# Skills and Sentiment in Sustainable Investing

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**Abstract**

We document a positive Environmental Social Governance (ESG) premium amongst stocks with high socially unconstrained ownership. Unconstrained investors are mutual funds, hedge funds and other investment advisors. This premium does not appear for stocks with high socially constrained ownership. In fact, we find that constrained investors unsuccessfully chase high ESG stocks with high abnormal returns. The returns do not seem to be driven by consumption risk as they are especially high during the financial crisis. Instead, they are explained by the new fact that unconstrained investors are skilled investors who research firms and are able to predict their future ESG scores. This earns them an abnormal return due to a ESG premium. We further show that they are able to exploit this especially during periods of high climate sentiment and in times of crisis. In the process, we construct a new text-based sustainability sentiment measure and create both an ESG and climate factor, that are useful for asset pricers to explain ESG firms' rise in value, their generally high valuations as well as risk exposures.

**Keywords**: Heterogeneous Investors, Revealed Preferences, ESG, Sentiment, Text data.

**JEL Codes**: G11, G12, G14, Q5.

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# 1 Introduction

Over the last two decades, Environmental Social Governance (ESG) scores have been a growing concept for investors as a result of increased sustainability awareness.[1,2] There are reports claiming that ethical firms outperform firms that do not engage in efforts for more sustainability in areas such as sales-growth and return on equity.[3] If ESG policies make a firm a safer investment, or if investors non-pecuniarly value ESG, a basic general equilibrium argument means that high ESG firms should display lower returns than their peers. On the other hand, if investors' non-pecuniary benefit rises or if these cash-flow effects are not expected, it could lead to a positive abnormal return for high ESG companies as argued by Pastor et al. (2019) and Pedersen et al. (2019).

Indeed, we document as our main finding that although ESG investing yields negative expected excess returns, a significant positive abnormal return can be achieved by investing sustainably in a smart way. As shown in Figure 1, high ESG stocks held by unconstrained investors have experienced large positive returns over the recent years. We define socially constrained investors as in Hong and Kacperczyk (2009), which means they are mutual funds, hedge funds, and other independent investment advisors. This leaves constrained investors as university endowments, pension plans, employee ownership plans, banks, and insurance companies. The sustainable strategy we consider is a self-financing strategy that goes long in high ESG firms and shorts low ESG firms. Interestingly, the premia from sustainable investing does not exist among stocks with a high degree of socially constrained ownership. In fact, we find that socially constrained investors unsuccessfully purchase high ESG stocks, which prior to their purchase have experienced high abnormal returns. Once purchased the

[1]The Forum for Sustainable and Responsible Investment in the USA *US SIF* mention in their 2018 report *on US Sustainable, Responsible and Impact Investing Trends* that the amount of assets invested which incorporates ESG principles has risen from just under $ 2 trillion in 2002 to $ 10 trillion by the end of 2017. Illustrating the increased attention and demand of ESG investments over our time period.

[2]Hartzmark and Sussman (2019) offers additionally evidence and suggests that investors value sustainability in the mutual fund industry. 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

[3]Friede et al. (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. And that over 90% report a non-negative relationship.

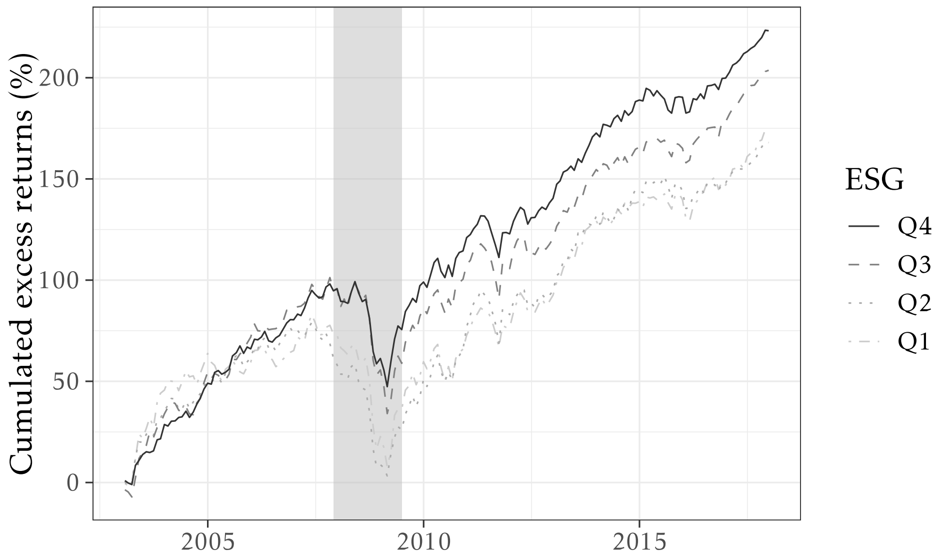



**Figure 1: Cumulative Excess Returns for stocks with different ESG levels within high unconstrained ownership**

Cumulative returns for different ESG levels for stocks with high amounts of socially unconstrained ownership (top quantile). The shaded area denotes the recession.

abnormal returns disappear. This discovery is important for understanding how ESG scores impact stock returns in a time of increased demand for sustainable investing.

Our second finding is that the premium arises from skilled unconstrained investors being able to predict ESG scores.[4] Constrained investors without skill instead chase high ESG stocks with high abnormal returns prior, perhaps with the hope that the returns will persist. But to no avail. Thirdly, we rule out the premium arising from consumption risk, as it is stronger in times of low consumption, such as the recession. Instead, this could suggest that ESG is a noisy quality signal skilled investors are able to exploit, especially in times of high uncertainty. Fourth and finally, our findings are stronger during periods of increased *Sustainability sentiment*, giving further evidence towards our second finding.

Theoretically, these findings are consistent with a negative ESG premium, whose size varies with sustainability sentiment (Pastor et al., 2019), and of a hidden quality of ESG (Pedersen et al., 2019), and inconsistent with explanations based on traditional risk factor

[4] An observationally equivalent hypothesis is that unconstrained investors improve the ESG score of the firms they invest in.

models, such as the CAPM (Sharpe, 1964, Lintner, 1965), or even newer models, such as Carhart (1997). They are also inconsistent with models, which solely feature an ESG premium. Furthermore, our findings have important real implications, as these explanations suggest a lower future expected return for high ESG firms, which hence affects firms' expected cost of financing in the future.[5,6]

Empirically, this paper contributes to the literature by considering these seemingly contrasting ideas, and provides new evidence, as to how the benefits to sustainable investing and investor characteristics are related. Even fundamental questions of whether the main driver of ESG's potential abnormal returns are due to separate risks specific to ESG, or behavioral demand pressures that dislocates prices from fundamental values, remains yet to be answered. Recent papers have begun addressing these issues, such as Engle et al. (2019) who create a measure for climate change risk, and show that firms with high ESG scores load higher on this risk measure. Starks et al. (2017) documents proof of some of these behavioral demand effects as high ESG firms are less likely to be sold after low earnings announcements than their peers with low ESG ratings. Hartzmark and Sussman (2019) on the other hand, do not find any relationship between sustainability awareness and returns. However, our findings do not seem to be consistent with a risk based story, as alphas seem to be positive during crises, and when Climate sentiment is high.

The closest paper to ours is Cao et al. (2019) who document that high ESG firms are more prone to overpricing, and that this mispricing gets corrected to a lesser extend, leading high ESG firms to exhibit lower abnormal returns. We find, however, that high ESG stocks held to a large degree by socially unconstrained investors exhibit *high* abnormal returns, suggesting that the skill channel seems to be dominating the ESG utility channel. A difference in the results might arise from the fact that we use ESG scores from ASSET4, which were available to investors at the time, and hence are not back-filled, whereas other newer ESG scores are,

[5] This has direct consequences on whether or not capital flows to firms which invest in more sustainable projects to improve their ESG scores

[6] ESG scores are a proxy for a firm's engagement in sustainability and social responsibility. High scores imply high engagement, whereas low scores depict the opposite. We rely on the data provider of Thomson Reuters, which assigns scores to firms with sufficient information from 0 to 100. See Section 3 for how these scores are computed and its summary statistics.

but on the other hand often have a wider cross-section. As we have different objectives than Cao et al. (2019), who use a revealed preference approach, we separate investors into socially constrained and unconstrained following Hong and Kacperczyk (2009). Our main contribution is adding to this research by showing that there are opposing forces driving ESG returns; a sustainability premium drives down expected returns, whereas investor skill increases the returns.

Our main finding, that unconstrained investors are able to achieve a significant positive abnormal return, is demonstrated by forming value-weighted portfolios based on the information of ESG scores and differences in ownership structures. To determine risk-adjusted returns, we follow the classical empirical asset pricing literature and utilize a number of multi-factor models on our portfolios. We find that, generally, there is no evidence of an ESG premium amongst all owners, but conditioning our ESG factor on stocks in the largest quantile of unconstrained ownership, such as hedge funds, it emerges. We also see that for stocks with a high ownership share of socially constrained investors, such as endowments and public pension funds, the ESG premium disappears. This is consistent with the idea that unconstrained investors thoroughly research companies and invest in stocks they think will increase their ESG scores over the next period, and through the sustainability premium therefore increase in value, leading us to our second finding.

Conducting empirical work on ESG naturally brings along some worries. Our first worry is using data that has been back-filled, and hence would give us a forward-looking bias. To alleviate this worry we use the only ESG database that to our knowledge is not back-filled. The database we use is the original Thomson-Reuters ASSET4 scores, before their methodology were revised and back-filled in the current online scores. This insures that we only use data, which were able to the investor at the time, and not data, which later turned out to be important, hence leading to forward-looking bias. The drawback of this dataset is our second worry. The worry is that the dataset covers 15 years of 624 to 2,992 companies, which as we collapse to monthly returns by forming portfolios, gives us 180 observations for each portfolio, even though the cross-section is much larger. This is done to reduce noise and focus on the cross section.[7] The worry of a small dataset is that it might give us low power, and we will not be able to find small effects. However, for our baseline result our power is above 99%, which means we would expect to find our effect in 99 out of 100 experiments. These considerations, together with the many robustness checks we conduct in the paper, make us confident in the external validity of our findings.

Our second finding documents that unconstrained ownership predicts increases in future ESG scores, whereas constrained ownership does the opposite, although to a lesser degree. We consider future changes in the ESG scores of both a portfolio of firms with high socially unconstrained ownership and a portfolio with high socially constrained ownership. We look at horizons from 1 to 10 years, and find that the yearly future ESG increase peaks at around 4 years in the future, but stays positive for up to 8 years in the future. We consider this is a slowly revealing effect, which makes sense as the ESG score is based on firm fundamentals, which have a lot of inertia and hence take a while to move and update to their potential. For constrained firms we see a short term insignificant increase and then negative changes going forward with the lowest yearly change at 5 years ahead. This finding of heterogeneous skill is consistent with the theory, and can help explain the stylized fact of a positive alpha amongst unconstrained investors' sustainable investments. However, it does not explain why even constrained investors have non-negative increases in their portfolio's ESG scores, for this we turn to our third and fourth findings.

Our third finding arises from the time series of cross-sectional long-short ESG strategy returns. Our finding is that abnormal returns increase in recessions. That is, sustainability is a hedge for bad times. We show this by regressing the excess returns of the sustainability strategy of unconstrained investors on the risk factors and an alpha, that is allowed to be different in a recession than outside of it. Here, we find the alpha to be much larger during the recession. This observation provides scope for theories of time-varying risk aversion (Fama and French, 1989), investment opportunities (Merton, 1973), or changes in sentiment, as it does not seem to be compensation for risk.

