a_i and represents the excess return the fund manager can generate on the first dollar of actively managed capital. b_i measures the extent to which the fund suffers from diseconomies of scale, i.e., how difficult it is for the fund to scale its ideas as it grows in size. Lastly, $q_{i,t-1}$ is lagged fund size in real terms, adjusted to December 2023 dollars. To create a clear link between value added and skill and scalability, value-added is defined as $va_i = \mathbf{E}[\alpha_{i,t} q_{i,t-1}] = \mathbf{E}[(a_i - b_i q_{i,t-1}) q_{i,t-1}]$.[4]

My analysis shows that sustainable funds, on average, add 1.20 USDm *less* in value each year than conventional funds. This difference is persistent and significant across different regression specifications. Investigating skill, I find weak evidence that sustainable funds are more skilled than conventional funds. The difference amounts to 0.35% per year. Differences between the proportions of sustainable and conventional funds that exhibit positive and negative skill are slim, with approximately a third of funds in each category exhibiting negative skill ($a_i < 0$). The average difference in skill is overall persistent across regression specifications, but with varying levels of statistical significance. Thus, I conclude that sustainable and conventional funds are equally skilled on average. I also find that sustainable funds are more sensitive to diseconomies of scale, where a one standard deviation increase in size reduces gross alpha by 1.43% for sustainable funds, relative to 1.09% for conventional funds. Testing this difference in the cross-section also shows that this difference is persistent across regression specifications and statistically significant. In sum, these results suggest that sustainable funds create *less* value than conventional funds because they are *equally* skilled, but *more* sensitive to diseconomies of scale. This dynamic has evolved over time, with sustainable funds adding less value due to a combination of an insignificant differential increase in skill and a significant differential

[3]For the sub-sample of sustainable funds, the cross-sectional correlation is 0.82, and 0.80 for conventional funds.

[4]I don't directly consider the validity of this specification but assume that the robustness checks done in Barras et al. (2022*a*) carry over from the U.S to a global sample.

increase in diseconomies of scale.

I also investigate differences between fund groups across different investment strategies. To proxy for investment strategy, I use size style (small, mid, and large cap), company investment style (value, blend, and growth), as well as how much they trade using turnover. Overall, I find considerable heterogeneity, particularly in how well sustainable and conventional funds within these categories are able to balance skill and scalability towards adding value. Lastly, I find that the most valuable funds, regardless of fund grouping, are those that are slightly more skilled than average and are slightly less sensitive to diseconomies of scale. This suggests that higher skill is not necessarily better if the investment opportunities become harder to scale up. The best approach seems to be a good balance between the two, and sustainable funds are currently less able to strike this balance.

1.1 Related literature

My thesis is mainly related to two large strands of literature on mutual funds and active management. First, the literature on skill among active managers is vast. One of the earliest studies, Jensen (1968), concluded that mutual fund managers lack skill. Following this, many others have contributed to this area (Carhart, 1997; Barras et al., 2010; Sharpe, 1991; Fama and French, 2010; Giglio et al., 2021; Pástor et al., 2017; Grinblatt and Titman, 1989; Berk and Van Binsbergen, 2015; Kaniel et al., 2023). Most of this literature has focused on returns, whereas value creation has gained more attention after Berk and Van Binsbergen (2015) introduced their measure of value added. Building on this, and the model for skill proposed by Berk and Green (2004), Barras et al. (2022*a*) proposed an alternative decomposition of value added that depends on the funds' skill and scalability. That paper is closely related to this thesis, given that I rely on their methodology to estimate skill, scale, and value added. Where that paper is focused on developing the estimation procedure itself and applying it to the U.S mutual fund industry, my focus is on using the estimation technique to investigate differences in value creation between sustainable and conventional mutual funds in a global setting.

Another strand of literature is concerned with the performance of sustainable investing. The empirical literature that focuses on realized returns from sustainable investing finds varying results conditional on time and setting. A group of papers finds that sustainable companies have desirable climate hedging qualities (Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2021, 2023; Hsu et al., 2023), meaning their equilibrium returns should be lower. Other papers (Edmans, 2011; In et al., 2017; Görgen et al., 2020; Hong et al., 2019; Derrien et al., 2021;

Glossner, 2021) find a positive return premium associated with sustainable stocks. The common theme for why sustainable firms yield this premium is because of market under-reaction.

A closely related paper is Ceccarelli et al. (2023), who studies the ESG skill of mutual fund managers. They propose a new way of measuring the ESG-specific skill of a mutual fund manager by modeling the relationship between their explicit trading decisions and future changes in ESG ratings. Their logic is that mutual fund managers whose trades predict changes in ESG scores are more skilled than fund managers whose trades react to changes in ratings. As such, their paper specifically links skill to the managers' ability to predict future ESG ratings. My thesis is different in that I study skill in the traditional sense of Berk and Green (2004). Moreover, I also study the interplay between skill, scale, and value added, not just skill.

Another relevant paper is Brøgger and Kronies (2020), which shares similarities with Ceccarelli et al. (2023) in that they look into ESG-specific skill. Where the latter paper defines a new measure to capture ESG-specific skill in actual trades, the former paper follows Hong and Kacperczyk (2009) and divides their sample of investors into two groups based on the flexibility of their investment mandates. Their logic is that flexible investors (e.g., mutual funds and hedge funds) are better at investing in stocks that subsequently experience an increase in their ESG scores than investors with stricter investment mandates (e.g., endowments, banks, pension plans, etc.). They also find that the abnormal positive return earned by the flexible investors on their ESG stocks does not translate into abnormal return on other stocks they hold. As such, their paper documents a specific skill in buying stocks that later receive better ESG ratings, which spurs demand from the strict mandate investors who buy the stocks from the flexible group at a premium. In addition to focusing on the skill in predicting ESG scores, this paper also focuses on returns, whereas I investigate overall skill, scale, and value creation.

The rest of the paper is organized as follows. Section 2 describes data, relevant variables, and the estimation procedure. In Section 3, I report results on funds' value added, on funds' skill in Section 4, and scale in Section 5. Section 6 investigates differences in funds across different investment strategies, and Section 7 concludes.

2 Research design

In this section, I provide details on data collection, data cleaning, final sample characteristics, approach for measuring skill, scale, and value added, as well as my main empirical regression specification.

2.1 Data

Here, I provide details on data collection and data cleaning. I largely follow Sjuve (2022) in constructing the data set, but extend the sample period through year-end 2023. Below, I briefly explain the data gathering process in Section 2.1.1, and data cleaning in Section 2.1.2.

2.1.1 Data collection

I begin by collecting data from Morningstar Direct. For each country listed in Table A.4, I gather data on living and non-surviving long-only open-ended mutual funds for the period from January 2010 to December 2023. In addition to cross-sectional information, I also download data on USD-converted time series of gross and net returns, net assets, and fund size for all share classes. Morningstar also provides their own rating variable on performance, i.e., their ”Star” rating. Time series data on this rating was also downloaded. Morningstar's stars are a risk-adjusted measure of performance for each fund Del Guercio and Tkac (2008). Funds receive a rating ranging from 1 to 5 stars, with more stars indicating better performance.

Morningstar treats share-class variables as individual observations; therefore, variables like total net assets are aggregated to the fund level. The oldest share class or a fund's main share class is used where available, and if not available, I use the share-class with the earliest inception date. Funds with less than two years of monthly observations are excluded to ensure meaningful inference. Additionally, funds lacking data on age, total net assets, fees, flows, and their Morningstar global category are excluded. Lastly, I winsorize all continuous variables at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile.

Table A.4 presents the composition of the sampled data. A total of 14,114 unique funds are included, with approximately 17% categorized as sustainable funds and the remaining 83% as conventional mutual funds.

2.1.2 Data cleaning

Here I describe the data cleaning process done to go from raw data to the finalized cross-sectional dataset. I start by filtering out funds not eligible for sample inclusion based on cross-sectional information. Funds that are alive for less than two years after my sample period starts are excluded, as well as funds that are launched within two years before my sample period ends. Given that the objective of my thesis is to understand value creation, I require that funds manage their own portfolios and make discretionary choices on their composition. Therefore, I exclude fund-of-funds as well as index funds. For funds with multiple share classes, I keep the oldest as indicated by Morningstar. If this information is missing, I use the share class with the oldest inception date.

Next, I join in time series data on fund gross and net returns, star ratings, and net assets. Here, I filter out funds where data is missing for all these variables for the entire sample period. To aggregate the time series variables from fund share class level to fund level, I take the net asset weighted averages. Then, I compute additional fund level variables such as fund fees and net flows. Morningstar reports both gross and net returns, where the difference is the fund's fees. Therefore, based on these, I can infer the fund fees as follows:

$$\text{Monthly fee} = 1 - \frac{1 + r_{net}}{1 + r_{gross}}$$

$$\text{Yearly fee} = (1 + \text{Monthly fee})^{12} - 1$$

As for the other fund level variables, I compute the fund level fee as the asset weighted average across share classes. Similarly, based on fund returns, I compute net flows as:

$$\text{Net flow} = \frac{AUM_t - (1 + r_{gross}) \cdot AUM_{t-1}}{AUM_{t-1}}$$

which is the net of returns growth in assets. I define fund age as the difference between the current date and the inception date of the fund's oldest share class.

To further process the data, I add in the three-month US Treasury bill as a proxy for the risk-free interest rate, adjust fund assets and net flows for inflation, and express these in December 2023 levels. I also exclude funds that never grew above five USDm in assets to account for the incubation bias (evans, 2010). Funds that have less than two years of data on size and returns are also excluded.

The last step is to identify sustainable funds. Morningstar has some variables indicating this. Based on these variables and matching fund names with a dictionary of sustainability keywords, I classify 2,425 funds as sustainable. In constructing the dictionary of sustainability keywords, I follow Van der beck (2021). Lastly, I collapse the panel data into a cross-sectional dataset by taking the time-series averages for each fund.

2.2 Summary statistics

In this section, I provide summary statistics for the entire sample as well as for the sustainable and conventional funds separately. Table 1 reports summary statistics on key fund characteristics for the cross-sectional sample of mutual funds, while Table 2 reports summary statistics on key fund characteristics for the different fund groups. For variable definitions, see Table A.1 in Appendix A.

Table 1. Summary statistics I
This table presents summary statistics on key fund characteristics for the full cross-sectional sample of mutual funds. For each variable, I report the observation frequency (N), which is the number of different funds across all countries. In addition, the mean, median, minimum, and maximum values, as well as the standard deviation, are presented. Return, alpha, and net flow are average monthly values, whereas the fee is the average yearly fund fee.

Variable	N	Min	Median	Mean	Max	SD
Gross return (%)	14,114	-2.72	0.75	0.74	2.62	0.39
Gross alpha (%)	14,114	-2.78	0.03	0.02	1.57	0.27
Net flow (%)	14,114	-5.10	0.14	0.63	16.00	2.03
Size (USDm)	14,114	0.83	103	456	8,884	1,093
Age (Years)	14,114	1.14	8.06	11.00	50.00	9.45
Fee (%)	14,110	0.10	1.36	1.42	4.00	0.65
Star rating (1-5)	11,932	1	3.1	3.2	5	0.85

In the cross-section, the average fund has a monthly return of 0.74% and a gross alpha of 0.02% (2 basis points). Moreover, both the average and median mutual fund experience positive monthly inflows of 0.63% and 0.14%, respectively. Thus, in this sample, the average fund grows in size despite the large transfer from actively managed mutual funds to passive investment alternatives.[5] The average fund in this cross-sectional sample manages about 500 USDm and charges a fee of 1.42%, and is is 11 years old.

Table 2 reports the differences between sustainable and conventional funds' mean and standard deviation for the variables in Table 1. The average conventional fund outperforms sustainable funds both in gross returns (5 basis points per month) and gross alphas (3 basis points per month). Despite conventional funds outperforming sustainable funds in these return measures, sustainable funds experience on average 0.73% more in monthly inflows of capital. This speaks to the widespread popularity of sustainable investing and supports the notion that sustainable investors are willing to sacrifice returns in order to invest in a sustainable manner. Lastly, we can see that conventional funds, on average, are larger, older, more expensive, and have a lower performance rating.

[5] See Morningstar (2023)

Table 2. Summary statistics II
This table presents the mean and standard deviation on key fund characteristics for the full cross-sectional sample of mutual funds split by fund category (sustainable and conventional). Columns 3 and 6 reports the differences between sustainable and conventional funds. Return, alpha and net flow are average monthly values, whereas fee is the average yearly fund fee.

	Mean			Standard deviation		
Variable	Sustainable	Conventional	Difference	Sustainable	Conventional	Difference
Gross return (%)	0.70	0.75	-0.05	0.36	0.40	-0.04
Gross alpha (%)	-0.01	0.02	-0.03	0.25	0.27	-0.02
Net flow (%)	1.24	0.50	0.73	2.25	1.96	0.30
Size (USDm)	336	481	-144	647	1,163	-516
Age (Years)	9.39	11.00	-2.09	8.64	9.57	-0.93
Fee (%)	1.33	1.44	-0.11	0.60	0.66	-0.06
Star rating (1-5)	3.28	3.18	0.10	0.84	0.85	-0.01

Furthermore, one can see that sustainable funds have a lower standard deviation than conventional funds on all variables except net flow. This means that the there is less dispersion among the sustainable funds, which is not necessarily strange, given the big difference in observations between funds as seen in Table A.4.

2.3 Measuring skill, scale and value added

In this section, I provide details on how I measure skill, scale, and value added. I define the key variables of interest in Section 2.3.1, and their theoretical underpinnings in Section 2.3.2. Here, I go into greater detail than in Section 1.1 on how the literature has treated skill, scale and value added. Lastly, in Section 2.3.3, I provide a step-by-step guide to the empirical approach.

2.3.1 Definitions

There are three key variables related to my research question: Skill, scale and value added. To estimate these, I rely on Barras et al. (2022*a*), and therefore, I adopt their definitions and notation. Further definitions for other variables used can be found in table A.1 in the appendix.

Skill is the managers ability to identify profitable investment strategies and extracting value from the markets. Equation 6 below presents the empirical model from Barras et al. (2022*a*), that I use, which is the same linear model as proposed by Berk and Green (2004) in Equation 2. Skill is measured by the variable a_i, which captures the return on first actively managed dollar.

Scale, measured by b_i, is the fund's sensitivity to diseconomies of scale. It captures how it becomes harder to invest in profitable opportunities as the fund grows in size because investment opportunities are usually only profitable up to a certain threshold. As the fund becomes larger, the set of profitable opportunities decline. A positive coefficient suggests that a fund is faced with such constraints, whereas a negative estimate implies that a fund experiences economies of scale, becoming more efficient allows for extracting value while still growing in size. Diseconomies of scale is the norm in the mutual fund industry (e.g., see Reuter and Zitzewitz (2021)).

Value added, as presented by Barras et al. (2022*a*) in Equation 8, is the measured amount of value a manager is able to extract from the markets. It is the product of the funds skill, scalability and their size. Berk and Van Binsbergen (2015) previously defined it as the product of the funds gross alpha and size in Equation 5. However, given my research question, the former definition is most suitable, seen as it provides a clear link between skill, scale and value-added.

