Skills and Sentiment in Sustainable Investing

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Abstract

We document a significant difference in the returns to sustainable investing across investor types. Investors with strict ESG mandates earn 3.1% less than flexible investors. The mechanism is that flexible investors are able to react on expected ESG improvements. Without engaging in activism, flexible investors buy stocks that subsequently experience ESG score increases. After ESG improvements have realized, demand from strict mandate investors pushes up stock prices, resulting in positive returns for flexible investors. A new climate sentiment measure shows that the performance gap is higher when accompanied by rising sentiment, as seen during the 2010s. Our channel accounts for 51% of the return difference between strict and flexible ESG investment mandates. Hence, going from backward to forward-looking ESG ratings could reduce both capital misallocation and wealth transfer from strict investors, such as pension funds, to more flexible investors, such as hedge funds.

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1 Introduction

The consequences of the sustainable investment transition are not yet well understood. Fundamentally, general equilibrium theory would tell us that a higher demand of sustainable stocks today should lead to low returns going forward (as in Pástor, Stambaugh and Taylor, 2021). On the other hand, Baker and Wurgler (2006) would argue that exactly because there is a high demand, this sentiment will yield high returns in the short term. Finally, a third view is that high returns could arise if environmental, social and governance (ESG) metrics are a hidden quality signal (Pedersen, Fitzgibbons and Pomorski, 2020).

This paper documents a significant difference in the returns of sustainable investing across investor types. To reconcile this difference with current theories, we develop a new channel. The channel is that if some investors are under strict ESG mandates, other investors can use their flexibility to invest in stocks with expected ESG improvements. When the improvements materialise, demand for sustainable investments then leads to high returns for flexible investors.

Institutional investors have experienced an unprecedented shift in their clients' capital allocation towards assets with an ESG focus.[1] Because of this sudden inflow to ESG investing, institutional investors have had to integrate sustainable investments into their portfolios. However, as institutional investors typically vary in the strictness of their mandates, it has created heterogeneity across institutional investors' sustainable investment portfolios.[2]

[1] The capital invested in ESG funds more than doubled in 2020 (Morningstar's 2020 Sustainable Funds Landscape Report). Additionally, new ESG investments of \$51.1 billion make up nearly one fourth of the total inflows into U.S. funds. Over a longer horizon, from 2002 the amount of assets incorporating ESG principles has risen from just under \$ 2 trillion to \$ 10 trillion by the end of 2017 (Forum for Sustainable and Responsible Investment in the USA's 2018 Report). Figure 8 in Appendix A shows this evolution over time at the global level.

[2] One might think that investors with a flexible mandate would not care to incorporate sustainable preferences into their investment strategy, but that is in fact not the case. For example, BlackRock has committed to take sustainability concerns into consideration to capture the opportunities presented

We show that the inflow to ESG investing has been accompanied by an increased climate sentiment. During this period, the investors with flexible mandates act as skilled investors: They purchase stocks, which they expect will experience future ESG score increases. We see that they capitalise on this, as they later sell their stocks to strict mandate investors. Hence, strict investors' demand for sustainable investments leads to high returns for those stocks, which have realised a higher ESG score.[3] This means that the flexible investors' sustainable investments yields an ESG premium. In summary, this paper documents the effects of skills and sentiment in sustainable investing.

To explain these findings, we introduce skills and sustainability sentiment to the standard capital asset pricing model (CAPM). We do so by allowing flexible investors to be able to exploit their prediction of future ESG score increases, an addition to the model of sustainable investments by Pástor, Stambaugh and Taylor (2021). This flexibility leads to positive abnormal returns as the prediction materialises.

Earlier models fall short in explaining our findings. For example, we see a negative general ESG premium, whose size varies with sustainability sentiment (as in Pástor, Stambaugh and Taylor, 2021), and that it can occasionally yield positive returns, as in Pedersen, Fitzgibbons and Pomorski (2020) where ESG serves as a hidden quality factor. However, neither model can explain the difference in sustainable investing returns across investors.

To empirically tease out the effects of skill from a general ESG premium, we separate our investors into two groups following Hong and Kacperczyk (2009). We refer to the first group of investors as flexible investors, as they tend to be have more flexible

by the net zero transition (BlackRock's letter to CEO's 2020).

Additionally, there is evidence that hedge funds short firms that they believe have bad ESG prospects and enter as activist investors. See Activist hedge funds prefer to fight ESG stars, Global Capital, 27th August 2020, and DesJardine, Marti and Durand (2020), DesJardine and Durand (2020).

[3] Hartzmark and Sussman (2019) show that investors value sustainability and chase sustainable stocks. Investor sentiment for funds with high sustainability ratings resulted in net inflows of more than $24 billion, whereas funds regarded as less sustainable experienced net outflows of $12 billion dollar, after Morningstar first published sustainability ratings in March 2016.

investment mandates (these include mutual fund managers, hedge funds, and other investment companies and independent investment advisors). Correspondingly, the group of investors with stricter investment mandates is referred to as strict mandate investors (they include university endowments, pension plans, employee ownership plans, banks, and insurance companies). By distinguishing between these two types of investors, we document how mandates affect the investors' returns to sustainable investing.

We see ESG investing yielding negative excess returns on average. However, when separating our investors, we find that flexible investors' ESG stocks have yielded large positive returns over recent years. Interestingly, this positive sustainable investment return does not exist for strict mandate investors' stocks. Hence, despite the observation that sustainable investing generally yields negative expected excess returns, a significant positive abnormal return can be achieved by investing sustainably in a smart way.

We go on to explore what may be driving the difference in returns to sustainable investing across the two groups. First, we consider whether there is a difference in the two investors' behavior. Specifically, we see how the investments' ESG scores develop after the purchase by either type. Here, we find that flexible investor ownership predicts future ESG score increases, whereas strict mandate ownership does not. The effect does not seem to be arising from a general skill of the flexible investor, as we only see abnormal returns amongst their ESG stocks, and not stocks in general.

Second, we consider whether strict mandate investors indeed buy the flexible investors' stocks after their higher scores materialise. In line with our model, we see that strict investors have purchased high ESG stocks most prominently from flexible investors. Specifically, strict investors excess purchase from flexible investors during the 2010s amount to close to half of the outstanding high ESG shares.

Third, we test whether strict mandate investors' purchases of high ESG stocks have lead to positive abnormal returns for the flexible investors. We test this by running a

Fama MacBeth regression of returns on changes in ESG scores whilst controlling for risk factors. In line with our hypothesis, we find that ESG scores changes are associated with higher returns.

We use the findings to calibrate our model. When we do, we see that the ESG prediction channel explains 51% of the return differential across strict mandate and flexible investors' sustainable investment returns. That is, an investor's ability to use their skill in ESG performance prediction is economically meaningful.

We extend our analysis by exploring how climate sentiment has affected the difference in returns to sustainable investing. To measure sentiment, we retrieve climate sentiment shocks from Google search volumes on the term *Climate change*. Our sentiment measure shows that the 2010s have been associated with a rising climate sentiment, a trend that is matched by inflows into ESG funds.

Using our measure in a regression setup, we see that when climate sentiment rises, it increases the difference in returns to sustainable investing between the two investor types. Additionally, sentiment also gives positive abnormal returns to sustainable investments in general. Finally, we see that climate sentiment tends to be negatively correlated with economic sentiment as measured by Baker and Wurgler (2006), making it a potential recessionary hedge.

We conclude by contrasting the costs with the benefits of sustainable investing. Sustainable investors incur a cost due to their strict mandate, however they incentivize firms to become greener, which describes the welfare channel of Pástor, Stambaugh and Taylor (2021). For the cost estimate we use the difference in returns between strict and flexible investors, and for the benefit measure we use the improvements in carbon emissions for the firms owned by flexible investors. Comparing the two, we find that sustainable investing has been a promising, yet somewhat inefficient, channel for decreasing emissions, as investors have incurred a cost of USD 424 billion to reduce annual carbon emissions by 1.34 billion tons CO_2. This amount equates to USD 9 to 69 billion in the carbon credit market.

The welfare channel's relative inefficiency can be improved by introducing the right policy. Specifically, a policy which replaces backward-looking ESG ratings with forward-looking ESG ratings doubles the sustainable investments' welfare effects. The new ESG ratings would reduce the costs without affecting the benefits, as it would allow strict investors to invest directly into the firms which reduce emissions. This is in line with Oehmke and Opp (2020) and Green and Roth (2021), who propose that for investors to have an impact on firm behaviour they need to have broad mandates and invest in line with a new ESG metric that takes into account the changes in emissions of the firm from the investments itself.

This paper's central contribution is to document a difference in the returns to sustainable investing across investors. Specifically, our paper is the first to consider why returns to sustainable investing vary across investors. The closest papers to ours is Cao et al. (2019) and Hwang, Titman and Wang (2021), who in the first paper document that the investments of ESG investors are more prone to overpricing, and that this mispricing gets corrected to a lesser extend, leading these investments to exhibit lower abnormal returns, and in the second, that CSR investor ownership increases predict increases in firms CSR ratings, lowering returns, which they assume is due to the cost of improving such ratings. In addition to considering general investments and not sustainable investments, Cao et al. (2019) and Hwang, Titman and Wang (2021) follow a different identification strategy through their revealed preference approach, in the latter case controlling for institutional type, making their classification orthogonal to our classification. Our classification circumvents potential issues that may arise from defining groups by the output variable, as we separate investors into strict mandate and flexible investors following Hong and Kacperczyk (2009), which means whether the institutional investor is under public pressure to follow strict mandates. It is therefore not surprisng that we, in contrast to Cao et al. (2019) and Hwang, Titman and Wang (2021), find that high ESG stocks held by flexible investors yield *high* abnormal returns, suggesting that the skill channel of our flexible investors seems to be dominating the general xESG sentiment channel.

Our findings differ from the seminal work on 'Sin' stocks by Hong and Kacperczyk (2009), as our main result originates in the top quartile of ESG scores rather than the bottom. Furthermore, our results are present within each industry, rather than comparing 'Sin' industries to the rest. Hence, the results cannot be driven by 'Sin' stocks, and are instead driven by investors' opportunities to utilize skill within high ESG stocks. While we see insignificant but negative returns for a general ESG strategy, our results also show that flexible investors manage to achieve positive abnormal returns for their ESG strategy, illustrating the importance of skill, and not just sustainability preferences. These findings are interesting, as they show the cost to investors' strict mandates in sustainable investment.[4]

This paper's secondary contribution is to help explain why some find that sustainable investing leads to higher abnormal returns and some find that it lowers them. Our answer is that it depends to which degree assets are held by which type of investor. Moreover, we show that it can be difficult to measure the sign of the expected ESG premium, as there have been positive realizations due to the increasing climate sentiment in the 2010s.[5]

Previous papers have looked at the general returns to ESG investing. Friede, Busch

[4]Narrow mandates may be optimal when there are costs to broad mandates such as in He and Xiong (2013). However, it is then important to realize this trade-off and possibly redefine your mandate to take advantage of expected ESG score improvements.

[5]Engle et al. (2020) also construct a text-based climate measure, which is based on an advanced high-dimensional multi-stage textual model of *Climate* news coverage in the Wall Street Journal. Instead we see our the simplicity and transparency of our measure as a virtue, as it gives a complementary and intuitive interpretation.

and Bassen (2015) conducts a meta study of over 2000 studies from 1970's to 2015 and find that a large majority of studies report a positive relationship between ESG and financial performance. Over 90% report a non-negative relationship. Specific papers that investigate the relationship between social responsibility and stock performance include Dimson, Karakaş and Li (2015), Eccles, Ioannou and Serafeim (2014), Krüger (2015), Ge and Liu (2015), Fatemi, Fooladi and Tehranian (2015), Porter and Kramer (2006), who argue that there is a positive relationship between an increase in sustainability efforts and returns. Furthermore, Porter and Van der Linde (1995), Greening and Turban (2000), Xie (2014) argue that there are additional benefits as improved resource productivity, motivated employees, or more customer satisfaction (as cited in Fatemi, Glaum and Kaiser, 2018). On the other hand, others argue that there is no causal relationship between returns and sustainabaility efforts (e.g. Alexander and Buchholz, 1978, McWilliams and Siegel, 2000, Renneboog, Ter Horst and Zhang, 2008, Bauer, Koedijk and Otten, 2005, Hamilton, Jo and Statman, 1993). Finally, there is also evidence for a negative relationship as provided by, for example, Fisher-Vanden and Thorburn (2011), Boyle, Higgins and Rhee (1997), El Ghoul and Karoui (2017).

The remainder of this paper is structured as follows. Section 2 lays out the theoretical framework and defines our hypotheses to be tested in our empirical analysis. Section 3 describes the data used, as well as how we construct our climate sentiment measure. Section 4 first documents the difference in returns across investor types. Secondly, it explores the role of strict ESG mandates, and, thirdly, it illustrates the effects of climate sentiment. Section 5 estimates the importance of our results in explaining the difference to sustainable investing. Section 6 compares the costs to the benefits achieved by sustainable investing. Section 7 concludes the paper.

2 A Theory of Sustainable Investing with Skill

To guide our empirical approach, this section describes the theoretical foundation of the study. We follow Pástor, Stambaugh and Taylor (2021) and consider a general equilibrium economy with a continuum of agents who dislike risk and have heterogeneous preferences for ESG. We deviate from their setup by assuming some investors are skilled in the sense that they are able to predict a stock's ESG score. Their approach deviates from the standard CAPM of Sharpe (1964) and Lintner (1965) by adding the sustainability preference. Specifically, the model is set in a single period, from time 0 to time 1, and the agent's utility is

$$U[W_{1i}, \boldsymbol{X}_i] = -e^{-aW_{1i} - b_i' \boldsymbol{X}_i}, \tag{1}$$

where the utility of investor i stems from their wealth at the end of period 1, W_{1i}, and is proportional to the absolute risk aversion a. The utility the investors get from holding sustainable stocks is proportional to the non-pecuniary benefits b_i. $\boldsymbol{X}_i$ is a vector of stock weights. $\boldsymbol{b}_i$ is a vector, which depends on the greenness $\boldsymbol{g}$ of the stock's ESG score and the agent's individual sustainability preference d_i ($\boldsymbol{b}_i = d_i \boldsymbol{g}$).

The wealth evolves as $W_{1i} = W_{0i}(1 + r_f + \boldsymbol{X}_i' \boldsymbol{r}^e)$, where $\boldsymbol{r}^e$ are returns in excess of the risk-free rate r^f. The excess returns will be determined in equilibrium as

$$\boldsymbol{r}^e = \boldsymbol{\mu} + \boldsymbol{\epsilon}, \tag{2}$$

where $\boldsymbol{\mu}$ are expected returns and $\boldsymbol{\epsilon}$ captures the risk distributed as $N(\mathbf{0}, \boldsymbol{\Sigma})$.

This means that the investor's optimal weights will be

$$\boldsymbol{X}_i = \frac{1}{\gamma} \boldsymbol{\Sigma}^{-1} (\boldsymbol{\mu} + \frac{1}{\gamma} \boldsymbol{b}_i), \tag{3}$$

where $\gamma \equiv a_i W_{0i}$ is the relative risk aversion. Note that if $\boldsymbol{b}_i$ is a zero vector, we get back the standard CAPM result.

For the market to clear, the expected excess returns has to be

$$\boldsymbol{\mu} = \gamma \boldsymbol{\Sigma} \boldsymbol{x} - \frac{\bar{d}}{\gamma} \boldsymbol{g}, \tag{4}$$

where x is the supply of risky assets, $\bar{d}$ is the wealth-weighted average sustainability preference. Again, if $\bar{d}$ is zero, we obtain the CAPM result. This can be written in terms of the market return as

$$\boldsymbol{\mu} = \mu_M \boldsymbol{\beta} - \frac{\bar{d}}{\gamma} \boldsymbol{g}, \tag{5}$$

where $\boldsymbol{\beta}$ are the market betas $(1/\sigma_M^2)\boldsymbol{\Sigma}\boldsymbol{x}$. Finally, this means that the alpha of a stock n will be

$$\alpha_n = -\frac{\bar{d}}{\gamma} g_n. \tag{6}$$

For our empirical work we use Equation (5) to rewrite Equation (2) to the testable form for a stock

$$r_n^e = \underbrace{-\frac{\bar{d}}{\gamma} g_n}_{\alpha_n} + \mu_M \beta_n + \epsilon_n. \tag{H1}$$

By combining Equation (3) and (5), and noting δ_i as the preference deviation from the mean $(d_i - \bar{d})$, we can see the equilibrium portfolio weights must be

$$\boldsymbol{X}_i = \boldsymbol{x} + \frac{\delta_i}{\gamma^2} (\boldsymbol{\Sigma}^{-1} \boldsymbol{g}). \tag{7}$$

It is interesting to note that this implies three-fund separation, as this can be achieved for each agent using the risk-free asset, the market portfolio $\boldsymbol{x}$ and an ESG portfolio, the last term above. Hence, the second term illustrates investors' ESG tilt. If all investors had the same preference, δ_i would be zero, and no investors would have an ESG tilt as everyone holds the market portfolio.

Skill in sustainable investing. Our addition to Pástor, Stambaugh and Taylor (2021) is that we now consider the case where a small fraction of skilled investors is able to predict future ESG scores, for example through the analysis of firm fundamentals and strategy. The shock to the greenness of firm n of $\tilde{g}_n$ leads to a new total excess return for a stock of

$$r_n^e = \beta_{M,n} r_M^e + g_n \mu_g + \tilde{g}_n \frac{\bar{d}}{\gamma} + \epsilon, \tag{H2}$$

and hence effectively boosts the return of the skilled investor.

Equation (H2) will allow us in Section 4 to estimate how much of the investors' return difference to sustainable investing is due to an ability to predict ESG scores.

Sentiment in sustainable investing. Returns could also be affected by changes to climate sentiment. These changes can arise from unexpected changes in the average investor preference or the end consumers' taste for green goods. These two changes will lead to lower future expected return, and positive unexpected realized returns of

$$\boldsymbol{r}^u = s_g \boldsymbol{g} + \boldsymbol{\epsilon}, \tag{8}$$

where s_g is sentiment. Additionally, sentiment is the combination of the two random preference shocks

$$s_g = z_g + \frac{1}{\gamma}(\bar{d}_1 - E_0[\bar{d}_1]), \tag{9}$$

where z_g is the consumer taste shock. This means that sentiment shocks can arise from consumer or investor preference changes, which we jointly refer to as sentiment shocks. We will, for simplicity, treat sentiment shocks as the investor channel in this paper, even though they could be customer shocks. This choice has no impact on our results later in the paper. By separating out the transcendental effects of changes to climate sentiment, we can now estimate the expected return to sustainable investing. We will estimate this in the section 4 using the following result.

The total excess return of a stock can then be closely approximated by

$$r_n^e = \beta_{M,n} r_M^e + g_n(s_g + \mu_g) + \epsilon_n, \tag{H3}$$

where $E_0[\epsilon_n] = 0$ and μ_g is the expected return on the ESG portfolio $\mu_M \beta_g - \bar{d}/\gamma$. Here, β_g is the ESG portfolio's beta with the market portfolio, making the ESG factor's realized return $s_g + \mu_g$ and $E_0[s_g + \mu_g] = \mu_g$.[6] Hence, Equation (9) illustrates how increased sentiment (changes in ESG preferences) enters into the excess returns of Equation (H3), and boosts the returns of green stocks.

In the empirical work that follows, we test three hypotheses. Our first hypothesis is whether investors have a sustainability preference. Specifically, we test that the wealth-weighted average sustainability preference is positive $\bar{d} > 0$. A positive sustainability preference implies that green stocks have a negative alpha, as according to Equation (H1). This also implies that an ESG factor has negative alpha. We test this against the null-hypothesis that investors sustainability preference is zero, which means that the alphas are also zero.

Our second hypothesis is that some investors are able to predict future ESG score changes $\tilde{\boldsymbol{g}}$, which means they can achieve a positive alpha in their investments into green stocks, as according to Equation (H2). This is tested against the null that $\tilde{g}_g = \mu_g = 0$, which is a stronger test than $\mu_g < 0$, as the latter is easier to reject. One could also use a one-sided test, as there is no reason to expect a negative sustainability preference, and we just want to see if it is significantly larger than zero.

[6] β_g can be negative either if the covariance with the fundamental risk is negative or if the stock market is value-weighted brown. From our empirical analysis, our negative β_g seems to be explained by the ESG-factor doing well in bad times, implying a negative correlation with fundamental payoff risk.

Our final hypothesis is whether an increased worry of climate change, as well as a tenfold increase in assets with an ESG mandate, over the last fifteen years has lead to positive unexpected return for green stocks, an effect which we will refer to as *Sentiment*. The expected return is then governed by Equation (H3), which we test against the null that $f_g = \mu_g = 0$, which, again, is a stronger test than $\mu_g < 0$ as our hypothesis is that $f_g > 0$.

3 Data

This section outlines the data sources and places them within our analysis.

Returns. The objective of the analysis requires us to combine data on equity returns and sustainability. First, we obtain monthly stock returns from the Center for Research in Security Prices (CRSP). We also obatin monthly data points on the number of stocks and their share price to compute market values. We follow Fama and French (1993) and only include stocks that are listed on NYSE, AMEX, or NASDAQ and have a CRSP share code of 10 or 11.

ESG. We utilize a unique ESG dataset to tackle the research question. Specifically, we download yearly ESG score data from Thomson Reuters, referred to as ASSET4. This data depicts equally-weighted ratings on the metrics of companies' economic, environmental, social and corporate governance performance. In particular, the ESG score is a measure from 0 to 100. A low score suggests that a given company behaves poorly with regards to overall sustainability, and vice versa. The higher a company's score, the more sustainable it is with regards to the pillars mentioned above.

We address the usual issues of using ESG scores. The ASSET4 database experienced an update of scores in the year of 2020, however, we use scores downloaded in

2018.[7] These 'original' scores, as Berg, Fabisik and Sautner (2020) put it, have not been backfilled, meaning that there would not be an assignment of scores for any other than the most recent year. For example, if Thomson Reuters did not assign a score for the year 2005 due to insufficient information but then receives valuable insights in 2008 for the year of 2005, they would not go back in time and assign a score for the year of 2005.[8] This is important because our analysis makes the implicit assumption that investors had the relevant ESG score information for the previous year available at the time. Furthermore, Berg, Fabisik and Sautner (2020) point out that the update of scores in 2020 is systematic and related to past performance. It seems as if firms that have outperformed others in a given year have received higher ex-ante scores in the update. The updated data would therefore distort our results and it is hence important for us to use the 'original' data instead as we analyze the skill to invest sustainably with information at the time. Finally, although Berg, Kölbel and Rigobon (2019) find that the ASSET4 data is not perfectly correlated with other widely used sustainability assessment data, it still displays a strong positive correlation. For example, the correlation between ASSET4 and Sustainalytics and Vigeo Eiris is 0.67 and 0.69, respectively. This is equivalent to an R^2 of 81% and 83%. The facts that scores have been available to investors at the time, high correlations to other data providers, and a long time horizon are the deciding factors for us to use the ASSET4 database in our study.

Thomson Reuters computes the scores themselves and follows a strict methodology when doing so. For every firm, they consider a total of 750 questions, which they attempt to gather information for. Data are collected from multiple sources, including: a) company reports; b) company filings; c) company websites; d) NGO websites; e) CSR Reports; and f) reputable media outlets. Thomson Reuters writes that every data

[7] Other studies having used the same data include, for example, Dyck et al. (2019), Stellner, Klein and Zwergel (2015), Breuer et al. (2018).

[8] We gathered this information from an interview with the persons responsible for the ESG data bank at Thomson Reuters.

point goes through a multi-step verification process, including a series of data entry checks, automated quality rules, and historical comparisons. These data points reflect more than 280 key performance indicators and are rated as both a normalized score (0 to 100, with 50 as the industry mean) and the actual computed value. The equally-weighted average is normalized by ASSET4 so that each firm is given a score relative to the performance of all firms in the same industry around the world; in other words, the ratings are industry-benchmarked.

We merge the return data from CRSP with the ESG data according to their CUSIP codes. ESG data points are available on a yearly basis, whereas returns are available at a monthly frequency. This means that the individual firm's ESG score is the same throughout a given year, i.e. for every monthly return observation. ESG scores are available from 2002 until 2016, which defines our sample period. This is a longer time period than most other data providers can offer, which additionally encourages us to use the ASSET4 scores.[9]

Investigating the ESG data set in greater detail, Table I.15 exhibits distribution statistics and developments in ESG scores over time. In the first year of the sample period, 2002, a total number of 624 firms in the sample were assigned an ESG score. This number significantly increases to a maximum of 2,992 firms in the final year of 2016. The distribution of ESG scores over time remains relatively stable. We see scores on both the low and the high end of the scale.

For the empirical analysis in the next section, the entire universe of ESG score firms are taken into account. The total number of firms is thereby identical to the number of firms in Table I.15. This also implies that the cross-section's total number of firms in later performance analysis rises over time.

[9] The MSCI KLD data is available for a slightly longer time horizon, however, their dataset experienced significant updates in between. These updates violate our binding constraint that investors need to be ensured to have had access to the very scores we use in our analysis.