[7] For details on the pros and cons of this approach see for example Fama and French (1992).

This leads us to highlight our fourth finding, where we instead of risk see that sentiment does explain the abnormal returns of our sustainable strategies. As we wanted an intuitive measure of sustainability sentiment, we chose to use Google search volumes on the term *Climate change*. We notice that search volumes are highly seasonal, so we correct for this by subtracting the value a year ago, to get the year-by-year difference. Finally, as sentiment is likely autocorrelated, it does not randomly rise and fall each period, but builds on previous sentiment each time - a fact we later verify; we use the innovations from fitting an AR(1) model. One might be worried that this is an overly simplistic measure, and might instead reflect the searches of climate deniers. However, there are a lot of correlation between different climate measures, and we see the simplicity and transparency of our measure as a virtue. An example of this is that when we instead use the more complicated text-based measure of (Engle et al., 2019), which is constructed from a high-dimensional dataset, we get qualitatively similar results. We also believe climate deniers to be a small fraction of the population and their searches to be relatively constant, whereas the worry of climate change has varied over the last decades, with a rising trend; hence as we use the variation of the searches we believe it more likely captures climate worry than climate denial.

Having retrieved our sentiment measure, we see that sentiment rose in the good times before the financial crisis, then fell in the recession, to then peak again after. Finally, after a low period thereafter, it has had an unprecedented long and strong rise from around 2013 until the end of our sample. To understand if the positive return of the sustainability sentiment could be driven by a rise in sentiment rather than originating in risk premia, we regress the returns on our factor, whilst controlling for the risk factors just as before. What we find is that as *Sustainability sentiment* rises, it leads to positive abnormal realized returns. However, the alphas are still positive unconditionally for unconstrained investors, where as it is zero for the factor in general. To understand this, remember that unconstrained investors are skilled in the sense that they achieve an extra abnormal return from predicting firms ESG scores, our second finding. Additionally, we accept that sustainability sentiment is about more than just climate change, and that even climate sentiment is difficult to accurately measure using observed data. This result helps to empirically show that there has been a strong increase in sustainability sentiment over the last decade; which helps understand the the positive abnormal returns, as well as the growth of the ESG investment industry over the same period.

An additional finding is that for investors to hold ESG stocks to a different extend and an ESG sector to exist, it must be that investors have heterogeneous ESG preferences. Through a revealed preference result we show that this indeed is the case. When we consider the investors' holdings we find that both investor types have an ESG tilt overall with large deviations within each investor group. However, as constrained investors always have had this, it only arises from 2007 for the unconstrained investors. It appears that constrained investors value ESG higher than unconstrained, as we see their holdings increase more depending on the firms ESG scores. This measure of how much investors value sustainability is a good addition to our previous evidence of sustainability preference, as it is not confounded in the same way returns are.

To our knowledge, our study is the first to document the difference in sustainable investment returns between different investor types. This is interesting, as it sheds new light on investors' skills and preferences. Moreover, our findings are important to the investment community, as it illustrates how socially-motivated restrictions on asset holdings have affected previous returns, and what implications they have on expected returns going forward.

The remainder of this paper is structured as follows. A literature review finishes off Section 1. Section 2 sets up our theoretical framework, as well as deriving the equations to be estimated in our empirical analysis. Section 3 describes our data, including ESG score availability. Section 4 illustrates investor holdings of ESG stocks, and considers investors revealed preferences for sustainability. Section 5 reports our findings. Section 6 concludes the paper.

**Related Literature.** Milton Friedman (1970) once famously argued that the firm's only social responsibility is to maximize its owners' profits. However, this paradigm seems to have changed in the investment community.[8] Academia is catching up and has long investigated relevant economic implications. Our study relates to this recent strand of literature, that investigates the relationship between social responsibility and stock performance. Among others, Dimson et al. (2015), Eccles et al. (2014), Krüger (2015), Ge and Liu (2015), Fatemi et al. (2015), Porter and Kramer (2006) 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 et al., 2018). Others, on the other hand, argue that there is no causal relationship between returns and sustainabaility efforts (e.g. Alexander and Buchholz, 1978, Siegel and McWilliam, 2000, Renneboog et al., 2008, Bauer et al., 2005, Hamilton et al., 1993). Finally, there is also evidence for a negative causality as provided by, for example, Fisher-Vanden and Thorburn (2011), Boyle et al. (1997), El Ghoul and Karoui (2017). As the literature review suggests, a clear connection between sustainability, financial performance, and ownership structures remains to be fully understood. We add to the literature by showing that different owners experience different tradeoffs when investing sustainably.

## 2 Theoretical Framework

To guide our empirical approach and to gain an increased understanding of our results, we here describe the theoretical foundation of our study. We follow Pastor et al. (2019) and consider a general equilibrium economy with a continuum of agents who dislike risk and have heterogeneous preferences for ESG. This deviates from the standard CAPM of Sharpe (1964) and Lintner (1965) by adding the sustainability preference. Specifically, the agents utility is

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

[8] The concept of ESG scores has become so popular amongst the investment community that fund managers have long started ESG-only mutual or exchange-traded funds. Asset managers like BlackRock, JPMorgan, UBS, and many others have long started their own ESG funds, in which they pick particular companies that fulfills their investment agenda. They often refer to them as sustainable and impact investing.

where the utility of investor $i$ stems from the amount owned 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 $b_i$. $X_i$ is a vector of stock weights. $b_i$ is also a vector, which depends on the greenness $g$ of the stock and the agents individual sustainability preference $d_i$ ($b_i = d_i g$).

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

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

where $\mu$ is the expected return and $\epsilon$ captures the risk distributed as $N(0, \Sigma)$.

This means that the investor's optimal weights will be

$$X_i = \frac{1}{\gamma}\Sigma^{-1}(\mu + \frac{1}{\gamma}b_i), \tag{3}$$

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

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

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

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 original result. This can be written in terms of the market return as

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

where $\beta$ is the market betas $(1/\sigma_M^2)\Sigma x$. 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

$$r^e = \underbrace{-\frac{\bar{d}}{\gamma} g}_{\alpha} + \mu_M \beta + \epsilon. \tag{7}$$

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

$$X_i = x + \frac{\delta}{\gamma^2}(\Sigma^{-1} g). \tag{8}$$

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 $x$ and an ESG portfolio, the last term above. Hence, the second term illustrates investors' ESG tilt. If all investors had the same preference, $\delta_i$ would be zero, and no investors would have a ESG tilt. Everyone holds the market portfolio and there is no reason for advisors to offer ESG products to their investors.

It is further interesting to note that as risk aversion increases, the portfolio tilt decreases, as investors start worrying more about risk than sustainability, as compared to before.

Now, if consumers preference of green goods or the investor preference average unexpectedly increases, it will lead to lower future expected return, and a positive unexpected realized return of

$$r^u = f_g g + \varepsilon, \tag{9}$$

where $f_g$ is the combination of the two random preference shocks

$$f_g = z_g + \frac{1}{\gamma}(\bar{d}_1 - E_0[\bar{d}_1]), \tag{10}$$

where $z_g$ is the consumer taste shock. We hence note that the unexpected ESG factor return $f_g$ can arise from consumer or investor preference changes, however, we will for simplicity treat ESG 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.

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

$$r^e = \beta_M r_M^e + g(f_g + \mu_g) + \nu, \tag{11}$$

where $E_0[\nu | r_M^e, f_g] = 0$ and $\mu_g$ is the expected return on the ESG portfolio $\mu_M \beta_g - \bar{d}/\gamma$. Here, $\beta_g$ is the ESG portfolios beta with the market portfolio, making the ESG factors realized return $f_g + \mu_g$ and $E_0[f_g + \mu_g] = \mu_g$.[9] Hence, Equation (10) illustrates how increased sentiment (changes in ESG preferences) enters into the excess returns of Equation (11), and boosts the returns of green stocks. Another interesting note is that stocks will now have zero alpha when regressed against the market excess returns and the ESG portfolio returns.

As an addition we consider the case where a small fraction of skilled investors are able to predict future ESG scores, for example through thorough analysis of firm fundamentals and strategy. The, for the general investor, unexpected shock to the greenness of the firm $\tilde{g}$, leads to a new total excess return of

$$r^e = \beta_M r_M^e + g\mu_g + \tilde{g}\frac{\bar{d}}{\gamma} + \epsilon, \tag{12}$$

and hence effectively boosts the return of the skilled investor.

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 (7). 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 also are zero.

Our second hypothesis is that some investors are able to predict future ESG score changes $\tilde{g}$, which means they can achieve a positive alpha in their investments into green stocks, as

[9] $\beta_g$ 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 $\beta_g$ seems to be explained by the ESG-factor doing well in bad times, implying a negative correlation with fundamental payoff risk.

according to Equation (12). The effect is stronger for green stocks, as these are the stocks that ESG constrained firms can invest in. This is tested against the null that $\tilde{g} = \mu_g = 0$, which is a stronger test than $\mu_g < 0$, as one would expect with a positive sustainability preference.

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 (11), which we test agains the null that $f_g = \mu_g = 0$, that 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 company values. We follow Fama French and only include stocks that are listed on the NYSE, AMEX, or NASDAQ and have a CRSP share code of 10 or 11. We use the returns to form portfolios in the standard way of Fama and French (1992). Details on sorting can be found in Appendix D.

**ESG.** We download yearly ESG score data from Thomson Reuters, an equal-weighted rating on companies' sustainability focuses with regards to economic, environmental, social and corporate governance pillars (referred to as the *ASSET4's* pillar). 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 sustainability, and vice versa. The higher the company's score, the more sustainable it is with regards to the three pillars.

There are a few important facts to consider on the assignment of the scores. Thomson Reuters assures that data on ESG scores is not backfilled, meaning that there would be not assignment of scores for years that does not concern the previous 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. This is important because in our analysis we make the implicit assumption that investors have the information for the previous year available. There might be minor adjustments in the magnitude of a score in later years, however, this happens rarely and even if it does, adjustments are small in size.[10]

Thomson Reuters computes the scores themselves and follows a strict methodology when doing so. In essence, they collect as many as possible data points from universe of 750 possibilities for each firm. 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 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 then 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. All ratings are provided on a yearly basis.[11]

We merge the return data from CRSP with the ESG data according to their CUSIP codes. As they differ in their frequencies, ESG data points are available on a yearly basis. ESG scores are available from 2002 until today (2016), which defines our sample period.

Investigating the ESG data set in greater detail, Table 1 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 list an ESG score. This number significantly increases to 2,992 firms in the final year of the sample, 2016. The distribution of ESG scores remains relatively stable over time with a mean scores in between approximately 43 to 58. Scores on the very low end as well as on the high end are found.

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

[11] The interested reader can find a more detailed description on how Thomson Reuters determines their ESG scores here.

**Table 1: 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. It ranges from 624 companies that exhibit an ESG score in 2002 up to 2,992 in 2016. The distribution estimates remain relatively stable across the years except for the last two years of 2015 and 2016.

| 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 | 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 |

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 1. This also implies that the cross-section's total number of firms in later performance analysis rises significantly over time.