2.3.2 Methodology

With prior literature offering different conclusions to the question of skill in the mutual fund sector, Berk and Green (2004) pioneered the research of mutual fund performance, capital flows, and managerial talent. While Carhart (1997) focused on net alphas as the explanation behind performance persistence, the idea of managerial talent was disregarded as theoretically significant but practically irrelevant. In contrast, Berk and Green (2004) proposed a simple model of active portfolio management and fund flows to provide a natural benchmark for evaluating observed returns, flows, and performance outcomes. Their model consisted of three elements: First, competitive allocation of capital by investors to mutual funds. Secondly, differences in managerial ability to generate high average returns, with diminishing returns to scale. Thirdly, past returns inform about managers' skill. Based on this model, Berk and Green (2004) provided a solution for the relationship between performance and flows.

$$R_t = \alpha + e_t \tag{1}$$

Equation 1 represents how Berk and Green (2004) model the skill of managers. This equation doesn't represent the actual return earned by investors, but rather the return a manager makes on the first dollar actively managed, before accounting for any costs and fees. The α in Equation 1 is the key indicator of a manager's skill. This α is unknown to both the manager and the market. The term e_t represents errors, which are normally distributed with a mean of zero and a variance of σ^2. R_t denotes the excess return of the fund at date t, excluding costs and fees.

$$\alpha = a_i - b_i q \tag{2}$$

Equation 2 presents the linear model proposed by Berk and Green (2004), which shifts the focus from net alphas to gross alphas in measuring managerial talent. Berk and Van Binsbergen (2015) show that net alphas do not measure skill. Under neoclassical assumptions—rational investors, competitive markets, and optimizing managers—net alpha will be zero for all investors as it is competed away, reflecting market competitiveness and rationality. A negative net alpha indicates irrational markets with excessive capital investment, while a positive net alpha indicates non-competitive markets. They further argue that gross alpha is not a good proxy for managerial skill either, since gross alpha would only measure talent if all funds were the same size at 1 USD. Like net alpha, gross alpha measures return, not value. A fund managing 1 USDbn with a 2% gross alpha extracts more value than a 100 USDm fund with a 10% gross alpha.

Berk and Van Binsbergen (2015) then propose a new measurement for skill that they term *value added*. They argue that this is the proper measure of managerial talent in a field of research that is unsure of its existence. They define value added as the amount of value a manager can extract from the markets. They calculate this by multiplying the benchmark-adjusted realized gross return, $R^g_{i,t} - R^b_{i,t}$, by the real size of the fund (AUM adjusted for inflation) at the end of the previous period, $q_{i,t-1}$, to obtain the realized value added between times $t-1$ and t.

$$V_{i,t} \equiv q_{i,t-1}(R^g_{it} - R^b_{it}) \tag{3}$$

Berk and Van Binsbergen (2015) follows Berk and Green (2004) and assume that the alpha manager i generates before fees and expenses, is given by Equation 2. Here the $a_i > 0$ is the alpha on the first cent actively invested, while $b_i > 0$ is a parameter that captures the decreasing returns to scale. q is the amount of money the manager puts into active management. Furthermore Berk and Van Binsbergen (2015) show that, with the third neoclassical assumption being that managers optimize, value added becomes a optimization problem defined as:

$$V_{i,t} = \max_q \quad (a_i - b_i q) \cdot q \tag{4}$$

And after they derive the first order condition, they go on to find that the skill of the manager is equal to:

$$V_{i,t} = (a_i - b_i q_i^*) \cdot q_i^* \tag{5}$$

Equation 5 is according to Berk and Van Binsbergen (2015) the best way to measure managerial skill as it captures the amount of value a manager is able to extract from the markets. Barras et al. (2022*a*) takes the insight they present in Equation 4 and 5 and proposes an alternative decomposition of value added. Where Berk and Van Binsbergen (2015) defines value added as the product of assets under management and realized gross alpha, they takes a non-parametric approach to estimating skill (a_i) and scale (b_i) for all funds individually, then replacing the gross alpha from Equation 5 in Berk and Van Binsbergen (2015) with the actual factors that make up the gross alpha for their value added (va_i).

$$\alpha_{i,t} = a_i - b_i q_{i,t-1} \tag{6}$$

I follow the literature Barras et al. (2022*a*) in obtaining the empirical model in Equation 6: The total benchmark adjusted revenue for fund i at time t is given by $TR_{i,t} = a_i q_{i,t-1}$. $TC_i,_t = b_i q_{i,t-1}^2$ is the total cost of trading for fund i at time t, and is a convex function of fund size. $q_{i,t-1}$ denotes the lagged fund size in real terms in both $TR_{i,t}$ and $TC_{i,t}$. The empirical model in Equation 6, is obtained by dividing a funds profit-function ($TR_{i,t}$ - $TC_{i,t}$) with the lagged fund size. a_i measures the skill exhibited by a fund, and I measure scalability with b_i, which is the funds sensitivity to diseconomies of scale. The gross alpha changes linearly with the fund size ($q_{i,t-1}$), but as the fund puts more capital into active management and experience scale constraints, the b_i changes the gross alpha as $q_{i,t-1}$ grows. With this approach, skill (a_i) and scale (b_i) are allowed to be fund specific. Following the literature in Barras et al. (2022*a*), the coefficients are treated as random realizations from the funds cross sectional distribution rather than fixed parameters.

Next turning the focus over to value added; By following Berk and Van Binsbergen (2015) and use their concept of value added, which is the average product of the funds gross alpha and size (Equation 7), I make the same adjustments to value added as Barras et al. (2022*a*) does; replacing $\alpha_{i,t}$ with $a_i - b_i q_{i,t-1}$ gets me Equation 8, which is value added for fund i:

$$va_i = \mathbf{E}[\alpha_{i,t} q_{i,t-1}] \tag{7}$$

$$va_i = a_i \mathbf{E}[q_{i,t-1}] - b_i \mathbf{E}[q_{i,t-1}^2] \tag{8}$$

2.3.3 The estimation process

Here, I briefly reiterate the estimation procedure as detailed in Barras et al. (2022*b*).[6] I estimate the measure Y_i for each fund, where $Y_i \in \{a_i, b_i, va_i\}$. By following their procedure, the small-sample bias in Equation 9 is controlled for.

$$r_{i,t} = a_i - b_i q_{i,t-1} + \beta_i' f_t + \epsilon_{i,t} \tag{9}$$

Equation 9 suffers from a bias because fund size is endogenous. The small sample bias, which disappears asymptotically, arises because the error term, $\epsilon_{i,t}$, in Equation 9 and innovation in size, $\epsilon_{qi,t}$, are positively correlated due to ψ_i being positive in Equation 10:

$$\epsilon_{i,t} = \psi_i \epsilon_{q_i,t} + v_{i,t} \tag{10}$$

The size innovation is denoted by $\epsilon_{qi,t}$, and is projected onto the space defined by the factors f_t: $e_{q_i,t} - \beta_{q_i}' x_t$, where $x_t = (1, f_t')'$ and $e_{q_i,t}$ is the innovation of the size regression in $q_{i,t} = \theta q_i + \rho_{q_i} q_{i,t-1} + e_{qi,t}$. Not adjusting for the small-sample bias results in estimates for the skill and scale coefficients that are too high. Following Barras et al. (2022*b*) and according to Amihud and Hurvich (2004), adding the regressor $\epsilon_{q_i,t}$ to Equation 9 effectively eliminates the small-sample bias, yielding:

$$r_{i,t} = a_i - b_i q_{i,t-1} + \beta_i' f_t + \psi_i \epsilon_{qi,t} + v_{i,t} \tag{11}$$

However, since I cannot observe the true projected innovation $\epsilon_{q_i,t}$, a proxy for $\epsilon_{q_i,t}$, denoted $\epsilon_{q_i,t}^c$, is needed. I obtain the proxy by following a four-step procedure applied to each fund i individually ($i = 1, \ldots, N$). This four-step procedure for obtaining the proxy $\epsilon_{q_i,t}^c$ is detailed in Barras et al. (2022*b*), originally proposed by Amihud and Hurvich (2004) and Avramov et al. (2013).

1. First, I run the regression of size on lagged size and obtain the coefficient estimates $\hat{\theta}_{q_i}$ and $\hat{\rho}_{q_i}$.

$$q_{i,t} = \theta q_i + \rho_{q_i} q_{i,t-1} + e_{qi,t} \tag{12}$$

[6]The entire code base can be found here. I used this together with ChatGPT to translate the code from MATLAB to R.

2. Compute the adjusted size innovation as

$$e^c_{qi,t} = q_{i,t} - (\hat{\theta}^c_{q_i} + \hat{\rho}^c_{q_i} q_{i,t-1}) \tag{13}$$

here the second-order coefficients corrected for the small-sample bias are given by

$$\hat{\rho}^c_{qi} = \min\left(\hat{\rho}_{q_i} + \frac{(1+3\hat{\rho}_{q_i})}{T_i} + \frac{3(1+3\hat{\rho}_{q_i})}{T_i^2}, 0.999\right)$$

$$\hat{\theta}^c_{q_i} = (1-\hat{\rho}^c_{qi})\bar{q}_i$$

3. Regress $e^c_{qi,t}$ on the factors to obtain

$$\epsilon^c_{q_i,t} = e^c_{qi,t} - \beta'_{q_i} x_t \tag{14}$$

4. Insert $\epsilon^c_{q_i,t}$ in Equation 9 to obtain

$$r_{i,t} = a_i - b_i q_{i,t-1} + \beta'_i f_t + \psi_i \epsilon^c_{qi,t} + v_{i,t} \tag{15}$$

From this regression, following Barras et al. (2022*b*), I obtain the estimated values for Y_i that are adjusted for small-sample bias. Given that my sample is global, I limit f_t to only consist of the market factor, as I don't have data on the size, value, and momentum factors for each of my sample countries. The market factor consists of the excess returns over the risk-free rate for each fund's Morningstar-assigned benchmark. For further details on the estimation process, see Barras et al. (2022*b*).

2.4 Main empirical specification

Here, I briefly outline the main regression specifications that all regression analyses will be based upon going forward. I consider a population of N funds, where each fund is denoted by subscript $i \in \{1,\ldots,N\}$. Any given fund is classified as either a conventional fund or a sustainable fund. Therefore, I let the set $\mathscr{S}$ denote the set of sustainable funds, and $\mathscr{C}$ denote the set of conventional funds. The main outcome variables of interest are the funds' value added ($\hat{va}$), skill ($\hat{a}$) and scale ($\hat{b}$) coefficients. I group all outcome variables into $Y \in \{\hat{a}, \hat{b}, \hat{va}\}$.

The cross-sectional base specification can be written as:

$$Y_i = \varphi + \beta \mathbb{1}_{\mathscr{S}} + \theta \mathbf{X}_i + \varepsilon_i \tag{16}$$

where Y_i denotes one of the outcome variables as described above. $\mathbb{1}_{\mathscr{S}}$ is an indicator function equal to one if fund i belongs to the set of sustainable funds $\mathscr{S}$, and zero otherwise. $\mathbf{X}$ is a vector of additional controls including, but not limited to: fund age, total net assets (size), fees, and net flows of capital.[7] If other controls are included in $\mathbf{X}$, it will be indicated in the corresponding table text. φ is a vector of fixed effects or the intercept. All results clearly indicate which fixed effects are included in φ.

In the main results, I use both domicile and Morningstar global category (category) fixed effects. Domicile fixed effects control for country-specific factors that can affect funds' skill, scalability, and value added, whereas category fixed effects control for unobserved shocks hitting funds investing in different markets. I include these two fixed effects both independently and in interaction. The difference in interpretation between including the fixed effects independently and in interaction is that in the former specification, I constrain any shock to the investment categories to have an identical effect across countries, whereas the latter specification is less restrictive in that it allows for shocks to investment categories to differ across countries.

I make this distinction because, as we observe from Table A.3 in Appendix A, the different investment categories include both country-specific categories such as Mexico Equity, sector-specific categories such as Healthcare Sector Equity, and size style categories such as Europe Equity Large Cap. Thus, a shock in the Healthcare Sector Equity category can have a different impact on a US mutual fund and a Swiss mutual fund because, despite investing in the same type of stocks, the funds can hold different types of healthcare companies that can be differently affected by category-specific shocks. This can, for instance, be due to the well-documented home-bias (see, e.g., Coval and Moskowitz 1999; Schumacher 2018).

3 Value added

I start my empirical analysis by investigating value added, and how it is distributed within sustainable and conventional mutual funds. This section is structured as follows: In Section 3.1, I plot the bias-adjusted distributions of value added for sustainable and conventional funds

[7]As argued by both Berk and Green (2004) and Berk and Van Binsbergen (2015), in rational markets, gross alpha equals fees. Therefore, I do not explicitly control for gross alpha in most regressions since I include fund fees in my standard set of additonal control variables.

and tabulate accompanying summary statistics. Next, in Section 3.2, I estimate the empirical model specified in Equation 16 to test for differences in value added between fund groups.

Next, in Section 3.3, I check for differences within funds with similar star ratings. It is well-known that investors often act irrationally (Ben-David et al., 2022), and that they often rely on simple metrics regarding fund performance that are easily understood, with Morningstar's star rating being one of the most prominent (Del Guercio and Tkac, 2008).[8] To investigate if value added is related to these mechanisms, I introduce dummy variables for whether a fund is low-skilled (1 or 2 stars), average-skilled (3 stars), or highly skilled (4 or 5 stars), as well as interaction terms for sustainable funds within these rankings.

Pástor and Stambaugh (2012) discuss how investors need time to correctly identify the correct level of skill and scale in funds to appropriately allocate capital. Thus, to try to capture the effect of this learning, I re-estimate value added using the time periods 2010-2019 and 2010-2022. These time intervals capture the time period leading up to the pandemic (2010-2019), and the time period including the pandemic (2010-2022). The main results capture the time periods pre-pandemic, pandemic, and post-pandemic. This division is interesting because investing in sustainable funds experienced rapid growth during the pandemic (e.g., see Figure 4 in Starks (2023)), which has later tapered off (Morningstar, 2024). Results on the effect on differences in value added due to these varying conditions are presented in Section 3.4.

3.1 Distribution and magnitude of value added

In this section, I plot, in Figure 1, the bias-adjusted distributions of value added for sustainable and conventional funds for $\hat{va} \in (-20, 20)$. For the full distribution, see Figure B.1 in Appendix B.

[8] See also Evans and Sun (2021) on this. Investors are also return chasing (Chevalier and Ellison, 1997; Choi and Robertson, 2020).

Figure 1. Distribution of Value Added
This figure plot the bias-adjusted distribution of the annualized value added across sustainable and conventional mutual funds for estimates in the interval $(-20, 20)$.