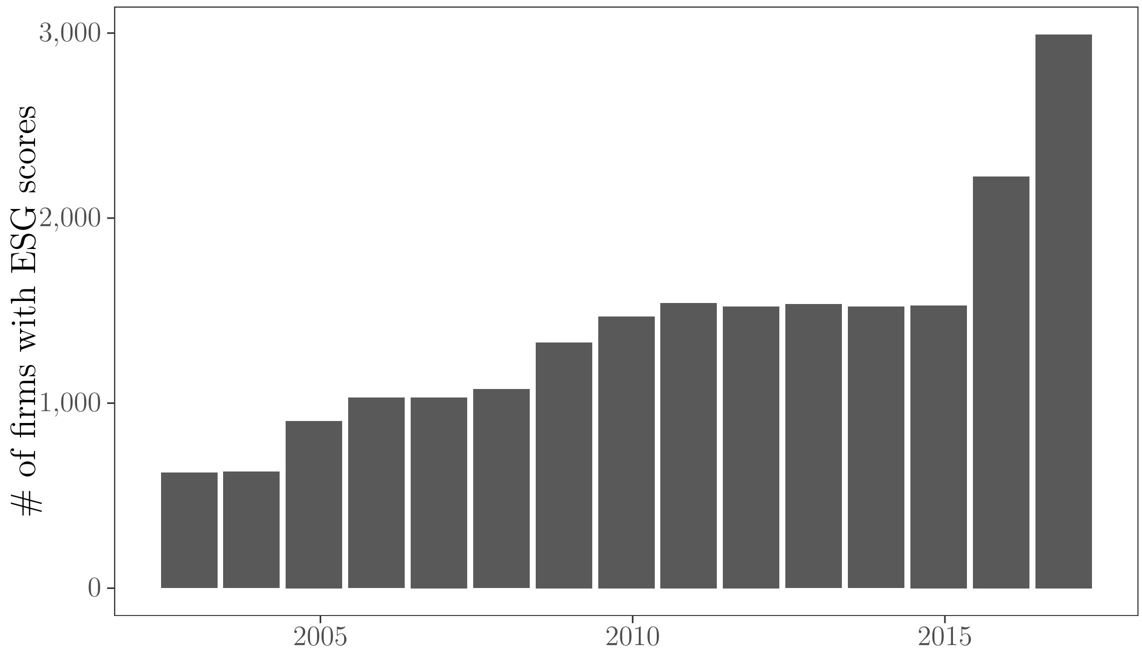


Figure 1: ESG data availability

This figure shows the data availability of the ASSET4 ESG score dataset for each year from 2002 to 2016.

Risk factors. To control for risk factors we use the risk-free rate and factor-returns of the Fama and French (1993) three factor model as well as the momentum factor from Ken French's website. We test our hypotheses against the CAPM, Fama-French three factor model and Carhart four-factor model.

Business cycles. We use the NBER Business Cycle Reference Dates to identify recessions and use these to define good and bad economic times. We use these bad times as a proxy to investigate how ESG returns perform during periods of high risk and low consumption. In a later analysis, we further utilize price-dividend ratios (PD) as a measure for the state of the stock market. The PD data is gathered from Shiller's website.

Ownership. We obtain quarterly institutional holding data (13F) from Thomson Reuters. According to the SEC, all institutional investors with assets under management over \$100 million need to report their holdings to the commission.The data includes the number of shares held by every institutional investor. We use this number to calculate the relative holding of a firm by each institutional investor. Specifically, each investors' number of shares divided by the total number of shares outstanding depicts the holdings of a given firm. Sometimes, the data does not adjust for stock splits or repurchases and the relative share might increase above one, in which case we exclude it from the data. We further follow standard asset pricing literature and exclude stale data, whenever there are several filing dates ($fdate$) for the same report date ($rdate$). In such a case, we only keep the data points of the report date with the earliest filing date.[10]

The institutional ownership data (13F) exhibits five different types of owners which we categorize into strict and flexible investors as in Hong and Kacperczyk (2009) (they refer to strict investors as norm-constrained). Strict owners are banks (Type 1), insurance companies (Type 2) as well as all other other institutions, which includes universities, pension plans, and employee ownership plans (Type 5). Flexible owners are investment companies (Type 3) and independent investment advisors (Type 4), which also includes hedge funds. We aggregate holding data for these two groups and merge it with returns.

We explore each investor types' ESG investments in Appendix A. Here we show that responsible investing has evolved from excluding sin stocks to incorporating ESG principles in a broader sense. Responsible investors include UN PRI signatories. UN PRI practice involves excluding low ESG and over-weighing high ESG companies. We go on to show that strict investors are more likely to have signed the UN PRI. Additionally, when comparing strict and flexible signatories, strict investors also sign earlier. We also see that strict investors are more likely to overweight and exclude stocks in their high

[10]For similar applications, see, for example, Brunnermeier and Nagel (2004) or Blume, Keim et al. (2017).

ESG portfolio compared to flexible investors. Strict investor flow is also more sensitive to ESG score, in the sense that they allocate more capital based on ESG scores, than flexible investors do. Lastly, UN PRI have grown tremendously over the last 10 years and assets invested under UN PRI principles now make up a large fraction of total invested assets.

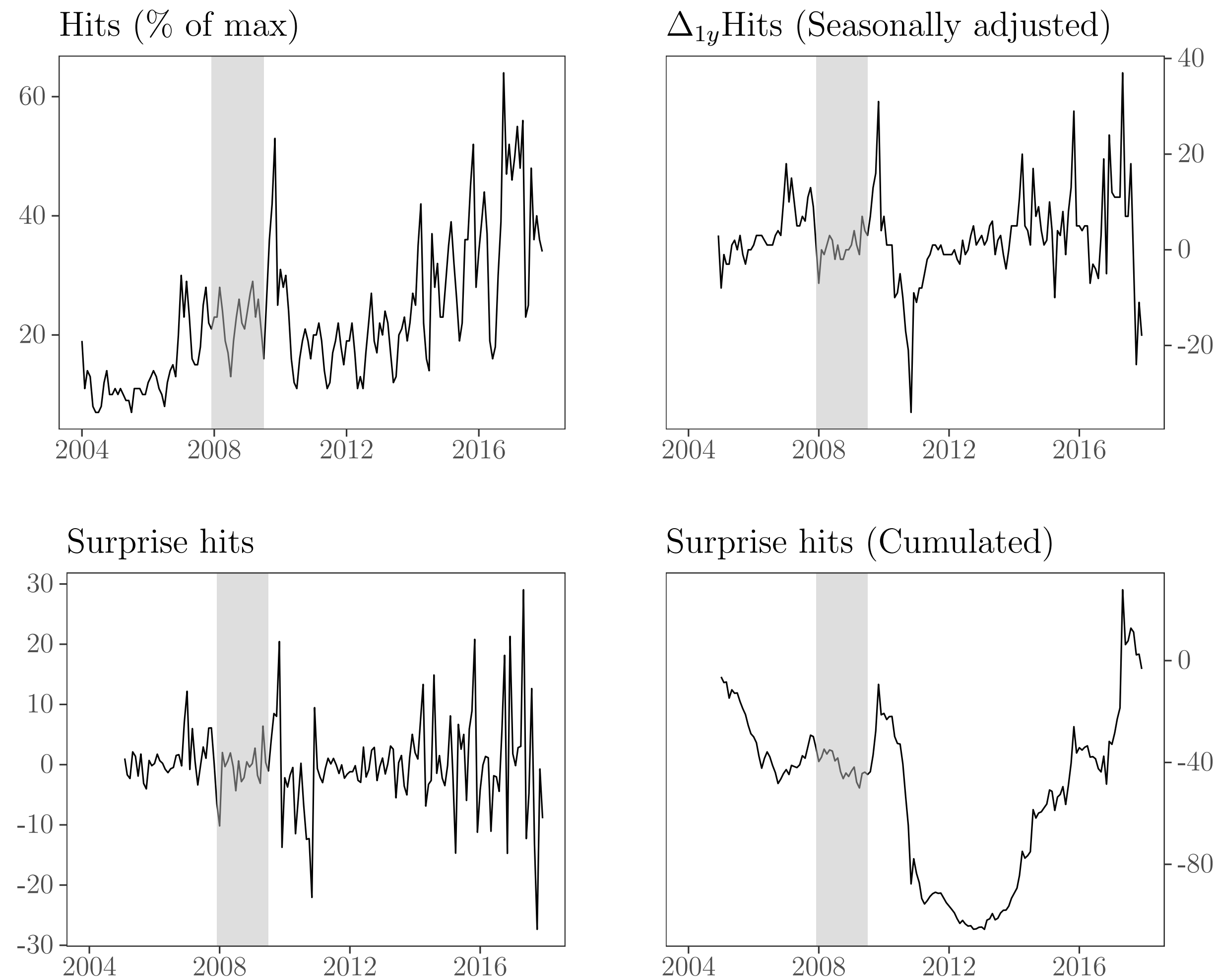


Figure 2: Climate sentiment

Here we show how our sentiment measure is constructed. The top left panel shows the monthly Google searches for *Climate change*. As it is clearly seasonally affected, we show the difference to the same month a year ago in the top right panel. The bottom left panel shows the innovations from fitting an AR(1) model on the seasonally adjusted hits. Bottom right shows the cumulated hit innovations. The shaded area denotes recession.

Climate sentiment. We test for climate sentiment by using the search interest of 'Climate change' on Google, which we retrieve from Google Trends. Figure 2 shows how our sentiment time series is constructed. The general hits measure is the search volume in the United States expressed relative to the maximum search volume in percent (top left). As it is clearly seasonally affected, we show the difference to the same month a year ago in the top right panel. The bottom left panel shows the innovations from fitting an AR(1) model on the seasonally adjusted hits, which serves as our sentiment measure. The bottom right shows the cumulated hit innovations. The shaded area denotes recession. We notice a general fall in sentiment in the recession, a sharp peak between the recession and the European debt crisis, and a steep rise since 2014.

We compare results from our climate sentiment measure to the economic sentiment measure of Baker and Wurgler (2006), which is the principal component of five sentiment proxies ($perp$). As a robustness test we also compare our results to using the Engle et al. (2020) text-based climate measure, which is based on text coverage of *Climate* in the Wall Street Journal. They have two measures. One for general coverage (wsj) and one for negative coverage ($chneg$).

One might be concerned that our measure is overly simplistic or that climate deniers account for a significant fraction of the time series' movements. We argue that climate change deniers only represent a negligible fraction of the population and that their search intensity is relatively constant over time, whereas the worry of climate change has varied over the last decades with an overall rising trend. Hence, by using the variation of search volumes, we believe to capture climate change worries to a large degree. However, we show that more complicated text-based sentiment measures, such as (Engle et al., 2020), which is constructed from a high-dimensional dataset, are qualitatively similar. So in fact, we see the simplicity and transparency of our measure as a virtue.

4 Results

In this section we test our hypotheses as developed in Section 2. First, we investigate the relationship of a stock's greenness and its expected return for two types of investors (Equation (H1)). Second, we test whether investors are compensated for predicting ESG scores (Equation (H2)). Third and finally, we examine whether climate sentiment has increased abnormal returns of green stocks (Equation (H3)).

4.1 Returns to sustainable investing across investor types

In this subsection, we compare the returns to sustainable investing for two types of investors (Equation (H1) in Section 2). We consider both the returns to high ESG investing, as well as the ESG premium achieved by strict and flexible investors.

Before doing so, however, we test for a general ESG premium in the market, meaning under no consideration of ownership. We create the ESG premium from a long-short portfolio (LS), which goes long in the top decile ESG firms and shorts the lowest decile of ESG firms. Table 1 shows the results. We see that there does not seem to be a general ESG premium after adjusting for risk, which confirms the findings by Berg, Fabisik and Sautner (2020). We find partial evidence that the firms in the lowest decile portfolio earn a positive abnormal return, though not at a significant level. These results suggest that the market, in general, pays neither a positive nor negative premium for investing sustainably.

We shift our focus to ESG investing across ownership types and evaluate if either one earns a premium for investing sustainably. We construct the results by first sorting returns according to lagged ESG scores in a total of four portfolios.[11] In the next step, we conditionally sort returns according to their previous quarter's strict and flexible

[11]We form portfolios in the standard way of Fama and French (1992). More details on sorting can be found in Appendix IG.

Table 1: Returns to sustainable investing in general

We construct value-weighted decile portfolios based on previous year ESG scores and adjust them in the beginning of each calender year. P1 (P10) depicts the low (high) ESG score portfolio. LS is a time series of returns that goes long in high ESG firms (P10) and shorts low ESG firms (P1). The returns of all ESG portfolios are risk-adjusted through the application of the CAPM, Fama-French 3-factor, and Carhart 4-factor models and we report the alphas. We further disclose monthly excess returns, volatility and Sharpe ratio estimates. $t-values$ test if the estimated returns are significantly different from zero and bold numbers signal significance at the 10% level or less. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	LS
Excess Return	**1.047**	**0.712**	**0.886**	**0.973**	**0.792**	**0.908**	**0.921**	**0.870**	**0.747**	**0.705**	**-0.343**
t-stat	2.997	2.084	2.516	2.855	2.463	2.674	2.676	2.738	2.536	2.736	2.868
CAPM	0.170	-0.171	-0.034	0.092	-0.043	0.020	0.012	0.028	-0.031	0.022	-0.148
t-stat	0.972	-1.407	-0.274	0.987	-0.313	0.196	0.132	0.355	-0.412	0.341	-0.750
3-Factor	0.161	-0.188	-0.041	0.085	-0.043	0.009	0.017	0.038	-0.018	0.029	-0.133
t-stat	0.916	-1.451	-0.277	0.887	-0.327	0.097	0.185	0.493	-0.245	0.419	-0.654
4-Factor	0.193	**-0.205**	-0.039	0.098	-0.041	0.025	0.039	0.035	-0.027	0.028	-0.166
t-stat	1.129	-1.718	-0.264	1.015	-0.324	0.271	0.426	0.454	-0.367	0.414	-0.807
Volatility	4.675	4.584	4.716	4.560	4.298	4.543	4.607	4.257	3.945	3.450	2.712
Sharpe Ratio	0.224	0.155	0.188	0.213	0.184	0.200	0.200	0.204	0.189	0.204	-0.126

institutional ownership share and assign them into another four portfolios. We value-weight each portfolio and risk-adjust returns.

We show the returns to sustainable investing under different ownership, the estimation of Equation (H1), in Table 2.[12] Comparing flexible and strict investors' returns under the Carhart 4-factor model, we find that flexible investors earn a significant ESG premium of 30 bp, whereas strict investors do not. This result is driven by the high returns in the long leg. The long leg, which is the high ESG and high flexible ownership portfolio, earns an abnormal return of 39 bp. The difference between the investor types' returns to high ESG investing is 26 bp per month adding up to 3.15% on an annual basis. We further find a positive and significant differences in the second and third ESG quartiles from flexible to strict investor returns. These results provide evidence that

[12] In Table I.1 in Internet Appendix IA, we show the same table but with a total number of ten portfolios across the ESG score.

strict and flexible investors in general earn different returns when investing sustainably.

We additionally examine the performance of stock holdings by flexible and strict investors as if they were bought one period earlier. For example, if an investor held 10% of Stock A in Q2 2015, we assume that investor held 10% of Stock A in Q1 2015 (which we refer to as sorted on *future* holdings). This gives us a way to consider the performance of stocks that the two investor types are demanding. We follow our double-sort methodology and sort stocks on ESG scores as well as future holdings. Table 3 shows results on value-weighted and risk-adjusted returns on the high flexible and strict future ownership portfolios, the long-short portfolios as well as the differences.

This additional test shows that high ESG stocks held by both investor types in the next quarter yield positive and significant abnormal returns. Based on the Carhart four-factor model, flexible investors earn 42 bp per month and strict investors earn 33 bp per month. This suggests that ESG demand pushes up the price for ESG stocks. This implies that there has been a larger increase in ESG demand than there has been for other stocks, or that the price elasticity is lower. In either case, this ESG demand leads, ceteris peribus, to lower ESG premiums in the future. However, as we observe a difference between the two types of investors in their returns to sustainable investing using actual holdings, it suggests that some investors can use their flexibility to increase their returns to ESG investing. In this analysis, we observe smaller and not always significant differences between the returns of flexible and strict investors across ESG quartile portfolios.

Before exploring what may be driving the difference in returns to sustainable investing across investor types in Subsection 4.2, we conduct a wide array of robustness tests for this result. We start by confirming our results by using all risk factor models to document alphas of the long-short equity strategy held to a large and small degree

Table 2: Returns to sustainable investing across investors

This table shows returns of portfolios with high flexible investor ownership (Panel A), strict investor ownership (Panel B), and the difference across the two (Panel C), across firms with low to high ESG scores. High flexible (strict) ownership depicts the stocks in the top quantile of flexible (strict) investor ownership. Specifically, we sort monthly returns according to lagged ESG scores in a total of four portfolios. In the next step, we conditionally sort returns according to their previous quarter's flexible and strict institutional ownership share and assign them into another four portfolios, ending up with a total of 16 portfolios. We rearrange portfolios every quarter, where new holding data is available. ESG data is updated every year. LS is the abnormal return from a long-short strategy which goes long in high ESG and short in low ESG firms, giving us another four portfolios each. We value-weight each portfolio, risk-adjust returns according to the CAPM, 3-Factor and Carhart 4-factor model and document the alpha and t-statistic. Finally, we show risk-adjusted returns to portfolios that go long in high flexible ownership portfolios and short in strict ownership portfolios (Panel C). Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months. Bold numbers depict statistical significance of 5% or below.

	ESG low	Q2	Q3	ESG high	LS
Panel A: Flexible					
CAPM	0.08	0.02	0.19	**0.40**	**0.32**
t-stat	0.64	0.14	1.19	3.89	2.21
3-Factor	0.06	0.01	0.17	**0.39**	**0.33**
t-stat	0.56	0.05	1.15	3.71	2.20
4-Factor	0.09	0.01	0.17	**0.39**	**0.30**
t-stat	0.77	0.04	1.20	3.78	2.03
Panel B: Strict					
CAPM	-0.02	-0.31	-0.21	0.12	0.14
t-stat	-0.11	-1.53	-1.38	1.03	0.84
3-Factor	-0.04	-0.34	-0.22	0.12	0.16
t-stat	-0.28	-1.77	-1.26	1.06	0.97
4-Factor	-0.05	-0.32	-0.19	0.13	0.18
t-stat	-0.37	-1.76	-1.14	1.11	1.09
Panel C: Difference					
CAPM Monthly	0.10	**0.33**	0.40	**0.28**	
CAPM Yearly	1.15	**4.01**	4.75	**3.36**	
t-stat	0.69	2.38	1.97	2.81	
3-Factor Monthly	0.10	**0.34**	0.39	**0.27**	
3-Factor Yearly	1.20	**4.11**	4.71	**3.27**	
t-stat	0.72	2.41	1.86	2.52	
4-Factor Monthly	0.14	**0.33**	0.36	**0.26**	
4-Factor Yearly	1.65	**3.94**	4.36	**3.15**	
t-stat	0.96	2.37	1.84	2.35	

Table 3: Returns to sustainable investing across investors' future holdings

This table shows returns of portfolios with high flexible (Panel A) or strict (Panel B) *future* investor ownership across firms with low to high ESG scores. Specifically, we sort monthly returns according to lagged ESG scores in a total of four portfolios. In the next step, we conditionally sort returns according to their next quarter's flexible and strict institutional ownership share and assign them into another four portfolios, ending up with a total of 16 portfolios. This gives us an indication for what the return on these portfolios would have been if investors would have held firms at the same level a period earlier. We rearrange portfolios every quarter, where new holdings data is available. ESG data is updated every year. LS is the abnormal return from a long-short strategy which goes long in high ESG and short in low ESG firms, giving us another four portfolios each. We value-weight each portfolio, risk-adjust returns according to the CAPM, 3-Factor and Carhart 4-factor model and document the alpha and t-statistic. Finally, we show risk-adjusted returns to portfolios that go long in high *future* flexible ownership portfolios and short in *future* strict ownership portfolios (Panel C). Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months. Bold numbers depict statistical significance of 5% or below.

	ESG low	Q2	Q3	ESG high	LS
Panel A: Flexible					
CAPM	0.14	0.003	0.13	**0.44**	**0.30**
t-stat	1.11	0.02	0.87	5.97	2.14
3-Factor	0.12	-0.01	0.12	**0.43**	**0.31**
t-stat	0.91	-0.05	0.79	5.56	1.99
4-Factor	0.13	-0.01	0.12	**0.42**	0.29
t-stat	0.98	-0.07	0.82	5.55	1.74
Panel B: Strict					
CAPM	0.01	-0.19	-0.06	**0.30**	0.29
t-stat	0.11	-0.67	-0.31	1.99	1.52
3-Factor	-0.01	-0.21	-0.06	**0.31**	0.31
t-stat	-0.06	-0.83	-0.35	2.17	1.50
4-Factor	-0.02	-0.17	-0.04	**0.33**	0.34
t-stat	-0.15	-0.76	-0.21	2.23	1.66

by flexible investors in Table I.2 in Appendix IA.[13] The robustness check further documents that the premium loads on the market itself as well as the small minus big and momentum factors. The fact that risk cannot explain returns under any model serves as a motivation for us to explore whether less risk-based factors may be driving these returns as, for example, sentiment. An alternative research design at the fund level based on their portfolio weights in considered in Internet Appendix IB. Here we find that the results carry through with similar magnitudes.

We continue by showing results for other sustainability metrics. We download scores from Sustainalytics, another ESG data provider, as well as data points on firms' CO_2 emissions per dollar of revenue. The latter is used by both ASSET4 and Sustainalytics as part of their scoring approach. Table 4 shows the results for portfolios under high flexible ownership and high scores under the alternative metrics (for CO_2 per revenue, the 'sustainable' portfolio is that of firms with lowest emissions). We see that our results are robust under the application of these different sustainability metrics. Furthermore, we show that the results under alternative ESG metrics also hold when using different risk models in Table I.3 in Appendix IA. For the flexible investor, investing in firms with high sustainability scores (or low emission scores) pays high returns.

We finish by using these alternative ESG metrics to also explore the robustness of the long-short ESG portfolio under high flexible ownership. Table 5 shows the results. We observe a significant sustainability premium under the Sustainalytics Environment (S:E) and the CO_2 scoring models. For the general Sustainalytics scores, we document positive abnormal returns, though not at a significant level under the Carhart 4-factor

[13]Table I.21 in Internet Appendix IF shows results for all 16 portfolios as well as for four long-short portfolio within each ownership quantile. This is shown for the flexible investor under both the Carhart and CAPM risk models. Table I.22 in Appendix IF shows results for the same portfolios, but for both the flexible and the strict investor as well as for the future holdings. The results are also robust to first sorting according to ownership and secondly to ESG. Table I.4 in Appendix IF shows results for the same portfolios, but using a more precise, but smaller coverage, of investor classifications by (Bushee, 2001), updated up to date, with no substantial difference. We additionally show that the outperformance is driven by independent investment advisors in both classifications.

Table 4: Robustness test for returns to sustainable investing for flexible investors using different sustainability metrics

We sort returns according to lagged scores in a total of four portfolios based on ASSET4 (A4), Sustainalytics (S), Sustainalytics Environment (S:E) and Carbon per Revenue (CO2) scores. Data goes from 2002 until 2016 under ASSET4 and 2011 until 2016 otherwise. In the next step, we conditionally sort returns according to their previous quarter's flexible institutional ownership share and assign them into another four portfolios, ending up with a total of 16 value-weighted portfolios. In another step we construct value-weighted and risk-adjusted returns according to the Carhart four-factor model for a portfolio that goes long in high (H) score (low score for CO2 metric) firms with high flexible ownership (F). We adjust standard errors according to Newey and West (1987) with a lag of 12 months and report relevant coefficients and t-values.

	Dependent variable:			
	$r_t^{F,H}$			
	A4	S	S:E	CO2
	(1)	(2)	(3)	(4)
α	0.392***	0.384***	0.372***	0.585***
	t = 3.784	t = 4.579	t = 3.051	t = 4.080
mkt-rf	0.987***	0.963***	0.988***	1.046***
	t = 39.925	t = 13.709	t = 13.789	t = 16.699
smb	−0.042	0.134**	0.150**	0.088
	t = −0.594	t = 2.113	t = 2.296	t = 0.763
hml	−0.091*	−0.177***	−0.271***	−0.427***
	t = −1.690	t = −2.775	t = −4.350	t = −3.057
mom	−0.001	0.023	0.029	−0.042
	t = −0.039	t = 0.357	t = 0.456	t = −0.647
Observations	180	72	72	72
R^2	0.877	0.816	0.797	0.732
Note:				*p<0.1; **p<0.05; ***p<0.01

model. This seems to be because the social and governance aspects of the Sustainalytics score (S:S and S:G) are less related to positive returns than the environment aspect (S:E).[14] These results confirm our main result and suggest that the ESG premium for flexible investment strategies is driven by environmentally-related scores.

In the next subsection we consider what may be driving the difference in returns to sustainable investing across the two investor types.

[14]However, the premium from using the general Sustainalytics scores is significant to a p-value of below 5% under the CAPM and the Fama-French 3-factor model.

Table 5: Robustness test for sustainability premia under flexible ownership using different sustainability metrics

We sort returns according to lagged scores in a total of four portfolios based on ASSET4 (A4), Sustainalytics (S), Sustainalytics Environment (S:E), Sustainalytics Social (S:S), Sustainalytics Government (S:G) and Carbon per Revenue (CO2) scores. Data goes from 2002 until 2016 under ASSET4 and 2011 until 2016 otherwise. In the next step, we conditionally sort returns according to their previous quarter's flexible institutional ownership share and assign them into another four portfolios, ending up with a total of 16 portfolios. In a final step we construct value-weighted and risk-adjusted returns under the Carhart four-factor model for a portfolio that goes long in high score firms and short in low score firms with high flexible ownership (LS_t^F); in the case of CO2, we go long in low emission firms and short in high emission firms, both with high flexible ownership. We adjust standard errors according to Newey and West (1987) with a lag of 12 months and report relevant coefficients and t-values.