**Risk Factors.** To control for risk factors we use the risk-free rate and factor-returns of Fama-French's 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.

**Good times.** 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.[12] Specifically, we utilize data that contains information on institutional ownership as a percentage of a firm.

The data exhibits the number of shares held by every institutional investor. We use this number to calculate the relative share of each institutional investor as a proxy for their holdings. Sometimes, the data did 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.[13]

The institutional ownership data (13F) exhibits five different types of owners which we categorize into socially constrained and unconstrained investors as in Hong and Kacperczyk (2009). Socially constrained 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). Socially unconstrained owners are mutual funds (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.

**Sentiment.** We test for sentiment by using the search interest of 'Climate change' on Google. This $hits$ measure is the search volume in the United States expressed relative to the maximum search volume in percent. A breakdown into states is also possible. The data is retrieved from Google Trends. Results are robust to using just 'Climate', and searches for 'Social' and 'Governance' have the same sign, but do not seem to explain the sentiment as well suggesting that ESG sentiment are driven more by climate concerns than social or governance. We also use measures such as the Baker and Wurgler (2006) sentiment measure which is the principal component of five sentiment proxies, that have first been orthogonalised to a set of six macroeconomic indicators ($perp$). Finally we also use Engle et al. (2019) text-based

[12]A short overview of the SEC's regulatory requirements is found here. It generally defines which type of investor is categorized as institutional and what rules they are ought to follow.

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

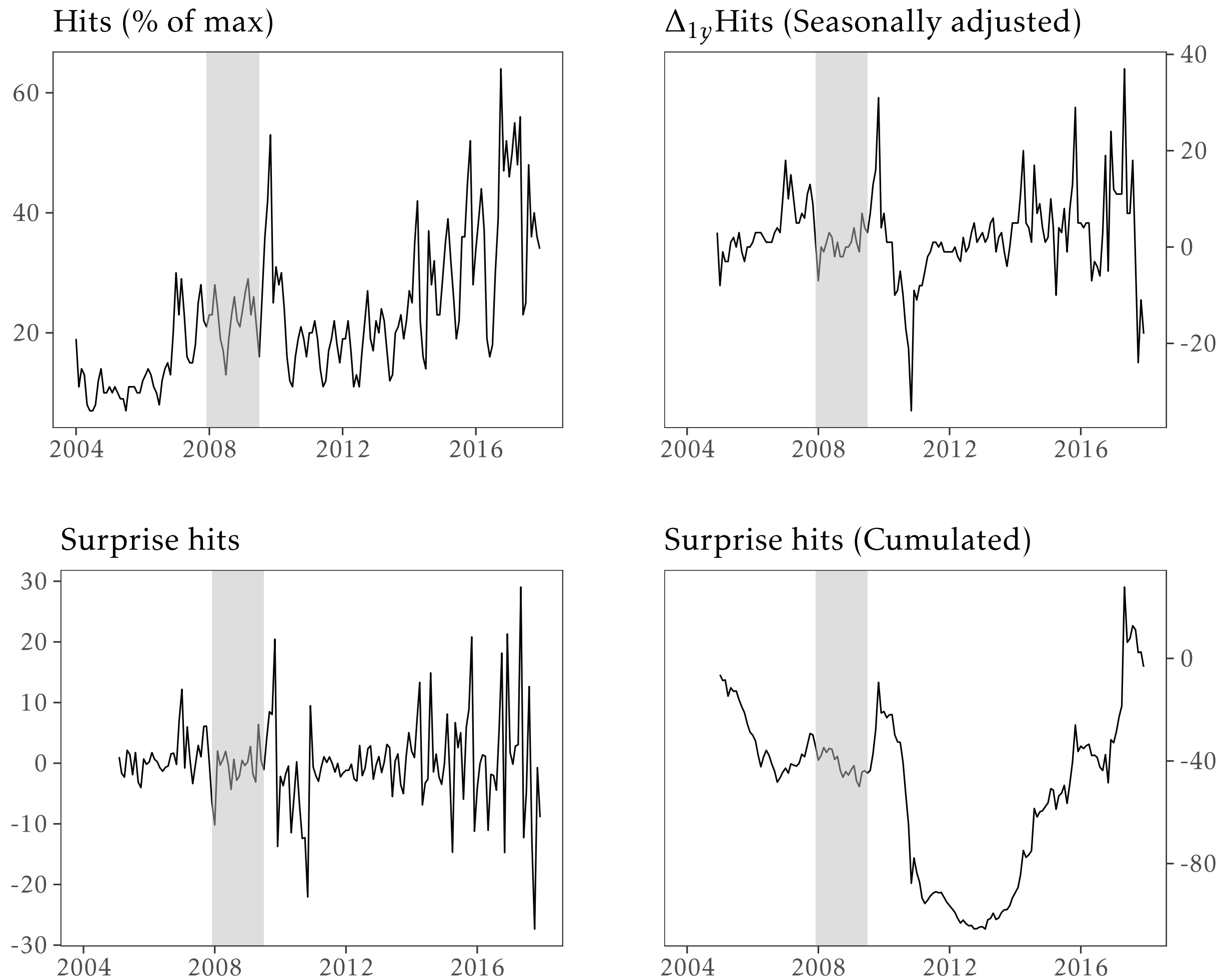



**Figure 2: Climate Sentiment**

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. 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.

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*). Figure 2 shows how our *hits* 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. 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. The observed rise in sentiment in good times, and decline in crises is consistent with theory. From theory, it arises because as risk aversion grows in the economy, economic risk becomes a relative larger worry for the investors than sustainability.

## 4 ESG Ownership and Preferences

In this section we review our findings on ownership of ESG stocks. Specifically, we consider our two ownership groups.

Figure 3 plots the relative ownership of socially constrained and unconstrained owners in firms with ESG scores. Specifically, we subdivide into four portfolios, which we rearrange every year in the sample according to the previous year's score. We value-weight results and plot ownership over time. The 1st Quartile are low ESG firms, whereas the 4th Quantile represents high ESG firms.

The level of ownership by socially constrained investors seems to be more volatile in low ESG firms, see Figure 3. This might relate to findings by Starks et al. (2017), suggesting that long-term investors are less patient with low ESG firms than with high ESG firms. Although not clear at all points in time, the level of socially constrained and unconstrained owners is lower in high ESG firms. This might be due to retail investors (who make out the remainder of the ownership share) have a larger ESG tilt, and institutional investors are left with the rest.

With respect to socially unconstrained investors there is not much difference between relative shares of ownership among different levels of ESG. However, Figure 3 shows a large increase in total ownership of socially unconstrained ownership between 2006 and 2009. We further notice that the difference in ownership shares between the two ownership groups narrow in the crisis, indicating that socially constrained investors sold ESG stocks to uncon-

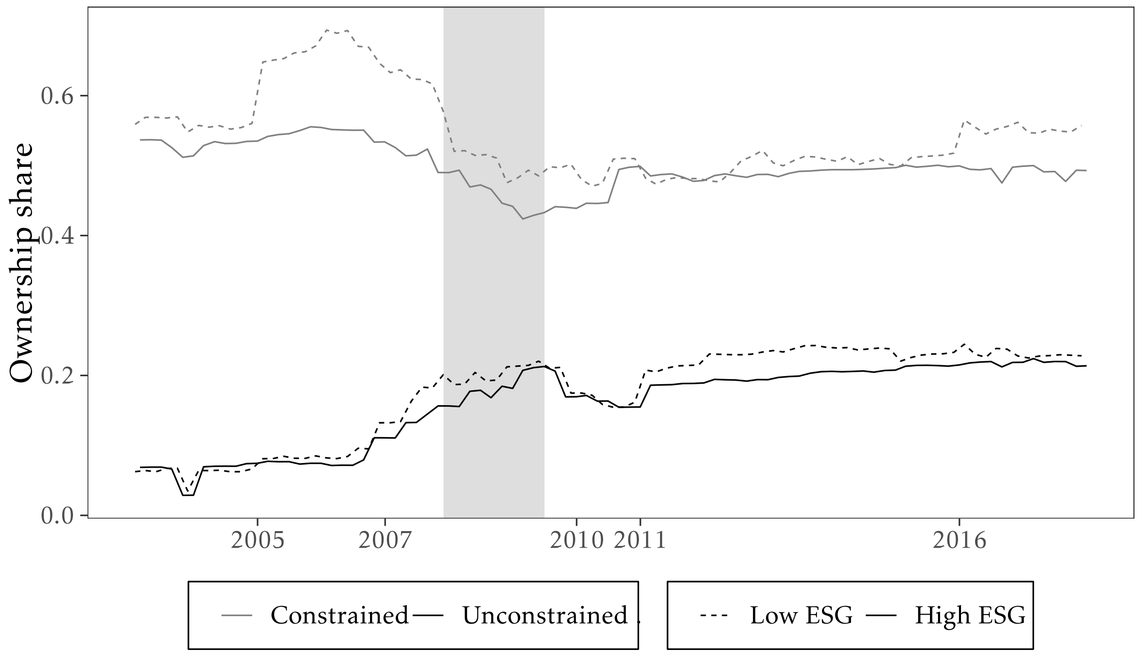



**Figure 3: ESG Ownership**

We plot the ownership structures of firms with ESG scores. We subdivide the sample of ESG firms in four different portfolios and rearrange them every year according the previous year's ESG score. The 1st quartile (4th quartile) includes firms with the lowest (highest) ESG scores. Holdings are value-weighted. At the top in grey, we exhibit the ownership share (relative to shares outstanding) of socially constrained owners of all ESG firms. Socially constrained investors are either banks (Type 1), insurance companies (Type 2) or other institutions (Type 5). Below in black the ownership concentration of socially unconstrained investors in ESG firms is shown. Socially unconstrained investors are either mutual funds (Type 3) or independent investment advisors (Type 5). The shaded area denotes recession.

strained investors, particularly high ESG stocks. To some extend reversing after the crisis, where the stocks were sold back from unconstrained investors to constrained as well as retail investors. During the sovereign debt crisis around 2011 both constrained and unconstrained purchase shares from retail investors. Lastly it seems that retail investors sold off low-ESG stocks to socially constrained firms in 2016.

It is further interesting to note that portfolio tilts (difference in ownership of high and low ESG stocks) become smaller in the crisis as risk aversion increases (In Figure 3). To connect this with the theory, it may be because retail investors, who may have the highest ESG preference, increased their high ESG ownership in the good years before the crisis, and then reduced their tilt in the crisis, which meant that Constrained and Unconstrained investors had to pick up the difference. We see a similar pattern happening in the late years from 2016.