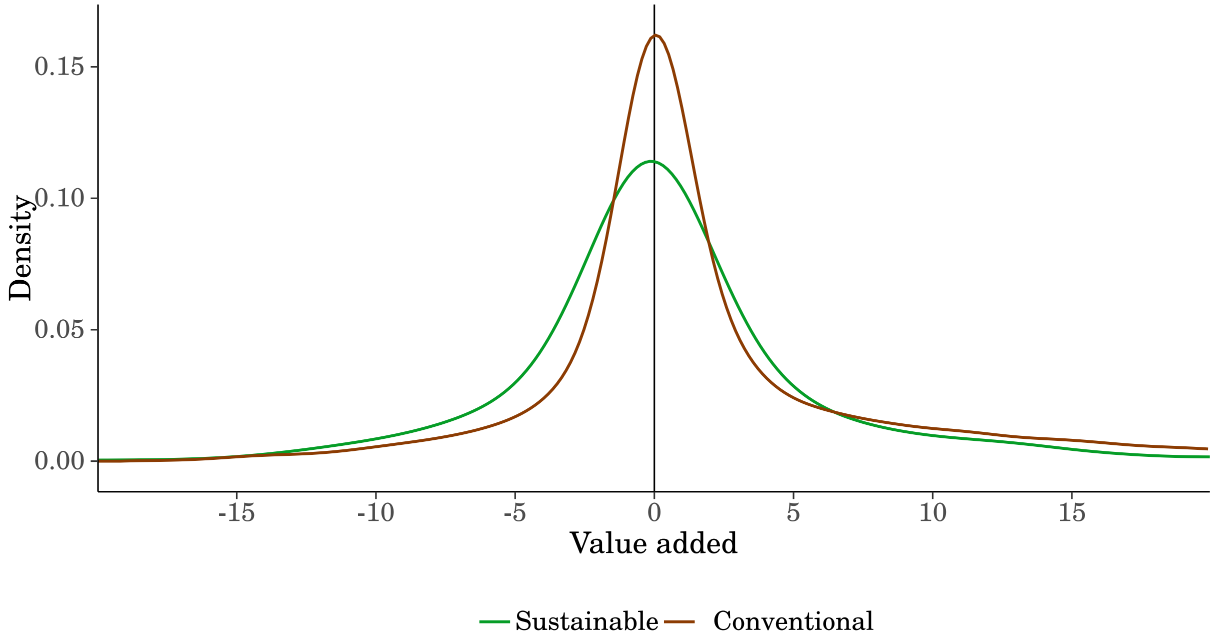

Figure 1 shows that both groups exhibit the highest density around zero. Moreover, the sustainable funds show a larger dispersion in observations, given that the conventional funds more tightly cluster around the mean. The tails of the distributions suggest that the extreme conventional funds produce more value added than the extreme sustainable funds on the right tail. Likewise, the left tail implies that the poorest sustainable funds destroy more value than the worst conventional funds. Related summary statistics are presented in Table 3.

Table 3. Summary statistics: Value Added

This table presents summary statistics on the distributions of value added for the cross-sectional sample of mutual funds. Panel A presents summary statistics for the distribution of value added for the entire period and for all funds in the sample, as well as for the subsamples of sustainable and conventional mutual funds. Reported are the mean (annualized), standard deviation (annualized), skewness, kurtosis, the proportions (%) of funds with a negative and positive value added, and the quantiles (annualized) at 5% and 95%. All cross-sectional estimates are computed following the approach of numerically integrating the bias-adjusted density obtained from the non-parametric approach put forward in Barras et al. (2022*a*). Panel B repeats the analysis for the last subperiod of value added.

Panel A: Entire period

	Moments				Proportions		Quantiles	
Group	Mean	SD	Skewness	Kurtosis	Negative	Positive	5%	95%
All	1.11	10.19	1.96	36.48	0.42	0.58	-7.18	14.77
Sustainable	0.35	10.00	1.23	29.20	0.49	0.51	-8.87	12.04
Conventional	1.26	10.07	2.07	36.92	0.40	0.60	-6.69	15.73

Panel B: Last sub-period

	Moments				Proportions		Quantiles	
Group	Mean	SD	Skewness	Kurtosis	Negative	Positive	5%	95%
All	2.24	11.53	2.52	32.24	0.33	0.67	-4.09	23.24
Sustainable	0.67	10.13	2.59	42.22	0.44	0.56	-8.75	12.86
Conventional	2.57	11.96	2.12	26.11	0.31	0.69	-3.51	26.11

Using the funds' entire return history, panel A in Table 3 shows that the average fund, regardless of fund group, extracts 1.11 USDm from the markets per year.[9] While these findings are close to Barras et al. (2022*a*) in showing that the majority of funds are able to extract positive value from the markets, other studies (e.g., Berk and Van Binsbergen (2015) and Zhu (2018)) find that the majority of funds destroy value.

On average, sustainable funds extract far less value from the markets than conventional funds, with a difference of approximately 0.9 USDm per year. The standard deviations between the groups are close, but conventional funds exhibit both higher skewness and kurtosis. The groups are also different in terms of the share of funds that are able to extract value, with about 50% of sustainable funds extracting positive value from the markets compared to 60% of conventional funds. The bottom 5% of sustainable funds destroy more value per year on average than the bottom 5% of conventional funds. The worst sustainable funds destroy on average 8.87 USDm per year while the worst conventional funds on average destroy 6.69 USDm. The top 5% of conventional funds beat out the top 5% of sustainable funds as well, with conventional funds

[9]This estimate is close to the average 1.9 USDm estimate for U.S funds in Barras et al. (2022*a*). For the other statistics, my global sample exhibits a lower standard deviation, skewness, and kurtosis.

extracting 3.69 USDm more. Given that Berk and Van Binsbergen (2015) argues for value added being the superior method of examining skill in the mutual fund industry, Table 3 Panel A indicates that conventional funds are more skilled than sustainable funds. In Panel B, I investigate value added from the funds' last sub-period.[10] Focusing on the last sub-period, the differences between sustainable and conventional funds become larger.

3.2 Value added in the cross-section

In this section, I test the difference in cross-sectional value added using the regression setup described in Section 2.4 and Equation 16. Results are reported in Table 4.

Table 4. The cross-section of Value Added
This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{va}_i$ (see Section 2.3 for details on the estimation approach). Value added is annualized, and control variables include net flows, and the natural logarithm of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides, and category is short for Morningstar global category fixed effects. For details, see Appendix A and Table A.3. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)	(5)	(6)
β	−0.91	−0.88	-1.60^{***}	-1.42^{***}	-1.20^{**}	-1.04^{**}
	(1.04)	(1.09)	(0.56)	(0.51)	(0.55)	(0.49)
Size		1.26		1.56^{**}		1.59^{**}
		(0.78)		(0.72)		(0.74)
Age		0.10		0.28		0.29
		(0.47)		(0.27)		(0.24)
Fee		0.59		0.20		0.18
		(0.69)		(0.37)		(0.37)
Net flows		−0.17		−0.08		0.00
		(0.14)		(0.12)		(0.13)
Fixed effects:						
Domicile (D)			×	×		
Category (C)			×	×		
D×C					×	×
N	14,064	14,060	14,063	14,059	14,064	14,060
R^2	0.00	0.02	0.10	0.12	0.17	0.19

As Table 3 shows, the average sustainable fund extract *less* value from markets compared to conventional funds, both for the entire sample period and for the last sub-period. In Table 4, I test whether the difference in value creation is significant. Columns 1 and 2 present the cross-sectional estimated differences, in the absence of any fixed effects. Testing the difference from Table 3 in Column 1 reveals that it is not statistically significant. Controlling for additional

[10]Again, I follow Barras et al. (2022*a*) and split the funds' return history into ten periods.

factors in the pooled sample reduces the estimated difference marginally, and with no change to the level of statistical significance.

In Columns 3-6, I repeat the analyses and include different fixed effects. In Columns 3 and 4, I include domicile and category fixed effects independently, thus controlling for systematic differences between countries and different investment categories. Controlling for these effects, I find that the difference between fund types is statistically significant at the 1% level and economically meaningful.

In Columns 5 and 6, instead of including domicile and category fixed effects independently, I include their interaction (see Section 2.4 for a discussion of the difference in interpretation). The estimated difference in Column 5 is smaller in magnitude than the corresponding estimate in Column 3. However, it is still significant at the 5% level, meaning that whether I control for country and investment categories independently or in interaction does not change the conclusion in the unconditional setting. The same picture applies when comparing Column 6 and 4, the estimated effect decreases, but remains statistically and economically significant.

Looking at the association between value added and other fund characteristics, it is evident that the relationship with size is positive. This differs from prior literature (Berk and Green, 2004; Zhu, 2018), which establishes diseconomies of scale, where performance reduces as fund size increases. The relationship between value added and fund age, fees and net flows are all statistically insignificant.

In sum, there is persistence in my results on the difference between sustainable and conventional funds in how much value they are able to add. Across models, I find that sustainable funds, on average, extract 1.2 USDm *less* in value each year. These results are, with the exception of the pooled models, statistically significant the the conventional levels, as well as economically significant. As such, I conclude here that sustainable funds add less value than their conventional counterparts.

3.3 Value added across performance ratings

Here, I test the differences in value added between sustainable and conventional funds across performance ratings. The regression setup used is the one described in Section 2.4 and Equation 16.

Table 5. Value Added and performance ratings

This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{va}_i$ (see Section 2.3 for details on the estimation approach). Value added is annualized. The variables "Low star rating" and "High star rating" are indicator variables equal to one if fund i has an average star rating of one or two stars, and four or five stars, respectively. Funds with an average rating of three stars comprise my reference group. Coefficients for the interaction between β and Low and High star rating capture the difference in Y_i between sustainable and conventional funds within their respective star rating categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Category fixed effects are short for Morningstar global category. For details, see Appendix A and Table A.3. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)	(5)	(6)
β	0.34	0.33	−0.66	−0.65	−0.20	−0.23
	(1.39)	(1.47)	(0.68)	(0.70)	(0.65)	(0.68)
Low star rating	-1.86^{*}	-1.24^{**}	-1.88^{**}	-1.11^{**}	-1.79^{**}	-0.98^{**}
	(1.10)	(0.50)	(0.74)	(0.48)	(0.77)	(0.49)
High star rating	6.28^{***}	6.29^{***}	5.66^{***}	5.33^{***}	5.80^{***}	5.40^{***}
	(0.70)	(0.70)	(0.77)	(0.68)	(0.80)	(0.70)
$\beta\times$Low star rating	−0.10	−0.10	−0.01	0.08	−0.01	0.04
	(1.32)	(1.35)	(1.01)	(1.07)	(1.01)	(1.07)
$\beta\times$High star rating	-2.30^{**}	-2.13^{**}	−1.89	−1.61	-2.01^{*}	−1.75
	(1.07)	(1.04)	(1.15)	(1.09)	(1.18)	(1.12)
Size		1.13		1.52^{*}		1.54^{*}
		(0.87)		(0.80)		(0.82)
Age		0.11		0.16		0.25
		(0.49)		(0.33)		(0.33)
Fee		1.54^{*}		0.91^{*}		0.91^{*}
		(0.82)		(0.49)		(0.47)
Net flows		-0.47^{**}		-0.42^{**}		-0.29^{*}
		(0.19)		(0.19)		(0.17)
Fixed effects:						
Domicile (D)			×	×		
Category (C)			×	×		
D×C					×	×
N	11,885	11,884	11,885	11,884	11,885	11,884
R^2	0.03	0.05	0.14	0.15	0.21	0.23

In line with expectations, conventional funds with low star ratings add less value than funds with average ratings. This effect is relatively stable and persistent across the different regression models. This also applies to the group of conventional funds with high star ratings, which on average add between 5.3 and 6.3 USDm *more* in value per year than funds with an average performance rating. Across regression models, it is also apparent that sustainable funds are able to extract less value than conventional funds within their respective performance groups.

In Columns 1 and 2, this effect is relatively large and significant at the 5% level when comparing the high star rating groups, but otherwise, the effect is mostly negligible in size and statistically insignificant.

Looking at the influence of other control variables, size shows similar results as seen in Table 4, but the level of statistical significance is weaker. There is no association between fund age and value added, fees are weakly positively associated with value added, but net flows are negatively associated with value-added. However the level of statistical significance varies across the different specifications. In sum, when testing for differences in value added between sustainable and conventional mutual funds within different groups based on star ratings, I find little evidence of any significant differences.

3.4 Value added over time

In this section, I test the differences in value added for different time periods, namely 2010-2019 and 2010-2022, in order to speak to the effect of investor learning on and subsequent allocation of capital on differences in the funds' ability to add value. Moreover, there was a shift towards sustainability during the pandemic, with Al Amosh and Khatib (2023) finding that ESG performance was positively and significantly impacted by it. This shift might be associated with changes to the difference in value added between fund types. The results from testing the difference in value added across time is reported in Table 6.

Columns 1-3 use value added estimates from the pre-pandemic years (2010-2019), while columns 4-6 include the pandemic years. Columns 1 and 4 report pooled OLS regressions, Columns 2 and 5 use domicile and investment category fixed effects independently, and Columns 3 and 6 use their interaction. Unlike previous analyses, I only report regression models with additional control variables.

In contrast to earlier results, the length of the return history used to estimate value added greatly influence the resulting differences between the two fund groups. Moreover, comparing the magnitude of the estimated differences (Column 2 and 5 in Table 6 and Column 4 in Table 4, and Column 3 and 6 in Table 6 and Column 6 in Table 4) reveals that as more of the funds' return history is included, the estimated differences increase (-0.24 and -0.61 pre-pandemic, -1.11 and -0.78 including the pandemic, and -1.42 and -1.04 including post-pandemic). This suggests that over time, sustainable funds become less able to extract value relative to conventional funds. This aligns with Van der beck (2021), who find that without the positive price pressure on ESG stocks caused by capital flows to sustainable funds, these funds would

Table 6. Value Added over time

This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{va}_i$ (see Section 2.3 for details on the estimation approach). Value added is annualized. In Columns 1-3, $Y_i = \hat{va}_i^{pp}$ is estimated using fund returns in the pre-pandemic (pp) years (2010-2019). In Columns 4-6, $Y_i = \hat{va}_i^{ip}$ is estimated using fund returns in the pre-pandemic and pandemic (ip) years (2010-2022). Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Category fixed effects are short for Morningstar global category. For details, see Appendix A and Table A.3. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

Sample period	2010-2019			2010-2022		
	(1)	(2)	(3)	(4)	(5)	(6)
β	−0.24	−0.61	−0.23	−0.99	−1.11**	−0.78*
	(1.50)	(0.60)	(0.61)	(0.93)	(0.47)	(0.47)
Size	2.35**	2.78***	2.80***	1.70**	2.00***	2.04***
	(1.01)	(0.93)	(0.95)	(0.67)	(0.62)	(0.63)
Age	0.08	0.40	0.51	0.19	0.41	0.36
	(0.53)	(0.42)	(0.44)	(0.52)	(0.27)	(0.24)
Fee	2.50**	1.88***	1.83***	0.44	0.08	0.05
	(1.06)	(0.62)	(0.62)	(0.62)	(0.37)	(0.37)
Net flows	0.43	0.46*	0.65**	−0.12	−0.00	0.06
	(0.27)	(0.27)	(0.27)	(0.17)	(0.16)	(0.16)
Fixed effects:						
Domicile (D)		×			×	
Category (C)		×			×	
D×C			×			×
N	12,275	12,275	12,275	14,060	14,059	14,060
R^2	0.03	0.15	0.22	0.03	0.11	0.17

have underperformed the market on a return basis. Therefore, these findings point in the same direction.

Furthermore, size consistently has a positive and statistically significant effect on value added across sub-periods. This contrasts with prior literature, which shows a negative relationship between size and performance. The age coefficient is consistently insignificant. Pre-pandemic, fees had a positive significant effect on value added, suggesting that more expensive funds extracted more value from the markets (as shown in Table 4). This effect disappears when including the pandemic and post-pandemic period. During the pre-pandemic years, net flows is positively associated with value added, but as with fees, this effect disappears when the funds' return history is extended to include the pandemic and post-pandemic years.

In sum, breaking up the funds' return history shows that the estimated differences increase in magnitude over time. Additionally, the fund characteristics associated with value added have shifted over time. For example, fees and net flows influenced value added pre-pandemic but are not associated with it when including the pandemic and post-pandemic years.

4 Skill

In Section 3, I found that that sustainable funds struggle to extract value from the markets compared to conventional funds. In this section, I decompose value added as in Barras et al. (2022*a*), and specifically test whether sustainable and conventional funds differ in their skill levels. For consistency, this section follows the same structure as Section 3.