	Dependent variable:					
	LS_t^F					
	A4	S	S:E	S:S	S:G	CO2
	(1)	(2)	(3)	(4)	(5)	(6)
α	0.304**	0.226	0.393***	0.160	0.034	0.681**
	t = 2.027	t = 1.414	t = 2.811	t = 0.531	t = 0.155	t = 1.970
mkt-rf	−0.019	−0.055	−0.039	−0.016	−0.071	0.159
	t = −0.355	t = −0.871	t = −0.964	t = −0.133	t = −0.963	t = 0.867
smb	−0.502***	−0.021	−0.034	0.103	−0.139*	−0.048
	t = −4.002	t = −0.256	t = −0.452	t = 0.692	t = −1.701	t = −0.326
hml	0.119	0.255***	−0.011	0.238	0.273***	−0.552***
	t = 1.446	t = 4.023	t = −0.157	t = 1.540	t = 3.215	t = −2.916
mom	0.113**	0.144**	0.022	−0.094	0.018	0.137
	t = 2.492	t = 2.277	t = 0.265	t = −0.855	t = 0.263	t = 1.324
Observations	180	72	72	72	72	72
R^2	0.226	0.092	0.012	0.088	0.106	0.193
Note:						*p<0.1; **p<0.05; ***p<0.01

4.2 Skills in sustainable investing across investor types

Section 4.1 showed that flexible investors earn an ESG premium, whereas strict investors do not. We build on this finding and give an explanation as to where flexible investors' abnormal returns to sustainable investing come from. Specifically, we test our second hypothesis, that investors are compensated for predicting ESG scores (Equation (H2) in Section 2).

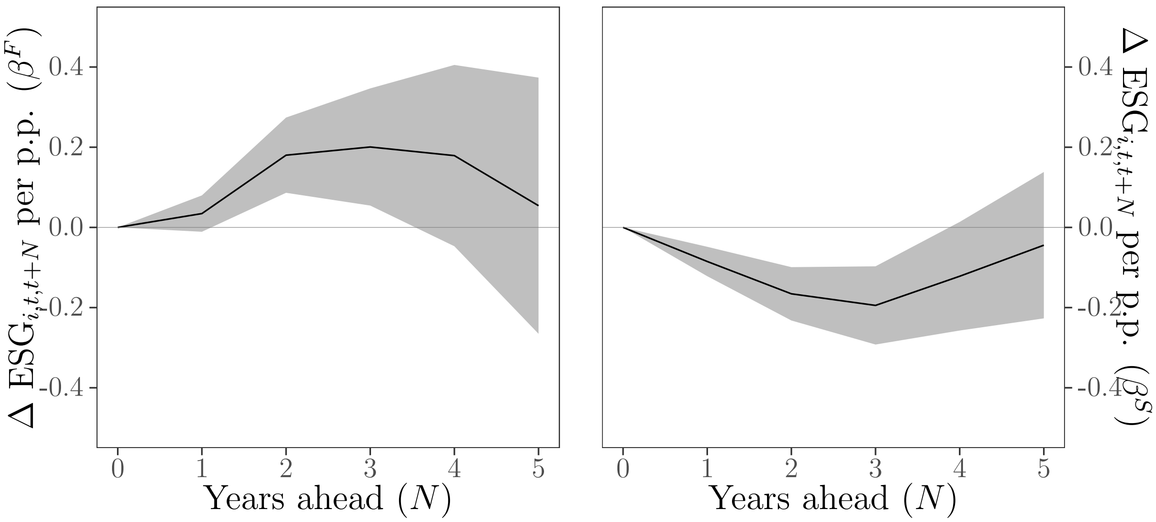
ESG score changes across investor types' holdings

The first step is to see whether flexible investors are better at predicting changes in firms' ESG scores. We test this by estimating

$$\Delta ESG_{i,t,t+N} = \alpha + \beta^I O^I_{i,t} + \epsilon_{i,t}, \tag{10}$$

where $\Delta ESG_{i,t,t+N}$ is the cumulative ESG score difference between the lagged ESG score in year t and $t + N$ years ahead. The variable $O^I_{i,t}$ is the relative institutional ownership of firm i at time t held by flexible or strict investors $I = \{F, S\}$. Additionally, we allow for heteroskedastic standard errors and control for industry-year effects. The results are displayed in Figure 3.

Figure 3a shows that an increase in ownership by flexible investors leads to future increases in the ESG score of the stock. We see that, if a stock is bought by a flexible investor, the stock experiences positive changes every year for three years in a row. The most significant yearly change is between year one and two, where it rises about 17 ESG points or half a standard deviation. This makes sense as ESG scores can be updated from January to December, the second year will be the first time, that the change reflects a whole year of ownership prior to the change. Instead, had the stock remained in the hands of a strict investor, see Figure 3b, its ESG score would decrease



(a) Flexible Investors

(b) Strict Investors

Figure 3: Predicting ESG score changes

Figure 3a shows flexible (F) ownership in firms and their correlation to future changes in ESG scores, whereas Figure 3b shows this effect for strict (S) investors. Specifically, the β-estimate gives an indication for how much the ESG score changes in N years ahead of time, when investor $I = \{F, S\}$ increases ownership by one percent today. Allowing for heteroskedasticity, the gray shade shows White standard errors. Additionally, we control for industry-year effects, and cluster by time to allow for correlation in the cross-sectional error terms.

on average, though a little less than the increase for a flexible investor.

This stylized fact indicates that flexible investors are better able to detect ESG firms with the potential of increases in their sustainability score. Flexible investors therefore seem to have superior skill to detect future ESG value, which may be explained by these firms spending a lot on fundamental analysis of companies, which they hope pays off through higher returns. Alternatively, it may be due to strict investors' mandates preventing them from purchasing these promising stocks.

This finding can help explain why flexible firms earn superior returns when they invest in ESG firms. A firm with a low ESG score could be of value for investors once a higher score materializes and the market prices in this new publicly available information. This would lead to price appreciation, which current holders would yield abnormal returns from, see Equation (H2) in Section 2. If this is true, then ESG score increases should lead to abnormal returns. We test this in the next section.

Before doing so, we conduct a robustness check to our findings in Figure 3. An alternative explanation to flexible investors being able to predict future ESG score increases could be that ESG score changes correlate with future cash flows as in Pedersen, Fitzgibbons and Pomorski (2020). This would mean that flexible investors are really able to predict future cash flow changes rather than changing ESG scores. We test this by exchanging deltas in ESG scores by deltas in dividend yields and re-estimate Equation (10). Figure I.1 in Appendix IA shows these results. We find that even though dividend yields tend to increase in the future when flexible ownership goes up, this effect is not significant. When strict ownership increases, dividend yields decrease significantly. However, the magnitude in either case is minor. Specifically, we estimate this effect to be 0.2 bp and -0.5 bp per p.p. of ownership under flexible and strict mandates, respectively. We therefore conclude that changes in ESG scores depict a skill by flexible investors that is unlikely to be explained by changes in dividend yields.

Strict investors' purchases of high ESG stocks from flexible investors

As a second step, we provide evidence on how flexible investors profit from sustainable investing. Our previous results show that flexible investors buy stocks, which later experience an increase in their ESG scores. Whilst we see for both types of investors that high ESG stocks rise in value when purchased, the strict investors' returns are not sustained. This suggests that flexible investors benefit from finding ESG firms which later increase in their score and by then selling them off, perhaps to the strict managers, which may be subject to a mandate to only invest in stocks with some of the highest ESG scores. To test this formally, we check whether strict investors indeed purchase high ESG firms from strict investors. This also serves as a test of where the

ESG demand arises from.

To do so we compare the change in strict ownership of two types of stocks. Specifically, we test if strict investors purchase more high ESG stocks from stocks mainly held by flexible investors versus high ESG stocks mainly held by other investors. In other words, we compute

$$Purchase_t^S = \Delta Ownership_t^{C^{HESG,HF}} - \Delta Ownership_t^{C^{HESG,LS}},$$

where $\Delta Ownership_t^{S^{HESG,HF}}$ represents the quarterly change in strict ownership share in the high ESG and high flexible ownership portfolio, and similarly for $\Delta Ownership_t^{S^{HESG,LF}}$, but with low flexible ownership. Hence, $Purchase_t^S$ documents how much more strict owners purchase their high ESG stocks from flexible investors compared to other investors.

We plot the time series of results in Figure 4. The results show that strict investors demand and purchase high ESG score stocks held by the flexible investors. They have increased their purchases since the onset of the financial crisis, and over time build up a significant positive cumulated ownership share.

Returns to ESG score changes

The previous sections show that flexible investors are able to predict ESG score increases and that strict investors purchase high ESG scores from flexible investors. We build on these findings and test how changes in ESG scores affect returns, or put differently, whether additional demand due to higher scores increases returns. We test this by regressing returns onto ESG score changes, whilst controlling for risk (Equation (H2) in Section 2).

As a standard panel-regression restricts each firm to have the same β, we also include

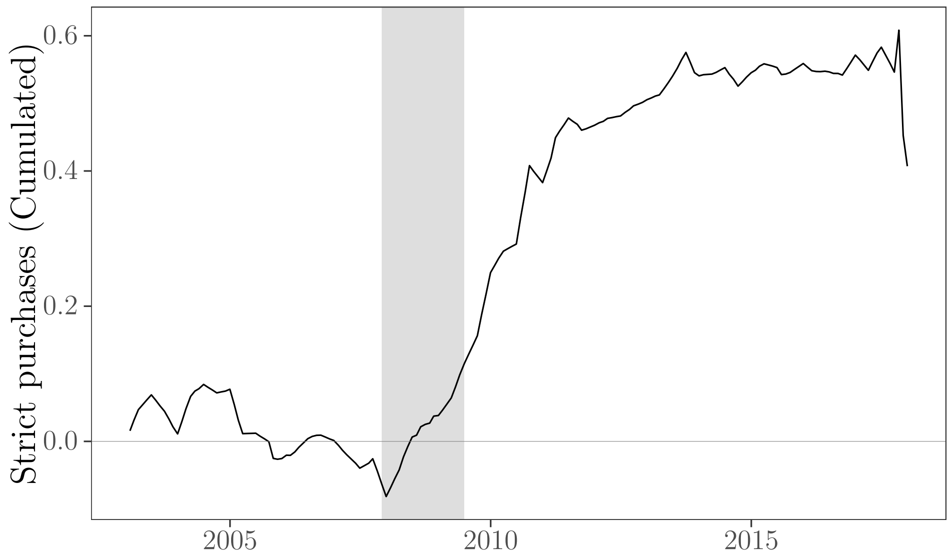


Figure 4: Flexible investors sell to strict investors

This figure shows the the difference in ownership shares in the high ESG ($HESG$) and high (HF) versus low (LF) flexible ownership portfolio with respect to the ownership share of strict investors (C). This means we first calculate the delta of strict ownership levels in the high ESG and high flexible ownership portfolio over time. In a second step, we subtract the delta of the strict ownership change in the high ESG and low flexible ownership portfolio over time. Thereby, a positive difference indicator at time t suggests that strict investors indeed buy high ESG and high return (see Table 2) stocks from flexible investors. This indicator is calculated on a quarterly basis.

a Fama and MacBeth (1973) specification, allowing the β estimates to vary at the firm level. We run

$$r_i^e = \gamma_0 + \gamma_{mkt}\hat{\beta}_{i,mkt} + \gamma_{smb}\hat{\beta}_{i,smb} + \gamma_{hml}\hat{\beta}_{i,hml} + \gamma_{mom}\hat{\beta}_{i,mom} + \gamma_{\Delta ESG_t}\Delta ESG_{i,t} + \epsilon_i \ , \quad (11)$$

where $\hat{\beta}_{i,f}$ are firm-specific β estimates onto the factor f. The change in ESG scores from the previous year to the current year t is denoted by $\Delta ESG_{i,t}$, where we have added a time subscript as we also use $\Delta ESG_{i,t-1}$ in the analysis, which in turn is the change from two years ago to the previous year $t-1$. The variables of r_i^e and ϵ_i are the excess and unexplained return for firm i. Table 6 shows the results.

We find that changes in ESG scores in the current year lead to positive excess

Table 6: Returns to ESG score increases in the cross-section

This table shows the results of a standard panel (Column (1) and (2)) as well as a Fama and MacBeth (1973) (Column (3) and (4)) cross-sectional regression approach including the changes in ESG scores on a yearly basis. The panel regression clusters standard errors on a firm level. The Fama and MacBeth (1973) approach first estimates $\hat{\beta}_{i,j}$ exposures for every firm i and every risk factor j. In a second step, we regress excess returns against risk exposures for every time instance t, while including the exposure to changes in ESG scores. Specifically, the factor of ΔESG_t depicts the change in the ESG score of the firm that occurs in the current year relative to the last year. In a second approach we use ΔESG_{t-1} instead, documenting the change in the ESG score of the firm from two years ago to last year. We document t-test statistics below the coefficients.

	Dependent variable:			
	r^e			
	(1)	(2)	(3)	(4)
ΔESG_t	0.008***		0.008***	
	t = 3.635		t = 3.200	
ΔESG_{t-1}		0.002		0.001
		t = 0.822		t = 0.620
mkt-rf	1.046***	1.045***		
	t = 136.945	t = 136.881		
hml	0.029**	0.029**		
	t = 2.439	t = 2.439		
smb	0.328***	0.329***		
	t = 26.590	t = 26.685		
mom	−0.144***	−0.144***		
	t = −20.856	t = −20.840		
$\hat{\beta}_{mkt}$			0.425	0.425
			t = 1.074	t = 1.077
$\hat{\beta}_{smb}$			−0.241	−0.241
			t = −1.138	t = −1.138
$\hat{\beta}_{hml}$			−0.135	−0.140
			t = −0.503	t = −0.523
$\hat{\beta}_{mom}$			−0.066	−0.069
			t = −0.134	t = −0.140
γ_0			0.736***	0.758***
			t = 4.638	t = 4.924
Observations	107,310	107,310	107,308	107,308
R^2	0.235	0.235	0.390	0.390
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Robustness test of returns to ESG score increases controlling for cash flow changes

This table shows the results of a Fama and MacBeth (1973) (Column (3) and (4)) cross-sectional regression approach including the changes in ESG scores on a yearly basis and the dividend return. The Fama and MacBeth (1973) approach first estimates $\hat{\beta}_{i,j}$ exposures for every firm i and every risk factor j. In a second step, we regress excess returns against risk exposures for every time instance t, while including the exposure to changes in ESG scores and dividends. Specifically, the factor of ΔESG depicts the change in the ESG score of the stock that occurs in the current year relative to the last year. d depicts the dividend return, and Δd is its yearly change. Column (1) documents results for the excess return r^e, and Columns (2) to (5) for $r^{e,exd}$, which is the excess return purely coming from price changes and not dividends. We document t-test statistics below the coefficients.

	Dependent variable:				
	r^e	$r^{e,exd}$			
	(1)	(2)	(3)	(4)	(5)
ΔESG	0.008***	0.009***		0.008***	0.009***
	t = 3.200	t = 3.491		t = 3.217	t = 3.544
Δd			−0.551***		−0.561***
			t = −4.148		t = −4.205
d				−0.887***	
				t = −11.722	
$\hat{\beta}_{mkt}$	0.425	0.460	0.440	0.428	0.439
	t = 1.074	t = 1.164	t = 1.110	t = 1.083	t = 1.104
$\hat{\beta}_{smb}$	−0.241	−0.195	−0.167	−0.230	−0.166
	t = −1.138	t = −0.923	t = −0.777	t = −1.090	t = −0.775
$\hat{\beta}_{hml}$	−0.135	−0.187	−0.218	−0.144	−0.212
	t = −0.503	t = −0.697	t = −0.817	t = −0.535	t = −0.791
$\hat{\beta}_{mom}$	−0.066	−0.062	−0.095	−0.058	−0.087
	t = −0.134	t = −0.126	t = −0.192	t = −0.118	t = −0.176
γ_0	0.736***	0.538***	0.565***	0.712***	0.545***
	t = 4.638	t = 3.381	t = 3.624	t = 4.578	t = 3.400
Observations	107,308	107,308	107,308	107,308	106,983
R^2	0.390	0.389	0.391	0.392	0.391
Note:					*p<0.1; **p<0.05; ***p<0.01

returns, see Columns (1) and (3). If a firm, for example, has an ESG score of 30, but gets a higher score during the current year of 80, our results indicate that the excess return increases by 40 bp, or equivalently 10 bp for a standard deviation move in the ESG score. We do not observe any effect for lagged ESG score changes (Columns (2) and (4)), suggesting that the returns are realised as the new score gets published.

One might be worried that returns could be confounded by dividend changes. That is, if dividend increases are associated with both a positive return and ESG changes, ESG changes could be picking up the return effect from the increase to cash flows. We control for this in Table 7. To be able to control for dividends we consider returns purely coming from price changes, so they do not include returns coming mechanically from dividend payments. Columns (1) and (2) show that the results for the total excess return and excess return excluding dividends are very similar; the ESG effect increases a little when excluding dividend returns. In Column (3) we see that changes in the dividend return from a year ago are associated with a negative return. This is similar when considering just the dividend return as in Column (4). Finally, in Column (5) we include both and see that the ESG effect remains constant. Table I.5 in the Appendix shows the same results but for total returns. These robustness results are very similar to our baseline results, except that the dividend effect is not significant. Our findings show that cash flow changes are not a confounding factor for returns arising from changes to ESG scores.

These findings shed light on how flexible investors profit from sustainable investing (Equation (H2) in Section 2). In a nutshell, flexible investors are able to predict positive ESG score changes (Figure 3) and later sell higher ESG score firms to strict investors (Figure 4). The additional demand due to higher scores leads to higher returns (Table 6), which the flexible investors capitalize on (Table 2).

4.3 Sentiment in sustainable investing

We go on to test our third hypothesis that the ESG premium can be influenced by climate sentiment, an indicator for the relevance of environmental concerns in the market. As documented in Equation (H3) in the theory section, unexpected increases in sustainability sentiment can lead to a positive ESG return even though the unconditional ESG premium is negative. This can help explain the positive returns earned by flexible investors' sustainable investments.

To test for the effects of climate sentiment, we consider the returns of a long-short equity portfolio, which goes long in high ESG firms and short in low ESG firms. The climate sentiment measure is developed from Google searches for 'Climate change' and is explained in Section 3. When conducting our analysis, we compute

$$LS_t^I = r_t^{HESG,I} - r_t^{LESG,I} = \alpha + \gamma\ Sentiment_t + Controls_t + \epsilon_t\ , \tag{12}$$

where $r_t^{HESG,I}$ ($r_t^{LESG,I}$) depicts the high (low) ESG portfolio return of investor I at time t. The abnormal return is denoted by α. The climate sentiment at time t and γ, the loading on this proxy, are depicted by $\gamma\ Sentiment_t$. Moreover, the controls always include the factors f_j together with their loadings β_j for all J factors, and sometimes a crisis indicator $\beta_{\mathbb{1}} \mathbb{1}_{NBER}$, which equals 1 in a crisis and 0 otherwise. Finally, ϵ_t is the unexplained return.

This is our empirical specification of Equation (H3), where α is the abnormal return due to the greenness of the firm, i.e. the greenness of the stock, multiplied by the return on the ESG portfolio $g\mu_g$. The notation of $\gamma Sentiment$ is the return from the preference shock, which also scales with the greenness of the firm gf_g. The variable f is the excess return on the factor (r_M^e in the theory specification). Hence, we expect γ to vary according to the greenness of the firm, and be especially pronounced in our factor as we capture the difference in greenness of the high ESG and low ESG firms.

Table 8 shows the results. Indeed, the results confirm that climate sentiment positively affects the returns to sustainable investing of the flexible investor (Columns (1) to (3)), as well as for the general investor (Columns (4) to (6)).

In terms of magnitude, we see that a standard deviation shock to *Climate sentiment* is associated with a realized abnormal return from sustainable investing of 6 bp and 4 bp for the ESG factor in general. These estimates remain the same if we control for the crisis effects, however different investors performed quite differently during the crisis, as the estimates rise for the flexible investors, but fall for the general factor.

As for robustness, we see that the results are not driven by the crisis, as it is equally strong outside the crisis, as seen by the $Climate : NBER_{false}$ interaction term. The results are consistent across the different asset pricing models: CAPM, Fama-French, and Carhart. The results are also robust to creating the factor based on searches on 'Climate' and to using just the Google searches coming from the news part. Lastly, the results are robust to using the changes in *Climate sentiment* instead of the AR(1) residual, as well as a non-seasonally adjusted time series.

Additionally, Table I.6 in Appendix IF confirms that *Climate sentiment* increases the difference in the returns earned by sustainable investing across the two investor types. It does so, as we see in line with theory that *Climate sentiment* drives the returns to sustainable investing for the strict investor less.

These results strengthen the idea that climate sentiment is a force that affects ESG stock valuations. Doing so, it helps explain the difference in returns to sustainable investing returns across the two investor types. Additionally, the results suggest that the value of predicting ESG scores might be higher in a period of high noise and uncertainty as, for example, the financial crisis.

As robustness, we test the general ESG factor against other sentiment measures,

Table 8: Sustainability sentiment from *Climate change* Google hits

In this table we test how climate sentiment explains abnormal returns on the sustainability strategy. The dependent variable for the first three columns is the return of a value-weighted long-short portfolio that goes long in the top quartile ESG firms with the top quartile of high flexible ownership and short in firms with low ESG scores but also top quartile of flexible ownership. The fourth to sixth column's dependent variable is constructed by the simple value-weighted long-short strategy that goes long in highest decile and short in lowest decile ESG firms. We test for sentiment in these portfolios using a proxy for climate salience and economic sentiment. The measures we use is the surprise innovations in the Google Hits on the term 'Climate change', as described in Section 3, and the $NBER$ recession indicator, which equals 1 in a crisis and 0 otherwise. We control for risk-factors of the Carhart four-factor model, though results are similar for the CAPM and Fama-French three-factor models. Lastly, we control for autocorrelation and heteroscedasticity in the residuals using Newey and West (1987) standard errors with 12 months lag.

	Dependent variable:					
	ESG Long-short return for:					
	Flexible (LS_t^F)			Factor (LS_t)		
	(1)	(2)	(3)	(4)	(5)	(6)
Climate sentiment	0.060***	0.060***		0.039**	0.038*	
	t = 3.120	t = 2.942		t = 1.992	t = 1.948	
α	0.396***			0.156		
	t = 2.692			t = 1.127		
Climate:NBER			0.331***			−0.190*
			t = 2.907			t = −1.836
Climate:NBER$_{False}$			0.055**			0.041**
			t = 2.416			t = 2.103
NBER		1.108**	1.214***		0.440	0.303
		t = 2.468	t = 3.280		t = 1.092	t = 0.680
NBER$_{False}$		0.282	0.305*		0.111	0.096
		t = 1.523	t = 1.668		t = 0.729	t = 0.645
mkt - rf	−0.036	−0.009	−0.029	−0.153***	−0.142**	−0.128**
	t = −0.625	t = −0.110	t = −0.379	t = −2.792	t = −2.572	t = −2.548
smb	−0.353***	−0.380***	−0.373***	−0.472***	−0.483***	−0.491***
	t = −3.288	t = −3.077	t = −3.209	t = −6.441	t = −6.542	t = −6.712
hml	0.115	0.131	0.165*	−0.048	0.042	0.069
	t = 1.438	t = 1.458	t = 1.916	t = −0.562	t = −0.463	t = −0.794
mom	0.139***	0.157***	0.147***	0.046**	0.053	0.058*
	t = 3.636	t = 3.116	t = 2.949	t = 1.738	t = 1.573	t = 1.970
Observations	155	155	155	156	156	156
R^2	0.236	0.268	0.281	0.453	0.458	0.467
Note:						*p<0.1; **p<0.05; ***p<0.01

including the highly complex Engle et al. (2020) climate change news measure, the Baker and Wurgler (2006) economic sentiment indicator, and the price dividend ratio as an index of optimism in the economy. The results are shown in Appendix IE. First, we see in that the Engle et al. (2020) climate change news associates with 80 bp of abnormal returns in periods of more than average amounts of negaive news. Second, returns on the ESG factor are higher outside of high sentiment periods under the Baker and Wurgler (2006) measure, indicating that sustainability sentiment is not correlated with general business sentiment and especially strong in recessions. Third, we find that a falling price dividend ratio increases the returns on the ESG factor and thereby confirm that sustainability sentiment seems negatively correlated with general business sentiment.

4.4 Stock Holder Prediction versus Activism

To test whether the outperformance of flexible investors is due to a prediction ability or extra monitoring I use exogenous variation in investor holdings arising from stock exclusions from the leading ESG indices. The idea behind this approach, which we will label as Instrumented Portfolios, is simple. In asset pricing we are interested in how accounting variables of a firm affects its cost of capital. However, these variables are endogenously decided by the firm and the analysis is prone to the case that there may be a third, potentially unobserved, variable that affects both the accounting variable and the cost of capital, such as financial frictions like illiquidity drying up certain markets making firms invest less and raising their cost of equity. This is where Instrumented Portfolios comes in as by using an exogenous change to a specific firm variable we circumvent worries of confounding third variables. Intrumented Portfolios then sorts portfolios on these exogenous changes and considers the difference in the resulting cost of equity. Another benefit of this method is that it can be extended beyond expected returns to other firm variables of interest, as for example changes in ESG scores.