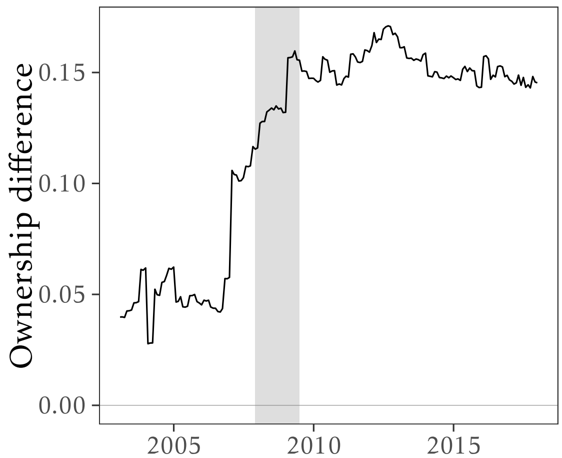
### Preferences

To get an understanding of preferences we first plot different portfolios of high and low degrees of socially constrained and unconstrained ownerships with high and low ESG firms in Figure 4. This gives us an idea about the heterogeneity of ESG preferences within the two investor types. The idea is that if everyone valued ESG equally, you would not have some people tilting towards higher ESG firms, leading to everyone owning the same ownership share of high ESG stocks, and a small difference between the high ESG stocks with the highest ownership share and lowest ownership share as plotted in Figure 4. On the other hand if there is a large heterogeneity of prefences we would expect to see a large difference between the investors ownership of high ESG stocks. It turns out that the latter is actually what we see. Specifically, what we see is that there is a large preference heterogeneity within Constrained investors across the whole period, and that preference heterogeneity in the beginning was low for the unconstrained, but that it grew from around 2007, as well as through the financial crisis, to finally be several orders of magnitude larger by 2011. We acknowledge that this is not a perfect proxy, but we think it serves as a useful measure of ESG preference heterogeneity.

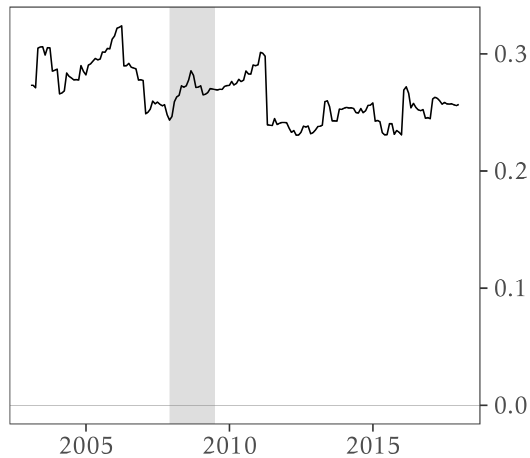
The results show differences between low and high ownerships shares range from about 15% to 25% in within the socially unconstrained and constrained owners, respectively. This is also important from a theoretical point of view, as it suggests that investors do value ESG, and some more than others.

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 ($V_{i,t}^{I}$) in firm $i$ at time $t$ according to

$$V_{i,t}^{I} = S_{i,t} \times O_{i,t}^{I} \times P_{i,t} \,, \tag{13}$$




**(a)** Unconstrained




**(b)** Constrained

**Figure 4: ESG Preferences**

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 socially unconstrained investors. Socially unconstrained investors are either mutual funds (Type 3) or independent investment advisors (Type 5). Panel (b) shows ownership concentration of socially constrained investors in ESG firms is shown. Socially constrained investors are either banks (Type 1), insurance companies (Type 2) or other institutions (Type 5). The shaded area denotes recession.

where $I$ is the ownership type constrained or unconstrained ($I = U, C$). $S_{i,t}$, $O^I_{i,t}$ 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

$$V^I_{i,t} = ESG_{i,t-1} + F_i + \epsilon_{i,t} \tag{14}$$

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 2 shows the results.

Table 2 shows that both socially constrained and unconstrained 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

**Table 2: Revealed Preferences: ESG Score Portfolio Tilts**

We run regression (14) for socially constrained ($C$) and unconstrained ($U$) owners. We control for firm fixed effects. The variable $V^I$, $I = \{U, C\}$, 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:* | |
|---|---|---|
| | $V^C$ | $V^U$ |
| ESG Score | 59,839*** | 41,160*** |
| | (7,541) | (3,959) |
| Firm Fixed Effects | Y | Y |
| Clustered Errors | Y | Y |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |

per investor type. We notice that constrained 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, constrained investors seem to assert a higher preference to ESG than unconstrained.

## 5 Results

In this section we empirically investigate the relationship between ESG scores and equity returns. Broadly speaking, we test the three hypothesis we developed from the theory in Section 2. Specifically, we test the relationship of a stock's greenness and its expected return (Equation 7), whether investors are compensated for predicting ESG scores (Equation 12), and finally whether climate sentiment has increased the abnormal returns to green stocks (Equation 11).

In this subsection, we provide evidence that investors' heterogeneity matters. We begin by briefly describing the negative but insignificant abnormal returns to a strategy that within all stocks goes long in high ESG and short in low ESG score stocks. Second, we consider returns to the same strategy, but solely looking within stocks held to a large degree by socially unconstrained investors. Here, we see significant positive abnormal returns.

The following subsections explore investors' heterogeneity further and we show that constrained investors chase high ESG high return stocks, but are not able to achieve the same abnormal returns as unconstrained investors. The second subsection gives an explanation as to where the abnormal return may be arising from, and conclude that it seems to be due to unconstrained investors' ability to predict ESG scores. The third considers another explanation, that it may be due to compensation for consumption risk, which we reject. The final subsection exhibits evidence that increased climate sentiment has promoted an increase to the abnormal returns of the sustainable strategy.

To do this, we need to calculate risk-adjusted returns. Our standard specification is to take value weighted single- or double-sorted portfolios and regress them against Carhart (1997)'s four factors. This ensures the results are not driven by return anomalies (for example by small stocks or momentum). Our main results are robust to using equally-weighted returns and alternative approaches as the CAPM or Fama-French three-factor model (Sharpe, 1964, Fama and French, 1992). This means we explicitly estimate Equation (7) as

$$r_{it} - r_t^f = \alpha_i + \sum_{j=1}^{J} \beta_{ij} f_{jt} + \epsilon_{it}, \tag{15}$$

where $r_{it}$ depicts portfolio $i$'s return at time $t$. Moreover, $r_t^f$, $\alpha_i$, and $J$ denote the risk-free rate, the abnormal return, and the number of factors. Finally, the $\beta_{ij}$, $f_{jt}$ and $\epsilon_{it}$ 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.[14]

For our first results, we see that when not considering ownership, there does not seem to be a general ESG premium (See Table 11 in Appendix B). A long-short portfolio, which goes long in the top decile ESG firms and shorts the lowest decile of ESG firms does not earn

[14]We also risk-adjust our returns for a variety of long-short portfolio, where we enter in a long position of portfolio of high ESG (HESG) firms and short low ESG (LESG) firms, so that $LS_t = r_t^{HESG} - r_t^{LESG}$. The regression equation then follows

$$LS_t = \alpha + \sum_{j=1}^{n} \beta_j f_{jt} + \epsilon_t.$$

significant abnormal returns. We find partial evidence that the firms in the lowest decile portfolio earn higher returns than others. Similar results are found for the highest decile portfolio of ESG firms in the equally-weighted case (Panel A). However, the value-weighted returns reject this finding. This suggest that this finding might be driven by small firms, and that there is neither a benefit or a cost of investing sustainably in general, when not incorporating additional information.

Secondly, we, on the other hand, find that socially unconstrained investors *do* earn a positive ESG premium when investing in high ESG firms and shorting low ESG firms, see Table 3. This trend is increasing monotonically from low to high ESG in both the CAPM and Carhart four-factor models, although always positive. Hence it is driven by a high abnormal return of high ESG stocks, rather than a low abnormal return of low ESG stocks, which means that the strategy returns are not driven by short-sale restrictions. The ESG premium consists of a statistical and economically significant 30 bp per month (in the Carhart four-factor model specification). We find similar results in an equally-weighted application. This shows that even though the sustainable strategy in general has negative expected returns, skilled unconstrained owners are able to achieve positive abnormal returns, when unconstrained are not. This is partly explained by unconstrained investors ability to predict ESG scores, as we illustrate in our next sub-section. We also note that it does not seem that unconstrained investors are better investors in all types of firms, as we do not see that amongst the two lowest ESG quantiles, that the abnormal returns increase as ownership increases.[15]

We exhibit more detailed regression results of the long-short equity strategy within unconstrained investors in Table 4. In Columns (1) to (3), we confirm the results for ESG firms over all factor models. We further see that the premium partially loads on the market developments themselves and the small minus big factor. We cannot confirm an ESG premium amongst stocks with low degrees of socially unconstrained ownership, see Columns (4) and (5). However, the ESG long-short strategy also significantly loads on the market and the small minus big factor. We further note, that the ESG factor loads on the momentum factor

[15] It may be that unconstrained also are able to find firms, whose ESG scores decline, however as our ownership data does not include short positions, we are not able to verify this.

**Table 3: Double sort of ESG and ownership of socially unconstrained institutions**

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 socially unconstrained 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 | | | | | |
| Unconstrained 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 |
| Unconstrained 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 | | | | | |
| Unconstrained 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 |
| Unconstrained ownership high | 0.088 | 0.005 | 0.173 | **0.392** | **0.304** |
| t-stat | 0.773 | 0.041 | 1.202 | 3.784 | 2.027 |

for both ownership types. This serves as a first motivation for us to explore whether less risk-based factors may be driving these returns, such as sentiment.

**Table 4: Long-short regressions with different degrees of socially unconstrained ownership**

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 socially unconstrained institutional ownership share and assign them into another four portfolios, ending up with a total of 16 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 socially unconstrained ownership level in $D = \{H,L\}$. Specifically, we test

$$LS_t^D = r_t^{D,HESG} - r_t^{D,LESG} = \alpha + \sum_{j=1}^{n} \beta_j f_{jt} + \epsilon_t,$$

where $\beta_j$, $f_{jt}$ and $\epsilon_{it}$ are the factor loadings, factors and the error term. Specifically, we test our long-short portfolio against 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) |
| $\alpha$ | 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 |

## 5.1 Unconstrained investors are able to achieve high returns whilst investing sustainably

In this subsection, we provide a comparison of the ESG premium between socially constrained and unconstrained investors.

We start by considering the sustainable investment returns for both investor types. Panel A of Table 5 is a replication of Panel B in Table 3. These are for the Carhart four-factor model, the model that best fits our data. Comparing socially unconstrained in Panel A and constrained investors in Panel C, we find that unconstrained investors earn a significant ESG premium of 30 bp a month, whereas constrained investors do not earn a significant abnormal return across ESG firms. We additionally find that among mid-level ESG firms (Q2 and Q3) and high socially constrained ownership, portfolios tend to earn negative abnormal returns. We do not find a similar observation among socially unconstrained investors. These results confirm our previous hypothesis that socially unconstrained investors are able to predict firms future ESG scores, whilst constrained investors lose out.

Table 5's panels B and D depict our second test. Here, we examine stock performance of socially unconstrained and constrained investors assuming that holdings would have been realized one quarter earlier. For example, if an investor holds 10% of stock A at time $t$ and 20% of that same stock at time $t+3$, we assume that investors held 10% of stock A at time $t-3$ and 20% at time $t$ (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 considering, and possibly doing back-tests on, and end up owning before the next quarter. Possibly revealing why these stocks may have been attractive investments for these investor types. We follow our double-sort methodology and sort on ESG scores as well as future holdings, and display the abnormal returns of the 16 normal portfolios and 4 long-short portfolios, under the Carhart four-factor model in Panel B and Panel D. Results show that stocks socially constrained investors will own in the next quart experienced a significant positive ESG premium of 34 bp per month. This suggests that socially constrained investors notice the high returns within high ESG stocks decide to increase their holdings of those. This, on the other hand, leads to

**Table 5: Double sort of ESG and ownership levels over time**

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 socially unconstrained and constrained 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 3 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. We value-weight these 16 portfolios with the previous month's market values. Finally, we run regressions according to the Carhart four-factor model 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.

| | *Sorted on actual holdings* | | | | | *Sorted on future holdings* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ESG low | Q2 | Q3 | ESG high | LS | ESG low | Q2 | Q3 | ESG high | LS |
| | Sorted on Socially Unconstrained 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 Socially Constrained 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 | 0.02 | 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 | -0.19 | 0.13 | 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 |

more demand, pushing up the price and lowering future abnormal returns as they evaporate for future realizations. It seems as if socially constrained investors chase high returns and high ESG firms at the same time. However, they only get higher ownership, but not high returns. This is different for socially unconstrained investors. Even though, high ESG stocks with high socially unconstrained ownership also gave them a premium in the previous quarter, they are able to keep exploiting these returns in the quarter where they actually hold them. This suggests that unconstrained investors are able to pick undervalued stocks within the high ESG realm as we see high abnormal returns in their actual holding periods too. Hence, they do not need to chase high returns in hope of high future returns, but instead buy undervalued stocks, which get hyped up to their fair value and sold off to the larger socially constrained investors.