4.1 Distribution and magnitude of skill

Figure 2 plots the bias-adjusted distributions of the annualized skill coefficients for sustainable and conventional mutual funds.

Figure 2 shows that both groups exhibit similar modes, and that these are both positive. As such, the most common fund of both types are able to identify profitable investments. Moreover, one can generally see that the dispersion is greater for the sustainable funds, but that the tails - i.e., funds that exhibit extreme high or low levels of skill - are lower. Both distributions exhibit a long right tail (positive skew), whereas the sustainable funds have a shorter left tail. In Table 7, I present related summary statistics.

Figure 2. Distribution of Skill
This figure plot the bias-adjusted distribution of the annualized skill coefficients across sustainable and conventional mutual funds.

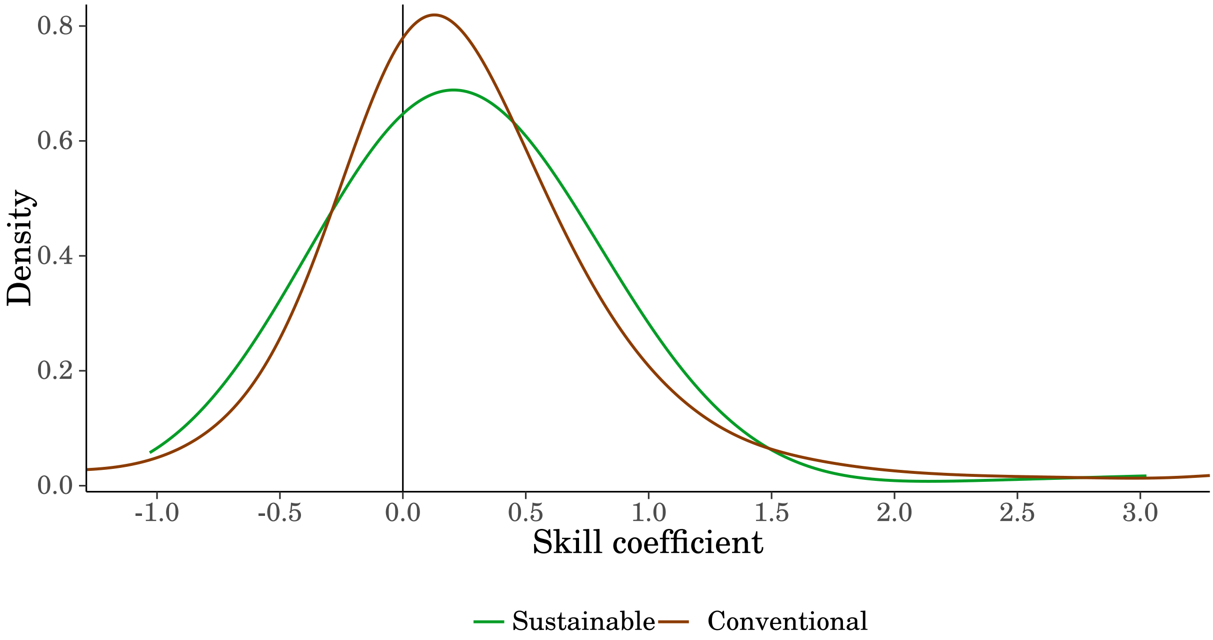

Table 7. Summary statistics: Skill
This table presents summary statistics on the distributions of the skill coefficient for the cross-sectional sample of mutual funds. Reported are the mean (annualized), standard deviation (annualized), skewness, kurtosis, the proportions (%) of funds with a negative and positive skill coefficient, and the quantiles (annualized) at 5% and 95%. All cross-sectional estimates are computed following the approach of numerically integrating the bias-adjusted density obtained from the non-parametric approach put forward in Barras et al. (2022*a*).

	Moments				Proportions		Quantiles	
Group	Mean	SD	Skewness	Kurtosis	Negative	Positive	5%	95%
All	3.55	2.20	1.16	6.14	0.33	0.67	-7.16	16.73
Sustainable	3.84	2.09	0.71	4.61	0.34	0.66	-7.73	15.01
Conventional	3.49	2.20	1.14	6.05	0.33	0.67	-7.22	16.61

The statistics reported in Table 7 are all bias-adjusted. Based on the pooled group of funds, the average fund has a positive skill coefficient of 3.55% per year. This estimate is quite close to the one reported for U.S. funds by Barras et al. (2022*a*) (3.0% per year). Comparing the other statistics, this sample exhibits a lower standard deviation, skewness and kurtosis. A larger share of funds in this sample have a negative skill coefficient ($\hat{a}_i < 0$), i.e., the majority of funds are skilled with 67% of all funds exhibiting a positive skill coefficient. However, this is lower than for the U.S funds sample in Barras et al. (2022*a*), where 83.1% of funds are skilled. The 5% and 95% quantiles are also more extreme. Given that this dataset spans multiple countries that differ, this is expected.

On average, sustainable funds have a higher skill coefficient compared to conventional funds (difference of 0.35% per year). This is surprising given that Tables 3 and 4 show that conventional funds consistently outperforms sustainable funds in creating value. The standard deviations between the two groups are close, but conventional funds have higher skewness and kurtosis. Across both groups, the share of funds with negative and positive skill coefficients are largely the same, with one third exhibiting a negative skill coefficient and two thirds a positive skill coefficient. The bottom third of funds thus struggle with identifying profitable investment ideas. This is puzzling, given that these funds have the option of investing passively and ensuring their alphas are zero without considering scale (Barras et al., 2022*a*). A possible explanation is proposed by Berk and Van Binsbergen (2022), who refers to these unskilled funds as charlatans. These charlatan funds actively try to mislead investors about their skill level and therefor willingly generate negative alphas.

The bottom 5% of all funds exhibit a negative skill coefficient of -7.16%.The 5$^{\text{th}}$ percentile of sustainable funds exhibits a lower skill parameter than the conventional funds, with a 0.51% difference. This implies that the least skilled sustainable funds generate lower alphas than the least skilled conventional funds. This is consistent with Table 3, which shows that the worst sustainable funds destroy more value than the worst conventional funds. The average fund within the top 5% has a positive skill coefficient equal to 16.73%. Also here conventional funds exhibit higher skill than sustainable funds, which is consistent with Table 3. Conventional funds have a 1.6% higher skill coefficient among the top 5%. Consequently, sustainable funds have a higher skill coefficient on average but are less skilled towards the tails (more negative coefficient for the bottom 5% and lower coefficient for the top 5%). From the skewness and kurtosis, this distribution can be described as relatively symmetrical, with a hint of a long tail to the right side. With a positive kurtosis, the peakedness of the distribution curve can be described as a sharper peak than the normal distribution.

4.2 Skill in the cross-section

Table 7 shows the average sustainable fund has a higher skill parameter (3.84) than conventional mutual funds (3.49). Given the difference in value added between fund types found in Section 3, it is interesting to see if this difference is statistically significant. In this section, I test the difference in cross-sectional skill estimates using the regression setup described in Section 2.4, Equation 16. The results from testing the difference in skill are reported in Table 8.

Table 8. The cross-section of Skill
This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{a}_i$ (see Section 2.3 for details on the estimation approach). The skill parameter is annualized, and control variables include net flows, and the natural logarithm of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides, and category is short for Morningstar global category fixed effects. For details, see Appendix A and Table A.3. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)	(5)	(6)
β	0.35	−0.11	0.64**	0.20	0.59**	0.15
	(0.31)	(0.31)	(0.27)	(0.26)	(0.28)	(0.26)
Size		0.23***		0.14		0.12
		(0.08)		(0.08)		(0.08)
Age		−0.71***		−0.68***		−0.74***
		(0.19)		(0.21)		(0.21)
Fee		0.40*		0.48**		0.58***
		(0.24)		(0.21)		(0.22)
Net flows		0.35***		0.37***		0.35***
		(0.10)		(0.11)		(0.11)
Fixed effects:						
Domicile (D)			×	×		
Category (C)			×	×		
D×C					×	×
N	14,114	14,110	14,113	14,109	14,114	14,110
R^2	0.00	0.02	0.04	0.06	0.10	0.12

In Table 8, I test whether the perceived difference is significant. Columns 1 and 2 present the cross-sectional estimated differences in the absence of any fixed effects. As Columns 1 and 2 show, the difference from Table 7 is not statistically significant in the pooled OLS regressions, with different signs for the β coefficients.

In Columns 3-6, I repeat the analyses and include the varying fixed effects as described for value added in Section 3.2. In Columns 3 and 4, I include domicile and category fixed effects independently. Controlling for these, I find that the positive difference in skill between sustainable and conventional funds is statistically significant at the 5% level in Column 3, but not significant in Column 4 when additional control variables are included. The coefficient estimate is also reduced by more than 50%.

In Columns 5 and 6, I include the interaction of domicile and investment category as fixed effects. Here, the coefficients are relatively unstable, as the statistical significance continues to vary. The difference in Column 5 is significant at the 5% level, but not significant in Column 6 when controlling for other fund characteristics. The coefficient size is also greatly reduced, which is similar to Columns 3 and 4.

Looking at the influence of other fund characteristics, it is clear that older funds tend to be less skilled than younger funds. This effect is robust, both with regards to magnitude and significance, across specifications. This is consistent with Pástor et al. (2015), who find that younger funds exhibit better skills by outperforming older funds. In Pástor et al. (2015) this effect disappears when they control for industry size, whereas it remains present in my results as I control for industry size by the inclusion of domicile fixed effects in Columns 3-6. Fees show a positive effect on skill, with varying degrees of statistical significance across all specifications. Net flows show a positive effect on skill, which is significant at the 1% level across all regressions, indicating that investors are able to identify skilled funds. Size is largely unrelated to skill.

In sum, there is persistence in the sign of the difference in skill between sustainable and conventional funds. The estimated difference is on average around 0.3 percentage points per year with low levels of statistical significance. Thus, I conclude that there are no differences in skill between sustainable and conventional funds.

4.3 Skill across performance ratings

In this section, I test the differences in skill across performance ratings. The regression setup used is the one described in Section 2.4 and Equation 16.

Table 9. Skill and performance ratings
This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{a}_i$ (see Section 2.3 for details on the estimation approach). The skill parameter is annualized. The variables "Low star rating" and "High star rating" are indicator variables equal to one if fund i has an average star rating of one or two stars, and four or five stars, respectively. Funds with an average rating of three stars comprise my reference group. Coefficients for the interaction between β and Low and High star rating capture the difference in Y_i between sustainable and conventional funds within their respective star rating categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Category fixed effects are short for Morningstar global category. For details, see Appendix A and Table A.3. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)	(5)	(6)
β	−0.23	−0.40	0.01	−0.13	−0.00	−0.17
	(0.31)	(0.31)	(0.30)	(0.31)	(0.31)	(0.32)
Low star rating	-1.53^{***}	-1.55^{***}	-1.30^{***}	-1.36^{***}	-1.31^{***}	-1.41^{***}
	(0.21)	(0.21)	(0.19)	(0.19)	(0.19)	(0.19)
High star rating	2.15^{***}	1.95^{***}	1.99^{***}	1.82^{***}	1.91^{***}	1.74^{***}
	(0.23)	(0.23)	(0.21)	(0.18)	(0.21)	(0.18)
$\beta\times$Low star rating	−0.13	−0.10	−0.45	−0.40	−0.44	−0.37
	(0.47)	(0.48)	(0.43)	(0.44)	(0.45)	(0.46)
$\beta\times$High star rating	−0.24	−0.23	−0.12	−0.13	−0.04	−0.05
	(0.35)	(0.35)	(0.33)	(0.33)	(0.33)	(0.33)
Size		0.09		−0.01		−0.01
		(0.08)		(0.08)		(0.08)
Age		0.21		0.23		0.16
		(0.27)		(0.19)		(0.19)
Fee		0.81^{***}		0.85^{***}		0.98^{***}
		(0.24)		(0.17)		(0.18)
Net flows		0.46^{***}		0.48^{***}		0.49^{***}
		(0.09)		(0.07)		(0.07)
Fixed effects:						
Domicile (D)			×	×		
Category (C)			×	×		
D×C					×	×
N	11,932	11,931	11,932	11,931	11,932	11,931
R^2	0.04	0.05	0.09	0.10	0.15	0.17

As Table 9 shows, there is little evidence any significant differences between sustainable and conventional funds within different star rating categories. In line with expectations and previous results from Section 3.3, conventional funds with low star ratings possess less skill than funds with average ratings. This effect is relatively stable and persistent across the different specifications, both in magnitude and level of statistical significance. High star-rated funds exhibit more skill than average-rated funds, which is again consistent with the results from Section 3.3 that indicated high star funds added *more* value. These results are relatively stable and persistently significant at the 1% level across all regressions, implying a 1.8 to 2.15 percentage points per year higher alpha. From the interaction terms, it is clear that sustainable funds are associated with less skill than conventional funds within the same performance group, consistent with what was seen for the value added interaction terms in Table 5 in Section 3.3. However, the measured differences in skill here are small and statistically insignificant across all specifications.

Looking at the influence of other fund characteristics, age is now unrelated to skill, whereas it showed a statistically significant negative effect in Table 8. Fees remain stable, exhibiting a positive effect which is now significant at the 1% level across all regressions, as opposed to varying levels of statistical certainty in Table 8. Net flows show an increase in the measured effect on skill, maintaining a similar level of statistical certainty from the cross-sectional analysis. Size continues to be unrelated to skill, with a decrease in magnitude from Table 8, moving closer to zero.

When testing for differences in skill between sustainable and conventional funds within the different rating groups, I find little evidence of any significant differences.

4.4 Skill over time

In this section, I test the differences in skill for the pre-pandemic years (2010-2019) and pre-pandemic and pandemic years (2010-2022), as done for value added in Section 3.4. I have used the setup described in Section 2.4, Equation 16. The results from testing the difference in skill over time are reported in Table 10.

Table 10. Skill over time

This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{a}_i$ (see Section 2.3 for details on the estimation approach). The skill parameter is annualized. In Columns 1-3, $Y_i = \hat{a}_i^{pp}$ is estimated using fund returns in the pre-pandemic (pp) years (2010-2019). In Columns 4-6, $Y_i = \hat{a}_i^{ip}$ is estimated using fund returns in the pre-pandemic and pandemic (ip) years (2010-2022). Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Category fixed effects are short for Morningstar global category. For details, see Appendix A and Table A.3. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

Sample period	2010-2019			2010-2022		
	(1)	(2)	(3)	(4)	(5)	(6)
β	−0.50	−0.35	−0.37	0.11	0.63*	0.53
	(0.42)	(0.38)	(0.39)	(0.38)	(0.34)	(0.34)
Size	0.22	0.01	0.01	0.29**	0.15	0.13
	(0.15)	(0.16)	(0.16)	(0.12)	(0.11)	(0.11)
Age	−1.29***	−1.21***	−1.33***	−0.81***	−0.71***	−0.78***
	(0.48)	(0.36)	(0.37)	(0.26)	(0.24)	(0.24)
Fee	−0.18	−0.02	0.07	0.50*	0.52*	0.56**
	(0.39)	(0.33)	(0.34)	(0.28)	(0.27)	(0.28)
Net flows	−0.12	−0.12	−0.12	0.27**	0.31**	0.29**
	(0.17)	(0.14)	(0.14)	(0.11)	(0.12)	(0.12)
Fixed effects:						
Domicile (D)		×			×	
Category (C)		×			×	
D×C			×			×
N	12,323	12,323	12,323	14,110	14,109	14,110
R^2	0.00	0.05	0.10	0.01	0.05	0.10

As seen for value added, the length of the return history used to estimate skill greatly influences the differences between the two groups. Moreover, comparing the magnitude of the estimated differences (Column 2 and Column 5 in Table 10 with Column 4 in Table 8, and Column 3 and Column 6 in Table 10 with Column 6 in Table 8) reveals that as more of the funds' return history is included, the estimated difference increases from pre-pandemic to including the pandemic, but then experiences a drop with the post-pandemic inclusion that is still larger than pre-pandemic conditions (-0.35 and -0.37 pre-pandemic, 0.63 and 0.53 including the pandemic, 0.20 and 0.15 post-pandemic). The sign of the differences suggests that sustainable funds become more skilled relative to conventional funds over time, but the initial increase in skill drops when I include the post-pandemic year (2023). Again, the differences are not statistically significant. This contrasts with what was seen for value added, which showed sustainable funds consistently adding less value than conventional funds.