The reason why we can use Instrumented Portfolios to test for monitoring or prediction is that purchases done by the flexible investor out of liquidity provision is different to purchases done because the investor believes the firm's ESG score to increase. In contrast, no matter the reason of purchase an investor can still pursue its monitoring efforts. Hence, if we still see the same effects from our Instrumented Portfolios relative to our original Portfolios, the effect is likely to be from monitoring, and alternatively from prediction.

A Test of Prediction or Monitoring. Specifically, we are interested in how investor type ownership affects returns and ESG scores, and as an instrument we will use exclusions of a stock from an ESG Index. In this case either the MSCI USA ESG Screened Index or the FTSE4Good index, where we get the holdings of the primary ETFs who follow these indeces (iShares MSCI USA ESG Screened and Vanguard FTSE Social Index Fund) from the S12 mutual fund holdings dataset. These two funds represents the two largest ESG index funds.

We use these exclusions to instrument for fund holdings. Hence, for each firm we compute the changes in their holdings happening at the same time as the index exclusion. Using our categorization of flexible and strict investors we summarize the purchases of flexible and strict investors and then use this group purchase measure to split the stocks into four portfolios for each investor type dependent on their ownership share. We always lag the firm variable, holdings in this case, before regressing an outcome variable on the portfolios. In the baseline case we keep their previous purchases up to time $t-1$, as would be normally done, however our coming results are robust to just considering the outcome variables for purchases in the previous period.

Doing this exercise for both flexible and strict investors, and comparing the difference, allows us to control for the fact that firms that are excluded from the ESG index may be trying to re-enter the index by increasing their ESG score, because this effect would impact firms owned by the strict and flexible investors equally.

Validity of Social Index Exclusions as an Instrument. The initial step in IP is to ensure instrument validity. This first of all requires the instrument to satisfy the exclusion restriction, meaning that the instrument does not effect the outcome variable directly, but only through the firm variable, which in our case is investor type ownership. And secondly, we need to ensure that the instrument is not weak, which we do below in Table 9. Here we see in Panel A that strict investors tend to sell stocks, which leave the social indices. Where our baseline measure is giving in column (1) where we take the changes in share numbers multiplied by the value of those shares in the previous period to not have any effects coming directly from price changes. Column (2) shows the effects purely for the share changes, and column (3) is similar to column (1) but allowing the prices to update. As our F-statistics in column (1) to (2) are 23 and 29 respectively we can reject that the instruments are weak and we can proceed to the next step. Panel B shows the effect for both strict and flexible investors separately and we see that each group generally sells, but the strict investor group sells the most.

Table 9: ESG Index Exclusions and Flexible Ownership: First stage of Instrumented Portfolios

This table shows tests the validity of our instrument of ESG index exclusions on investor holdership shares. Column (1) regresses the change to investor j's ownership of excluded stocks i keeping the value constant. Column (2) considers purely changes in share number and Column (3) looks at the change in investor value without keeping the value constant. In **Panel A**, for each column, the dependent variable is regressed on a constant and a dummy that is one when stock i is excluded from one of the ESG indices at time t interacted with Strict_j, which is a dummy that is one if investor j is a strict investor. In **Panel B**, for each column, the dependent variable is regressed on a constant and a dummy that is one when stock i is excluded from one of the ESG indices at time t interacted with both Strict_j and Flexible_j, which are dummies that are one if investor j is a strict or flexible investor respectively. The time step is in quarters. We use the exclusions from the ESG ETF's of iShares MSCI USA ESG Screened and Vanguard FTSE Social Index Fund, which are the primary funds following the ESG indices to identify the index exclusions. We show the F-statistic of our test at the bottom of the panels in bold.

Dependent Variable:	$\Delta\text{Shares}_{ijt} \times P_{i,t-1}$ (USD 1m)	$\Delta\text{Shares}_{ijt}$	ΔOwnership (USD 1m)$_{ijt}$
Panel A: Strict Ownership	(1)	(2)	(3)
Excluded_{it}:Strict_j	-11.0^{***}	$-197{,}658^{***}$	-2.78^{*}
	t = −4.8	t = −5.4	t = −2.0
Constant	8.2^{***}	$70{,}526^{***}$	−0.71
	t = 5.7	t = 3.0	t = −0.8
Observations	8,786	8,786	8,786
R^2	0.003	0.003	0.0004
F Statistic	**22.7*****	**28.8*****	**3.8***
Panel B: Strict and Flexible	(1)	(2)	(3)
Excluded_{it}:Strict_j	-12.5^{***}	$-220{,}832^{***}$	-2.84^{*}
	t = −5.2	t = −5.8	t = −1.9
Excluded_{it}:Flexible_j	-9.7^{**}	$-154{,}402^{**}$	−0.40
	t = −2.4	t = −2.4	t = −0.2
Constant	9.7^{***}	$93{,}699^{***}$	−0.65
	t = 6.2	t = 3.7	t = −0.7
Observations	8,786	8,786	8,786
R^2	0.003	0.004	0.0004
F Statistic	**14.2*****	**17.3*****	**1.9**

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

Instrumented Portfolio Results. We display the IP results for returns in Table 10 and changes to ESG scores in Table 11. Here we see that the returns of the flexible investor tends to be lower than for the strict investor, especially considering the spread between the high and low portfolios. This is also the case for the CAPM alpha, Carhart alpha, and controlling for the changes to the ESG score. This suggests that the original results do not derive from monitoring, however we additionally test for changes to ESG scores in the next table. Note that each cell is a different regression and hence the number of observations and R^2 differs across each and is not given for ease of clarity.

Table 11 displays the changes in ESG to the same stocks as before. As the portfolios always are lagged, we first see how ESG score develops over the first year in the top row and the second year in the bottom row as robustness, and we find that they evolve very similarly across the two investor types for this kind of forced purchases.

Table 10: Returns to Instrumented Portfolios across Investor Types

This table shows the results on returns from our instrumented portfolios. For each test we use the change in holdings for the flexible or strict investor arising exogenously from the exclusion of stocks from the leading ESG indices. We them sort and split the stocks cross-sectionally into quartiles dependent on their instrumented ownership for each investor type. Columns (1) and (2) shows results for portfolios with the highest degree of flexible and strict ownership respectively, and Columns (3) and (4) shows results for portfolios with the lowest degree of flexible and strict ownership respectively. The first row of results show the excess returns of each of the four portfolios. The following rows show results for the CAPM alpha, Carhart alpha, and Carhart alpha controlling for changes in the ESG scores respectively. The portfolios are sorted in quartiles and always lagged three months (one quarter) with respect to the returns. The returns are monthly and in percentages. We use the exclusions from the ESG ETF's of iShares MSCI USA ESG Screened and Vanguard FTSE Social Index Fund, which are the primary funds following the ESG indices to identify the index exclusions. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months.

Portfolio:	Flexible High	Strict High	Flexible Low	Strict Low
	(1)	(2)	(3)	(4)
Excess Returns	-0.145^{***}	0.842^{***}	0.868^{***}	-0.007
	t = -4.0	t = 17.8	t = 19.4	t = -0.2
α (CAPM)	-0.493^{***}	0.389^{***}	0.256^{***}	-0.255^{***}
	t = -15.3	t = 11.8	t = 9.0	t = -9.1
α (Carhart)	-0.572^{***}	0.716^{***}	0.236^{***}	-0.228^{***}
	t = -16.7	t = 19.1	t = 7.3	t = -7.2
α (Carhart + ΔESG)	-1.095^{***}	1.298^{***}	0.478^{***}	-0.434^{***}
	t = -15.0	t = 17.7	t = 6.2	t = -5.6
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 11: ESG Changes from Instrumented Portfolios across Investor Types

This table shows the results on changes to ESG scores from our instrumented portfolios. For each test we use the change in holdings for the flexible or strict investor arising exogenously from the exclusion of stocks from the leading ESG indices. We them sort and split the stocks cross-sectionally into quartiles dependent on their instrumented ownership for each investor type. Columns (1) and (2) shows results for portfolios with the highest degree of flexible and strict ownership respectively, and Columns (3) and (4) shows results for portfolios with the lowest degree of flexible and strict ownership respectively. The first row of results show the changes in ESG scores in the year following the portfolio holdings. The following row shows results for the year after that. The portfolios are sorted in quartiles and always lagged three months (one quarter) with respect to the returns. The ESG changes are in changes in fractions, for example 0.05 represents an improvement of 5 percentage-points. We use the exclusions from the ESG ETF's of iShares MSCI USA ESG Screened and Vanguard FTSE Social Index Fund, which are the primary funds following the ESG indices to identify the index exclusions. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months.

Portfolio:	Flexible High	Strict High	Flexible Low	Strict Low
	(1)	(2)	(3)	(4)
Δ ESG$_t$	0.050***	0.044***	0.025***	0.029***
	t = 12.7	t = 12.3	t = 16.2	t = 13.2
Δ ESG$_{t+1}$	0.067***	0.069***	0.034***	0.038***
	t = 46.1	t = 48.9	t = 56.2	t = 49.8
Note:				*p<0.1; **p<0.05; ***p<0.01

5 Interpretation of magnitudes

We can now get a sense of magnitudes from the returns to sustainable investing with skill. First, we can get a sense of how important skills are in explaining the returns to sustainable investing for the flexible investor. We isolate the skill effect by evaluating Equation (H2) from Section 2 using parameters estimated in Section 4, and compare it to the total returns achieved by the flexible investors sustainable investments. Additionally, we conduct a similar exercise for the difference between returns for different investor types.

We start off by quantifying the skill channel. Using Equation (H2) and subtracting the returns from the risk factors we get the abnormal return to sustainable investing to be

$$\alpha_n = g_n\mu_g + \tilde{g}_n\frac{\bar{d}}{\gamma} + \epsilon, \tag{13}$$

where $g_n\mu_g$ is the return from the ESG preferences for stock n, and $\tilde{g}_n\bar{d}/\gamma$ is the return from predicting ESG score changes $\tilde{g}_n$.

The first term is the return arising from the ESG factor. To see its effect we turn to Table 1 in Section 4. There, we see that we cannot reject that these returns are zero, and hence we use this estimate for the rest of the section. The second term is the returns from predicting the ESG score. We estimate this from how well the investors predict ESG scores $\tilde{g}_n$ (Figure 3) multiplied by the returns to increases in ESG scores $\bar{d}/\gamma$ (Table 6).[15] Hence, we get from our estimates that the alpha achieved from ESG

[15]To be able to do so, we make the implicit assumption that the investors own 100% of the stocks they invest in. This is of course a simplifying assumption. If we look at the ownership figure in the internet appendix we can see that they own 20% of all the ESG stocks. So the actual average ownership percentage of the ESG stocks they invest in, will be somewhere from 20 to 100%, however it is likely to be closer to 100 than 20% as there are many stocks they do not invest in.

skill (E) for the flexible investor is

$$\alpha_E^F = g_n \mu_g + \tilde{g}_n \frac{\bar{d}}{\gamma} + \epsilon = 0 + 17\Delta ESG \times 0.8 \frac{\text{bp}}{\Delta ESG} = 13.6 \text{ bp}.$$

When comparing this to the total abnormal return achieved by the flexible investor α_T^F (Table 2), we see that skill makes up 35%. The residual return is due to channels such as sentiment and other sources of skill than predicting ESG scores.

One way to control for the sentiment effect is to consider the difference in returns to sustainable investing for the two types. Here, we see that skill explains 51% of the difference. In summary, these results suggest that the skill of predicting ESG scores is economically an important driver for the differing returns to sustainable investing, especially when controlling for sentiment.

5.1 Discussion of difference in magnitudes

In terms of magnitude we find that the flexible investors earn 26 bp per month higher returns from sustainable investments than their strict mandate counterparts. This size seems reasonable as Hong and Kacperczyk (2009) find in their study that Sin stocks earn the same 26 bp higher returns relative to comparable stocks in their specification with the same risk model as ours. Where as our returns vary from 26 to 28 bp dependent on the model, theirs vary between 25 and 30 bp.

Another way to think about the magnitude is to consider what size of demand and price elasticity is needed to achieve this effect. United Nations Principles for Responsible Investing (UNPRI) write in their report that the amount of assets invested under responsible investing principles exceeded USD 25 trillion in 2021. As this corresponds to 25% of the global asset management industry, it is a significant fraction.[16]

[16]The assets managed globally is estimated by BCG as USD 100 trillion by 2020 (https://web-assets.bcg.com/79/bf/d1d361854084a9624a0cbce3bf07/

To get the total impact on returns we lastly need elasticity estimates. Estimates that are least likely to suffer from bias are from the index-inclusion literature such as Chang, Hong and Liskovich (2015). They find that price elasticity, meaning how much the price is affected by demand in percentage terms, is around 1. Specifically, they find a price elasticity between 0.39 and 1.46, depending on whether you take passive assets following the index or all assets benchmarked to the index. With an estimate of 1 we would only need a demand change of 3.1% to get an annual return difference of 3.1%, which is equal to 26 bp per month. Or 5% to 1.2% demand change for Chang, Hong and Liskovich (2015)'s two individual estimates. However, this also means that if occurring continuously throughout the year, for example every month, then the demand increase has to be even lower. Specifically in this example a 12th of the conservative 5% is 0.4%.

Additionally, we argue that indeed only 51% of the difference to sustainable investing between investment mandates is due to the ESG improvement strategy and hence the demand needed is only 1.6%. These results are further supported by Koijen and Yogo (2019), Koijen, Richmond and Yogo (2020), and Gabaix and Koijen (2021) who find the stock market to be relatively inelastic and the demand elasticity of institutional investors to be around 1. Additionally Koijen, Richmond and Yogo (2020) find that if all large active investors changed their demand to holding the market, the market would experience a repricing of 18%. A similar size is found for small or large passive investors. These elasticity estimates suggest that the demand needed is within what could reasonably be expected making the magnitude of the return to sustainable investing for flexible investors sensible.

bcg-global-asset-management-2021-jul-2021.pdf).

Consistent with the 25% demand following ESG principles measured by the UNPRI, Berk and van Binsbergen (2021) write that the percent of wealth owned by ESG investors is between 2 and 33%, so even the most conservative estimates are several trillion USD.

6 Cost and benefit to sustainable investing

Taking a step back, this section gives an estimate of the welfare effects of sustainable investing. Specifically, we estimate the cumulated cost of sustainable investing incurred by the strict investor due to his ESG mandate.[17] We go on to compare the cost estimate to an estimate of the benefit gained by sustainable investing over the same period. The section finishes by giving policy recommendations based on these welfare considerations.

6.1 The cost to strict mandate investing: Costly mandates

Our results allow us to estimate the cumulated cost C to strict ESG investing. We estimate the yearly cost c_t due to strict mandates simply by combining the difference in alphas to sustainable investing times the strict investors capital invested in sustainable assets at time t, $K^g_{t,s}$:[18]

$$C = \sum_t c_t = \sum_t \Delta\alpha K^g_{t,s} \tag{14}$$

We plot the cumulated cost in Figure 5. We see that the cumulated costs to sustainable investing has been increasing over time. This is because sustainable assets held by strict investors grew before the crisis and then again gradually after 2010. Over our sample period, the cumulated cost to sustainable investing exceeds USD 400 billion. This is equivalent to 1.54 times Apple's 2020 revenue.

[17]Our analysis complements He and Xiong (2013) who show there may be gains from limiting an investment managers mandate due to decreasing agency costs. We show that even taking these gains into account, investing with a strict ESG mandate leaves you worse off.

[18]In our case $K^g = 1/4K$ from how we construct our sorts.

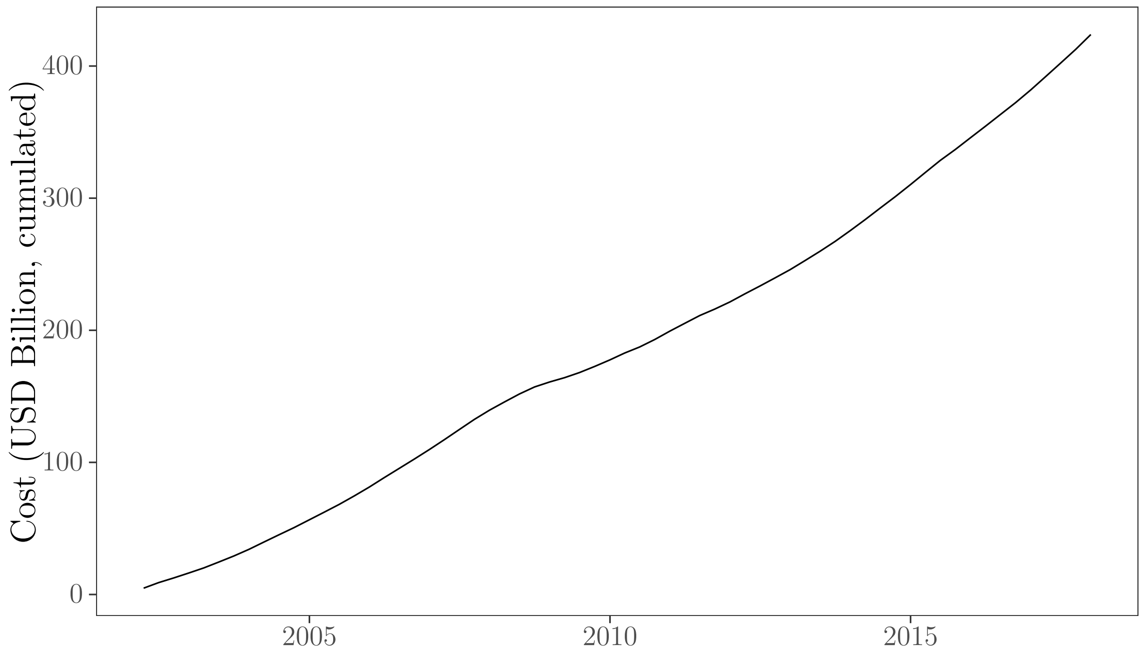


Figure 5: Cost to sustainable investing

This figure plots the cumulated cost to sustainable investing estimated using Equation $C = \sum_t c_t = \sum_t \Delta\alpha K^g_{t,s}$. Hence, it exploits our estimates for the difference in returns across investor types to sustainable investing together with the AUM of sustainable investing for the strict investor.

6.2 The benefit to strict mandate investment: Reduced carbon emissions

After considering the cost, we can also consider the benefit (b) for the strict investor. As the strict investor values ESG stocks, it incentivizes companies to improve their ESG score. As we see that flexible investors are able to purchase these the cumulated benefit from strict ESG investing is hence the improved ESG score (Δg) incentivized times the capital that is improved, which in our case is the capital owned by the flexible investors in high ESG stocks at time t[19]

[19] This is equivalent to the welfare effect from Pástor, Stambaugh and Taylor (2021)'s second channel.

$$B = \sum_t b_t = \sum_t \Delta g K^g_{t,f}. \tag{15}$$

As ESG scores and CO_2 emissions are related we can show the benefit in terms of reduced CO_2 emissions from strict mandates. We show this in Figure 6. We observe that CO_2 savings have been growing over time. In addition, the rate of CO_2 savings really picked up after the financial crisis and in the latter part of the previous decade as the sustainable investments of flexible investors grew. Over our sample period, more than a billion tons of CO_2 have been saved. This is equivalent to 59 times of what Apple has emitted in 2020 and 20% of what the US emits per year.[20] This also means that CO_2 emissions would be 11% higher had it not been for sustainable investing.[21]

Table 12 documents the relationship between ESG scores and CO_2 emissions used for the above calculation.[22] We find that an increase in the ESG score by 1 level decreases the CO_2 intensity by 0.1 bp. This is equivalent to 10 tons of CO_2 emissions per USD one million of revenue. When including firm fixed effects to only consider variation between firms, the effect is similar at 8 tons CO_2 emissions per USD one million of revenue. This finding is statistically significant and robust to clustering by time and firm.

Also note that reducing CO_2 intensity is impactful because not only does a firm reduce CO_2 emissions this year, but every following year as well. In this regard it is similar to the effect of compounding returns. This effect is the same for the costs, and both are not shown in the figures.

[20]Numbers from Apple's climate progress report for the 2020 fiscal year (https://www.apple.com/environment/pdf/Apple_Environmental_Progress_Report_2021.pdf). Numbers for the US are taken from the World Bank (https://data.worldbank.org/indicator/EN.ATM.CO2E.KT?locations=US)

[21]The carbon savings in 2018 were 561 million tons and the total US emissions in 2018 were 4,981 million tons.

[22]We retrieve CO_2 emissions data from Refinitiv, which includes CO_2 equivalents from other green house gas emissions.

One can also consider the benefits in USD dollars. An estimate of the negative externality CO_2 emissions produce is the price of CO_2 emissions as seen in the European Union Emissions Trading System, the world's largest cap and trade greenhouse gas emissions market. Allowances for CO_2 emissions are first allocated considering EU directives for the maximum amount of greenhouse gases that can be emitted. Allowances for CO_2 emissions are then auctioned and traded. Based on CO_2 emission prices, reducing emissions by 1 billion CO_2 has reduced the negative externality by USD 9 to 69 billion.[23]

All in all, having reduced the emission equivalent of USD 9 to 69 billion, or 59 times

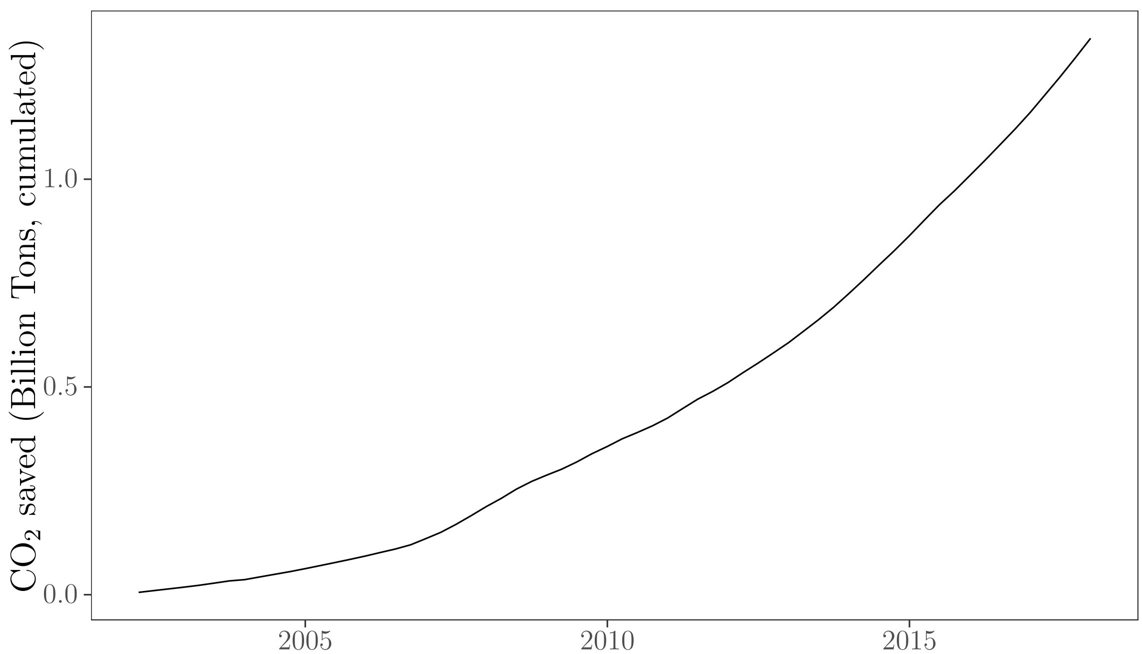


Figure 6: Benefit to sustainable investing

This figure plots the cumulated benefit to sustainable investing by estimating $B = \sum_t b_t = \sum_t \Delta g K^g_{t,f}$. Hence, it exploits our estimates for the increased greenness induced by the strict investors' sustainable investing demand, which the flexible investors exploit in their portfolio selection within sustainable investments.

[23]Calculated as plus minus 1 standard deviation from the average Carbon emissions allowance log price from https://tradingeconomics.com/commodity/carbon. Exchange rate data is from Morningstar and the data is available from April 22, 2005 until March 1, 2022.

Table 12: CO_2 change per ESG

This table shows how CO_2 intensities relate to ESG scores. To show this, we regress a firms' CO_2 intensity on its ESG score. The observations are updated on a yearly basis as ESG scores change once a year. CO_2 intensity means million tons of CO_2 per million revenues and is shown in basis points (bp). Standard errors are clustered by firm and their associated t statistics are shown below. The mean of the regressand and the standard deviation of the regressor are also displayed.