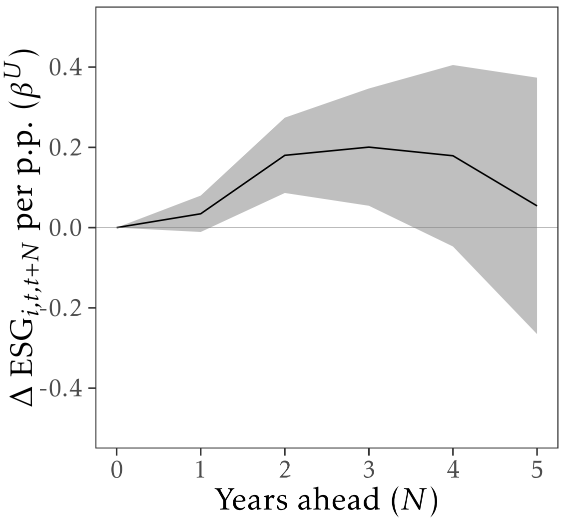
### 5.2 Skill is the ability to predict ESG scores

To understand where socially unconstrained investors abnormal returns may be coming from, we test whether they are better than socially constrained investors at predicting changes in firms ESG scores. To test this, we run:

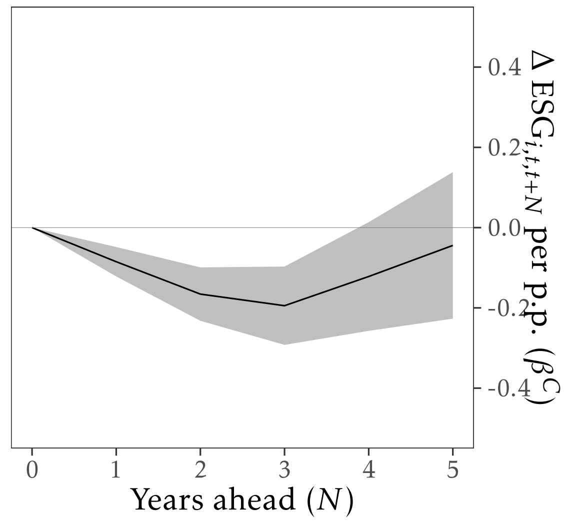
$$\Delta ESG_{i,t,t+N} = \alpha + \beta O^{I}_{i,t} + \epsilon_{i,t}, \tag{16}$$

where $\Delta ESG_{i,t,t+N}$ is 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 socially constrained or unconstrained investors $I = \{U, C\}$. Additionally, we allow for heteroskedastic standard errors. Figure 5 shows the results.

Figure 5a exhibits that an increase in ownership by socially unconstrained investors leads to future increases in the firms ESG portfolio's score. Here, if a stock is bought by an unconstrained investor from an unconstrained investor it yields on average positive changes every year for three years, with the largest yearly change being between year one and two of about 15 ESG points or half a standard deviation. Instead, had the stock remained in the hands of the socially constrained investors, see Figure 5b, its ESG score would on average decrease,




**(a)** Unconstrained Investors




**(b)** Constrained Investors

**Figure 5: Predicting ESG Score Changes**

Figure 5a shows socially unconstrained ownership in firms and their correlation to future changes in ESG scores, whereas Figure 5b shows this effect for for socially constrained investors, see equation (16). $N$ depicts the number of years into the future of the regression equation. Allowing for heteroskedasticity, the gray shade depict White standard errors. Additionally, we use time and firm fixed effects, and cluster by time to allow for correlation in the cross-sectional error terms.

though a little less than the increase for unconstrained. This effect is mainly materialized in the first two years into the future.

This stylized fact indicates that socially unconstrained investors are better able to detect ESG firms with the potential of increases in their sustainability score, or put differently: undervalued ESG score firms. Unconstrained investors therefore seem to have superior skill to detect ESG value, which may be explained by these firms spending a lot of money and energy on fundamental analysis of companies, which pays off. Alternatively, it may be due to the constraints of the constrained investors preventing them from purchasing these promising stocks.

This finding helps explain why socially unconstrained firms earn superior returns when they invest in ESG firms. A firm with an undervalued ESG score could be of value for investors once the the correct score is materialized and markets price in this new publicly available information. Potentially, this could lead to price appreciation, which current holders might yield abnormal returns from.

### 5.3 ESG hedges recessions

To gain an increased understanding of where the sustainability premium of stocks with high socially unconstrained ownership arises from, we consider whether they are a compensation for consumption risk. If so, we would expect negative excess returns at times of low consumption, such as the great financial crisis.

We test this by considering ESG portfolios' returns under varying economic environments. Different economic environments are introduced through the NBER Business Cycle Reference Dates, which we label as bad and good times, dependent on whether the economy was in a recession or not at time $t$. We use this to split the $\alpha$ from Equation (15) into two abnormal return coefficients $\{\alpha^G, \alpha^B\}$. We utilize value-weighted portfolios, which are characterized by a degree $D = \{H, L\}$, that is either high ($H$) or low ($L$) of constrained or unconstrained investors $I = \{C, U\}$ and calculate returns for a long-short ESG strategy.

Specifically, we go long in high socially unconstrained or constrained ownership firms with high ESG scores (HESG) and short those firms in the same ownership category $I$ but with a low ESG scores (LESG). Hence, we compute:

$$LS_t^I = r_t^{HESG,I} - r_t^{LESG,I} = \alpha^G NBER_{FALSE_t} + \alpha^B NBER_t + \sum_{j=1}^{n} \beta_j f_{jt} + \epsilon_t, \tag{17}$$

where $NBER_{FALSE_t}$ is an indicator variable that equals 1 in good times and 0 otherwise. $NBER_t$, on the other hand, equals 1 in bad times and 0 otherwise. This means that the factor loadings of $\alpha^G$ and $\alpha^B$ capture the abnormal performance for every long-short strategy according to good and bad times. The conditional factor models imply that $\alpha^G = \alpha^B = 0$ (see, for example, Ferson et al., 2009, Christopherson et al., 1998, for similar applications).

To gain an increased understanding of where the sustainability premium of stocks with high socially unconstrained ownership arises from, we plot cumulated excess returns of the four ESG quantile portfolios within this ownership type in Figure 1. In this plot, Q4 refers to high ESG firms, and Q1 for low. It shows that high ESG firms with high socially unconstrained ownership seem to do better, especially during the crises.[16]

These findings lead us to further investigate how ESG stocks with different ownership perform during the financial crises. Specifically, we estimate how the abnormal return of a long-short equity strategy within each ownership type differs in a recession. Table 6, exhibit results for long-short ESG portfolios under both high socially unconstrained (Columns 1 to 3) and constrained (Columns 4 to 6) investor ownership. We find significant positive abnormal returns in the recession for both ownership types, adjusting for risk using the CAPM, Fama-French three-factor and Carhart four-factor model. The loading of the $NBER$ variable in the regressions depicts what the ESG premium in the time of recession is among socially constrained and unconstrained investors. The results suggest that during the crisis, high ESG firms exhibit higher risk-adjusted stock returns relative to low ESG firms when these stocks have high socially constrained or unconstrained ownership. Numbers vary from the simple CAPM model to the Carhart four-factor model and go up to 1.163% for the months in the recession. This finding partially explains the abnormal returns exhibited in Panel A and C in Table 5.

Perhaps a driver of the high ESG return in recession is that as the government goes in to support the economy, there is pressure that it is done with a sustainable outlook, as is seen in 2020 with support for the Covid-19 crisis. The peak in returns is further shown in the figures of Appendix E.

The findings from Table 6 are an indicator that sustainability returns arise in the crises, as investors are more patient with high ESG stocks. Absolute numbers of the *NBER* regression indicator in Table 6 are high and suggest that a large fraction of the total abnormal returns from long-short equity strategies in ESG firms is earned in difficult economic times. These findings suggest that the increased uncertainty in the crisis might have made the unconstrained investors thorough research into ESG firms more valuable. Furthermore, the empirical evidence of high returns during the crisis also have real implications for investors in the future as high ESG firms seem to a hedge in recessions.

[16]We additionally plot the long-short portfolio for socially unconstrained and constrained investors in Figure 11 and 12 in Appendix E. Furthermore, we show the same plot for socially constrained investors in Figure 10.

**Table 6: Abnormal sustainability returns in the recession**

We sort returns according to lagged ESG scores in a total of four value-weighted portfolios. In the next step, we conditionally sort returns according to their previous quarter's socially unconstrained ($U$) and constrained ($C$) institutional ownership share and assign them into another four portfolios, ending up with a total of 16 portfolios. We then construct a long-short strategy, one where we buy high socially unconstrained or constrained ownership firms with high ESG ($HESG$) scores and short those with high socially unconstrained or constrained ownership and low ESG ($LESG$) scores. We test how this long-short strategy performs during crisis through utilizing the NBER recession indicator $NBER$, which equals one during the crisis and 0 otherwise. $NBER_{False}$ equals one when there is no crises and 0 otherwise. We test

$$LS_t^I = r_t^{HESG,I} - r_t^{LESG,I} = \alpha^B NBER_t + \alpha^G NBER_{FALSE_t} + \sum_{j=1}^{n} \beta_j f_{jt} + \epsilon_t,$$

where $\beta_j$, $f_{jt}$ and $\epsilon_{it}$ are the factor loadings, factors and the error term. Here, $I = U, C$ refers to the whether the firm has a high level of socially unconstrained $U$ or constrained $C$ ownership. Specifically, 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 $LS_t^I$ for ownership type $I = \{U, C\}$: | | | | | |
| | | $LS_t^U$ | | | $LS_t^C$ | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| NBER | 0.155 | 0.760*** | 1.163*** | 0.424 | 0.850*** | 0.603** |
| | t = 0.578 | t = 3.010 | t = 2.972 | t = 1.323 | t = 2.931 | t = 1.981 |
| $NBER_{FALSE}$ | 0.342** | 0.275 | 0.188 | 0.099 | 0.069 | 0.122 |
| | t = 2.097 | t = 1.643 | t = 1.125 | t = 0.542 | t = 0.396 | t = 0.714 |
| mkt - rf | −0.173*** | −0.043 | 0.011 | −0.173*** | −0.118** | −0.151*** |
| | t = −3.793 | t = −0.870 | t = 0.148 | t = −3.444 | t = −2.397 | t = −3.007 |
| smb | | −0.503*** | −0.528*** | | −0.327*** | −0.312*** |
| | | t = −3.765 | t = −3.899 | | t = −3.890 | t = −3.634 |
| hml | | 0.057 | 0.136 | | 0.212*** | 0.164** |
| | | t = 0.693 | t = 1.532 | | t = 2.858 | t = 2.386 |
| mom | | | 0.132** | | | −0.081* |
| | | | t = 2.419 | | | t = −1.773 |
| Observations | 180 | 180 | 180 | 180 | 180 | 180 |
| $R^2$ | 0.063 | 0.206 | 0.239 | 0.085 | 0.185 | 0.201 |
| *Note:* | | | | | *p<0.1; **p<0.05; ***p<0.01 | |

We consider robustness checks of the result with an alternative specification of economically good and bad times based on the value of the price dividend ratio over our time period. When the price-dividend ratio is below the unconditional mean of our time series (indicating bad times), it equals 1, and 0 otherwise. Table 17 in Appendix E exhibits the results of a long short-short equity strategy for unconstrained investors. Here the bad times abnormal return remains significant for the Carhart four-factor model, and remains to some extend, and at a similar size, even when not accounting for as many risk factors.