Furthermore, size continues to be unrelated to skill, as seen from the previous analyses. This is strange given that size had a positive and statistically significant effect on value added in Section 3.4. Opposed to the insignificant effect of age on value added across time, here age once again shows a significant negative effect on skill across all regressions, maintaining consistency with prior literature. The measured effect is persistently significant at the 1% level but experiences a drop in magnitude as the estimation window increases. Pre-pandemic, fees had no effect on skill. Including the pandemic, fees show a positive effect which is significant at the 10% level in Columns 4 and 5, and at the 5% level in Column 6. This is similar to the relationship shown between post-pandemic fees and skill in Table 8. The same change in effect and significance for fees is experienced with net flows when including further time periods.

In sum, breaking up the funds' return history shows that the estimated differences in skill between fund types change when including the during- and post-pandemic time periods. As discussed in Section 3.4, Van der beck (2021) found that sustainable funds would have underperformed the market without the positive price pressure from investor flows on ESG stocks. This could be a possible explanation for the initial increase and then drop in skill for sustainable funds when including the pandemic and post-pandemic time periods. The initial increase in popularity towards the ESG sector during the pandemic (as shown by Al Amosh and Khatib (2023)) could increase the skill of sustainable funds through economies of scale as they grew, but perhaps after growing too big, they started experiencing decreasing returns to scale while still delivering positive alphas. This leads into the next section of my empirical analysis.

5 Scale

In this section, I investigate the scale parameter. With Section 3 showing sustainable funds consistently adding *less* value than conventional funds, I expected that Section 4 would show conventional funds exhibiting higher skill. In contrast, I found little evidence of differences in skill between fund types. Thus, I have found so far that conventional funds outperform sustainable funds in value creation, despite being equally skilled. This leads me to investigate the second factor influencing *value added*: scale. This section follows the same structure as Sections 3 and 4, with subsections 5.1, 5.2, 5.3, and 5.4 conducting the same types of analyses.

5.1 Distribution and magnitude of scale

Figure 3 plots the bias-adjusted distributions of the scale coefficients for sustainable and conventional mutual funds.

Figure 3. Distribution of Scale
This figure plot the bias-adjusted distribution of the annualized scale coefficients across sustainable and conventional mutual funds.

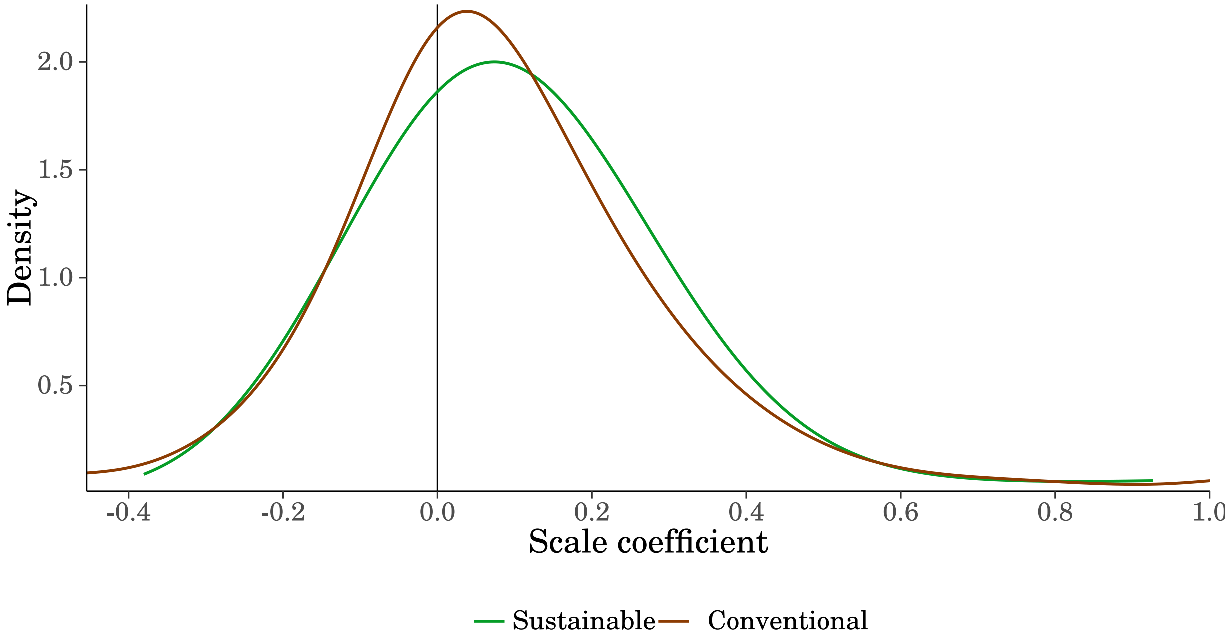

Figure 3 shows, similar to Figure 2, that both groups exhibit similar modes and that these are positive. The most common fund of both types in this distribution shows a positive scale coefficient. Given the sign of the scale coefficient in Equation 6, this means that the most common fund in both groups experiences decreasing returns to scale, i.e., diseconomies of scale. Moreover, the dispersion in observations is greater for sustainable funds, but the tails, i.e., funds that exhibit extreme high or low sensitivity to scale constraints, are quite similar between the groups. Both fund distributions also show a long right tail, indicating positive skew, with sustainable funds having a shorter left tail. In Table 11, I present related summary statistics.

The statistics reported in Table 11 are all bias-adjusted. Based on the pooled group of funds, the average fund exhibits a positive scale coefficient of 1.15.[11] This means that a one standard deviation increase in fund size reduces the gross alpha by 1.15% per year for the average fund. Comparing the other statistics, this sample exhibits lower standard deviation, skewness, and

[11]This estimate is quite close to the one reported in Barras et al. (2022*a*) for U.S. funds (1.3)

Table 11. Summary statistics: Scale
This table presents summary statistics on the distributions of the scale coefficient for the cross-sectional sample of mutual funds. Reported are the mean (annualized), standard deviation (annualized), skewness, kurtosis, the proportions (%) of funds with a negative and positive skill coefficient, and the quantiles (annualized) at 5% and 95%. All cross-sectional estimates are computed following the approach of numerically integrating the bias-adjusted density obtained from the non-parametric approach put forward in Barras et al. (2022*a*), and I follow them in standardizing the scale parameter for each fund, so that it corresponds to the change in gross alpha in response to a one-standard-deviation change in fund size.

	Moments				Proportions		Quantiles	
Group	Mean	SD	Skewness	Kurtosis	Negative	Positive	5%	95%
All	1.15	0.75	0.81	4.64	0.34	0.66	-2.70	5.78
Sustainable	1.43	0.73	0.59	3.82	0.32	0.68	-2.57	5.58
Conventional	1.09	0.75	0.77	4.59	0.35	0.65	-2.78	5.65

kurtosis. A smaller share of the funds in this sample exhibits positive scale coefficients.[12] This means that in my sample compared to Barras et al. (2022*a*), I have a larger number of funds that do not experience diseconomies of scale. 66% of this sample exhibits a positive scale coefficient compared to 82.4% in the U.S. funds sample in Barras et al. (2022*a*).

On average, sustainable funds exhibit a higher sensitivity to diseconomies of scale compared to conventional funds. A one-standard-deviation increase in assets under management reduces gross alpha by 1.43% per year, while the common conventional fund only experiences a 1.09% reduction (0.34% difference). The standard deviation is also close here, with conventional funds once again exhibiting higher skewness and kurtosis. Across both groups, the number of funds experiencing diseconomies of scale is largely the same, with one third in both groups not facing constraints in value creation as they grow.

The bottom 5% of all funds exhibit a negative scale coefficient, meaning that when they grow in size, their alphas increase by 2.7% on average per year. The average sustainable fund within the bottom 5% experiences an increase in alpha equal to 2.57% per year, while conventional funds experience a 2.78% increase per year. In the top 5%, the average fund reduces their alpha by 5.78% per year. Sustainable funds within the top 5% exhibit a lower degree of sensitivity to scale constraints than conventional funds within the top 5% (0.07 percentage point difference). The worst and average conventional funds are more efficient as they grow than sustainable funds within the same groups, but within the top 5%, sustainable funds show a lower sensitivity

[12] Negative scale coefficients are inconsistent with Berk and Green (2004). Thus, the relatively larger presence of these funds in my sample compared to Barras et al. (2022*a*) can indicate that i) The model is to a greater extent misspecified in a global sample, or ii) My estimates are noisier, possibly due to my relatively shorter sample period (2011-2023) vs. (1975-2019) in Barras et al. (2022*a*).

to scale constraints than conventional funds.

5.2 Scale in the cross-section

Table 11 showed that, on average, sustainable funds are more sensitive to diseconomies of scale than conventional funds. In this section, I test the differences in cross-sectional scale estimates using the regression setup described in Section 2.4 and Equation 16. The results from testing the differences are reported in Table 12.

Table 12. The cross-section of Scale
This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{b}_i$ (see Section 2.3 for details on the estimation approach). The scale parameter is annualized and standardized for each fund, so that it corresponds to the change in gross alpha in response to a one-standard-deviation change in fund size. Other control variables include net flows, and the natural logarithm of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides, and category is short for Morningstar global category fixed effects. For details, see Appendix A and Table A.3. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$..

	(1)	(2)	(3)	(4)	(5)	(6)
β	0.34^{***}	0.04	0.47^{***}	0.20^{**}	0.45^{***}	0.19^{**}
	(0.12)	(0.11)	(0.10)	(0.09)	(0.10)	(0.09)
Size		0.10^{***}		0.03		0.03
		(0.03)		(0.03)		(0.03)
Age		-0.34^{***}		-0.33^{***}		-0.34^{***}
		(0.06)		(0.06)		(0.06)
Fee		0.28^{***}		0.33^{***}		0.35^{***}
		(0.07)		(0.07)		(0.07)
Net flows		0.29^{***}		0.26^{***}		0.25^{***}
		(0.04)		(0.04)		(0.04)
Fixed effects:						
Domicile (D)			×	×		
Category (C)			×	×		
D×C					×	×
N	14,114	14,110	14,113	14,109	14,114	14,110
R^2	0.00	0.06	0.07	0.12	0.12	0.16

In Table 12, I test whether the perceived difference in scale is significant. Columns 1 and 2 present the cross-sectional estimated differences in the absence of any fixed effects. As shown in Columns 1 and 2, the difference from Table 11 is statistically significant at the 1% level in the univariate pooled OLS regression (Column 1). In Column 2, when including fund characteristic controls, the difference in scale loses all statistical significance and magnitude.

In Columns 3-6, I repeat the analyses and include the varying fixed effects as described in

Sections 3.2 and 4.2. In Columns 3 and 4, I include domicile and category fixed effects independently. Controlling for these effects, I find that the estimated difference in scale is statistically significant at the 1% level in the univariate regression and at the 5% level when including controls. The measured difference in Column 4 implies that sustainable funds experience a 0.2 percentage point further reduction in yearly alpha in response to one-standard-deviation increase size compared to conventional funds.

In Columns 5 and 6, I include the interaction of domicile and investment category as fixed effects. Here, the coefficients and the statistical significance remain relatively stable from Columns 3 and 4, with the measured differences being significant at the 1% level in Column 5 and the 5% level in Column 6.

Looking at the influence of other fund characteristics, as a fund gets older, it becomes less sensitive to scale constraints. When analyzing the skill parameter in Table 8, the results showed funds becoming less skilled as they became older. This might indicate capital allocation towards younger firms, which is in line with Pástor et al. (2015). The effect is robust in both magnitude and significance across specifications. Fees show a positive effect on a fund's sensitivity to scale constraints. With the relationship between fees and skill found in Section 4 suggesting that more skilled funds charge higher fees, and with Chevalier and Ellison (1997) finding investors chase past returns (performance), a fund charging higher fees might imply better skill and thus an increase in capital flows and fund size. This would also explain the positive significant effect exhibited by net flows. Interestingly, size seems unrelated to scale, only showing a significant effect at the 1% level in Column 2. This is consistent with previous analyses in this paper, where size has not shown any significant relationship with any of the previous parameters of interest.

In sum, there is persistence in the sign of the difference in scale between sustainable and conventional funds. The estimated difference is, on average, a 0.34 percentage point reduction in alpha per year as they grow in size, with relatively consistent levels of statistical certainty.

5.3 Scale across performance ratings

In this section, I test the differences in scale across performance ratings. Table 13 reports the results of these differences. The regression setup used is the one described in Section 2.4 and Equation 16.

Table 13. Scale and performance ratings

This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{b}_i$ (see Section 2.3 for details on the estimation approach). The scale parameter is annualized and standardized for each fund, so that it corresponds to the change in gross alpha in response to a one-standard-deviation change in fund size. The variables "Low star rating" and "High star rating" are indicator variables equal to one if fund i has an average star rating of one or two stars, and four or five stars, respectively. Funds with an average rating of three stars comprise my reference group. Coefficients for the interaction between β and Low and High star rating capture the difference in Y_i between sustainable and conventional funds within their respective star rating categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Category fixed effects are short for Morningstar global category. For details, see Appendix A and Table A.3. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)	(5)	(6)
β	0.14	−0.02	0.30***	0.16*	0.28***	0.14
	(0.12)	(0.12)	(0.10)	(0.10)	(0.10)	(0.10)
Low star rating	−0.12	−0.11	−0.03	−0.08	−0.05	−0.11
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
High star rating	0.64***	0.38***	0.63***	0.43***	0.60***	0.41***
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
$\beta\times$Low star rating	0.00	0.03	−0.12	−0.08	−0.11	−0.06
	(0.16)	(0.16)	(0.15)	(0.15)	(0.15)	(0.15)
$\beta\times$High star rating	−0.05	−0.10	−0.07	−0.12	−0.02	−0.06
	(0.13)	(0.12)	(0.12)	(0.11)	(0.12)	(0.11)
Size		0.08***		−0.00		0.00
		(0.03)		(0.03)		(0.03)
Age		−0.05		−0.05		−0.07
		(0.08)		(0.06)		(0.06)
Fee		0.30***		0.37***		0.40***
		(0.07)		(0.08)		(0.08)
Net flows		0.40***		0.37***		0.36***
		(0.04)		(0.04)		(0.04)
Fixed effects:						
Domicile (D)			×	×		
Category (C)			×	×		
D×C					×	×
N	11,932	11,931	11,932	11,931	11,932	11,931
R^2	0.02	0.08	0.09	0.14	0.15	0.20

Table 13 show that there are no discernible differences in scale between sustainable and conventional funds within different star rating categories. Looking at the signs only, sustainable funds in the low and high star rating categories seem less sensitive to diseconomies of scale than conventional funds, whereas the sustainable funds with an average performance rating are more sensitive. The difference within this average-rated group has varying degrees of statistical significance. Conventional funds with a high star rating, in turn, also exhibit higher scale coefficients than average-rated funds. This might occur because investors allocate capital towards the higher-rated funds, as shown by Del Guercio and Tkac (2008), and therefore experience stronger growth than lower-rated funds. This difference is significant at the 1% level across all regression specifications, implying a 0.38pp to 0.64pp further drop in alpha as they grow compared to average-rated funds. Low star-rated conventional funds exhibit no significant difference in scale coefficients compared to average funds.