	Dependent variable:			
	CO_2 intensity (bp) (Mean is 6.5)			
	(1)	(2)	(3)	(4)
ESG	-0.10^{***}	-0.10^{***}	-0.10^{*}	-0.08^{**}
(SD is 29.71)	t = −5.02	t = −4.59	t = −1.72	t = −2.06
Constant	14.62^{***}	14.62^{***}	14.62^{***}	12.06^{***}
	t = 8.77	t = 7.77	t = 2.92	t = 3.88
Model	Pooled	Pooled	Pooled	Between
Clustering	None	Time	Firm	None
Observations	3,125	3,125	3,125	499
R^2	0.01	0.01	0.01	0.01
Note:			*p<0.1; **p<0.05; ***p<0.01	

Apple's emissions, for the cost of USD 424 billion, or 1.54 times Apple's revenues, under our modelling framework, it seems like a promising channel for reducing emissions, but also not as efficient in its current form compared to more direct approaches such as carbon capture.[24]

6.3 Policy recommendations

What would the policy recommendation be based on these welfare results? Based on our framework, it is not likely that policy can affect the benefit side. However, they

[24] Carbon capture costs are estimated at USD 52-60 per ton (USD 70-80 bil for 1.34 bil tons CO_2) by the following paper https://royalsocietypublishing.org/doi/10.1098/rsfs.2019.0065.

may be able to affect the costs through how ESG ratings are defined. Currently, the strict ESG mandates mean that the investors cannot invest in the companies which will have a positive climate impact in the future. Instead, the mandates based on current ESG ratings lead them to purchase higher priced high ESG companies, and hence losing out on positive returns. Today, ESG ratings are calculated based on current factors as, for example, carbon intensity. Were they instead designed to be forward looking, it would mean that from the beginning investors could within their mandate purchase the stocks with impact, and would no longer lose out on the positive returns associated with increasing ESG scores. As a consequence, this would reduce the cost of sustainable investing.

This is in line with the article *The meaning of green* in The Economist published Jan 8, 2022. The article argues that the new EU green investment labelling system, the Taxonomy Complementary Climate Delegated Act, is flawed. This is because the simple labelling may lead to funds excluding dirty assets, instead of buying dirty companies and managing down their emissions. This issue arises because the labels are static. Their solution is to make it easier for investors to track the CO_2 emissions, especially those that have the capacity to reduce their emissions greatly. This will require new disclosure. There has been set up a new global green-disclosure body, The International Sustainability Standards Board, but it has yet to publish their norms for disclosure. However, it is not clear how long this will take or if they will even go away from this static view of ESG scores.

A dynamic view is also in line with Oehmke and Opp (2020) and Green and Roth (2021). The authors propose that for investors to have an impact on firm behaviour they need to have broad mandates and invest compared to a new ESG metric that takes into account the changes in emissions of the firm from the investors' engagements. This further relates to the voice vs. exit discussion, and would favour voice over exit

(Broccardo, Hart and Zingales, 2020).

7 Conclusion

We document a large difference in the returns to sustainable investing across investors. A closer look reveals that this discrepancy arises from investors with a strict mandate being unable to invest into stocks with expected ESG score increases. This implies that strict mandate investors could potentially also see the same investment opportunities, but cannot exploit them due to their strict mandates. In the time series we see that growing climate sentiment boosts the returns to sustainable investing.

Interest in sustainable investing has been accelerating over the last decades, and recent government and institutional changes have only increased the pace of this growth. As more and more assets are invested under sustainable mandates, understanding this shift in preferences becomes increasingly important. A consequence of this is a growing cost to sustainable investing with a strict mandate.

Our findings have real implications for investors and the economy as they show that sustainability is positively priced. From a firm's point of view, our findings affect their cost of capital. It decreases for sustainable firms. However, this does not seem to be the most impactful way towards a greener future. Instead, our results suggest that an additional sustainability demand by investors creates an incentive for firms to become greener. This is ultimately good news, as it both leads to higher returns for the investor, as well as a higher level of sustainability for the economy.

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Appendices

A ESG mandates across investor types

In this appendix we consider how strict and flexible investor types conduct their investments related to ESG.

ESG commitments

We follow Hong and Kacperczyk (2009) in the way we split investors. They argue that there is a clear societal norm against ethically low stocks, and hence that many may not want to support companies by investing in their stocks. Anecdotal evidence of this is the adoption of socially responsible investing (SRI) for managers of institutions such as pension funds and endowments. Since their paper, the signatories of the UN's principles of responsible investing (PRI) has had an enormous growth, growing from USD 20 trillion in 2009 to 120 trillion in 2021, and the principles has evolved to focus on incorporating ESG principles in the signatories investments.[25]

In Table 13 we display the largest strict and flexible investors and their ESG commitments as according to whether they have signed the UN's PRI. We can see that seven out of the nine strict investors have signed the principles of rosponsible investing. The two that have not are State Farm automotive insurers and Teachers advisors, two highly social companies that are likely to experience social pressures. For the flexible investors, the signing rate drops to four out of six, and one of the signatories, Vanguard, mainly provides index funds with no sustainable investment mandates. In addition to having fewer signatories, flexible investors also tend to sign later than the strict, a difference of two years, showing that flexible investors experience less pressure to follow

[25] See the UN PRI's Signatory relationship presentation of 2021 Q4 https://www.unpri.org/download?ac=14962

sustainable investment conventions.

Table 13: Investor types' ESG commitments

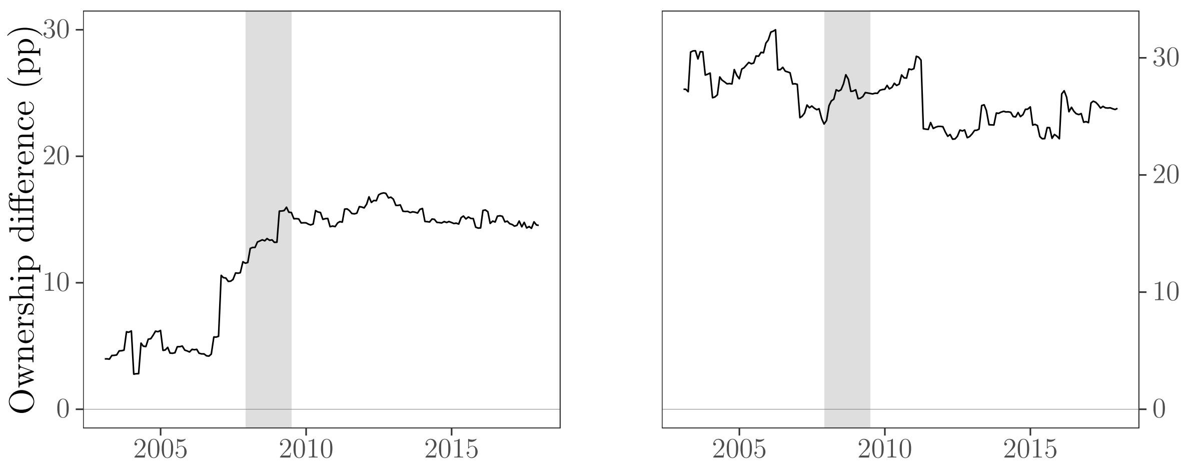
This table displays strict and flexible investors. Within each type, the three largest investors of each subtype are shown. For these investors it is shown whether they have signed UN's principles of responsible investing (PRI), and, if they have, since when.

Type	Subtype	Name	AUM (USD B)	PRI signatory	Since
strict	1	STATE STR	1202	✓	3 May 2012
strict	1	NORTHERN TRUST	386	✓	17 Nov 2009
strict	1	BANK OF AMERICA	367	✓	21 Nov 2014
strict	2	PRINCIPAL FINANCIAL	103	✓	8 Dec 2010
strict	2	STATE FARM AUTO INS	78	✗	-
strict	2	TEACHERS ADVR	75	✗	-
strict	5	BLACKROCK	2061	✓	7 Oct 2008
strict	5	JPMORGAN CHASE	426	✓	15 Feb 2007
strict	5	WELLINGTON	420	✓	26 Apr 2012
flexible	3	COLLEGE RETIRE EQTY	146	✗	-
flexible	3	ALLIANZ	49	✓	23 Apr 2007
flexible	3	GARTMORE MUT FUND	26	✗	-
flexible	4	VANGUARD GROUP	2207	✓	6 Nov 2014
flexible	4	FIDELITY	752	✓	23 Feb 2017
flexible	4	T. ROWE PRICE	586	✓	28 Jul 2010

Strictness

To get an understanding of how strict investors implement their preferences, we first plot different portfolios of high and low degrees of strict and flexible ownerships with high and low ESG firms in Figure 7. This gives us an idea about the heterogeneity of ESG preferences within the two investor types. The idea is that if stock exclusion is prevalent for an investor type, you will see a large ownership difference between the stocks mostly held by the investor type and the stocks held the least by that investor type. As an example if the investor type on average held the market, but 50% exclude stock A due to ESG concerns, you would see the ownership difference being 50% of the market ownership share. On the other hand if they do not exclude any stocks, the ownership difference would be 0%. This allows us to measure the 'strictness' of our investor types.

Figure 7 shows our strictness measure for the strict and flexible investors over time. The results show that our strict investor type is 6 times as strict in the beginning of the same dropping to twice as strict later in the sample. We the big change for the flexible investor occurring during the financial crisis. Please note that the recession is plotted in grey, but the financial crisis started earlier.



(a) Flexible

(b) Strict

Figure 7: Investor types' strictness

We plot the difference in institutional ownership among high ESG firms with either low or high ownership concentration. We use the quartile with most ownership and subtract the quartile with the least. The results are value weighted. We plot in Panel (a) results for flexible investors. Flexible investors are either investment companies (Type 3) or independent investment advisors (Type 5). Panel (b) shows ownership concentration of strict investors in ESG firms is shown. Strict investors are either banks (Type 1), insurance companies (Type 2) or other institutions (Type 5). The shaded area denotes recession.

Revealed ESG preferences

We further consider correlations between ESG scores and ownership, now looking how different investor types allocate their capital across firms with different ESG scores. We calculate the absolute value of holdings ($V^I_{i,t}$) in firm i at time t according to

$$V_{i,t}^{I} = S_{i,t} \times O_{i,t}^{I} \times P_{i,t}\ , \tag{16}$$

where I is the ownership type flexible or strict ($I = F, S$). $S_{i,t}$, $O_{i,t}^{I}$ and $P_{i,t}$ are the total number of shares, relative degree of ownership of owner I and the price of firm i at time t.

We use the data to test correlations between holding decisions and ESG scores according to the linear panel regressions of

$$V_{i,t}^{I} = ESG_{i,t-1} + F_i + \epsilon_{i,t} \tag{17}$$

where $ESG_{i,t}$ is the ESG score of firm i at time t, F_i is the firm fixed effects, and $\epsilon_{i,t}$ is the error term. Table 14 shows the results.

Table 14: Revealed preferences: ESG score portfolio tilts

We run regression (17) for strict (S) and flexible (F) owners. We control for firm fixed effects. The variable V^I, $I = \{S, F\}$, depicts the absolute invested capital. The ESG score is from the previous firm year of a given firm, i.e. the published score. The observations are updated on a yearly basis as ESG scores change once a year. Standard errors are clustered by firm and shown in parentheses below.

	Dependent Variable:		
	V^S	V^F	$V^S - V^F$
ESG Score	59,839***	41,160***	18,679***
	(7,541)	(3,959)	(5,750)
Firm Fixed Effects	Y	Y	Y
Clustered Errors	Y	Y	Y
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 14 shows that both strict and flexible investors increase their asset allocation with an increase in ESG scores. An increase in the ESG score by one point by one firm leads to an increase in capital allocated of roughly between 41 to 60 Thousand USD per investor type. We notice that strict have a stronger preference for ESG, as they are about 50% more sensitive to the ESG score of firms. So through a revealed preference argument, we see that both investors care about ESG. However, strict investors seem to assert a higher preference to ESG than flexible.

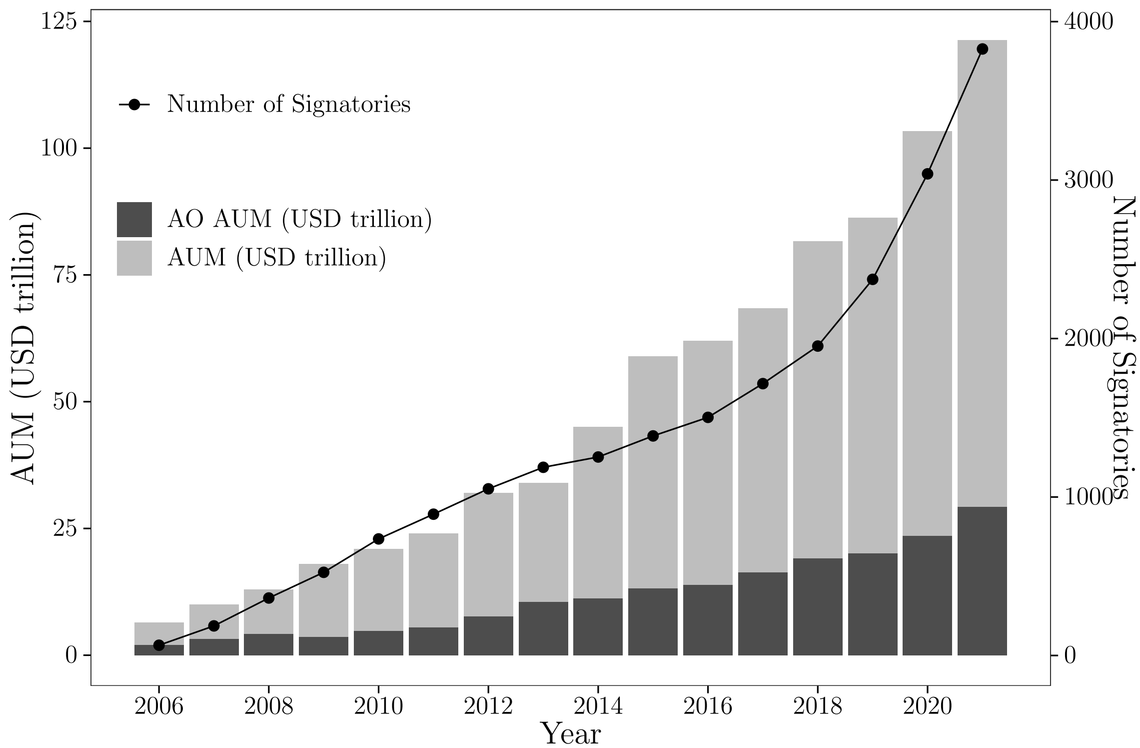


Figure 8: ESG assets and UN PRI signatories

This figure shows the number of UN PRI signatories and the sum of their assets under management (AUM). AO AUM only includes the AUM of asset owners and AUM also includes assets for other signatories. Total AUM includes reported AUM and AUM of new signatories provided in sign-up sheet that signed up by end of March of that year. Source: UN PRI https://www.unpri.org

Internet Appendix for: Skills and Sentiment in Sustainable Investing*

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Abstract

This Internet Appendix shows robustness checks and additional results outside of the main analysis of the paper. Specifically, we show more results on ESG ownership and preferences, robustness tests for our ESG premium under both flexible and strict investor ownership as well as additional findings with respect to sentiment considerations in the dynamics of returns. Finally, we show additional portfolio sorts for other variables of interest.

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IA Robustness Results

In this section we show robustness results.

Table I.1: Returns to sustainable investing across investors and decile portfolios

This table shows returns of portfolios with high flexible investor ownership (Panel A), strict investor ownership (Panel B), and the difference across the two (Panel C), across firms with low to high ESG scores. High flexible (strict) ownership is the stocks in top quartile of flexible (strict) investor ownership. Specifically, we sort monthly returns according to lagged ESG scores in a total of ten portfolios. In the next step, we conditionally sort returns according to their previous quarter's flexible and strict institutional ownership share and assign them into another four portfolios, ending up with a total of 40 portfolios for each investor. We rearrange portfolios every quarter, where new holdings data is available. ESG data is updated every year. LS is the abnormal return from a long-short strategy which goes long in high ESG and short in low ESG firms, giving us another four portfolios each. We value-weight each portfolio, risk-adjust returns according to the CAPM, 3-Factor and Carhart 4-factor model and document the alpha and t-statistic. Finally, we show risk-adjusted returns to portfolios that go long in high flexible ownership portfolios and short in strict ownership portfolios (Panel C). Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months. Bold numbers depict statistical significance significance of 5% or below.

	ESG low	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	ESG high	LS
Panel A: Flexible											
CAPM	-0.13	**0.50**	-0.06	-0.17	0.26	0.17	0.18	**0.40**	**0.42**	**0.44**	**0.57**
t-stat	-0.61	2.10	-0.27	-0.56	1.15	0.70	0.91	2.17	2.57	2.66	2.23
3-Factor	-0.15	**0.49**	-0.09	-0.16	0.24	0.16	0.17	**0.40**	**0.41**	**0.43**	**0.58**
t-stat	-0.79	2.18	-0.50	-0.54	1.05	0.67	1.00	2.06	2.52	2.58	2.18
4-Factor	-0.12	**0.53**	-0.09	-0.15	0.22	0.16	0.16	**0.41**	**0.41**	**0.43**	**0.55**
t.stat.2	-0.61	2.28	-0.50	-0.49	0.94	0.68	1.02	2.09	2.53	2.67	2.11
Panel B: Strict											
CAPM	-0.12	0.16	-0.23	**-0.71**	-0.19	-0.21	**-0.35**	0.23	0.27	0.18	0.30
t-stat	-0.43	0.89	-1.48	-2.14	-1.10	-1.15	-2.30	1.31	1.86	1.09	0.88
3-Factor	-0.15	0.15	-0.25	**-0.73**	-0.21	-0.22	**-0.36**	0.24	0.26	0.18	0.33
t-stat	-0.58	0.88	-1.81	-2.16	-1.49	-1.12	-2.06	1.39	1.91	1.11	1.00
4-Factor	-0.14	0.12	-0.25	**-0.68**	-0.22	-0.19	-0.35	0.29	0.25	0.19	0.33
t-stat	-0.57	0.78	-1.76	-2.11	-1.56	-1.03	-1.93	1.63	1.80	1.13	1.02
Panel B: Difference											
CAPM Monthly	-0.01	0.34	0.17	**0.54**	0.45	0.38	**0.53**	0.18	0.15	**0.26**	
CAPM Yearly	-0.09	4.08	2.07	**6.46**	5.40	4.51	**6.33**	2.12	1.84	**3.14**	
t-stat	-0.03	1.46	0.83	2.39	1.66	1.34	2.37	0.63	1.08	2.16	
3-Factor Monthly	-0.002	0.34	0.16	**0.56**	0.45	0.38	**0.53**	0.16	0.15	**0.25**	
3-Factor Yearly	-0.02	4.07	1.96	**6.76**	5.44	4.54	**6.35**	1.95	1.75	**3.02**	
t-stat	-0.01	1.38	0.84	2.51	1.69	1.26	2.26	0.58	0.99	2.02	
4-Factor Monthly	0.02	0.40	0.16	**0.53**	0.44	0.35	**0.51**	0.13	0.16	0.25	
4-Factor Yearly	0.28	4.83	1.93	**6.42**	5.31	4.25	**6.15**	1.51	1.93	2.95	
t-stat	0.10	1.63	0.82	2.51	1.66	1.23	2.21	0.45	1.07	1.87	

Table I.2: Robustness test of ESG premia for different degrees of flexible ownership across different models

We first sort returns according to lagged ESG scores in a total of four portfolios. In the next step, we conditionally sort returns according to their previous quarter's flexible institutional ownership share and assign them into another four portfolios, ending up with a total of 16 value-weighted portfolios. We construct long-short portfolios that go long in high ESG firms ($HESG$) and short in low ESG firms ($LESG$) on either a high (H) or a low (L) level of flexible ownership level in $D = \{H, L\}$. We risk-adjust our long-short portfolio returns with the CAPM, 3-Factor as well as the Carhart four-factor model. We adjust standard errors according to Newey and West (1987) with a lag of 12 months and report relevant coefficients and t-values.

	Dependent variable:					
	ESG Long-short return for high or low degree of ownership, LS_t^D, $D = \{H, L\}$:					
	LS_t^H			LS_t^L		
	(1)	(2)	(3)	(4)	(5)	(6)
α	0.321**	0.331**	0.304**	0.161	0.169	0.148
	t = 2.211	t = 2.199	t = 2.027	t = 0.704	t = 0.672	t = 0.565
mkt-rf	−0.169***	−0.055	−0.019	−0.212***	−0.148	−0.120
	t = −3.985	t = −1.295	t = −0.355	t = −2.673	t = −1.456	t = −1.126
smb		−0.491***	−0.502***		−0.295***	−0.304***
		t = −3.763	t = −4.002		t = −3.271	t = −3.207
hml		0.054	0.119		0.060	0.112
		t = 0.667	t = 1.446		t = 0.590	t = 1.161
mom			0.113**			0.091
			t = 2.492			t = 1.274
Observations	180	180	180	180	180	180
R^2	0.058	0.200	0.226	0.087	0.135	0.151
Note:						*p<0.1; **p<0.05; ***p<0.01

Table I.3: Robustness test for risk-adjusted returns under flexible ownership and sustainability using different models

We sort returns according to lagged scores in a total of four portfolios based on ASSET4 (A4), Sustainalytics (S), Sustainalytics Environment (S:E) and Carbon per Revenue (CO2) scores. Data goes from 2002 until 2016 under ASSET4 and 2011 until 2016 otherwise. In the next step, we conditionally sort returns according to their previous quarter's flexible institutional ownership share and assign them into another four portfolios, ending up with a total of 16 value-weighted portfolios. In another step, we construct value-weighted and risk-adjusted returns according to the CAPM, Fama-French three-factor, and Carhart four-factor model for a portfolio that goes long in high score (low score for CO2 metric) firms with high flexible ownership. We adjust standard errors according to Newey and West (1987) with a lag of 12 months and report relevant coefficients and t-values.

	Dependent variable:											
	$r_t^{F,H}$											
	A4			S			S:E			CO2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	0.400***	0.392***	0.392***	0.352***	0.399***	0.384***	0.337**	0.392***	0.372***	0.513**	0.556***	0.585***
	t = 3.889	t = 3.705	t = 3.784	t = 3.124	t = 4.154	t = 4.579	t = 2.266	t = 3.116	t = 3.051	t = 2.556	t = 3.335	t = 4.080
mkt-rf	0.961***	0.987***	0.987***	0.977***	0.955***	0.963***	1.000***	0.978***	0.988***	1.068***	1.061***	1.046***
	t = 48.180	t = 35.163	t = 39.925	t = 17.886	t = 14.574	t = 13.709	t = 20.391	t = 15.559	t = 13.789	t = 18.443	t = 17.203	t = 16.699
smb		−0.042	−0.042		0.134**	0.134**		0.149**	0.150**		0.090	0.088
		t = −0.594	t = −0.594		t = 2.077	t = 2.113		t = 2.233	t = 2.296		t = 0.796	t = 0.763
hml		−0.090*	−0.091*		−0.191***	−0.177***		−0.289***	−0.271***		−0.401***	−0.427***
		t = −1.704	t = −1.690		t = −3.147	t = −2.775		t = −4.363	t = −4.350		t = −2.602	t = −3.057
mom			−0.001			0.023			0.029			−0.042
			t = −0.039			t = 0.357			t = 0.456			t = −0.647
Observations	180	180	180	72	72	72	72	72	72	72	72	72
R^2	0.874	0.877	0.877	0.795	0.815	0.816	0.759	0.796	0.797	0.679	0.731	0.732

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

Table I.4: Robustness with Bushee Investor Classifications

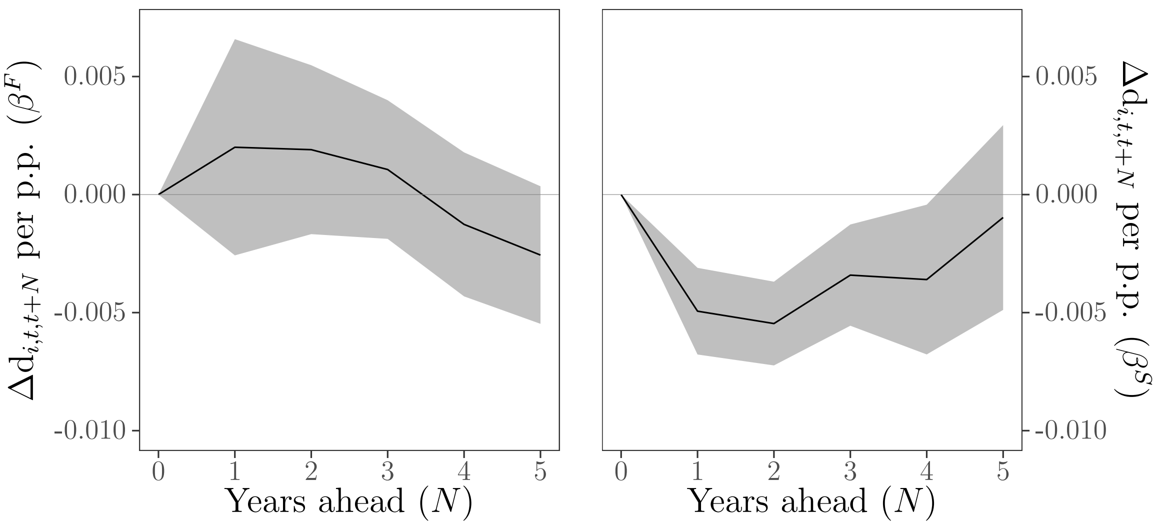
This table shows abnormal returns of portfolios with high flexible investor ownership (Panel A), high independent investment advisor ownership (Panel B), strict investor ownership (Panel C), across firms with low to high ESG scores. In each panel there are used two investor classification methods: First, the original used by Thomson Financial Network (TFN), which is available through the WRDS website. Second, the classification done by Brian Bushee, which is available on his website and used in, for example, Bushee (2001). High flexible (strict) ownership depicts the stocks in the top quantile of flexible (strict) investor ownership. We use the Carhart four-factor model to control for risk. Specifically, we sort monthly returns according to lagged ESG scores in a total of four portfolios. In the next step, we conditionally sort returns according to their previous quarter's flexible and strict institutional ownership share and assign them into another four portfolios, ending up with a total of 16 portfolios. We rearrange portfolios every quarter, where new holding data is available. ESG data is updated every year. LS is the abnormal return from a long-short strategy which goes long in high ESG and short in low ESG firms, giving us another four portfolios each. We value-weight each portfolio and document the alpha and t-statistic. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months. Bold numbers depict statistical significance of 5% or below.