### 5.4 Sustainability sentiment explains abnormal returns

As the abnormal returns yielded by unconstrained investors in high ESG stocks do not seem to be driven by risk, we next consider sentiment as a possible explanation. As we saw in the theory section an increase in sustainability sentiment over the period could have lead to an increase in ESG returns, even though the unconditional ESG premium is negative (Equation 11). In the remaining section we consider sentiment in the form of salience, the Baker and Wurgler (2006) measure, and measures of optimism in the economy from valuation ratios.

To test for investor 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 analysis utilizes three main proxies as measures for sentiment. First, we test against a dummy variable that is 1 when the negative climate news from the Wall Street Journal measure from Engle et al. (2019) is above its unconditional average, and 0 otherwise. Second, the sentiment index by Baker and Wurgler (2006) serves as an indicator for investor behaviour in the stock market. Lastly, we use the price dividend ratio as denoted by Robert Schiller. Specifically, we compute

$$LS_t^I = r_t^{HESG,I} - r_t^{LESG,I} = \alpha + \gamma \; Sentiment_t + \sum_{j=1}^{J} \beta_j f_{jt} + \epsilon_t, \tag{18}$$

where $r_t^{HESG}$ ($r_t^{LESG}$) depicts the high (low) ESG portfolio return at time $t$. Moreover, $\alpha$ and $J$ denote the the abnormal return and the number of factors. Finally, the $\beta_j$, $f_{jt}$ and $\epsilon_t$ are the factor loadings, factors, and the error term. $Sentiment_t$ depicts the investor sentiment at time $t$ and $\gamma$ the loading on this proxy. This is our empirical specification of Equation 11, where $\alpha$ is the expected 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 sentiment $\gamma Sentiment$ is the return from the preference shock which also scales with the greenness of the firm $gf_g$, and $f$ is the excess return on the factor ($r^e_M$ in the theory specification). Hence, we expect $\gamma$ to vary according to the greenness of the firm, and be especially pronounced in our factor in particular, as we capture the difference in greenness of the high ESG and low ESG firms.

**High Salience.** Sustainability sentiment could be driven by an increase in the salience of, for example, climate change risks. To test whether ESG stock returns illustrate evidence of sentiment, we test whether the amount of Google searches for 'Climate change', a proxy for sustainability salience, can explain the abnormal return seen for our ESG factor. What we find is exactly that, and additionally that the prediction is especially strong in the crisis. First we note that it is interesting that the sentiment measure has a persistent effect, as can be seen in Figure 2 in Section 3, and the significance of the AR(1) coefficient. This helps explain why returns on the ESG factor seems to be bunched together. For the factor, sentiment has a positive effect on returns outside crisis, which is consistent with the theory, that in crises economic worries dominate. However, we see that for the unconstrained case that it is stronger in the crisis, which may be more related to them being able to exploit market frictions at this time. We have also tested whether sentiment explains the returns to the constrained investors ESG long-short strategy, but it does not. This suggests that unconstrained pick stocks amongst those with a high ESG score that are closer to the *real* sustainability score of those stocks, hence making them more sensitive to Climate sentiment. The results are robust to the different asset pricing models: CAPM, Fama-French, and Carhart. The results are also robust to creating the factor on searches on $Climate$ and to using just the Google searches coming from the News part. The results are also robust to using the changes in $hits$ instead of an AR(1) residual, as well as not seasonally adjusting. For the sake of brevity these are not shown here, but are available on request. The standard errors are corrected for autocorrelation and heteroscedasticity using Newey and West (1987) standard errors. A

**Table 7: 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 constructed a value-weighted long-short portfolio that goes long in top quartile of ESG firms with the top quartile of high socially unconstrained ownership and short in low ESG but also high level of ownership. The fourth to sixth column's dependent variable is constructed by the simple long-short strategy into the highest and lowest portfolios of ESG. We test sentiment of this portfolio towards surprise innovations in the Google Hits on the word 'Climate' as described in Section 3, and the $NBER$ recession indicator, which equals 1 in a crisis and 0 otherwise. Specifically, we test

$$\{LS_t^U, LS_T\} = \alpha + \gamma\ Sentiment + \mathbb{1}_{NBER} + \sum_{j=1}^{n} \beta_j f_{jt} + \epsilon_t,$$

where $\beta_j$, $f_{jt}$ and $\epsilon_{it}$ are the factor loadings, factors and the error term. We control for the factors of the Carhart four-factor model, but 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: | | | | | |
| | Unconstrained ($LS_t^U$) | | | Factor ($LS_t$) | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Surprise hits | 0.060*** | 0.060*** | | 0.039** | 0.038* | |
| | t = 3.120 | t = 2.942 | | t = 1.992 | t = 1.948 | |
| $\alpha$ | 0.396*** | | | 0.156 | | |
| | t = 2.692 | | | t = 1.127 | | |
| NBER | | 1.108** | 1.214*** | | 0.440 | 0.303 |
| | | t = 2.468 | t = 3.280 | | t = 1.092 | t = 0.680 |
| $\text{NBER}_{False}$ | | 0.282 | 0.305* | | 0.111 | 0.096 |
| | | t = 1.523 | t = 1.668 | | t = 0.729 | t = 0.645 |
| hits:NBER | | | 0.331*** | | | −0.190* |
| | | | t = 2.907 | | | t = −1.836 |
| $\text{hits:NBER}_{False}$ | | | 0.055** | | | 0.041** |
| | | | t = 2.416 | | | t = 2.103 |
| 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 |

1 standard deviation shock to *hits* is associated with a realised abnormal return of 6 bp. This rises to 1.214% in the crisis. For the factor the effect is 4 bp in general and negative in the crisis. These results enforce the idea that sustainability sentiment could be a force that pushes prices within ESG stocks.

Sustainability sentiment could also be driven by an increase in the salience of, for example, climate change risks. To test whether our ESG returns illustrate evidence of this type of sentiment, we test whether salience in the form of high negative news coverage of our climate, can explain the return of our ESG factor. What we find is that when we regress our ESG factor on *good_chneg* a dummy variable that is 1 when there are more than average bad news on climate, and 0 otherwise; a measure developed by Engle et al. (2019). Together with our risk factors, this type of salience indeed matters for the returns of our factor, see Table 8 Column (1). In periods with more than average amounts of negative news, the factor exhibits 73 bp of abnormal returns, whereas in quiet periods it does not exhibit any abnormal returns.

**High Baker and Wurgler (2006) sentiment.** We also consider whether the classical measure of sentiment as developed by Baker and Wurgler (2006) can explain our ESG returns. And we indeed find, as shown in Table 8 Column (2), that there is some evidence for this conjecture. We use their variable *perp*, which is their sentiment measure (a principal component of five proxies) that has first been orthogonalised to a set of six macroeconomic indicators. We find that in periods with a higher than average amount of sentiment as measured by Baker and Wurgler (2006), there are no higher abnormal returns, but actually the abnormal return tends to be outside of their high sentiment periods (29 bp on average). This could be because sustainability sentiment is not as correlated with general business sentiment. In fact, we do see evidence of sustainability sentiment being especially strong in the recession.

**Good times.** To further test whether investors sustainability sentiment varies with general optimism in the economy, we test whether the ESG factor can be explained by changes in the dividend-price ratio in excess of traditional risk factors. Similarly to our previous results with the Baker and Wurgler (2006) measure, we find that a falling price dividend

**Table 8: 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. (2019), 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), whis 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:* | | |
|---|---|---|---|
| | $LS_t$ | | |
| | (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 | |
| Δ pd | | | −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 |
| $\alpha$ | | | 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 |

ratio is associated with positive returns on the ESG factor, hinting that investors care about ethics in times of crises Table 8 Column (3). A 1 % fall is associated with a decrease in the abnormal return of 21 bp.

## 6 Conclusion

We document an Environmental, Social and Governance (ESG) premia for stocks with a high degree of socially unconstrained ownership. Socially constrained investors, on the other hand, are unsuccessful to exploit this premia. They chase high ESG and high return stocks but once purchased, the returns drop. A closer look reveals that this discrepancy arises from the unconstrained investors' ability to predict the firms' future ESG scores. This provides evidence towards sustainability being priced. In the time series we see that a long-short equity strategy that goes long in high ESG firms and short in low ESG firms achieves positive abnormal returns that are high during the financial crisis, suggesting the returns are not driven by being exposed to consumption shocks. Instead, we consider whether the positive realised returns may be due to increases in sentiment over the period, which we indeed confirm to be the case. Taken together, our findings have real implications for investors as returns of high ESG stocks seem to be negative, but through smart investing, can yield positive abnormal returns. Additionally, our findings have implications for the cost of finance of sustainable firms. Hence, our paper shows that investors' preferences nudges the economy towards a more sustainable future, as more sustainable projects will be financed.

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# Appendices

## A ESG Scores

In this appendix we show describe our data on ESG scores in more detail. Figure 6 shows the distribution of ESG scores across the firms and years in our sample. Additionally Table 9 gives the distribution across industries, as well as the mean ESG, volatility of the ESG score and mean returns of those industries. Finally, Table 10 displays the names of the companies that have the most observations, as they are part of every year.