Looking at the influence of other fund characteristics, age is now unrelated to scale, as opposed to the significant negative effect shown in Table 12. Both fees and net flows remain stable from Table 12, exhibiting a similar positive effect, which is again significant at the 1% level across all specifications. Size continues to show no apparent effect on a fund's scale parameter, exhibiting only a low effect, which is significant at the 1% level in Column 2.

In sum, when testing for differences in scale between fund types across performance ratings, I find little evidence of scale differences between sustainable and conventional funds within the same rating groups.

5.4 Scale over time

In this section, I test the differences in scale for the time periods 2010-2019 and 2010-2022, as done for value added and skill in Sections 3.4 and 4.4. The analysis follow the setup described in Section 2.4 and Equation 16. The results from testing the difference in scale across time are reported in Table 14. The table here follows the same structure as described for Table 6.

As seen for both value added and skill, the length of the return history used to estimate scale greatly influences the differences between the two groups. Comparing the magnitude of the estimated differences (Column 2 and 5 in Table 14 with Column 4 in Table 12, and Column 3 and 6 in Table 14 with Column 6 in Table 12) reveals that as more of the fund's return history is included, the estimated differences increase (-0.15 and -0.17 pre-pandemic, 0.26 and 0.25 including the pandemic, 0.20 and 0.19 including post-pandemic). These differences are statistically significant at the 10% level pre-pandemic, 5% level including the pandemic and post-pandemic years. This suggests sustainable funds become more sensitive to diseconomies of scale as more return history is included, with conventional funds exhibiting higher sensitivity during the pre-pandemic years.

Furthermore, size continues to be unrelated to scale, only showing a significant effect in the pooled OLS regressions. Age shows once again a statistically significant at the 1% level negative

Table 14. Scale over time
This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{b}_i$ (see Section 2.3 for details on the estimation approach). The scale parameter is annualized and standardized for each fund, so that it corresponds to the change in gross alpha in response to a one-standard-deviation change in fund size. In Columns 1-3, $Y_i = \hat{b}_i^{pp}$ is estimated using fund returns in the pre-pandemic (pp) years (2010-2019). In Columns 4-6, $Y_i = \hat{b}_i^{ip}$ is estimated using fund returns in the pre-pandemic and pandemic (ip) years (2010-2022). Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Category fixed effects are short for Morningstar global category. For details, see Appendix A and Table A.3. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

Sample period	2010-2019			2010-2022		
	(1)	(2)	(3)	(4)	(5)	(6)
β	-0.19^{*}	-0.15^{*}	-0.17^{**}	0.08	0.26^{**}	0.25^{**}
	(0.11)	(0.08)	(0.08)	(0.12)	(0.10)	(0.11)
Size	0.08^{**}	0.01	0.02	0.12^{***}	0.04	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Age	-0.13	-0.16^{***}	-0.18^{***}	-0.37^{***}	-0.35^{***}	-0.35^{***}
	(0.09)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)
Fee	0.07	0.14^{*}	0.16^{**}	0.37^{***}	0.39^{***}	0.40^{***}
	(0.09)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)
Net flows	0.16^{***}	0.13^{***}	0.12^{***}	0.26^{***}	0.24^{***}	0.23^{***}
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Fixed effects:						
Domicile (D)		×			×	
Category (C)		×			×	
D×C			×			×
N	12,323	12,323	12,323	14,110	14,109	14,110
R^2	0.01	0.08	0.13	0.05	0.09	0.15

effect on scale, except for the pre-pandemic pooled OLS regression. Fees show a weakly positive effect on scale with varying statistical certainty before COVID-19. Including the pandemic, it experiences an increase in measured magnitude equal to more than 100%, exhibiting a consistently increased statistical inference. Net flows show a consistent statistical significance at the 1% level across all regression specifications, but including the pandemic net flows show a stronger magnitude than pre-pandemic effect.

In sum, breaking up the fund history shows that the estimated differences in scale between fund types change when including additional time periods. From the pre-pandemic regressions in Table 14, conventional funds exhibit a higher sensitivity to diseconomies of scale, but as the pandemic unfolds, a shift occurs and sustainable funds now become the more sensitive ones to diseconomies of scale. This is in line with what was described in Sections 3.4 and 4.4. With the shift towards sustainability, and increased performance in the ESG sector during the pandemic (Al Amosh and Khatib, 2023; Van der beck, 2021), this could lead to an increase in popularity for sustainable funds, thus making them experience further growth and delivering profits as a result of this increased popularity, and then making them more sensitive to diseconomies of scale.

6 Heterogeneity across investment strategies

In the previous sections, I have investigated differences in value added, skill, and scale between sustainable and conventional mutual funds. In this section, I extend my analyses by first considering the correlation between skill and scale and the interplay between these and value added. Then, I explore heterogeneity in value added, skill, and scale across different investment strategies.

6.1 Magnitude across investment strategies

The cross-sectional correlation between skill and scale for all funds is 0.81, indicating that it is hard to scale up good ideas. Computing the cross-sectional correlation within the sustainable and conventional fund groups reveals similar correlations, 0.82 for sustainable and 0.80 for conventional funds. Therefore, in the aggregate, both fund groups struggle to scale up their ideas. Based on Tables 3, 7, and 11, I have documented that sustainable funds on average add *less* value (0.35 vs. 1.26) than conventional mutual funds. This seems to mainly be due to them facing tighter scale constraints (1.43 vs. 1.09) while being similarly skilled (3.84 vs. 3.49) as the conventional funds. Consequently, this points to a trade-off between skill and scalability, where the most valuable funds are not necessarily the most skilled, but those that are best able to balance skill and scalability.

To investigate this further, I report in Table 15 average skill, scale, and value added for sustainable and conventional mutual funds across different investment strategies. As argued in Barras et al. (2022*a*), part of the correlation between skill and scalability is driven by the funds' investment strategies, which can be captured by how they invest based on either size or style, or how much they trade.

Table 15. Skill, scale and value added and investment strategies
This table presents sample averages on skill, scale and value added for sustainable and conventional mutual funds within different investment strategies. Size style refers to funds investing in companies with different levels of market capitalization (small, mid and large cap), and company style refers to different types of companies (value, blend and growth). Lastly, turnover refers to how active the funds are in their trading. I have ranked the funds into deciles based on average annual turnover and categorized the funds with the lowest turnover as ”Inactive”, those in turnover decile 2, 3, 4 as ”Active”, and those in the highest turnover decile as ”Aggressive”.

		Size style			Company style			Turnover		
Group	Y	Small	Mid	Large	Value	Blend	Growth	Inactive	Active	Aggressive
Sust.	$\hat{a}$	7.13	5.34	3.96	3.52	4.68	4.74	4.17	3.51	3.00
Conv.	$\hat{a}$	4.77	4.48	3.55	3.01	3.79	4.62	3.38	3.51	3.89
Sust.	$\hat{b}$	2.08	2.13	1.58	1.03	1.65	1.94	1.43	1.30	0.89
Conv.	$\hat{b}$	1.83	1.45	1.13	0.85	1.10	1.65	0.90	1.21	1.26
Sust.	$\hat{va}$	1.26	-1.24	0.05	2.06	0.17	-0.78	0.60	1.42	3.05
Conv.	$\hat{va}$	-5.41	0.52	2.53	-0.41	-0.26	1.94	3.22	0.87	1.84

As Table 15 shows, there is considerable heterogeneity in skill, scale, and value added both within fund groups across different size styles, company styles, and turnover, and within each style and turnover across fund groups. In small-cap stocks, both fund groups have higher skill and scale than in the mid-cap and large-cap segments (with the exception of slightly higher scalability for sustainable funds in the mid-cap segment). As in Barras et al. (2022*a*), this is consistent with differences in liquidity across these size styles, where liquidity is lower for companies with lower size, which increases their mispricing but also raises trading costs. However, comparing sustainable and conventional funds within small cap reveals that sustainable funds have much higher skill (7.13 vs. 4.77) but are also more sensitive to diseconomies of scale (2.08 vs. 1.83). Sustainable small-cap funds are better at balancing the trade-off between exploiting mispricing and trading costs due to illiquidity within this segment compared to conventional funds, seen as they add 1.26 USDm in value on average, relative to conventional funds destroying value ($\hat{va} = -5.41$ USDm). In the large-cap segment, however, conventional funds are better at balancing skill and scalability, adding 2.53 USDm per year versus 0.05 USDm for sustainable funds.

Across company styles, the pattern of sustainable funds exhibiting higher skill and scalability holds, but with differences in value creation. For both value and blend funds, the sustainable funds create more value than conventional funds (who, on average, destroy value), but for growth funds, the conventional funds strike a better balance between skill and scalability. Comparing the funds based on how often they trade, I find that it is only for the funds that trade the least, i.e., the inactive category, where sustainable funds are more skilled. In the active category, the fund groups are equally skilled on average, whereas in the aggressive category, the conventional funds are most skilled. On balance, however, the conventional funds add the most value when trading the least. In the other turnover categories, the sustainable funds are better able to balance the exploitation of opportunities ($\hat{a}$) and trading costs ($\hat{b}$).

In sum, the high correlation between skill and scalability indicates that all funds face challenges in scaling up their good ideas. In the aggregate, conventional funds are better at striking a balance (lower skill and scalability, but higher value added). Investigating the funds' ability to balance these considerations across different investment strategies reveals heterogeneity, where sustainable funds are better in small-cap stocks, value and blend stocks, and when trading more actively. In the next sections, I dig deeper into this by running regressions comparing value added, skill, and scale between sustainable and conventional funds across different investment strategies.

6.2 Value added and investment strategies

In this section, I test the differences in value added based on the funds' investment strategies. To proxy for investment strategy, I use three different variables: investment size, style, and turnover. Investment size separates funds into three groups based on the market capitalization of the companies they invest in, i.e., small cap, mid cap, or large cap. Investment style refers to company style, i.e., whether the funds predominantly invest in growth, blend, or value stocks. Lastly, turnover refers to how much the funds trade, and is known to predict fund performance (Pástor et al., 2017).

Table 16 reports results when considering size style, Table 17 details results on company style, and lastly Table 18 reports differences for varying levels of turnover. All analyses follow the same setup as before, which is described in Section 2.4 and Equation 16. Since the focus in this section is on differences between sustainable and conventional funds within different investment strategies, I exclude investment category fixed effects, since this is the variation I want to use. Thus, my results here are based on a pooled sample and one where I include domicile fixed effects only.

Size style

Table 16. Value Added and size style
This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{va}_i$ (see Section 2.3 for details on the estimation approach). Value added is annualized. The variables "Small cap" and "Large cap" are indicator variables equal to one if fund i invests in small or large cap companies, respectively. Funds that invest in mid cap companies comprise my reference group. Coefficients for the interaction between β and "Small cap" and "Large cap" capture the difference in Y_i between sustainable and conventional funds within their respective size style categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)
β	−1.76	−1.62	−2.34*	−1.95
	(1.66)	(1.71)	(1.39)	(1.39)
Small cap	−5.94	−6.17	−5.83	−5.81
	(3.86)	(4.08)	(3.58)	(3.71)
Large cap	2.00	1.76	2.05	1.78
	(2.00)	(2.12)	(2.04)	(2.09)
$\beta\times$Small cap	8.44**	8.71**	7.62**	7.83**
	(3.39)	(3.57)	(3.43)	(3.53)
$\beta\times$Large cap	−0.71	−0.72	−0.38	−0.45
	(1.97)	(2.00)	(2.00)	(2.00)
Additional controls		×		×
Fixed effects:				
Domicile (D)			×	×
N	9,869	9,865	9,869	9,865
R^2	0.02	0.03	0.03	0.04

The differences between sustainable and conventional mid cap funds (captured by β) are consistently negative, i.e., sustainable mid cap funds add less value compared to conventional mid cap funds. However, the estimates are not statistically significant. Furthermore, within conventional funds, there are no apparent differences across size segments in value added, i.e., all coefficients on small cap and large cap are statistically insignificant. Their signs indicate that small cap funds, on average, add less value than mid cap funds, whereas large cap funds add more value. There is also no difference between sustainable and conventional large cap funds, and the magnitudes are also small. However, when comparing sustainable and conventional small cap funds, I find a large and consistent difference in favor of sustainable funds. They add close to 8 USDm more in value per year than conventional small cap funds. This result is also in stark contrast to the overall results from Section 3. In sum, even though my main results point to sustainable funds adding less value than conventional funds, these results illustrate that within the small cap segment, this effect is reversed.

Company style

Table 17. Value Added and company style

This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{va}_i$ (see Section 2.3 for details on the estimation approach). Value added is annualized. The variables "Value" and "Growth" are indicator variables equal to one if fund i invests in value or growth companies, respectively. Funds that invest in blend companies comprise my reference group. Coefficients for the interaction between β and "Value" and "Growth" capture the difference in Y_i between sustainable and conventional funds within their respective company style categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)
β	0.43	0.72	−0.24	0.27
	(2.18)	(2.08)	(1.79)	(1.68)
Value	−0.15	−0.10	−0.33	−0.46
	(2.16)	(2.25)	(2.09)	(2.15)
Growth	2.20	2.10	2.11	1.97
	(1.81)	(1.81)	(1.82)	(1.80)
$\beta\times$Value	2.04	1.70	2.83	2.41
	(2.20)	(2.23)	(2.23)	(2.24)
$\beta\times$Growth	−3.15	-3.25^{*}	−2.98	-3.17^{*}
	(1.93)	(1.87)	(1.96)	(1.92)
Additional controls		×		×
Fixed effects:				
Domicile (D)			×	×
N	10,067	10,063	10,067	10,063
R^2	0.00	0.01	0.01	0.03

Table 17 reports differences in value added across company style. Overall, the results indicate that conventional value funds add less value than conventional blend funds, while conventional growth funds add more value, but none of these effects are statistically significant. Neither are the differences between sustainable and conventional funds within company style (the only exceptions are the estimated differences between sustainable and conventional growth funds in Columns 2 and 4, where the differences are significant at the 10% level).

Turnover

Here, I test for differences in value added for different levels of fund turnover. I have split the funds into three categories based on their average annual turnover across my sample period. The "Inactive" group consists of the funds with turnover rates in the lowest 20%. The "Active" group consists of the funds with average turnover in the middle 60% of the distribution, and the "Aggressive" funds comprise the 20% of funds that trade the most. The average turnover for funds in the "Inactive" group is only 2.65%, 56.7% for the "Active" funds, and 296% for the "Aggressive" funds. In other words, the funds that trade the least only turn over 2.65% of their portfolio in a year, whereas those that trade the most turn over their portfolios almost three times over a year. The regression setup used is the one described in Section 2.4 and Equation 16. I have followed the regression specifications described for Tables 16 and 17, including domicile fixed effects in Columns 3 and 4.