	ESG low	Q2	Q3	ESG high
Panel A: Flexible				
Thomson Financial Network	0.09	0.01	0.17	**0.39**
t-stat	0.77	0.04	1.20	3.78
Bushee	0.09	-0.09	-0.30	**0.28**
t-stat	0.65	-0.49	-1.81	2.67
Panel B: Independent Investment Advisors				
Thomson Financial Network	0.13	-0.01	0.14	**0.34**
t-stat	1.15	-0.10	0.89	3.77
Bushee	0.21	-0.01	-0.09	**0.39**
t-stat	1.63	-0.07	-0.51	3.18
Panel C: Strict				
Thomson Financial Network	-0.05	-0.32	-0.19	0.13
t-stat	-0.37	-1.76	-1.14	1.11
Bushee	0.029	-0.12	0.06	0.11
t-stat	0.25	-0.82	0.63	0.95

Table I.5: Robustness of returns from ESG score increases controlling for cash flow changes using total returns

This table shows the robustness results of a Fama and MacBeth (1973) (column 3-4) cross-sectional regression approach including the changes in ESG scores on a yearly basis and the dividend return for total excess returns r^e. The Fama and MacBeth (1973) approach first estimates $\hat{\beta}_{i,j}$ exposures for every firm i and every risk factor j. In a second step, we regress excess returns against risk exposures for every time instance t, while including the exposure to changes in ESG scores and dividends. Specifically, the factor of ΔESG depicts the change in the ESG score of the stock that occurs in the current year relative to the last year. d depicts the dividend return, and Δd is its yearly change. We document t-test statistics below the coefficients.

	Dependent variable:			
	r^e			
	(1)	(2)	(3)	(4)
ΔESG	0.008***		0.008***	0.008***
	t = 3.200		t = 3.217	t = 3.300
Δd		−0.046		−0.057
		t = −0.352		t = −0.430
d			0.113	
			t = 1.499	
$\hat{\beta}_{mkt}$	0.425	0.408	0.428	0.407
	t = 1.074	t = 1.028	t = 1.083	t = 1.023
$\hat{\beta}_{smb}$	−0.241	−0.220	−0.230	−0.219
	t = −1.138	t = −1.026	t = −1.090	t = −1.023
$\hat{\beta}_{hml}$	−0.135	−0.160	−0.144	−0.153
	t = −0.503	t = −0.596	t = −0.535	t = −0.572
$\hat{\beta}_{mom}$	−0.066	−0.090	−0.058	−0.082
	t = −0.134	t = −0.183	t = −0.118	t = −0.166
γ_0	0.736***	0.750***	0.712***	0.732***
	t = 4.638	t = 4.826	t = 4.578	t = 4.581
Observations	107,308	106,983	107,308	106,983
R^2	0.390	0.390	0.391	0.391
Note:			*p<0.1; **p<0.05; ***p<0.01	



(a) Flexible Investors

(b) Strict Investors

Figure I.1: Robustness test of predicting dividend changes

Figure I.1a shows flexible (F) ownership in firms and their correlation to future changes in dividends, whereas Figure I.1b shows this effect for strict (S) investors. Specifically, the β-estimate gives an indication for how much the dividend yield (in %) changes in N years ahead of time, when investor $I = \{F, S\}$ increases ownership by one percent today. Allowing for heteroskedasticity, the gray shade shows White standard errors. We control for firm fixed effects, and cluster by time to allow for correlation in the cross-sectional error terms.

Table I.6: Sentiment and strict mandate investors sustainable investments

In this table we test how climate sentiment explains abnormal returns on the sustainability strategy by strict investors. The dependent variable is constructed by a value-weighted long-short portfolio that goes long in the top quartile of ESG firms with the top quartile of high strict ownership and short in the low ESG but also high level of strict ownership. We test for sentiment in this portfolio using a proxy for climate salience. The measures we use is the surprise innovations in the Google Hits on the term 'Climate change', as described in Section 3. We control for risk-factors through the CAPM, Fama-French three-factor and Carhart four-factor model. Lastly, we control for autocorrelation and heteroscedasticity in the residuals using Newey and West (1987) standard errors with 12 months lag.

	Dependent variable:		
		LS_t^S	
	(1)	(2)	(3)
Climate saliance	0.029	0.012	0.014
	t = 1.071	t = 0.451	t = 0.540
mkt-rf	-0.160^{***}	-0.127^{**}	-0.162^{***}
	t = −3.440	t = −2.506	t = −3.151
smb		-0.270^{***}	-0.264^{***}
		t = −3.042	t = −3.036
hml		0.190^{**}	0.116
		t = 2.503	t = 1.458
mom			-0.121^{***}
			t = −2.695
Constant	0.147	0.153	0.183
	t = 0.769	t = 0.829	t = 1.007
Observations	155	155	155
R^2	0.076	0.149	0.189
Note:			*p<0.1; **p<0.05; ***p<0.01

IB Alternative Research Design

In this appendix we show additional results of our main thesis, that there is a difference in returns to sustainable investing across investor types, derived using a fund-level based analysis. Specifically, we consider fund-level panel regressions utilizing the investor types' portfolio weights of different stocks. This allows us to control for fund, stock, and time fixed effects in a more exhaustive manner.

There are three groups of results. The first group documents whether the stock picks by strict mandate investors within sustainable stocks have performed worse than flexible investors' picks. The second pillar of results shows whether the flexible investors' stock picks have experienced ESG score improvements relative to strict mandate investors' picks. The third set of results revolves around whether strict mandate investors purchase more high ESG stocks than flexible investors and hence exerts a demand effect.

In all three groups of results the independent variable "portfolio_share_lag" documents the portfolio share of either a strict or flexible investor at the end of the earlier period. The variable "esg_lag" is the ESG score of the stock at the end of the earlier period. "strict" is a dummy variable that is 1 if the investor is a strict mandate investor and 0 if not. Hence the effect will be relative to the average result of flexible and strict investors. Sometimes a variable is split into its quantiles or deciles.

The difference in returns to sustainable investing is estimated in Table I.7. Model 1 shows that the return for strict investors' high esg stocks are 3.89% lower compared to flexible investors and low esg stocks for a portfolio weight of 100%. This is controlling for the fact that strict investors in general achieve 1.29% higher returns from their general investments under a 100% portfolio weight. The estimate in this specification also controls for the stocks' correlation to the equity risk premium mkt_rf as well as an an unexplained average return of 30bp. Model 2 extends the risk model to include Fama-French's 3-factor model, which makes the cost of strict mandate investing rise slightly to 4.14%. Using the Carhart 4-factor model in Model 3 lowers it then slightly to 4.02%. Model 4 controls for year fixed effects and replaces the risk premia, which results in a more flexible and hence conservative specification than Models 1 to 3. Here, the estimate slightly drops to 3.72%. Under the even more flexible year-month fixed effects, it goes to 3.28%. As the average portfolio weight of strict investors in the top quantile of ESG is 4.4% (the unconditional average is 3.1%) this equates to a cost to strict mandate investing of between 14-18 bp. This is reassuring as this depicts the same size compared to our original approach in Section 5, where we estimate the magnitude of the effect to be 14 bp.

Table I.8 shows robustness of the main results using different fixed effects. Model 1 shows the result from including a fund type fixed effect where we see the effect slightly increasing in magnitude suggesting that the difference in returns to sustainable investing is not due to strict investor in general doing worse. Model 2 additionally includes stock fixed effects after which the result remains about the same suggesting that the effect is neither due strict investors generally owning specific stocks that always have lower returns. Model 3 adds manager fixed effects for which we see that it reduces the effect by about a forth suggesting that some of the difference comes from managers general investing mandates, however the majority is still from how specifically their sustainable investing turns out. Model 4 adds year-quarter time fixed effects effects for which the effect does not change so it is not due to differences in general timing either. Model 5 includes all four fixed effects at the same time giving about the same result as Model 3.

Table I.9 replaces the general risk factor controls with betas estimated at the stock level. Model 1 shows the effects for the market model, Model 2 for the Fama-French 3-factor model, and Model 3 for the Carhat 4-factor model. All three models show that the effect remains highly significant dropping less than 10% compared to the main specification (Model 1 in Table I.7).

Table I.10 shows robustness results of the costs to strict mandate investing. Model 1 is the same as in Table I.7 and shown as reference. Model 2 replaces the control for strict investors general performance with a form that has an equally sized effect no matter how large their portfolio weight is in the stock instead of the performance being relative to the portfolio weight. Here, the relevant estimate drops to about half. However, this seems to root in misspecification as the more flexible Model 3 includes both effects and the coefficient then drops to 3.75%. Model 4 allows for different skill dependent on the investors' sub-type, again increasing the flexibility of the model. Similarly to Model 5, Model 2 has a fixed effect per type and sees the same drop. As before, when including both effects in a more flexible manner in Model 6, the effect is back at 3.78%. Though not shown, the results are the same with betas instead of risk premia. To sum up, this table suggests the effect to be robust and consistent at a bit below 4% for a correctly specified model.

Table I.11 shows the same results but split by ESG quantiles or deciles, respectively, where a higher quantile or decile represents a higher score. Model 2 shows that the effect is concentrated in the top ESG quantile suggesting the investors may be following a best-in-class investment rule. Additionally, Model 3 has more granularity and shows that indeed the effect arises from the 9th decile meaning the stocks that are close to the top but not quite there yet. Hence, strict investors lose out on return by investing in firms that are close to the top in their class, but only later continue to increase to the top decile.

Table I.12 shows the results split by investor sub type. The effect concentrates in types 1, 4, and 5, which are banks, independent advisors and other (which includes endowments and pension funds). Types 2 and 3, that is insurances, mutual funds and hedge funds, seem to be performing best.

Table I.13 shows how ESG scores of flexible investors' high ESG investments change over the following year relative to low ESG investments and strict mandate investors for a 100% portfolio weight investment. Model 1 shows that these investments tend to increase in their ESG score by 21 (out of 100). In the model, we control for how non-esg investments performs for the flexible investor and find this to be negative in general. Model 1 also controls for stocks' ESG scores as stocks in general tend to mean revert in their score. Additionally, we employ time-quarter fixed effects. For the mean portfolio size of 4.4%, this equates to an effect of an ESG score improvement of 9 points per year on average. Taking the effects into account that ESG scores tend to decrease in general as does flexible investor ownership, this equates to an improvement of around 2 points for stocks near the top of possible ESG scores. Models 2 and 3 show this is consistent for different or no time fixed effects. Model 4 shows that the effect concentrates in the top quantile of ESG stocks. Hence, we confirm our finding that flexible investors are able to find stocks which increase in their ESG score following the flexible investment. The size of the effect is also close to the 17 points found in section 4.2.

Table I.14 shows the purchases of stocks dependent on their ESG scores across investor types. Model 1 shows that when looking exclusively at strict mandate investors, their portfolio weights increase more for higher ESG stocks than for lower ESG stocks, hence they on average have been a net buyer of high ESG stocks. Contrary to this, Model 2 shows that the flexible investors have been selling, although not on statistically significant level. Models 3 to 6 show this to be consistent when using different types of time fixed effects. In terms of magnitude, the increase in portfolio weights for high ESG stocks have been 12 bp per year per stock. This means that for a 80 stock portfolio, the portfolio weights of high ESG stocks have increased by 10 percentage points per year for the strict investor.

Figure I.2 shows the coefficient of the underperformance in ESG investing for strict mandate investors interacted with a year dummy to get the effect in each year. We also control for the general effect of strict mandate investing and ESG scores as well as the Carhart model. We see that the effect has been negative most years, the strongest time being before the financial crisis and from 2011 to 2014. Strict investors lost less money during the financial crisis.

Table I.7: Table shows the heterogenous returns to sustainable investing across investor types

The dependent variable is excess returns in percentages per month of stock i. The variable *strict* is a dummy variable that is 1 for strict mandate investors and 0 otherwise, *portfolio_share_lag* is how much stock i makes up of investor j's total investments in stocks at the end of the previous period, and *esg_lag* is the ESG score of stock i at the end of the previous period. Risk factors are included as controls. Standard errors are robust standard errors. T-statistics are shown in square brackets.

	Model 1	Model 2	Model 3	Model 4	Model 5
portfolio_share_lag · esg_lag · strict	**-3.89*****	**-4.14*****	**-4.02*****	**-3.72*****	**-3.28*****
	[−4.94]	[−5.25]	[−5.10]	[−4.44]	[−4.16]
portfolio_share_lag · strict	1.29**	1.39**	1.32**	1.27*	1.07*
	[2.11]	[2.26]	[2.15]	[1.95]	[1.75]
esg_lag	−0.34***	−0.32***	−0.33***	−0.36***	−0.39***
	[−12.11]	[−11.38]	[−11.47]	[−11.63]	[−13.66]
mkt_rf	0.97***	0.99***	0.97***		
	[585.83]	[506.85]	[468.77]		
smb		−0.12***	−0.09***		
		[−48.65]	[−35.49]		
hml		0.11***	0.08***		
		[37.72]	[29.69]		
mom			−0.04***		
			[−23.72]		
(Intercept)	0.30***	0.38***	0.39***	2.01***	0.50***
	[12.54]	[15.70]	[16.47]	[61.80]	[39.57]
Year Fixed Effects	NA	NA	NA	Year	Year-Quarter
Num.Obs.	1 573 168	1 573 168	1 573 168	1 573 168	1 573 168
R2	0.277	0.279	0.280	0.120	0.283

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table I.8: Table shows robustness tests of the heterogenous returns to sustainable investing across investor types when including further fixed effects.

The dependent variable is excess returns in percentages per month of stock i. The variable *strict* is a dummy variable that is 1 for strict mandate investors and 0 otherwise, *portfolio_share_lag* is how much stock i makes up of investor j's total investments in stocks at the end of the previous period, and *esg_lag* is the ESG score of stock i at the end of the previous period. The fixed effects are calculated for a specific group by subtracting the unconditional average of each unit in that group conditioning only on the unit. Standard errors are robust standard errors. T-statistics are shown in square brackets.

	Model 1	Model 2	Model 3	Model 4	Model 5
portfolio_share_lag · esg_lag · strict	**-4.57*****	**-4.49*****	**-3.31*****	**-4.57*****	**-3.22*****
	[−5.28]	[−5.34]	[−3.83]	[−5.29]	[−3.81]
portfolio_share_lag · strict	2.21***	2.10***	2.02***	2.21***	1.90***
	[3.32]	[3.24]	[3.03]	[3.32]	[2.91]
strict	0.02*	0.12***	0.02	0.02	0.11***
	[1.70]	[8.89]	[1.11]	[1.57]	[8.18]
esg_lag	−0.37***	0.07**	−0.09***	−0.37***	0.35***
	[−11.60]	[2.11]	[−2.79]	[−11.62]	[11.10]
(Intercept)	0.87***	−0.07***	−0.05*	0.86***	−1.01***
	[30.90]	[−2.62]	[−1.77]	[30.58]	[−36.37]
Fixed Effects	None	Stock	Manager	Year-Q	Stock, Manager, Year-Q
Number of Observations	1 573 168	1 573 168	1 573 168	1 573 168	1 573 168
R2 (of variation after fixed effects)	0.00	0.00	0.00	0.00	0.00

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table I.9: Table shows robustness results of the heterogeneous returns to sustainable investing across investor types when controlling for stock betas.

The dependent variable is excess returns in percentages per month of stock i. The variable *strict* is a dummy variable that is 1 for strict mandate investors and 0 otherwise, *portfolio_share_lag* is how much stock i makes up of investor j's total investments in stocks at the end of the previous period, and *esg_lag* is the ESG score of stock i at the end of the previous period. The betas are calculated for each stock i with respect to the respective factor. Standard errors are robust standard errors. T-statistics are shown in square brackets.

	Model 1	Model 2	Model 3
portfolio_share_lag · esg_lag · strict	**-3.56***	**-3.63***	**-3.54***
	[−4.28]	[−4.37]	[−4.28]
portfolio_share_lag · strict	2.16***	2.18***	2.11***
	[3.35]	[3.39]	[3.30]
esg_lag	0.11***	0.00	0.00
	[3.51]	[−0.08]	[0.09]
beta_mkt	0.13***	0.22***	0.16***
	[7.47]	[9.88]	[4.54]
beta_smb		−0.14***	−0.13***
		[−8.68]	[−6.93]
beta_hml		0.02	−0.01
		[1.61]	[−0.81]
beta_mom			−0.14***
			[−2.66]
(Intercept)	−0.16***	−0.08***	−0.10***
	[−4.77]	[−2.63]	[−3.02]
Stock fixed effect (Alpha)	✓	✓	✓
Number of Observations	1 573 168	1 573 168	1 573 168
R2 (of variation after fixed effects)	0.00	0.00	0.00

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table I.10: Table shows robustness of the heterogenous returns to sustainable investing across investor types.

The dependent variable is excess returns in percentages per month of stock i. The variable *strict* is a dummy variable that is 1 for strict mandate investors and 0 otherwise, *portfolio_share_lag* is how much stock i makes up of investor j's total investments in stocks at the end of the previous period, *esg_lag* is the ESG score of stock i at the end of the previous period, and *as.factor(typecode)1-5* are dummy variables which are 1 when the investors typecode is 1,2,3,4 or 5 respectively. Risk factors are included as controls. Standard errors are robust standard errors. T-statistics are shown in square brackets.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
portfolio_share_lag · esg_lag · strict	**-4.02*****	**-2.00*****	**-3.75*****	**-4.07*****	**-2.06*****	**-3.78*****
	[−5.10]	[−7.69]	[−4.74]	[−5.13]	[−7.91]	[−4.75]
portfolio_share_lag · strict	1.32**		1.36**			
	[2.15]		[2.22]			
strict		−0.04***	−0.04***			
		[−3.11]	[−3.26]			
portfolio_share_lag · as.factor(typecode)1				−1.36*		0.54
				[−1.80]		[0.65]
portfolio_share_lag · as.factor(typecode)2				0.94		1.67
				[0.67]		[1.04]
portfolio_share_lag · as.factor(typecode)3				−1.81		2.52
				[−0.64]		[0.66]
portfolio_share_lag · as.factor(typecode)4				0.05		−0.62
				[0.16]		[−1.53]
portfolio_share_lag · as.factor(typecode)5				1.52**		1.38**
				[2.45]		[2.21]
as.factor(typecode)2					0.05	0.02
					[0.82]	[0.31]
as.factor(typecode)3					−0.04	−0.12
					[−0.41]	[−0.90]
as.factor(typecode)4					0.18***	0.18***
					[8.53]	[6.42]
as.factor(typecode)5					0.16***	0.14***
					[7.90]	[5.21]
esg_lag	−0.33***	−0.38***	−0.33***	−0.32***	−0.36***	−0.32***
	[−11.47]	[−16.04]	[−11.67]	[−11.20]	[−15.56]	[−11.30]
mkt_rf	0.97***	0.97***	0.97***	0.97***	0.97***	0.97***
	[468.77]	[468.76]	[468.76]	[468.77]	[468.77]	[468.77]
smb	−0.09***	−0.09***	−0.09***	−0.09***	−0.09***	−0.09***
	[−35.49]	[−35.45]	[−35.45]	[−35.49]	[−35.45]	[−35.45]
hml	0.08***	0.08***	0.08***	0.08***	0.08***	0.08***
	[29.69]	[29.78]	[29.82]	[29.72]	[29.88]	[29.92]
mom	−0.04***	−0.04***	−0.04***	−0.04***	−0.04***	−0.04***
	[−23.72]	[−23.67]	[−23.64]	[−23.69]	[−23.63]	[−23.60]
(Intercept)	0.39***	0.45***	0.42***	0.39***	0.27***	0.25***
	[16.47]	[21.27]	[16.81]	[16.10]	[9.80]	[7.69]
Num.Obs.	1 573 168	1 573 168	1 573 168	1 573 168	1 573 168	1 573 168
R2	0.280	0.280	0.280	0.280	0.280	0.280

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table I.11: Table shows the heterogenous returns to sustainable investing across investor types and ESG quantiles.

The dependent variable is excess returns in percentages per month. The variable *strict* is a dummy variable that is 1 for strict mandate investors and 0 otherwise, *portfolio_share_lag* is how much stock i makes up of investor j's total investments in stocks at the end of the previous period, *esg_lag* is the ESG score of stock i at the end of the previous period, and *esg_lag_quartile2-4* are dummy variables which are 1 when stock i's ESG score falls in the 2, 3, or 4th quantile respectively in that period. Hence esg_lag_quartile 1 is absorbed by the intercept. The variables *esg_lag_decile2-10* is the same but for deciles and instead of quantiles. Risk factors are included as controls. Standard errors are robust standard errors. T-statistics are shown in square brackets.

	Model 1	Model 2	Model 3
portfolio_share_lag·esg_lag·strict	**-4.02*****		
	[−5.10]		
portfolio_share_lag·strict	1.32**	−0.03	0.09
	[2.15]	[−0.04]	[0.07]
portfolio_share_lag·esg_lag_quartile4·strict		**-2.57*****	
		[−3.59]	
portfolio_share_lag·esg_lag_quartile3·strict		−0.47	
		[−0.60]	
portfolio_share_lag·esg_lag_quartile2·strict		−0.22	
		[−0.27]	
portfolio_share_lag·esg_lag_decile10·strict			−1.25
			[−0.95]
portfolio_share_lag·esg_lag_decile9·strict			**-5.08*****
			[−3.74]
portfolio_share_lag·esg_lag_decile8·strict			−1.67
			[−1.22]
portfolio_share_lag·esg_lag_decile7·strict			−1.45
			[−1.01]
portfolio_share_lag·esg_lag_decile6·strict			0.37
			[0.26]
portfolio_share_lag·esg_lag_decile5·strict			−0.14
			[−0.10]
portfolio_share_lag·esg_lag_decile4·strict			−1.58
			[−1.06]
portfolio_share_lag·esg_lag_decile3·strict			0.41
			[0.27]
portfolio_share_lag·esg_lag_decile2·strict			0.10
			[0.06]
esg_lag	−0.33***		
	[−11.47]		
esg_lag_quartile4		−0.28***	
		[−9.68]	
esg_lag_quartile3		−0.36***	
		[−11.90]	
esg_lag_quartile2		−0.21***	
		[−6.12]	
esg_lag_decile10			−0.28***
			[−5.17]
esg_lag_decile9			−0.35***
			[−6.54]
esg_lag_decile8			−0.39***
			[−7.06]
esg_lag_decile7			−0.27***
			[−4.88]
esg_lag_decile6			−0.56***
			[−9.99]
esg_lag_decile5			−0.40***
			[−6.65]
esg_lag_decile4			−0.10
			[−1.60]
esg_lag_decile3			−0.13**
			[−2.02]
esg_lag_decile2			−0.01
			[−0.20]
mkt_rf	0.97***	0.97***	0.97***
	[468.77]	[469.18]	[468.83]
smb	−0.09***	−0.09***	−0.09***
	[−35.49]	[−35.44]	[−35.56]
hml	0.08***	0.08***	0.08***
	[29.69]	[29.44]	[29.42]
mom	−0.04***	−0.05***	−0.05***
	[−23.72]	[−23.83]	[−23.86]
(Intercept)	0.39***	0.41***	0.45***
	[16.47]	[14.74]	[8.54]
Num.Obs.	1 573 168	1 573 168	1 573 168
R2	0.280	0.280	0.280

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table I.12: Table shows the heterogenous returns to sustainable investing across investor subtypes.

The dependent variable is excess returns in percentages per month. The variable *strict* is a dummy variable that is 1 for strict mandate investors and 0 otherwise, *portfolio_share_lag* is how much stock i makes up of investor j's total investments in stocks at the end of the previous period, *esg_lag* is the ESG score of stock i at the end of the previous period, and *as.factor(typecode)1-5* are dummy variables which are 1 when the investors typecode is 1,2,3,4 or 5 respectively. Risk factors are included as controls. Standard errors are robust standard errors. T-statistics are shown in square brackets.