**Table 9: ESG Industry Composition**

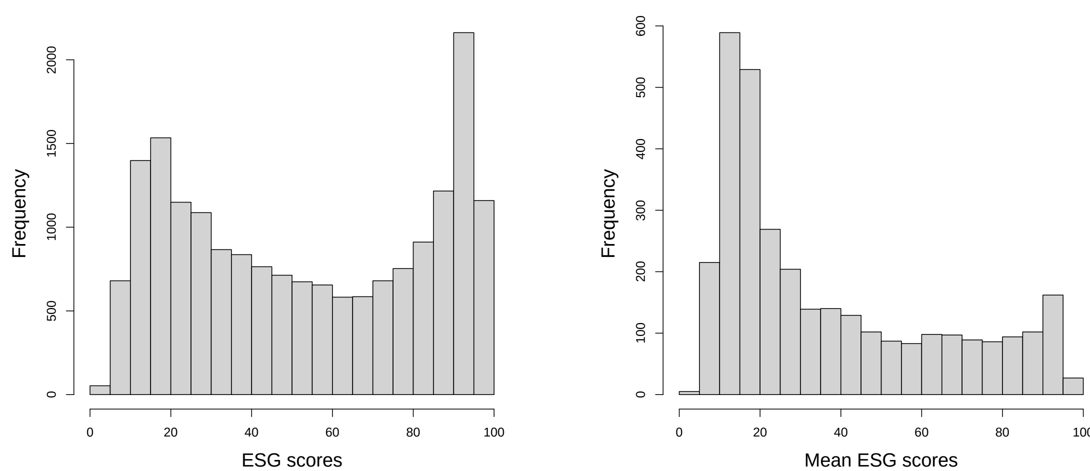
We exhibit the total number of observations, number of firms, average ESG scores, ESG score volatility and equally-weighted average returns according to different types of industries.

| | #observations | #firms | % of all firms | $\overline{ESG}$ | $\sigma_{ESG}$ | $\overline{r}$ |
|---|---|---|---|---|---|---|
| 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 |

Figure 6 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 9 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 10. 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 6: ESG Distribution**

Figure 6a represents the distribution of ESG scores across all single yearly scores. Figure 6b averages the firms' yearly ESG scores, so that every firm exhibits only one average score.

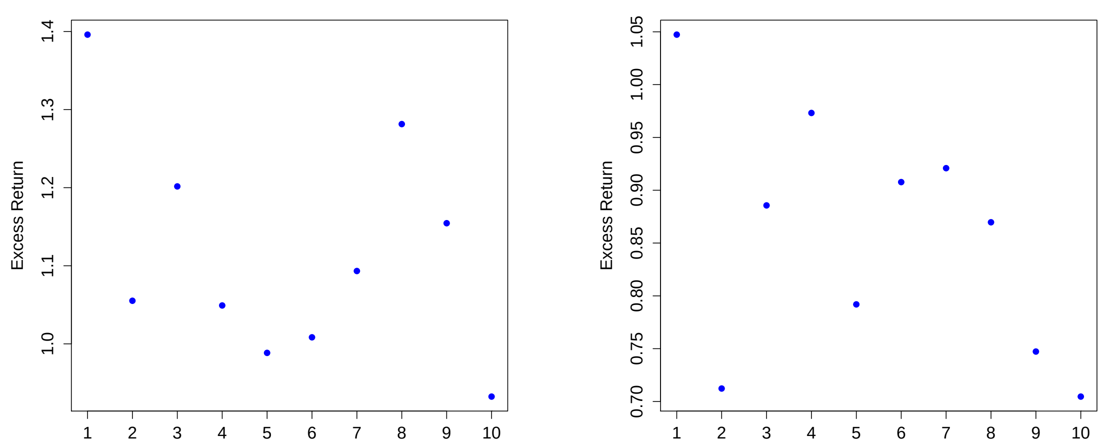
**Table 10: High Profile ESG Companies**

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 |

## B ESG Factor: Facts

This appendix exhibits summary statistics for our ESG sorted returns. First, Figure 7a 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. Table 11 displays the portfolio returns as well as the returns of a Long-short strategy that goes long in the top quantile and short in the lowest. As well as their abnormal return from three factor models: CAPM, three-factor Fama-French model and the four factor Carhart model. Additionally the volatility and sharpe ratio's are also displayed. Figure 8 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. Figure 9 gives us the aggregated market share of firms within each ESG bucket. We see that more firms with a high score (portfolio 10 is the highest) have entered the market, pushing down the market share of the rest.




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

**Figure 7: Raw Returns**

The plots 7a and 7b 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.

**Table 11: Risk-adjusted ESG Equity Returns**

We construct equally- and 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 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 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.

*Panel A:* Equally-weighted

| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | LS |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Excess Return | **1.396** | **1.055** | **1.202** | **1.049** | **0.988** | **1.008** | **1.093** | **1.281** | **1.155** | **0.932** | **-0.123** |
| t-value | 3.084 | 2.554 | 2.797 | 2.761 | 2.656 | 2.63 | 2.823 | 3.288 | 3.512 | 3.104 | 3.811 |
| CAPM alpha | 0.245 | -0.011 | 0.097 | 0.061 | 0.017 | -0.002 | 0.072 | **0.257** | **0.276** | **0.12** | 0.13 |
| t-value | 1.358 | -0.086 | 0.753 | 0.565 | 0.099 | -0.017 | 0.555 | 1.954 | 2.756 | 1.862 | 1.047 |
| 3-factor alpha | **0.257** | -0.008 | 0.108 | 0.064 | 0.023 | -0.001 | 0.084 | **0.267** | **0.29** | **0.118** | 0.127 |
| t-value | 1.696 | -0.083 | 1.007 | 0.661 | 0.177 | -0.005 | 0.921 | 2.33 | 3.195 | 1.868 | 1.138 |
| 4-factor alpha | 0.324 | 0.022 | **0.169** | 0.103 | 0.052 | 0.035 | 0.124 | **0.313** | **0.309** | **0.139** | 0.117 |
| t-value | 2.524 | 0.198 | 1.925 | 1.203 | 0.43 | 0.328 | 1.53 | 3.037 | 3.423 | 2.312 | 1.005 |
| 5-factor alpha | **0.363** | 0.08 | 0.141 | 0.095 | -0.004 | -0.001 | 0.066 | **0.205** | **0.247** | 0.069 | -0.011 |
| t-value | 2.592 | 0.843 | 1.404 | 1.047 | -0.034 | -0.008 | 0.744 | 1.957 | 2.711 | 1.109 | -0.102 |
| Volatility | 6.064 | 5.537 | 5.754 | 5.089 | 4.981 | 5.134 | 5.187 | 5.222 | 4.403 | 4.023 | 2.474 |
| Sharpe Ratio | 0.23 | 0.191 | 0.209 | 0.206 | 0.198 | 0.196 | 0.211 | 0.245 | 0.262 | 0.232 | -0.05 |

*Panel B:* Value-weighted

| | 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** | **0.87** | **0.747** | **0.705** | **-0.343** |
| t-value | 2.997 | 2.084 | 2.516 | 2.855 | 2.463 | 2.674 | 2.676 | 2.738 | 2.536 | 2.736 | 2.868 |
| CAPM alpha | 0.17 | -0.171 | -0.034 | 0.092 | -0.043 | 0.02 | 0.012 | 0.028 | -0.031 | 0.022 | -0.148 |
| t-value | 0.972 | -1.407 | -0.274 | 0.987 | -0.313 | 0.196 | 0.132 | 0.355 | -0.412 | 0.341 | -0.75 |
| 3-factor alpha | 0.161 | -0.188 | -0.041 | 0.085 | -0.043 | 0.009 | 0.017 | 0.038 | -0.018 | 0.029 | -0.133 |
| t-value | 0.916 | -1.451 | -0.277 | 0.887 | -0.327 | 0.097 | 0.185 | 0.493 | -0.245 | 0.419 | -0.654 |
| 4-factor alpha | 0.193 | **-0.205** | -0.039 | 0.098 | -0.041 | 0.025 | 0.039 | 0.035 | -0.027 | 0.028 | -0.166 |
| t-value | 1.129 | -1.718 | -0.264 | 1.015 | -0.324 | 0.271 | 0.426 | 0.454 | -0.367 | 0.414 | -0.807 |
| 5-factor alpha | 0.308 | -0.132 | -0.014 | 0.091 | -0.095 | 0.08 | 0.032 | 0.015 | -0.056 | -0.023 | -0.331 |
| t-value | 1.635 | -1.004 | -0.099 | 0.841 | -0.685 | 0.779 | 0.378 | 0.197 | -0.8 | -0.364 | -1.556 |
| Volatility | 4.675 | 4.584 | 4.716 | 4.56 | 4.298 | 4.543 | 4.607 | 4.257 | 3.945 | 3.45 | 2.712 |
| Sharpe Ratio | 0.224 | 0.155 | 0.188 | 0.213 | 0.184 | 0.2 | 0.2 | 0.204 | 0.189 | 0.204 | -0.126 |

**Table 12: Value-weighted ESG factor**

This table is an extension from *Panel B* in Table 11, 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) |
| $\alpha$ | −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 | | | |

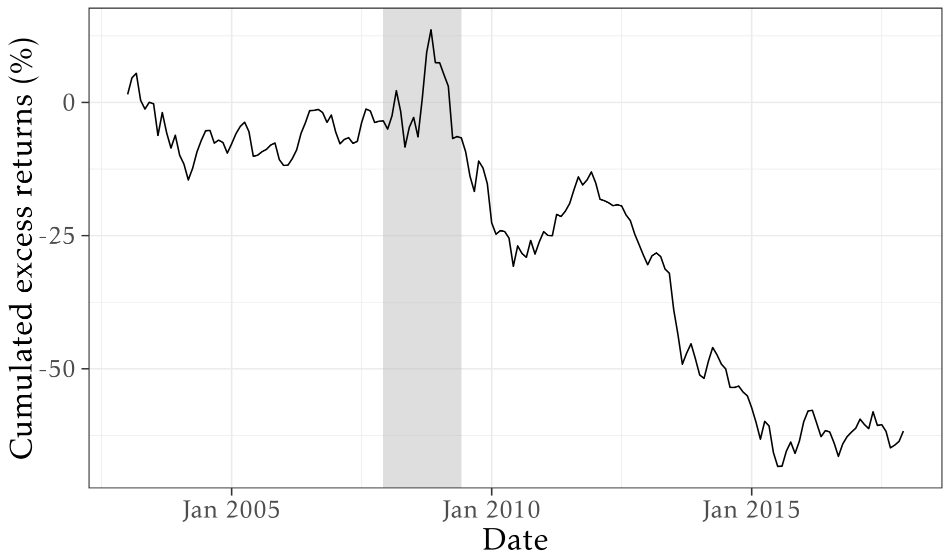



**Figure 8: Cumulative excess returns of ESG factor**

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.

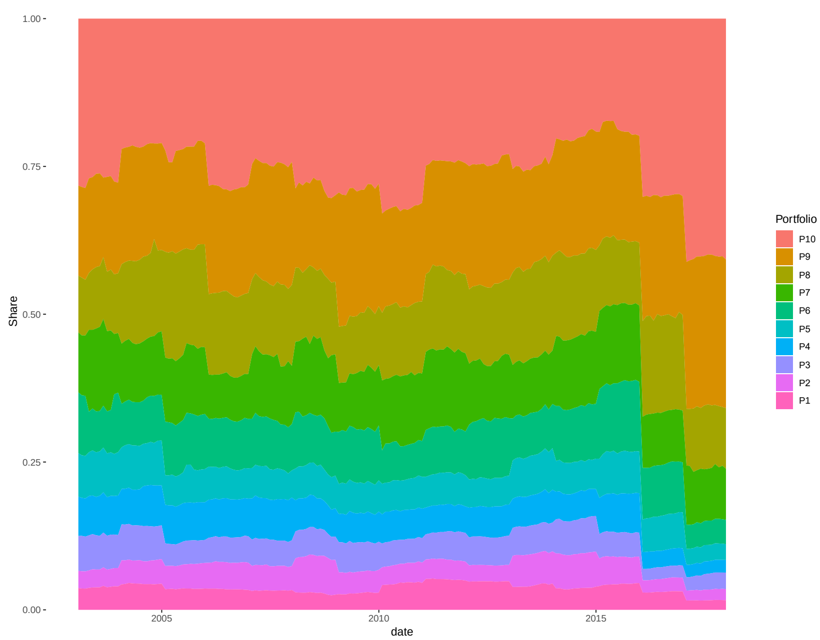



**Figure 9: Size Distribution**

The figure plots the size distribution over all decile ESG-portfolios. The high (low) ESG decile portfolio P10 (P1) depicts the highest (lowest) firms with the highest (lowest) ESG scores. Portfolios are rearranged every year according to the previous year's ESG score.