Table 18. Value Added and turnover
This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{va}_i$ (see Section 2.3 for details on the estimation approach). Value added is annualized. The variables "Inactive" and "Aggressive" are indicator variables equal to one if fund i belongs to the first quintile (lowest) or fifth quintile (highest) on turnover, respectively. Funds in turnover quintiles 2, 3, and 4 (labeled "Active") comprise my reference group. Coefficients for the interaction between β and "Inactive" and "Aggressive" capture the difference in Y_i between sustainable and conventional funds within their respective turnover categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)
β	0.54	0.53	−0.16	−0.15
	(1.97)	(1.85)	(0.98)	(0.88)
Inactive	2.34*	2.44**	2.21**	2.16**
	(1.23)	(1.15)	(1.00)	(0.98)
Aggressive	0.97	2.24***	0.49	1.34**
	(1.77)	(0.71)	(0.92)	(0.55)
$\beta\times$Inactive	−3.16**	−3.04**	−2.99**	−2.77**
	(1.44)	(1.42)	(1.33)	(1.31)
$\beta\times$Aggressive	0.67	−0.28	1.29	0.89
	(1.88)	(1.21)	(1.47)	(1.19)
Additional controls		×		×
Fixed effects:				
Domicile (D)			×	×
N	8,981	8,978	8,981	8,978
R^2	0.00	0.02	0.01	0.03

Across specifications, I find no difference between sustainable and conventional funds within the ”Active” group, i.e., β is not statistically significant. Within conventional funds, I find that ”Inactive” funds add significantly more value than ”Active” funds, on average 2.2 USDm more per year, which is also economically meaningful. Conventional ”Aggressive” funds also add more value than ”Active” funds. However, the estimated effect is a little weaker but still economically significant. Comparing sustainable and conventional funds within different turnover groups, I find that the sustainable funds that trade the least significantly add less value than conventional funds, on average close to 3 USDm less per year. This effect is both statistically and economically significant. For the group of funds that trade the most, there are no discernible differences.

6.3 Skill and investment strategies

In this section, I test for the differences in skill across different investment strategies. This section follows the same structure as Section 6.2.

Size style

Table 19 shows how my main results on skill from Table 8 apply across different size styles. I find no evidence of differing levels of skill between sustainable and conventional funds across size styles. The sign of the coefficient suggests that sustainable funds are more skilled in the small and mid cap segments, but less skilled in large cap. Comparing conventional funds across size styles, I find no difference in skill between small and mid cap funds. However, conventional large cap funds have consistently lower skill than mid cap funds across specifications.

Table 19. Skill and size style

This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{a}_i$ (see Section 2.3 for details on the estimation approach). The skill parameter is annualized. The variables "Small cap" and "Large cap" are indicator variables equal to one if fund i invests in small or large cap companies, respectively. Funds that invest in mid cap companies comprise my reference group. Coefficients for the interaction between β and "Small cap" and "Large cap" capture the difference in Y_i between sustainable and conventional funds within their respective size style categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)
β	0.86	0.30	0.90	0.35
	(0.61)	(0.61)	(0.55)	(0.54)
Small cap	0.29	0.35	0.13	0.17
	(0.41)	(0.43)	(0.35)	(0.35)
Large cap	-0.93^{**}	-0.95^{***}	-0.91^{**}	-0.87^{**}
	(0.37)	(0.36)	(0.36)	(0.35)
$\beta\times$Small cap	1.50	1.42	2.01^{*}	1.81
	(1.19)	(1.17)	(1.20)	(1.17)
$\beta\times$Large cap	−0.45	−0.46	−0.28	−0.28
	(0.68)	(0.69)	(0.64)	(0.64)
Additional controls		×		×
Fixed effects:				
Domicile (D)			×	×
N	9,902	9,898	9,902	9,898
R^2	0.00	0.02	0.02	0.04

Company style

Table 20. Skill and company style
This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{a}_i$ (see Section 2.3 for details on the estimation approach). The skill parameter is annualized. The variables "Value" and "Growth" are indicator variables equal to one if fund i invests in value or growth companies, respectively. Funds that invest in blend companies comprise my reference group. Coefficients for the interaction between β and "Value" and "Growth" capture the difference in Y_i between sustainable and conventional funds within their respective company style categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)
β	0.89	0.38	1.09	0.53
	(0.80)	(0.81)	(0.73)	(0.73)
Value	-0.79^{*}	-0.80^{*}	-0.78^{*}	-0.74^{*}
	(0.41)	(0.41)	(0.43)	(0.42)
Growth	0.82^{*}	0.62	1.09^{***}	0.89^{**}
	(0.46)	(0.46)	(0.39)	(0.39)
$\beta\times$Value	−0.38	−0.14	−0.20	0.11
	(0.96)	(0.96)	(0.91)	(0.90)
$\beta\times$Growth	−0.76	−0.82	−0.81	−0.78
	(0.86)	(0.86)	(0.77)	(0.77)
Additional controls		×		×
Fixed effects:				
Domicile (D)			×	×
N	9,902	9,898	9,902	9,898
R^2	0.01	0.02	0.03	0.04

Table 20 focuses on the company style of the mutual funds' investment strategies. The signs on β, $\beta\times$Value, and $\beta\times$Growth indicate that sustainable funds are more skilled than conventional funds in the blend segment, but less skilled in the value and growth segments. However, none of these differences are statistically significant. Comparing conventional funds, I find weak evidence that value funds are less skilled than blend funds (Value coefficients are all negative and significant at the 10% level), and that growth funds are more skilled than blend funds. In summary, sustainable and conventional funds are equally skilled within company styles.

Turnover

Table 21 shows that there is no evidence of differences in skill between sustainable and conventional funds when grouping them according to how much they turn over their portfolios. The estimated difference in skill between fund types varies both in magnitude and sign. This

Table 21. Skill and turnover

This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{a}_i$ (see Section 2.3 for details on the estimation approach). The skill parameter is annualized. The variables "Inactive" and "Aggressive" are indicator variables equal to one if fund i belongs to the first quintile (lowest) or fifth quintile (highest) on turnover, respectively. Funds in turnover quintiles 2, 3, and 4 (labeled "Active") comprise my reference group. Coefficients for the interaction between β and "Inactive" and "Aggressive" capture the difference in Y_i between sustainable and conventional funds within their respective turnover categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)
β	−0.00	−0.25	0.45	0.14
	(0.38)	(0.38)	(0.31)	(0.30)
Inactive	−0.13	−0.26	0.31	0.13
	(0.31)	(0.30)	(0.29)	(0.30)
Aggressive	0.38	0.39	0.31	0.16
	(0.36)	(0.34)	(0.28)	(0.26)
$\beta\times$Inactive	0.79	0.83	0.50	0.57
	(0.55)	(0.55)	(0.53)	(0.54)
$\beta\times$Aggressive	−0.88	−0.62	-1.00^{*}	−0.65
	(0.72)	(0.69)	(0.57)	(0.56)
Additional controls		×		×
Fixed effects:				
Domicile (D)			×	×
N	9,015	9,012	9,015	9,012
R^2	0.00	0.01	0.02	0.03

also applies to the comparison between "Inactive" and "Active" conventional funds, where the sign flips between Columns 1-2 and Columns 3-4. The estimated difference between "Aggressive" and "Active" conventional funds is stable at approximately 0.30% per year. However, the estimates are not statistically significant. The estimated difference between sustainable and conventional funds that trade the least, i.e., the "Inactive" group, is consistently positive but insignificant. For the "Aggressive" groups, the opposite holds, i.e., that sustainable funds are less skilled. In sum, I find no indicative evidence to suggest that sustainable and conventional funds differ in their skill levels based on how much they trade.

6.4 Scale and investment strategies

In this section, I test for the differences in scale across investment strategies. Again, the structure is the same as in Section 6.2 and Section 6.3.

Size style

For mid cap funds in Table 22, β is persistently positive, with varying degrees of statistical significance, indicating that sustainable funds struggle more to scale up their ideas as they grow in size compared to conventional mutual funds. However, this is the only size segment where I find statistically significant differences between sustainable and conventional funds. In both small and large cap, the sign of the interaction terms is negative, suggesting that conventional funds struggle more to scale than sustainable funds, but these estimates are not significant. Comparing conventional funds across size segments, I find no difference between small and mid cap funds, but a consistent and negative difference between mid and large cap funds. This is somewhat surprising, as one would think that it is easier to scale up when investing in stocks that have a higher market capitalization. These estimates, therefore, suggest that in this segment, more capital is chasing the same opportunities, making it harder to scale up profitable ideas.

Table 22. Scale and size style

This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{b}_i$ (see Section 2.3 for details on the estimation approach).The scale parameter is annualized and standardized for each fund, so that it corresponds to the change in gross alpha in response to a one-standard-deviation change in fund size. The variables "Small cap" and "Large cap" are indicator variables equal to one if fund i invests in small or large cap companies, respectively. Funds that invest in mid cap companies comprise my reference group. Coefficients for the interaction between β and "Small cap" and "Large cap" capture the difference in Y_i between sustainable and conventional funds within their respective size style categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)
β	0.69***	0.32	0.76***	0.40*
	(0.23)	(0.22)	(0.22)	(0.21)
Small cap	0.39	0.43	0.27	0.30
	(0.31)	(0.34)	(0.21)	(0.23)
Large cap	−0.32**	−0.32**	−0.33***	−0.30***
	(0.13)	(0.13)	(0.12)	(0.11)
β×Small cap	−0.44	−0.51	−0.19	−0.32
	(0.42)	(0.41)	(0.40)	(0.39)
β×Large cap	−0.23	−0.24	−0.19	−0.19
	(0.24)	(0.24)	(0.23)	(0.23)
Additional controls		×		×
Fixed effects:				
Domicile (D)			×	×
N	9,902	9,898	9,902	9,898
R^2	0.01	0.08	0.03	0.10

Company style

Table 23. Scale and company style
This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{b}_i$ (see Section 2.3 for details on the estimation approach). The scale parameter is annualized and standardized for each fund, so that it corresponds to the change in gross alpha in response to a one-standard-deviation change in fund size. The variables "Value" and "Growth" are indicator variables equal to one if fund i invests in value or growth companies, respectively. Funds that invest in blend companies comprise my reference group. Coefficients for the interaction between β and "Value" and "Growth" capture the difference in Y_i between sustainable and conventional funds within their respective company style categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)
β	0.55^{*}	0.20	0.71^{**}	0.33
	(0.31)	(0.31)	(0.29)	(0.28)
Value	−0.25	−0.25	−0.23	−0.20
	(0.16)	(0.16)	(0.15)	(0.15)
Growth	0.55^{***}	0.42^{**}	0.65^{***}	0.52^{***}
	(0.17)	(0.17)	(0.15)	(0.14)
$\beta\times$Value	−0.37	−0.19	−0.32	−0.12
	(0.35)	(0.35)	(0.33)	(0.33)
$\beta\times$Growth	−0.26	−0.29	−0.30	−0.28
	(0.34)	(0.31)	(0.30)	(0.29)
Additional controls		×		×
Fixed effects:				
Domicile (D)			×	×
N	9,902	9,898	9,902	9,898
R^2	0.02	0.08	0.04	0.10

In Table 23, I find some evidence suggesting that sustainable blend funds face tighter scale constraints than conventional funds (β is persistently positive, but inconsistently statistically significant). Both sustainable value and growth funds have negative coefficient estimates suggesting they face looser scale constraints, but they are not statistically significant. Conventional growth funds have significantly higher scale parameters, indicating that within the growth segment, these funds struggle more to scale up their ideas. Consequently, I find some evidence of heterogeneity in the difference between sustainable and conventional funds' sensitivity to diseconomies of scale, but they are relatively weak.

Turnover

Table 24. Scale and turnover

This table reports estimates from my baseline regression specification described in Equation 16, where $Y_i = \hat{a}_i$ (see Section 2.3 for details on the estimation approach). The scale parameter is annualized and standardized for each fund, so that it corresponds to the change in gross alpha in response to a one-standard-deviation change in fund size. The variables "Inactive" and "Aggressive" are indicator variables equal to one if fund i belongs to the first quintile (lowest) or fifth quintile (highest) on turnover, respectively. Funds in turnover quintiles 2, 3, and 4 (labeled "Active") comprise my reference group. Coefficients for the interaction between β and "Inactive" and "Aggressive" capture the difference in Y_i between sustainable and conventional funds within their respective turnover categories. Other control variables include net flows, and the logarithms of size, age, and fees. Domicile fixed effects correspond to the country where the fund management resides. Standard errors clustered by domicile-category are in parentheses. Statistical significance is denoted by asterisks: $^{***}p<1\%$, $^{**}p<5\%$, $^{*}p<10\%$.

	(1)	(2)	(3)	(4)
β	0.09	−0.10	0.39***	0.12
	(0.16)	(0.15)	(0.12)	(0.11)
Inactive	−0.31***	−0.42***	−0.13*	−0.27***
	(0.09)	(0.09)	(0.08)	(0.09)
Aggressive	0.05	0.06	0.22*	0.13
	(0.13)	(0.10)	(0.12)	(0.11)
β×Inactive	0.44***	0.45***	0.32**	0.33**
	(0.16)	(0.16)	(0.16)	(0.17)
β×Aggressive	−0.46**	−0.22	−0.66***	−0.41**
	(0.22)	(0.20)	(0.19)	(0.17)
Additional controls		×		×
Fixed effects:				
Domicile (D)			×	×
N	9,015	9,012	9,015	9,012
R^2	0.00	0.06	0.03	0.08

Table 24 shows varying degrees of differences in scale between fund types. For the "Active" fund groups, I find diverging results, both in magnitude, sign, and statistical significance. However, comparing sustainable and conventional funds that either turn over their portfolios slowly ("Inactive") or rapidly ("Aggressive") shows that sustainable funds in the former category are consistently more sensitive to diseconomies of scale, whereas sustainable funds in the latter category are consistently less sensitive to scale constraints. Within conventional funds, I find that "Inactive" funds are significantly less sensitive to diseconomies of scale than "Active" funds. There is no difference between "Active" and "Aggressive" funds. In total, sustainable and conventional funds that trade the same amount seem to face very different scale constraints.

6.5 Balance between skill and scalability

As Table 3 shows, most funds create value, especially when looking at the last sub-period. Above, I also explored how funds with different investment strategies strike different balances between skill and scalability, and how this affects value added. Here, I rank sustainable and conventional mutual funds based on skill, scale, and value added. Then, I consider the most valuable funds (those in the 8^{th}, 9^{th}, and 10^{th} value-added deciles), and find the median rank values for skill and scale. This reveals that for both fund groups, the most valuable funds are those that are slightly more skilled than the average (median skill decile is six) and are slightly less sensitive to diseconomies of scale (median scale decile is four). In other words, the most valuable funds are not necessarily the most skilled funds, but those that achieve the best balance between skill and scalability.

7 Conclusion

The debate on the impact of integrating sustainability on fund performance is ongoing and currently stands without a consensus. In this thesis, I focus on funds' value creation, rather than returns, to study the effect of integrating sustainability into the funds' investment strategies. Adopting the rationale of Berk and Van Binsbergen (2015) and focusing on value added as the relevant performance measure over returns, and explicitly linking value added to funds' skill and scalability following the arguments and approach of Barras et al. (2022*a*), I find that sustainable funds add *less* value than conventional funds. This difference has also grown over time. Investigating the two drivers of value added from the Berk and Green (2004) model, I find weak evidence of sustainable funds being more skilled than conventional funds, leading me to conclude that sustainable and conventional funds are equally skilled. The predominant driver of why sustainable funds create less value, therefore, seems to be because they are *more* sensitive to diseconomies of scale (they face a tighter scalability constraint via higher $\hat{b}$'s). This dynamic has evolved over time, with sustainable funds adding less value due to a combination of an insignificant differential increase in skill and a significant differential increase in diseconomies of scale.