	Model 1	Model 2	Model 3
portfolio_share_lag · esg_lag · as.factor(typecode)1	−3.52*	−1.30	2.10
	[−1.81]	[−1.28]	[0.98]
portfolio_share_lag · esg_lag · as.factor(typecode)2	6.09	−1.09	5.97
	[0.72]	[−0.73]	[0.71]
portfolio_share_lag · esg_lag · as.factor(typecode)3	−1.18	3.48	1.28
	[−0.11]	[0.89]	[0.12]
portfolio_share_lag · esg_lag · as.factor(typecode)4	**-4.40***	**-1.91***	**-5.17***
	[−3.51]	[−4.16]	[−4.10]
portfolio_share_lag · esg_lag · as.factor(typecode)5	**-4.74***	**-2.16***	**-4.72***
	[−5.62]	[−7.92]	[−5.59]
portfolio_share_lag · as.factor(typecode)1	−1.82		−2.65*
	[−1.25]		[−1.83]
portfolio_share_lag · as.factor(typecode)2	−7.34		−6.22
	[−0.99]		[−0.82]
portfolio_share_lag · as.factor(typecode)3	−1.07		1.73
	[−0.12]		[0.19]
portfolio_share_lag · as.factor(typecode)4	2.96***		2.63***
	[2.96]		[2.60]
portfolio_share_lag · as.factor(typecode)5	1.90***		1.96***
	[2.91]		[3.00]
as.factor(typecode)2		0.04	0.06
		[0.55]	[0.80]
as.factor(typecode)3		−0.09	−0.09
		[−0.70]	[−0.64]
as.factor(typecode)4		0.23***	0.24***
		[7.77]	[7.78]
as.factor(typecode)5		0.17***	0.18***
		[6.06]	[6.20]
esg_lag	−0.28***	−0.35***	−0.27***
	[−8.79]	[−14.90]	[−8.68]
mkt_rf	0.97***	0.97***	0.97***
	[468.79]	[468.77]	[468.79]
smb	−0.09***	−0.09***	−0.09***
	[−35.49]	[−35.44]	[−35.44]
hml	0.08***	0.08***	0.08***
	[29.69]	[29.88]	[29.93]
mom	−0.04***	−0.04***	−0.04***
	[−23.72]	[−23.64]	[−23.62]
(Intercept)	0.36***	0.24***	0.17***
	[13.84]	[7.27]	[4.69]
Num.Obs.	1 573 168	1 573 168	1 573 168
R2	0.280	0.280	0.280

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table I.13: Table shows the one year evolution of ESG scores of sustainable stocks across investor subtypes.
The dependent variable is changes in ESG scores in fraction per year. The variable *strict* is a dummy variable that is 1 for strict mandate investors and 0 otherwise, *portfolio_share_lag* is how much stock i makes up of investor j's total investments in stocks at the end of the previous period, *esg_lag* is the ESG score of stock i at the end of the previous period, and *as.factor(typecode)1-5* are dummy variables which are 1 when the investors typecode is 1,2,3,4 or 5 respectively. Risk factors are included as controls. Standard errors are robust standard errors. T-statistics are shown in square brackets. Year-Q is year-quarter.

	Model 1	Model 3	Model 4	Model 5
portfolio_share_lag · esg_lag · flexible	**0.21*****	**0.21*****	**0.24*****	
	[19.90]	[19.94]	[21.42]	
portfolio_share_lag · esg_lag_quartile4 · flexible				**0.12*****
				[13.30]
portfolio_share_lag · esg_lag_quartile3 · flexible				**0.09*****
				[7.70]
portfolio_share_lag · esg_lag_quartile2 · flexible				0.03*
				[1.82]
portfolio_share_lag · flexible	−0.16***	−0.16***	−0.19***	−0.10***
	[−17.45]	[−17.46]	[−18.70]	[−10.87]
esg_lag	−0.15***	−0.15***	−0.15***	
	[−392.40]	[−392.57]	[−386.13]	
esg_lag_quartile4				−0.10***
				[−276.15]
esg_lag_quartile3				−0.06***
				[−149.97]
esg_lag_quartile2				−0.01***
				[−10.51]
(Intercept)	0.14***	0.10***	0.14***	0.12***
	[1284.22]	[155.84]	[392.45]	[1718.30]
Time Fixed Effects	Year-Q	Year	None	Year-Q
Num.Obs.	1 715 463	1 715 463	1 715 463	1 715 463
R2	0.191	0.191	0.135	0.188

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table I.14: Table shows the purchases of stocks dependent on their ESG scores across investor types.

The dependent variable is changes in portfolio weight in the following quarter. Models 1, 3, and 5 show results just for Strict investor types and Models 2, 4, and 6 just for Flexible types. Standard errors are robust standard errors. T-statistics are shown in square brackets. Year-Q is year-quarter.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Investor Type	Strict	Flexible	Strict	Flexible	Strict	Flexible
esg_lag	**0.0012*****	−0.0001	**0.0012*****	−0.0001	**0.0010*****	−0.0002
	[11.7331]	[−0.8914]	[11.5951]	[−0.8979]	[9.8652]	[−1.1785]
(Intercept)	−0.0028	−0.0021	−0.0039***	−0.0032***	−0.0037***	−0.0024***
	[−0.9994]	[−0.4021]	[−39.9747]	[−9.8343]	[−43.5434]	[−20.7108]
Time Fixed Effects	Year-Q	Year-Q	Year	Year	None	None
Num.Obs.	1 279 019	496 650	1 279 019	496 650	1 279 019	496 650
R2	0.002	0.003	0.002	0.002	0.000	0.000

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

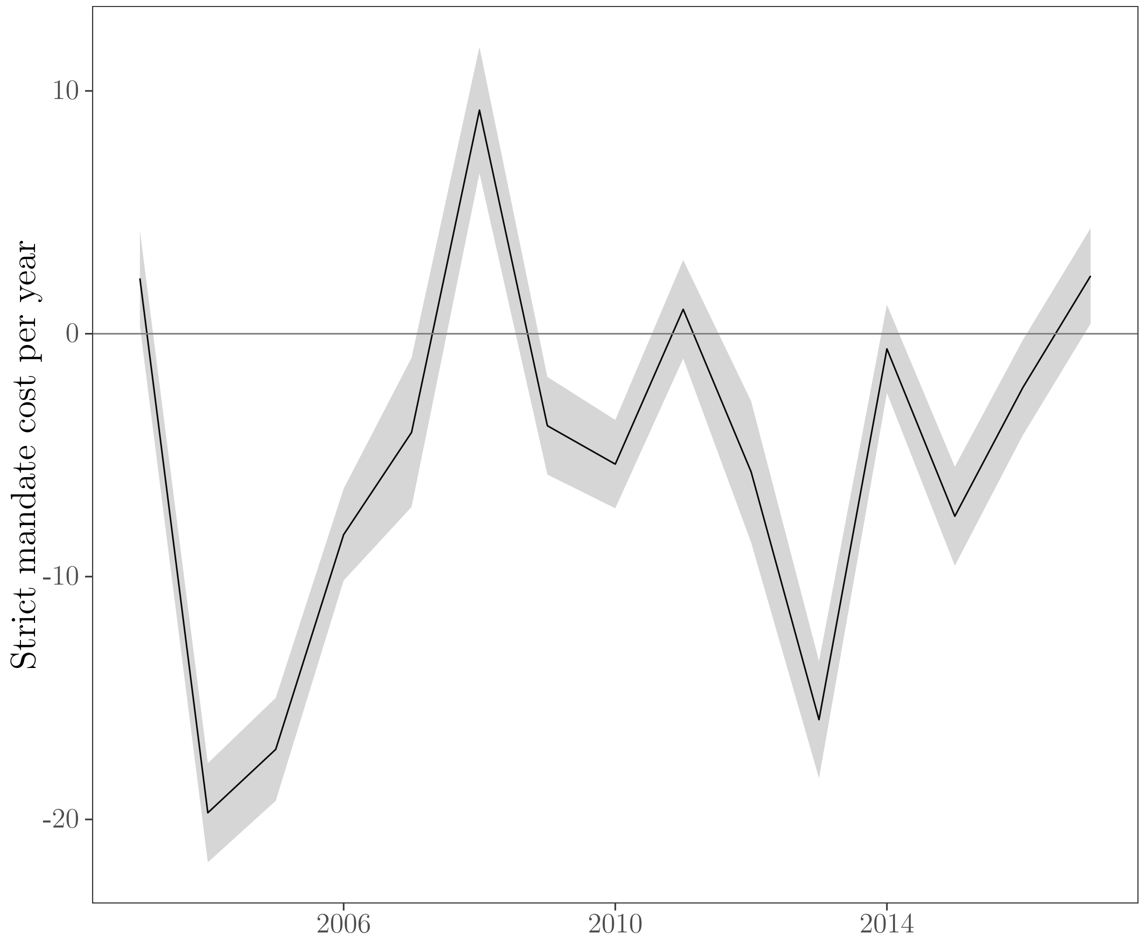


Figure I.2: Strict mandate cost per year

This figure shows the coefficient on the underperformance in ESG investing for strict mandate investors interacted with a year dummy to get the effect in each year. There is also controlled for the general effect of strict mandate investing and esg scores as well as the Carhart model. The grey area depicts the 95% confidence interval using robust standard errors.

IC ESG Scores

In this appendix we show describe our data on ESG scores in more detail. Figure I.3 shows the distribution of ESG scores across the firms and years in our sample. Additionally Table I.16 gives the distribution across industries, as well as the mean ESG, volatility of the ESG score and mean returns of those industries. Finally, Table I.17 displays the names of the companies that have the most observations, as they are part of every year.

Figure I.3 plots ESG scores over all scores available and across companies' yearly averages. Interestingly, many scores locate in the upper and lower score distribution, which might suggest that a company would rather exhibit a low score than not having one at all despite the fact that a low score implies low sustainability.

We also distinguish between different types of industries according to SIC Codes.

Table I.15: ESG data availability

The table covers the descriptive statistics of the ESG data set used in the analysis. The minimum, quartiles, maximum and standard deviation (equally-weighted) are computed over all companies exhibiting an ESG score for a given year.

Year	# of firms	Min	1. Quartile	Median	Mean	3. Quartile	Max	Std
2002	624	3.260	20.688	41.265	48.168	78.302	98.720	30.722
2003	629	3.800	20.570	42.950	48.663	78.390	98.680	30.364
2004	903	3.740	29.555	54.180	55.151	82.865	98.380	28.482
2005	1,029	4.660	31.590	55.590	57.137	85.860	98.490	28.661
2006	1,030	4.250	31.675	55.045	56.947	85.222	98.250	28.373
2007	1,075	3.880	31.140	57.640	57.548	86.170	97.300	28.326
2008	1,327	3.570	26.680	53.320	54.599	85.345	97.500	29.536
2009	1,469	2.960	27.290	51.920	54.572	85.110	97.460	29.660
2010	1,541	3.580	29.810	55.250	56.883	86.900	97.100	28.884
2011	1,522	3.920	28.395	58.545	57.055	86.980	96.600	29.353
2012	1,534	2.970	27.055	56.760	55.713	86.490	96.800	29.745
2013	1,521	2.970	29.210	57.800	57.057	87.150	96.950	29.386
2014	1,527	3.000	31.575	59.910	57.757	86.515	97.110	28.938
2015	2,225	4.320	14.940	45.590	48.525	82.740	96.590	32.527
2016	2,992	4.830	15.360	28.050	43.897	79.983	96.430	32.300

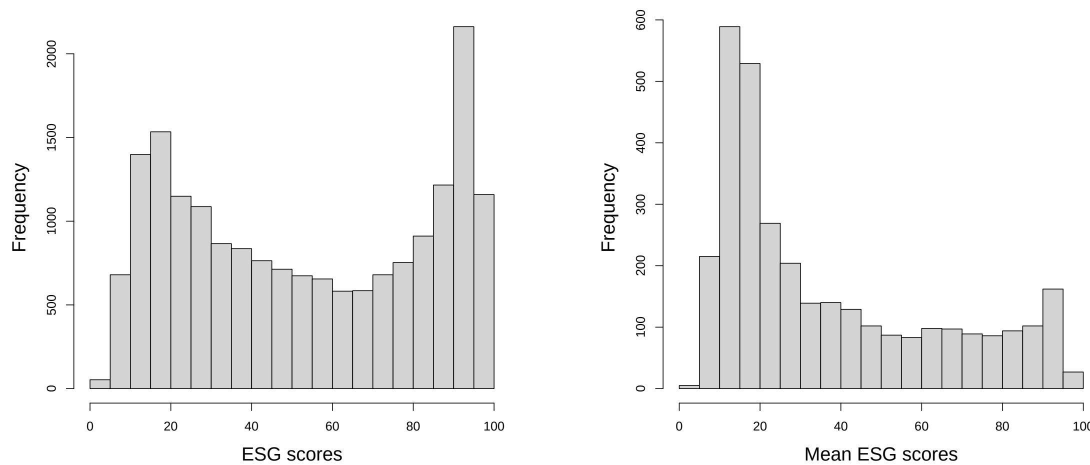
Table I.16: ESG industry composition

We exhibit the total number of observations, number of firms, average ESG scores, ESG score volatility and equally-weighted average returns according to different types of industries.

	#observations	#firms	% of all firms	$\overline{ESG}$	σ_{ESG}	$\overline{r}$
Agriculture, Forestry and Fishing	202	8	0.269	26.123	13.771	1.292
Mining	8,162	136	4.571	47.260	26.544	1.090
Construction	2,445	38	1.277	37.639	23.993	1.309
Manufacturing	65,476	972	32.672	58.595	30.005	1.395
Transportation, Communications, Electric Gas and Sanitary service	20,296	288	9.681	53.195	29.804	1.069
Wholesale Trade	5,035	115	3.866	46.647	27.095	1.204
Retail Trade	12,210	180	6.050	53.691	28.545	1.308
Finance, Insurance and Real Estate	28,161	482	16.202	40.477	26.485	1.176
Services	23,724	453	15.227	40.670	26.473	1.423
PublicAdministration	24	1	0.034	14.745	0.312	0.941
Nonclassifiable	7,646	302	10.151	18.252	12.385	1.752

Table I.16 exhibits the results. The manufacturing industry represents the largest share of the sample with a total of 972 firms and a total of 65,476 observations. It also has the largest average score of above 59. Other well-represented industries are transportation, communications, electric gas and sanitary services, finance, insurance, and real estate as well as services. All subsequent findings are hence primarily driven by these industries rather than others. ESG scores vary heavily within most industries with volatilities of up to 30 points.

Out of 63 firms that were part of the highest decile ESG scores in 2002, a significant number of 33 were also part of this portfolio in the end of the sample, suggesting that ESG scores are sticky in the top decile, see Table I.17. Interestingly, also firms that one would think are not part of that group, as for example British American Tobacco PLC or Occidental Petroleum Corporation, are members of the high profile ESG group. This suggests that not the objective of the firm matters but instead how well the criteria to obtain a high score are fulfilled. Though this procedure seems rather arbitrary, it proves to allow every firm to obtain a high score regardless of their business model.



(a) ESG Scores

(b) Mean ESG Scores

Figure I.3: ESG distribution

Figure I.3a represents the distribution of ESG scores across all single yearly scores. Figure I.3b averages the firms' yearly ESG scores, so that every firm exhibits only one average score.

ID The ESG Factor

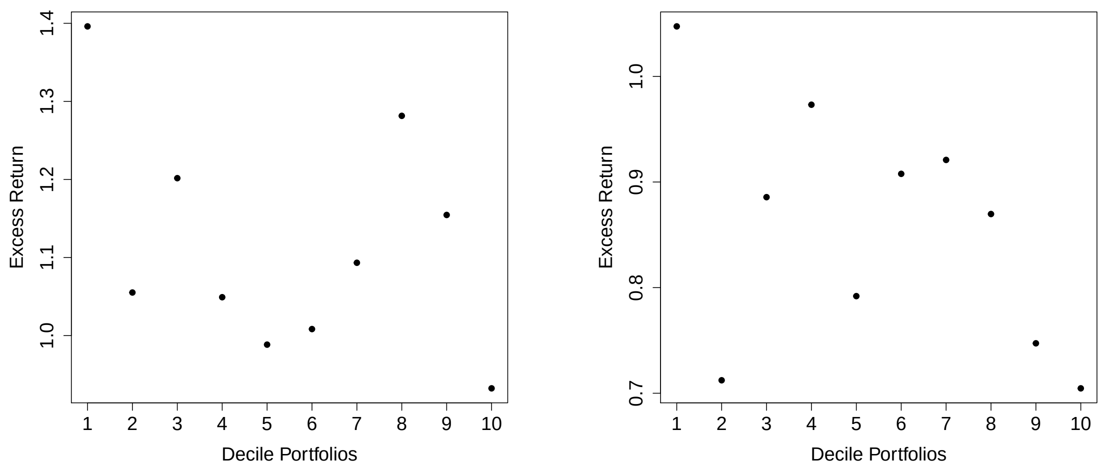
This appendix displays summary statistics for our ESG sorted returns. First, Figure I.4 shows the average return for each portfolio. Both for a equally-weighted and value-weighted approach, and we see that the results are relatively similar. Both display no clear relationship between ESG scores and return.

Figure I.5 displays the returns of the ESG factor over time. We can see that has had negative returns on average, but that it is fully explained through its negative exposure to risk factors as seen in the previous table. Additionally, we note the interesting fact that as the sentiment measure has a persistent effect, that is a significant AR(1) coefficient, as observed in Figure 2 in Section 3, this helps explain why cumulative returns on the ESG factor follow a boom-bust pattern.

Table I.17: High profile ESG companies

The table exhibits companies of the highest decile ESG portfolio that were part of this prtfolio in both 2002 and 2016 (beginning and end of the sample). In total, we see 33 companies to be part of this group. The according CUSIP codes can be used to access the companies' information through CRSP.

#	Name	CUSIP
1	A B B LTD	00037520
2	ABBOTT LABORATORIES	00282410
3	BANCO BILBAO VIZCAYA ARGENTARIA	05946K10
4	BANCO SANTANDER CENTRAL HISP SA	05964H10
5	BAXTER INTERNATIONAL INC	07181310
6	B H P LTD	08860610
7	BOEING CO	09702310
8	BRISTOL MYERS SQUIBB CO	11012210
9	BRITISH AMERICAN TOBACCO PLC	11044810
10	CHEVRON CORP	16676410
11	CISCO SYSTEMS INC	17275R10
12	DOW CHEMICAL CO	26054310
13	DU PONT E I DE NEMOURS & CO	26353410
14	DUKE ENERGY CORP	26441C20
15	EASTMAN CHEMICAL CO	27743210
16	ENBRIDGE INC	29250N10
17	GLAXOSMITHKLINE PLC	37733W10
18	HEWLETT PACKARD CO	40434L10
19	IMPERIAL OIL LTD	45303840
20	I N G GROEP N V	45683710
21	INTEL CORP	45814010
22	INTERNATIONAL BUSINESS MACHS COR	45920010
23	JOHNSON & JOHNSON	47816010
24	KONINKLIJKE PHILIPS ELEC N V	50047230
25	MERCK & CO INC	58933Y10
26	MOTOROLA INC	62007630
27	NOKIA CORP	65490220
28	OCCIDENTAL PETROLEUM CORP	67459910
29	PROCTER & GAMBLE CO	74271810
30	STMICROELECTRONICS NV	86101210
31	TEXAS INSTRUMENTS INC	88250810
32	MINNESOTA MINING & MFG CO	88579Y10
33	UNITED PARCEL SERVICE INC	91131210



(a) Equally-weighted **(b)** Value-weighted

Figure I.4: Raw returns

The plots I.4a and I.4b exhibit the decile portfolio raw return. The high (low) ESG decile portfolio *10* (*1*) depicts the firms with the highest (lowest) ESG scores. Portfolios are rearranged every year according to the previous year's ESG score.

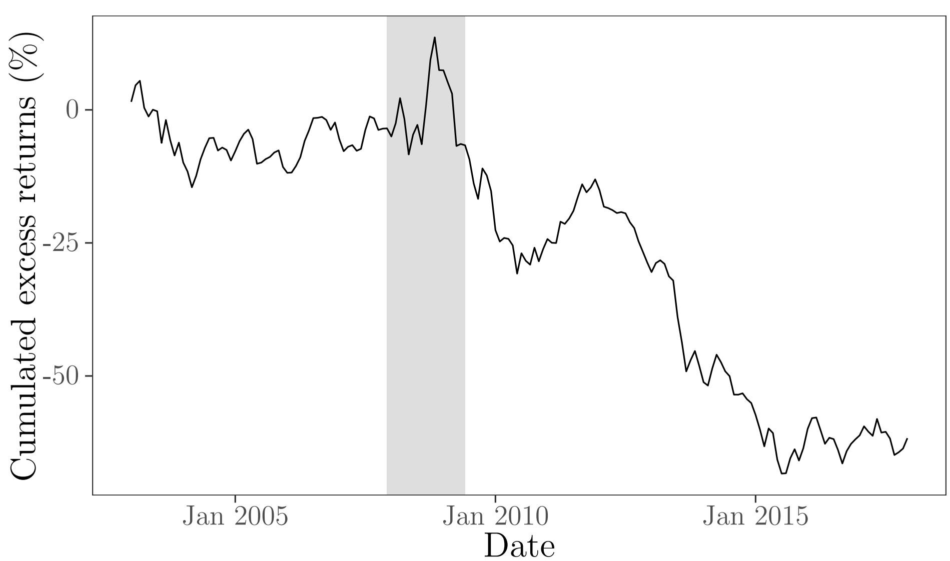


Figure I.5: Cumulative excess returns of ESG factor

We plot the value-weighted cumulated excess returns of a long-short portfolio that buys high ESG firms (top 10%) and shorts low ESG firms (bottom 10%). The portfolios are rearranged according to the previous year's ESG scores. The shaded area denotes the recession dates according to NBER.

Table I.18: Value-weighted ESG factor

This table is an extension from *Panel B* in Table 1, in which we construct value-weighted decile portfolios based on previous year ESG scores and adjust them in the beginning of each calender year. We then construct a long-short strategy (LS_t), which goes long in high ESG firms and shorts low ESG firms. The returns of all portfolios ESG portfolios are risk-adjusted through the application of the CAPM, Fama-French 3-factor, Carhart 4-factor, and Fama-French 5-factor models. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months.

	Dependent variable:			
	LS_t			
	(1)	(2)	(3)	(4)
α	−0.148	−0.133	−0.166	−0.331
	t = −0.750	t = −0.654	t = −0.807	t = −1.556
mkt-rf	−0.239**	−0.148	−0.103	−0.048
	t = −2.581	t = −1.353	t = −0.995	t = −0.464
smb		−0.442***	−0.455***	−0.372***
		t = −6.732	t = −7.479	t = −4.560
hml		0.118	0.200**	0.0001
		t = 1.192	t = 2.001	t = 0.002
mom			0.142**	
			t = 2.255	
rmw				0.474***
				t = 3.597
cma				0.422***
				t = 3.408
Observations	180	180	180	180
R^2	0.121	0.241	0.284	0.331
Note:	*p<0.1; **p<0.05; ***p<0.01			

IE Other Sentiment Measures

In this appendix section, we show additional findings on other sentiment measures. These include the Engle et al. (2020) climate change news indicator, the Baker and Wurgler (2006) investor measure as well as an analysis on dividend-price ratios.

Engle et al. (2020) climate change news

In our analysis, we make the argument that ESG returns are driven by salience and specifically the perceived risk of climate change. We provide empirical evidence that our measure of climate sentiment picks up this salience. To see if our sentiment measure shows results similar to other climate risk measures, we test whether salience in the form of high negative news coverage of climate can explain returns of our ESG factor. Specifically, we regress our ESG factor on *chneg*, a dummy variable developed by Engle et al. (2020), that is 1 when there are more than average bad news on climate, and 0 otherwise.

Table I.19 Column 1 document our findings. Incorporating other risk factors, this type of salience indeed matters for the returns of our general ESG factor. In periods with more than average amounts of negative news, the factor documents 80 bp of abnormal returns, where as in quiet periods it does not show any abnormal returns. Table I.20 confirms the results with different risk models.

Baker and Wurgler (2006) investor measure

We also consider whether the classical measure of sentiment as developed by Baker and Wurgler (2006) can explain our ESG returns. Our hypothesis is that sustainability concerns matter more or less depending on the time of general business sentiment. We use their variable *perp*, depicting their sentiment measure (a principal component of five proxies). We find that in periods with a higher than average amount of sentiment,

Table I.19: Robustness using other sustainability sentiment measures

We first sort returns according to lagged ESG scores in a total of 10 portfolios and value-weight them. We construct a long-short portfolio strategy that goes long in high ESG firms and short in low ESG firms (LS_t). We test sentiment of this portfolio towards three measures. In the first column and denoted by 'chneg' we test against the climate news series from Engle et al. (2020), which is either one in case of lots of news on climate change and 0 otherwise. The second column tests against the sentiment index by Baker and Wurgler (2006), which is one when sentiment is high and 0 otherwise. Finally, column 3 tests against log-changes in the price dividend ratio taken from Robert Schiller's data website. Additionally, we adjust for factor returns under the Carhart four-factor model. We control for autocorrelation and heteroscedasticity in the residuals using Newey and West (1987) standard errors with lag of 12 months.

	Dependent variable:		
	Factor (LS_t)		
	(1)	(2)	(3)
chneg = 1	0.803***		
	t = 3.102		
chneg = 0	0.013		
	t = 0.084		
perp = 0		0.288*	
		t = 1.703	
perp = 1		−0.041	
		t = −0.202	
Δpd			−0.214**
			t = −2.180
mkt - rf	−0.124**	−0.155***	−0.095
	t = −2.184	t = −2.883	t = −1.532
smb	−0.573***	−0.504***	−0.496***
	t = −6.765	t = −7.015	t = −6.860
hml	−0.003	−0.063	−0.081
	t = −0.030	t = −0.790	t = −1.045
mom	0.073***	0.047	0.032
	t = 2.674	t = 1.616	t = 1.217
α			0.068
			t = 0.577
Observations	109	180	179
R^2	0.517	0.465	0.470
Note:			*p<0.1; **p<0.05; ***p<0.01

Table I.20: Sustainability sentiment

We first sort returns according to lagged ESG scores in a total of 10 portfolios and value-weight them. We construct a long-short portfolio strategy that goes long in high ESG firms and short in low ESG firms. We test sentiment of this portfolio towards three measures. In Column (1) to (3) and denoted by 'chneg' we test against the climate news series from Engle et al. (2020), which is either one in case of lots of news on climate cheng and 0 otherwise. Column (4) to (6) tests against the sentiment index by Baker and Wurgler (2006), which is 1 when sentiment is high and 0 otherwise. Finally, column 3 tests against log-changes in the price dividend ratio as denoted by Robert Schiller. Additionally, we risk-adjust returns under the CAPM, Fama-French three-factor, and Carhart four-factor models. Standard errors are in parenthesis and are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months.