## B.1 ESG and Market Value

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

**Table 13: Doube-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 |

## B.2 ESG Persistence and Returns

We further test whether changes in ESG scores have an impact on firms' returns. Specifically, we double sort firms into a total of 16 portfolios. We sort firms according to their ESG score from the previous year and thereafter conditionally on the current year's score. Table 14 exhibits the results.

We find that changes in ESG scores indeed are an indicator for firms' abnormal performance. Specifically, we find that firms with high ESG scores in the previous year and low ESG scores in the current year underperformed the market on a risk-adjusted level. The concept of ESG itself adds to the inherent risk profile of firms.

We further find that upgrades in scores not necessarily increase firm's performance. On the other hand, it does also not become clear whether yearly decreases in scores have a positive or negative effect on risk-adjusted returns.

**Table 14: Double alphas on changes in ESG scores**

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 current year's ESG scores 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 four-factor model 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 | | | | | |
| $ESG_t$ 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 |
| $ESG_t$ 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 | | | | | |
| 4-Factor | | | | | |
| $ESG_t$ 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 |
| $ESG_t$ 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 |

# C 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 15.

**Table 15: 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 |

## D 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.[17] However, one should note that the value composition between decile portfolios is not evenly distributed, see Figure 9 in Appendix B. It seems 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 of how much ownership from socially constrained and unconstrained owners there 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 sorted portfolios. Additionally, we construct long-short portfolios according to ESG and ownership information. Equally-weighted returns are calculated as robustness checks.

[17]Nevertheless, we also conduct all subsequent analysis on an equally-weighted portfolio level for robustness checks.

## E Robustness Checks and Additional Figures and Tables

This section provides additional figures and tables to give additional insight into our empirical setting. This includes the cumulated excess returns for the ESG strategy amongst socially unconstrained owners in Figure 11 and constrained owners in Figure 12. Furthermore, exhibit results of the double-sort methodology of ESG scores and socially constrained investors, see Table 16.

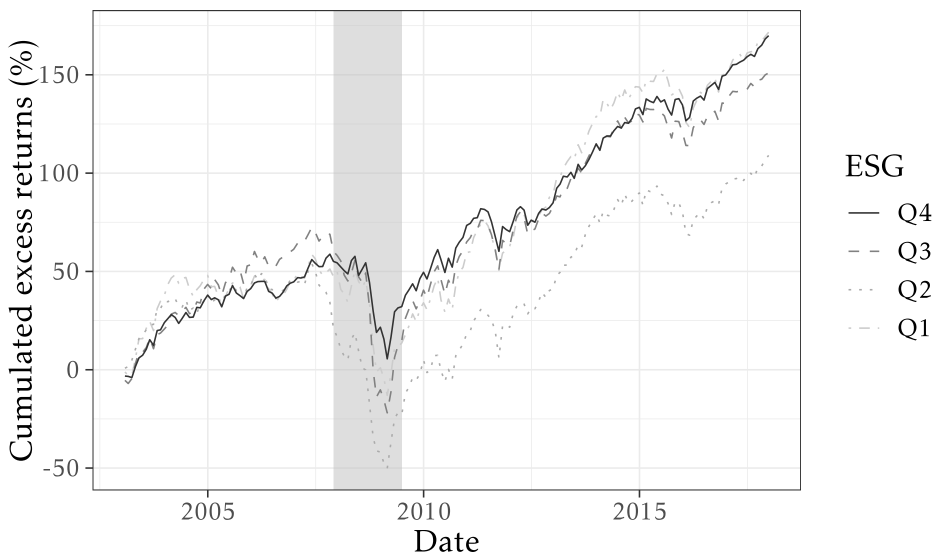



**Figure 10: Cumulative excess returns for stocks with different ESG levels and high socially constrained ownership**

Cumulative returns for different ESG levels for stocks with high amounts of social ownership (top quantile). The shaded area denotes the recession.

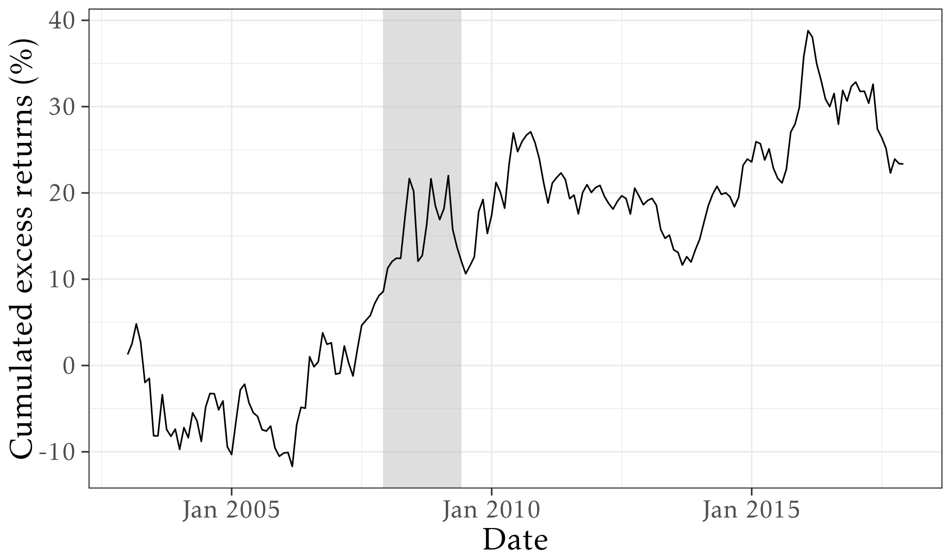



**Figure 11: Cumulative excess returns of long-short portfolio for stocks with the largest fraction of socially unconstrained owners**

Cumulative returns for long highest quartile ESG and short lowest quartile for stocks with high amounts of socially unconstrained ownership (top quantile). Shaded area denotes the recession.

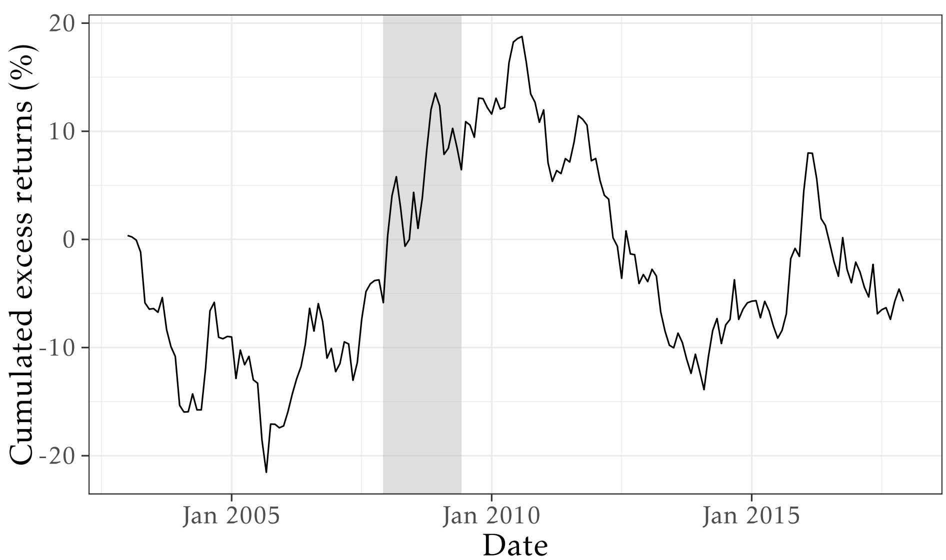



**Figure 12: Cumulative excess returns of long-short portfolio for stocks with the largest fraction of socially constrained owners**

Cumulative returns for long highest quartile ESG and short lowest quartile for stocks with high amounts of social ownership (top quantile). Shaded area denotes the recession.

**Table 16: Long-short regressions and socially constrained 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 socially constrained 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 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 socially constrained ownership as denoted by $D = \{H, L\}$. Specifically, we test

$$LS_t^D = r_t^{D,HESG} - r_t^{D,LESG} = \alpha + \sum_{j=1}^{n} \beta_j f_{jt} + \epsilon_t,$$

where $\beta_j$, $f_{jt}$ and $\epsilon_{it}$ are the factor loadings, factors and the error term. Specifically, 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 constrained ownership, $LS_t^D$, $D = \{H, L\}$: | | | | | |
| | $LS_t^H$ | | | $LS_t^L$ | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\alpha$ | 0.136<br>t = 0.838 | 0.158<br>t = 0.966 | 0.179<br>t = 1.089 | 0.292<br>t = 1.241 | 0.299<br>t = 1.184 | 0.273<br>t = 1.027 |
| mkt - rf | −0.179***<br>t = −3.579 | −0.137***<br>t = −2.655 | −0.166***<br>t = −3.162 | −0.214**<br>t = −2.351 | −0.125<br>t = −1.256 | −0.090<br>t = −0.872 |
| smb | | −0.307***<br>t = −3.679 | −0.299***<br>t = −3.518 | | −0.378***<br>t = −3.832 | −0.389***<br>t = −3.910 |
| hml | | 0.207***<br>t = 2.762 | 0.156**<br>t = 2.271 | | 0.037<br>t = 0.345 | 0.100<br>t = 0.945 |
| mom | | | −0.090**<br>t = −2.081 | | | 0.110*<br>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 |

**Table 17: Sustainability sentiment in different economic times**

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 socially unconstrained institutional ownership share (U) and assign them into another four portfolios, ending up with a total of 16 value-weighted return portfolios. We construct long-short portfolios that go long in high ESG firms and short in low ESG firms, all with high socially unconstrained ownership ($LS_t^U$). We test return performance of this portfolio in different times as denoted by whether the price-dividend ratio is above or below the unconditional mean. When the price dividend ratio is higher than the unconditional mean, good PD equals 1 and 0 otherwise. The variable bad PD equals 1 if the price dividend ratio is below the unconditional mean, and 0 otherwise. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) with a lag length of 12 months.

| | *Dependent variable:* | | |
|---|---|---|---|
| | | $LS_t^U$ | |
| | (1) | (2) | (3) |
| bad PD | 0.387 | 0.395 | 0.430 |
| | t = 1.355 | t = 1.489 | t = 1.643 |
| good PD | 0.252 | 0.264 | 0.173 |
| | t = 0.869 | t = 0.983 | t = 0.645 |
| mkt - rf | −0.168*** | −0.053 | −0.015 |
| | t = −3.279 | t = −1.003 | t = −0.273 |
| smb | | −0.491*** | −0.502*** |
| | | t = −5.554 | t = −5.759 |
| hml | | 0.055 | 0.123 |
| | | t = 0.682 | t = 1.465 |
| mom | | | 0.118** |
| | | | t = 2.506 |
| Observations | 180 | 180 | 180 |
| $R^2$ | 0.063 | 0.204 | 0.232 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

**Table 18: 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. (2019), 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) |
| $\alpha$ | | | | | | | 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 | | |