Investigating this further, by examining differences in value added, skill, and scale between fund groups across investment strategies, I find, contrary to the main results, that sustainable funds in the small cap segment add significantly more value than conventional funds, approximately 8 USDm more per year. Sustainable small cap funds are equally skilled as conventional small cap funds, and even though the former fund group is estimated to be less sensitive to diseconomies of scale, these results are statistically insignificant. Thus, within small cap funds, the positive difference in value added looks to be explained by something other than skill and scale. Moreover, sustainable funds that trade infrequently add significantly less value than conventional funds with similar levels of turnover. Again, this difference is mainly driven by differences in scale, with no detectable difference in skill.

My thesis shows the importance of scalability in determining the extent to which fund managers are able to create value. My main results showing that sustainable funds create less value than conventional funds oppose the recent empirical literature that documents high realized returns but are more aligned with the current theoretical arguments. They are also largely in agreement with the main findings in Van der beck (2021). Investors who want to integrate sustainability will likely have to accept lower value creation, with a couple of notable exceptions.

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Appendices

A Data and variables

In this appendix, I provide additional details on data, sample construction and variable definitions.

Table A.1. Variable definitions

Variable	Definition
Main variables	
Value Added	The amount of value in USDm fund i is able to extract from the markets. Denoted by va_i in Equation 8.
Skill	Gross alpha on first dollar invested. Denoted by a_i in empirical model, Equation 6. See 2 for further details.
Scale	The funds sensitivity to diseconomies of scale. Denoted by b_i in empirical model, Equation 6. See 2 for further details.
Fund controls	
Sustainable fund indicator (β)	Indicator variable equal to 1 if fund i is identified as a sustainable fund, zero otherwise.
Fund size	Total net assets (TNA) under management for fund i. Measured in December 2023 USDm. Used in log form across all analyses.
Age	Number of years since fund i launch date. Used in log form across all analyses.
Fees	Annualized expense ratio. Used in log form across all analyses.
Net flow	Percentage growth in total net assets.
Other fund characteristics	
Morningstar star-rating	Quantitative measurement of a fund's past performance. Measured from one to five stars.
Gross return	Return on investment before costs and expenses are deducted.
Benchmark-adjusted return (gross alpha)	Difference between the fund gross return and its benchmark return.

Table A.2. Distributional moments definition

Distribution measure	Definition
Moments	
Mean	The average of a set of values. $\bar{X} = \frac{\Sigma x}{N}$
SD	Measures how disperesed the data is in relation to its mean. Low values indicates that the data is clustered tightly around the mean. $SD = \sqrt{\frac{\Sigma_i^n (X_i - \bar{X})^2}{n-1}}$
Skewness	The third moment of distribution, measuring the degree of asymmetry of a distribution. A negative skewness indicates a long tail on the left side, a positive skewness value indicates a long tail on the right side. Zero skewness shows perfect symmetry. It's values ranges from negative infinity to positive infinity. It affects the centre of distribution in the data, and impacts the mean more than the median. $Skewness = \frac{\Sigma_i^n (X_i - \bar{X})^3}{(N-1) * \sigma^3}$
Kurtosis	Fourth moment of distribution, measuring the peakedness of a distribution. Platykurtic indicates a flatter peak than the normal distribution, also known as negative kurtosis. Positive kurtosis, or leptokurtic, indicates a sharper peak than the nomral distribution. Zero kurtosis indicates perfect normality over the distribution. $Kurtosis = n * \frac{\Sigma_i^n (Y_i - \bar{Y})^4}{\Sigma_i^n (Y_i - \bar{Y}^2)^2}$
Proportions	
Positive	The percentage amount of observations with a positive average value.
Negative	Percentage amount of observations with a negative average value.
Quantiles	
5% Quantile	Average for the bottom 5% of the sample.
95% Quantile	Average for the top 5% of the sample.

Table A.3. Morningstar Global Categories
This table presents an overview of the different investment categories assigned by Morningstar.

Category name
Africa Equity
Aggressive Allocation
Alternative Miscellaneous
Asia Equity
Asia ex-Japan Equity
Australia & New Zealand Equity
Canadian Equity Large Cap
Canadian Equity Mid/Small Cap
Communications Sector Equity
Consumer Goods & Services Sector Equity
Energy Sector Equity
Equity Miscellaneous
Europe Emerging Markets Equity
Europe Equity Large Cap
Europe Equity Mid/Small Cap
Financial Sector Equity
Global Emerging Markets Equity
Global Equity Large Cap
Global Equity Mid/Small Cap
Greater China Equity
Healthcare Sector Equity
India Equity
Industrials Sector Equity
Infrastructure Sector Equity
Japan Equity
Korea Equity
Latin America Equity
Mexico Equity
Moderate Allocation
Natural Resources Sector Equity
Precious Metals Sector Equity
Real Estate Sector Equity
Technology Sector Equity
Thailand Equity
UK Equity Large Cap
UK Equity Mid/Small Cap
US Equity Large Cap Blend
US Equity Large Cap Growth
US Equity Large Cap Value
US Equity Mid Cap
US Equity Small Cap
Utilities Sector Equity

Table A.4. Distribution by country

This table presents the number of funds, number of monthly observations of all funds, the percentage share each countries total amount of funds make up of the sample, the amount of ESG funds in each country, and the amount of normal funds.

Country	Funds	N ESG	N Conventional	Pct.share ESG	Pct.share Conventional
Austria	135	34	101	0.2	0.7
Belgium	75	34	41	0.2	0.3
Brazil	384	10	374	0.1	2.6
Canada	1,127	63	1,064	0.4	7.5
Chile	108	1	107	0	0.8
China	196	3	193	0	1.4
Denmark	218	78	140	0.6	1
Finland	125	33	92	0.2	0.7
France	865	406	459	2.9	3.3
Germany	393	93	300	0.7	2.1
Hong Kong	65	7	58	0	0.4
India	6	0	6	0	0
Ireland	526	115	411	0.8	2.9
Italy	88	19	69	0.1	0.5
Japan	1,025	53	972	0.4	6.9
Liechtenstein	56	16	40	0.1	0.3
Luxembourg	1,925	579	1,346	4.1	9.5
Mexico	80	4	76	0	0.5
Netherlands	141	91	50	0.6	0.4
New Zealand	83	5	78	0	0.6
Norway	111	38	73	0.3	0.5
Portugal	27	4	23	0	0.2
Singapore	76	2	74	0	0.5
South Africa	221	2	219	0	1.6
South Korea	155	16	139	0.1	1
Spain	276	60	216	0.4	1.5
Sweden	247	168	79	1.2	0.6
Switzerland	282	97	185	0.7	1.3
Taiwan	314	12	302	0.1	2.1
Thailand	476	11	465	0.1	3.3
United Kingdom	956	163	793	1.2	5.6
United States	3,352	208	3,144	1.5	22
Total	**14,114**	**2,425**	**11,689**	**17**	**83**

B Value added

This appendix contain additional details in relation to the main analyses of skill in Section 3.

Figure B.1. Full Distribution of Value Added
This figure plot the bias-adjusted distribution of the annualized value-added across sustainable and conventional mutual funds.

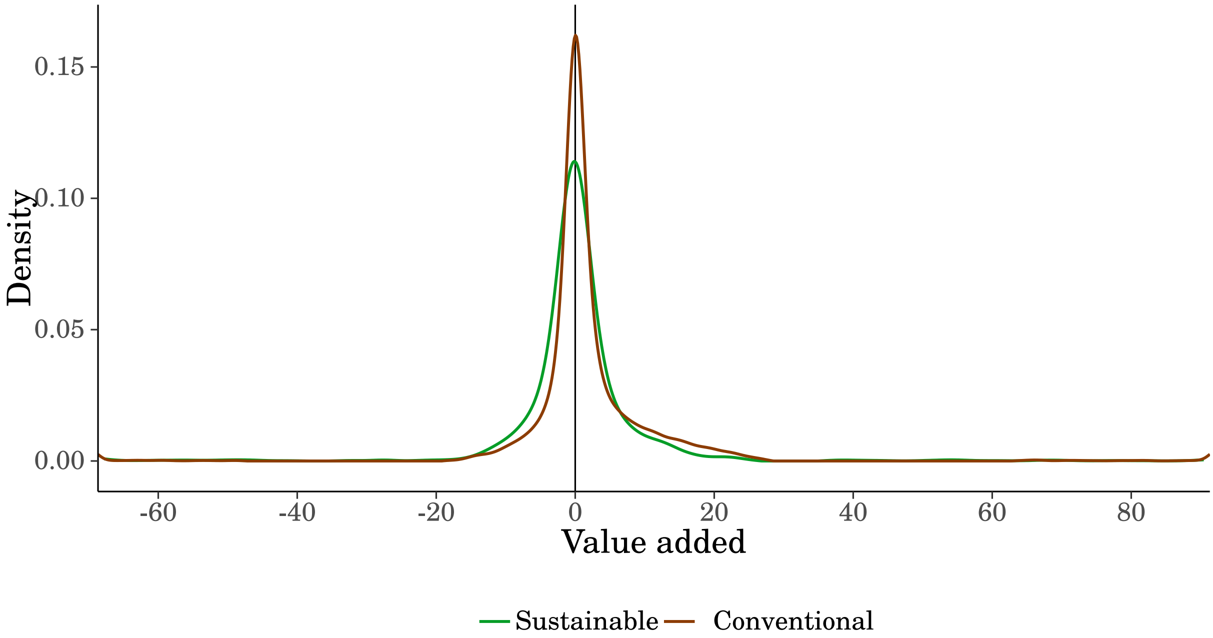
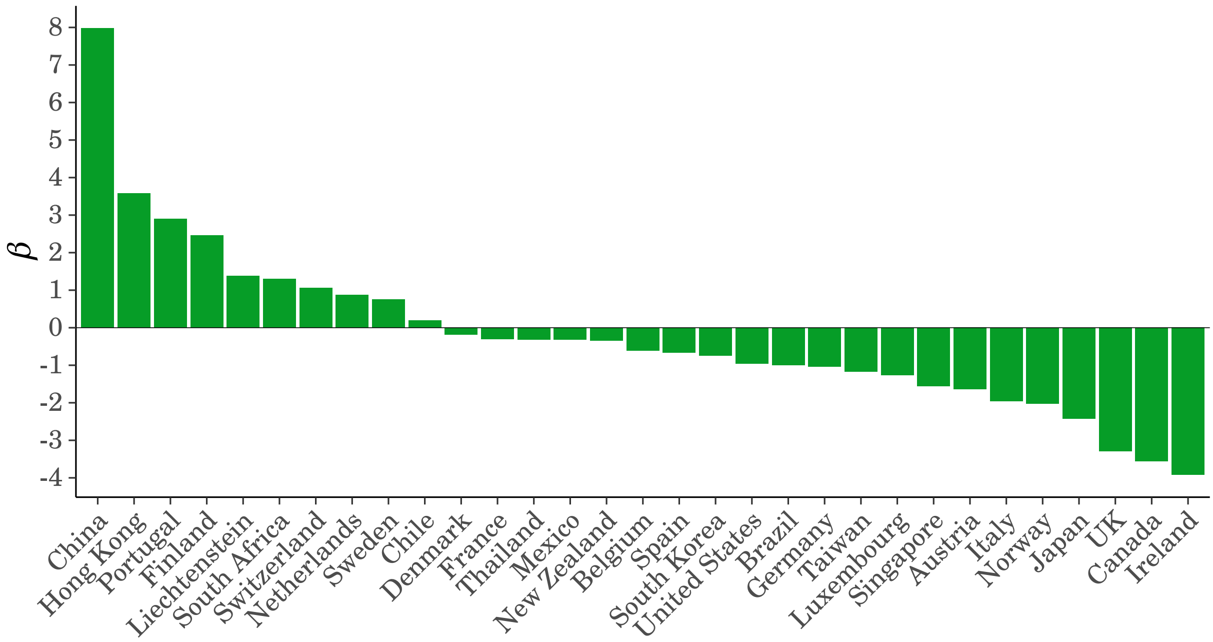


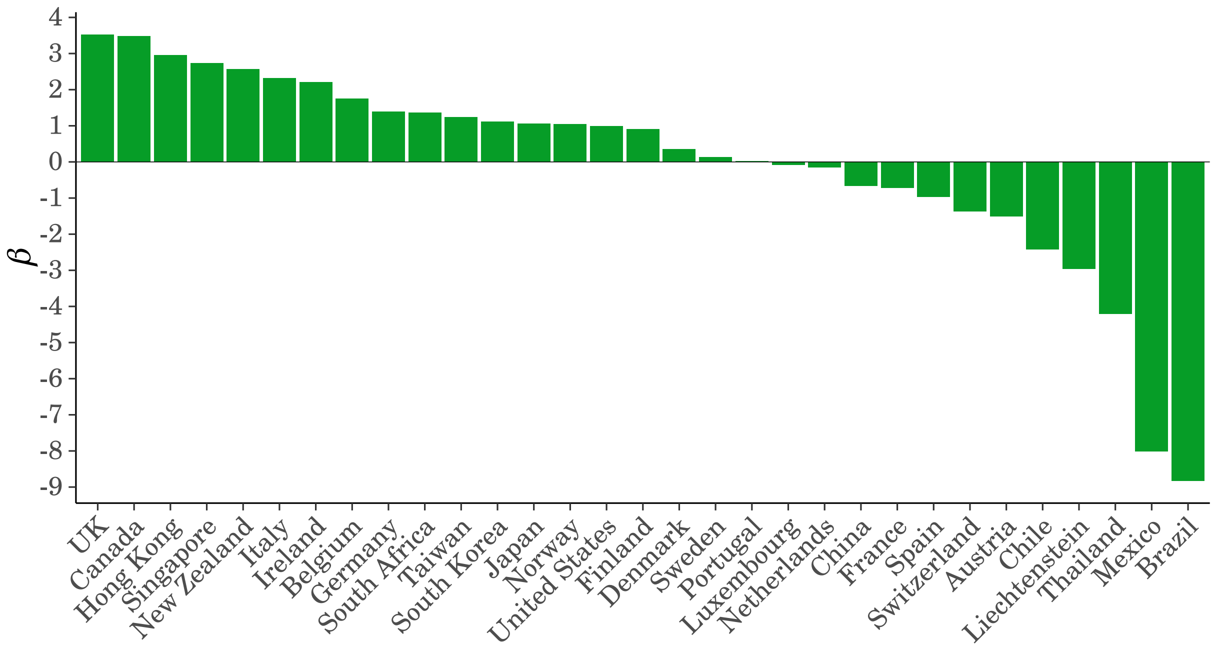
Figure B.2. Value added differences across countries
This figure plots the estimated difference (β) from running the baseline regression specification in Equation 16 for each sample country when $Y_i = v\hat{a}_i$.



C Skill

This appendix contain additional details in relation to the main analyses of skill in Section 4.

Figure C.1. Skill differences across countries
This figure plots the estimated difference (β) from running the baseline regression specification in Equation 16 for each sample country when $Y_i = \hat{\alpha}_i$.



D Scale

This appendix contain additional details in relation to the main analyses of skill in Section 5.

Figure D.1. Scale differences across countries
This figure plots the estimated difference (β) from running the baseline regression specification in Equation 16 for each sample country when $Y_i = \hat{b_i}$.