	Dependent variable:								
	LS_t								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
chneg = 1	0.53**	0.72***	0.80***						
	(0.24)	(0.27)	(0.26)						
chneg = 0	0.17	0.06	0.01						
	(0.14)	(0.14)	(0.16)						
perp = 0				0.25	0.26	0.29*			
				(0.21)	(0.16)	(0.17)			
perp = 1				0.02	0.001	−0.04			
				(0.22)	(0.19)	(0.20)			
Δ pd							−0.23**	−0.23**	−0.21**
							(0.10)	(0.09)	(0.10)
mkt - rf	−0.29***	−0.15**	−0.12**	−0.31***	−0.17***	−0.15***	−0.24***	−0.10	−0.10
	(0.05)	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
smb		−0.57***	−0.57***		−0.50***	−0.50***		−0.49***	−0.50***
		(0.09)	(0.08)		(0.07)	(0.07)		(0.07)	(0.07)
hml		−0.04	−0.003		−0.09	−0.06		−0.10	−0.08
		(0.09)	(0.09)		(0.08)	(0.08)		(0.08)	(0.08)
mom			0.07***			0.05			0.03
			(0.03)			(0.03)			(0.03)
α							0.08	0.07	0.07
							(0.13)	(0.11)	(0.12)
Observations	109	109	109	180	180	180	179	179	179
R^2	0.26	0.50	0.52	0.25	0.46	0.46	0.26	0.47	0.47

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

there are no higher abnormal returns. Instead, abnormal returns tend to be outside of of high sentiment periods (29 bp on average). In fact, we see sustainability sentiment being especially strong in the recession.

Business cycles

To further test whether investors' sustainability sentiment varies with general optimism in the economy, we test whether the ESG factor can be explained by developments in the dividend-price ratio in excess of traditional risk factors.

We find that a falling price dividend ratio is associated with increased returns on the ESG factor, see Table I.19 Column 3. A 1% drop is associated with a decrease in the abnormal return of 21 bp. We again confirm that sustainability sentiment is negatively correlated with general business sentiment.

To illustrate the business cycle effects we plot cumulated excess returns of the four ESG portfolios within this ownership type in Figure I.6. In this plot, Q4 refers to high ESG firms, and Q1 for low. It shows that high ESG firms with high flexible ownership especially seem to do better during the crisis.[2]

We again see that, although the top quartile has performed better throughout the sample, it also fell less in the crisis compared to the bottom two quartiles.

One argument for high ESG returns in the recession could be that as governments support the economy, there is public pressure that monetary support is given to those firms which emphasize more sustainable business models, as seen during the COVID-19 crisis. For example, the International Monetary Fund (IMF) emphasized and supported a "Green Recovery" to fight the aftermath of the pandemic.[3] Another argument is that investors care more about ethics in times of crises. Indeed Sapienza and Zingales (2012)

[2]We additionally plot the same plot for strict investors in Figure I.7. In the appendix, we furthermore show the long-short ESG portfolio for high degrees of flexible and strict investors in Figure I.8 and I.9.

[3]See under: https://www.imf.org/en/Topics/climate-change/green-recovery

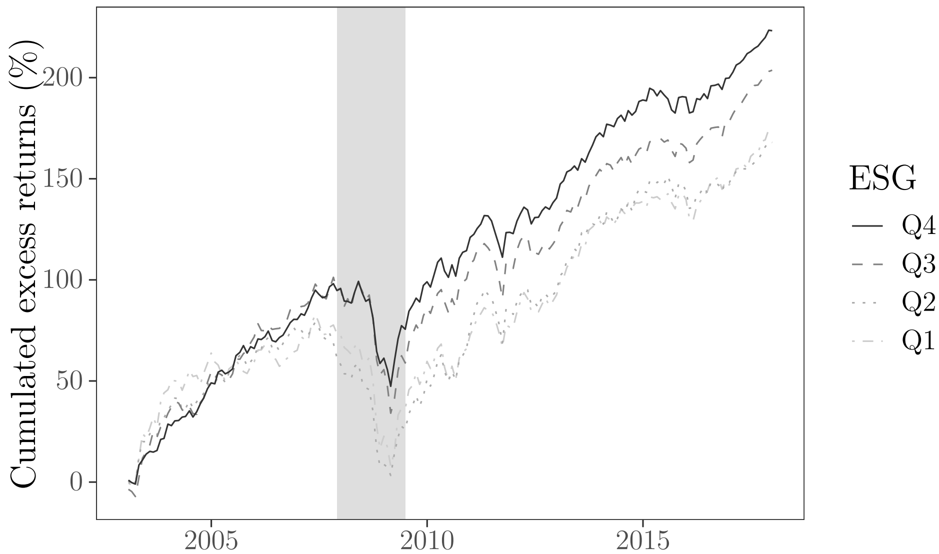


Figure I.6: Cumulative excess returns for stocks with different ESG levels within high flexible ownership

This figure shows cumulative returns for different ESG portfolios for stocks with high amounts of flexible ownership (top quartile). The portfolio Q1 (Q4) depicts the lowest ESG firms. The shaded area denotes the recession.

show that during the financial crisis we saw a rapid decline in the trust of the financial system, an observation validated by Jha, Liu and Manela (2021), who confirm the findings for a measure of popular sentiment towards finance.

These findings support that climate sentiment seems to correlate negatively with business cycles. In fact, sustainability sentiment may even rise during recessions.

IF Sustainable investment facts and additional robustness checks

This section provides additional figures and tables to give additional insight into our empirical setting. This includes ESG portfolio performance amongst strict investors, see Figure I.7, as well as an overview of cumulated excess returns for the ESG strategy amongst flexible owners in Figure I.8 and strict owners in Figure I.9. Furthermore, we exhibit results of the double-sort methodology of ESG scores and strict investors, see Table I.23.

IF.1 Additional figures

IF.1.1 Sustainable returns across investor types

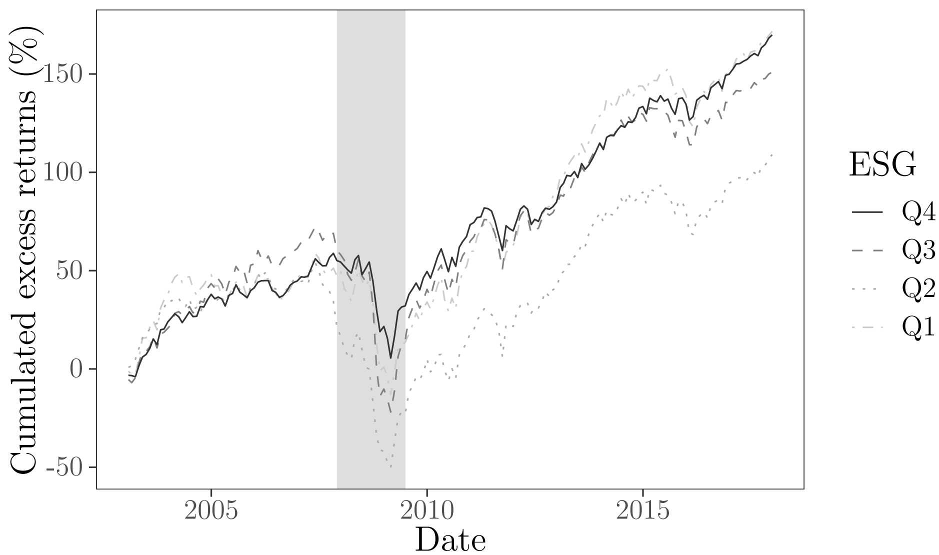


Figure I.7: Cumulative excess returns for stocks with different ESG levels and high strict ownership

This figure shows cumulative returns for different ESG portfolios for stocks with high amounts of strict ownership (top quartile). The portfolio Q1 (Q4) depicts the lowest ESG firms. The shaded area denotes the recession.

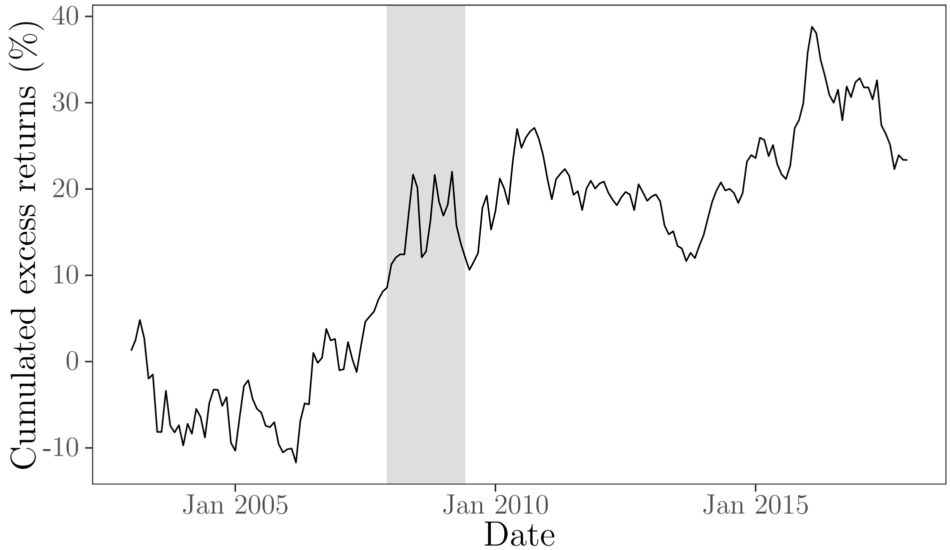


Figure I.8: Cumulative excess returns of long-short portfolio for stocks with the largest fraction of flexible owners

This figure shows cumulative returns for a value-weighted long short portfolio, which goes long in the highest ESG and high flexible ownership quartile and short in low ESG and high flexible ownership quartile portfolios. The shaded area denotes the recession.

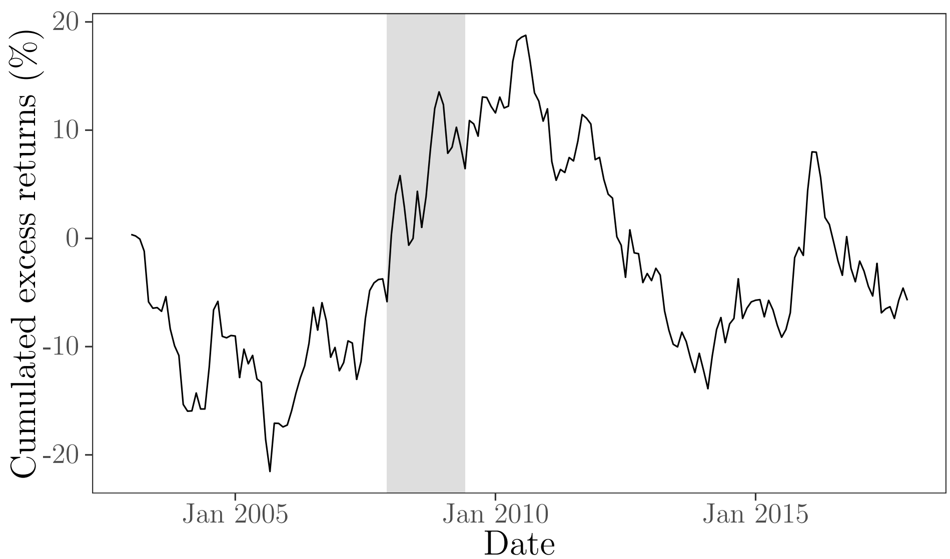


Figure I.9: Cumulative excess returns of long-short portfolio for stocks with the largest fraction of strict owners

This figure shows cumulative returns for a value-weighted long short portfolio, which goes long in the highest ESG and high strict ownership quartile and short in low ESG and high strict ownership quartile portfolios. The shaded area denotes the recession.

IF.2 Additional tables

IF.2.1 Sustainable returns across investor types

Table I.21: Double sort of ESG and ownership of flexible investors

We first sort returns according to lagged ESG scores in a total of four portfolios. In the next step, we conditionally sort returns according to their previous quarter's flexible institutional ownership share and assign them into another four portfolios, ending up with a total of 16 portfolios. LS is the abnormal return from a long-short strategy which goes long in high ESG firms and short in low ESG firms. We value-weight these 16 portfolios with the previous month's market values. Finally, we run regressions according to the CAPM and Carhart models and display alphas as well as relevant t-test statistics. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months. Bold numbers represent statistical significance at a level of 5% or below.

	ESG low	Q2	Q3	ESG high	LS
Panel A: CAPM					
Flexible ownership low	0	-0.086	-0.052	0.161	0.161
t-stat	-0.002	-0.75	-0.318	1.335	0.704
Q2	0.059	0.049	-0.159	0.012	-0.047
t-stat	0.48	0.39	-1.089	0.138	-0.258
Q3	0.02	0	0.011	0.004	-0.016
t-stat	0.126	0.001	0.086	0.032	-0.09
Flexible ownership high	0.079	0.02	0.186	**0.4**	**0.321**
t-stat	0.645	0.141	1.187	3.889	2.211
Panel B: Carhart					
Flexible ownership low	0.021	-0.064	-0.03	0.169	0.148
t-stat	0.123	-0.54	-0.177	1.278	0.565
Q2	0.046	0.065	-0.151	0.019	-0.027
t-stat	0.347	0.506	-1.067	0.21	-0.13
Q3	-0.033	-0.017	0.024	0.007	0.041
t-stat	-0.228	-0.121	0.191	0.057	0.217
Flexible ownership high	0.088	0.005	0.173	**0.392**	**0.304**
t-stat	0.773	0.041	1.202	3.784	2.027

Table I.22: Returns to sustainable investing across investor types and timings

We first sort returns according to lagged ESG scores in a total of four portfolios. In the next step, we conditionally sort returns according to their previous quarter's flexible and strict institutional ownership share and assign them into another four portfolios, ending up with a total of 16 portfolios. We conduct this procedure on actual holdings at time t (*sorted on actual holdings*), and also at time $t+1$ (*sorted on future holdings*), which gives us an indication for what the return on these portfolios would have been if investors would have held firms at the same level a period earlier. Here, one period equates to three quarters as holding data is available on a quarterly basis. LS is the abnormal return from a long-short strategy which goes long in high ESG and short in low ESG firms, giving us another four portfolios each. We value-weight these 20 portfolios and risk-adjust returns according to the Carhart four-factor model. We display alphas as well as relevant t-test statistics. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months. Bold numbers represent statistical significance at a level of 5% or below.

	Sorted on actual holdings					*Sorted on future holdings*				
	ESG low	Q2	Q3	ESG high	LS	ESG low	Q2	Q3	ESG high	LS
	Sorted on flexible ownership holdings									
	Panel A					*Panel B*				
Low	0.021	-0.064	-0.03	0.169	0.148	-0.118	-0.263	-0.194	-0.032	0.086
t-stat	0.123	-0.54	-0.177	1.278	0.565	-0.597	-1.612	-1.153	-0.253	0.313
2	0.046	0.065	-0.151	0.019	-0.027	-0.218	0.054	-0.039	0.071	0.289
t-stat	0.347	0.506	-1.067	0.21	-0.13	-1.59	0.381	-0.291	0.861	1.453
3	-0.033	-0.017	0.024	0.007	0.041	0.259	0.24	0.107	0.125	-0.134
t-stat	-0.228	-0.121	0.191	0.057	0.217	2.067	1.867	1.038	1.427	-0.841
High	0.088	0.005	0.173	**0.392**	**0.304**	0.132	-0.008	0.121	**0.419**	0.288
t-stat	0.773	0.041	1.202	3.784	2.027	0.975	-0.065	0.824	5.551	1.743
	Sorted on strict ownership holdings									
	Panel C					*Panel D*				
Low	-0.124	0.071	-0.024	0.149	0.273	-0.165	-0.038	-0.183	0.072	0.237
t-stat	-0.672	0.439	-0.174	1.258	1.027	-0.854	-0.236	-1.047	0.599	0.869
2	0.207	0.188	0.094	0.077	-0.129	0.193	0.073	0.193	0.108	-0.084
t-stat	2.72	2.051	0.841	0.933	-1.218	1.788	0.599	1.271	1.337	-0.689
3	0.054	0.038	-0.053	0.074	0.020	0.045	0.179	0.032	0.102	0.057
t-stat	0.296	0.33	-0.436	0.644	0.106	0.279	1.528	0.248	1.207	0.302
High	-0.049	-0.324	-0.190	0.130	0.179	-0.018	-0.171	-0.036	**0.325**	0.344
t-stat	-0.374	-1.765	-1.141	1.108	1.089	-0.145	-0.762	-0.205	2.232	1.661

Table I.23: Long-short regressions and strict ownership

We first sort returns according to lagged ESG scores in a total of four portfolios. In a next step, we conditionally sort returns according to their current quarter's strict institutional ownership share and assign them into another four portfolios, ending up with a total of 16 portfolios, which we value-weight. We construct a long-short portfolio (LS_t^D) that goes long in high ESG firms ($HESG$) and short in low ESG ($LESG$) firms on either a high (H) or a low (L) level of strict ownership as denoted by $D = \{H, L\}$. We test our long-short portfolio against the CAPM, Fama-French three-factor as well as the Carhart four-factor model. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months.

	Dependent variable:					
	ESG Long-short return for High or Low degree of strict ownership, LS_t^D, $D = \{H, L\}$:					
	LS_t^H			LS_t^L		
	(1)	(2)	(3)	(4)	(5)	(6)
α	0.136	0.158	0.179	0.292	0.299	0.273
	t = 0.838	t = 0.966	t = 1.089	t = 1.241	t = 1.184	t = 1.027
mkt - rf	-0.179^{***}	-0.137^{***}	-0.166^{***}	-0.214^{**}	-0.125	-0.090
	t = −3.579	t = −2.655	t = −3.162	t = −2.351	t = −1.256	t = −0.872
smb		-0.307^{***}	-0.299^{***}		-0.378^{***}	-0.389^{***}
		t = −3.679	t = −3.518		t = −3.832	t = −3.910
hml		0.207^{***}	0.156^{**}		0.037	0.100
		t = 2.762	t = 2.271		t = 0.345	t = 0.945
mom			-0.090^{**}			0.110^{*}
			t = −2.081			t = 1.693
Observations	180	180	180	180	180	180
R^2	0.084	0.176	0.198	0.081	0.155	0.176
Note:						*p<0.1; **p<0.05; ***p<0.01

IF.2.2 ESG and market value

In this subsection of the appendix we show results of double sorting on ESG and size.

Table I.24: Double-sort regression on size and ESG

We first sort firms according to lagged ESG scores in a total of four portfolios. In a next step, we conditionally sort firms according to their one-month lagged market values and assign them into another four portfolios, ending up with a total of 16 portfolios, which we value-weight with the previous month's market values. We run regressions according to the CAPM and Carhart 4-Factor (excluding the SMB factor) models and displays alphas as well as relevant t-test statistics. Bold numbers represent statistical significance at a level of 10% or below. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months.

	ESG_{t-1} low	2	3	ESG_{t-1} high	LS
Panel A: CAPM					
Market Value low	0.531	0.303	0.287	**0.553**	0.022
t-stat	1.332	1.005	1.428	2.85	0.066
Q2	-0.033	0.099	-0.03	**0.301**	**0.334**
t-stat	-0.219	0.663	-0.301	2.723	2.398
Q3	0.023	**-0.206**	0.03	0.132	0.109
t-stat	0.2	-1.791	0.24	1.562	0.822
Market Value high	-0.083	0.009	-0.079	-0.039	0.045
t-stat	-0.593	0.073	-1.006	-0.545	0.267
LS	-0.614	-0.294	-0.366	**-0.592**	0.022
t-stat	-1.211	-0.75	-1.571	-2.491	0.05
Panel B: Carhart (excl. SMB)					
Market Value low	**0.718**	**0.434**	**0.397**	**0.63**	-0.087
t-stat	2.133	1.768	2.585	3.597	-0.281
Q2	0.013	0.158	-0.007	**0.337**	**0.324**
t-stat	0.089	1.255	-0.075	3.303	2.269
Q3	0.027	**-0.211**	0.044	0.136	0.109
t-stat	0.235	-1.851	0.351	1.572	0.801
Market Value high	-0.11	-0.004	-0.077	-0.041	0.069
t-stat	-0.807	-0.032	-1.038	-0.576	0.413
LS	**-0.827**	-0.438	-0.474	-0.671	0.156
t-stat	-1.93	-1.291	-2.502	-3.028	0.387

IF.2.3 Ownership concentration, ESG and returns

In this appendix we show results of double sorting on ESG and ownership concentration as defined by the Herfindahl–Hirschman Index (HHI). We do not find an ESG premium when controling for HHI as exhibited in Table I.25.

Table I.25: Double sort of ESG and ownership concentration

We first sort returns according to lagged ESG scores in a total of four portfolios. In the next step, we conditionally sort returns according to their previous quarter's ownership concentration (HHI) and assign them into another four portfolios, ending up with a total of 16 portfolios, which we value-weight. LS is the abnormal return from a long-short strategy which goes long in high ESG and short in low ESG firms or long in the highly concentrated firms and short in the less concentrated firms, respectively. We value-weight these 16 portfolios with the previous month's market values. Finally, we run regressions on portfolio returns according to the CAPM and Carhart four-factor models and display alphas as well as relevant t-test statistics. Bold numbers represent statistical significance at a level of 10% or below. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months.

	ESG low	Q2	Q3	ESG high	LS
Panel A: CAPM					
HHI low	-0.204	0.079	**-0.247**	-0.26	-0.056
t-stat	-0.871	0.562	-1.917	-1.386	-0.273
2	0.166	-0.104	0.028	**0.255**	0.089
t-stat	0.726	-0.76	0.201	1.751	0.516
3	0.019	0.056	0.046	-0.01	-0.029
t-stat	0.147	0.317	0.34	-0.099	-0.158
HHI high	0.033	-0.052	-0.089	0.023	-0.009
t-stat	0.21	-0.542	-0.93	0.244	-0.06
LS	0.237	-0.131	0.157	0.283	0.046
t-stat	0.974	-0.755	1.1	1.344	0.189
Panel B: Carhart					
HHI low	-0.181	0.088	**-0.216**	-0.209	-0.028
t-stat	-0.686	0.573	-1.682	-1.214	-0.137
2	0.157	-0.099	0.01	**0.283**	0.126
t-stat	0.824	-0.658	0.072	1.703	0.762
3	0.022	0.057	0.058	0.007	-0.014
t-stat	0.176	0.332	0.482	0.081	-0.087
HHI high	-0.018	-0.057	-0.079	0.008	0.026
t-stat	-0.118	-0.608	-0.794	0.092	0.149
LS	0.163	-0.145	0.138	0.217	0.054
t-stat	0.68	-0.796	0.908	1.005	0.227

IG Sorting

Single-sorted portfolios. We start out by selecting only those firm-month observation for which we have ESG information available for the previous year. Within these firms, we distinguish between different degrees of ESG scores. In total, we subdivide our sample into ten portfolios, ranging from the highest to the lowest decile ESG firms. Specifically, we sort returns according to the previous year's ESG scores. For example, ESG scores in 2002 determine our portfolios in 2003 and so forth.

We construct value-weighted decile portfolios for the entire data period, where P10 (P1) depicts the highest (lowest) ESG portfolio, where we use the market-value of a firm from the previous month as a proxy for value. We choose to value-weight, because else portfolio returns would largely be driven by small firms.[4] However, one should note that the value composition between decile portfolios is not evenly distributed. Our data shows that high scores are primarily obtained by rather large firms, and vice versa. Finally, we use the self-developed portfolios to construct a long-short portfolio (LS), which goes long in the highest ESG decile portfolio and shorts the lowest ESG decile portfolio.

Double-sorted portfolios. We utilize ownership information to double-sort returns on two variables; that is, information on how high ownership by strict and flexible owners is in a given firm. Specifically, we first sort firms for a given month based on on the previous year's ESG scores into four portfolios. Thereafter, we conditionally sort on the level of ownership in the previous quarter, so that we end up with a total of 16 portfolios. These portfolios are rebalanced every month and rearranged every quarter as new holding data becomes available. Additionally we incorporate the new ESG data in the rebalancing at year-end. As previously, we value-weight returns within the

[4]Nevertheless, we conduct all analyses on an equally-weighted portfolio level as well for robustness checks.

sorted portfolios. Additionally, we construct long-short portfolios according to ESG and ownership information. Equally-weighted returns are calculated as robustness checks.

Risk-adjusting the sorts. To risk-adjust returns, we use the CAPM, Fama-French three-factor or Carhart model (Sharpe, 1964, Fama and French, 1992, Carhart, 1997). This means we explicitly estimate

$$r_{it} - r_t^f = \alpha_i + \sum_{j=1}^{J} \beta_{ij} f_{jt} + \epsilon_{it}, \tag{18}$$

where r_{it} depicts portfolio i's return at time t. Moreover, r_t^f, α_i, and J denote the risk-free rate, the abnormal return, and the number of factors. Finally, the β_{ij}, f_{jt} and ϵ_{it} are the factor loadings, factor returns, and the error term, where f corresponds to $\mu_M = r_M^e$ in our theory section for the CAPM model, and in general the factors of the specified risk-model.