ESG and the Market Return*

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Abstract

We propose an environmental, social, and governance (ESG) index. We find that it has significant power in predicting the stock market risk premium, both in- and out-of-sample, and delivers sizable economic gains for mean-variance investors in asset allocation. Although the index is extracted by using the PLS method, its predictability is robust to using alternative machine learning tools. We find further that the aggregate of environmental variables captures short-term forecasting power, while that of social or governance captures long-term. The predictive power of the ESG index stems from both cash flow and discount rate channels.

Keywords: ESG, Return Predictability, Partial Least Square, Elastic Net, Out-of-sample Forecast

***JEL* classifications**: C22, C53, G11, G12, G17

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Abstract

We propose an environmental, social, and governance (ESG) index. We find that it has significant power in predicting the stock market risk premium, both in- and out-of-sample, and delivers sizable economic gains for mean-variance investors in asset allocation. Although the index is extracted by using the PLS method, its predictability is robust to using alternative machine learning tools. We find further that the aggregate of environmental variables captures short-term forecasting power, while that of social or governance captures long-term. The predictive power of the ESG index stems from both cash flow and discount rate channels.

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1. Introduction

The concept of environmental, social, and governance (ESG) has received increasing attention of managers and investors. A growing number of professional institutions have incorporated a firm's sustainable performance into the investment decision making process. The 2020 report of the US. SIF foundation shows that total US-domiciled assets under management using sustainable investing strategies grew from $12.0 trillion at the start of 2018 to $17.1 trillion at the start of 2020. There is 1 in 3 dollars of the total US assets under professional management that was invested based on sustainable investing strategies. As of July 2020, 90% of companies in the S&P 500 have already made it a standard by publishing their annual corporate sustainability/ESG reports. Existing studies find that some corporate sustainable measures can predict the cross-section of U.S. stock returns. For example, Hong and Kacperczyk (2009) find firms in "sin" industries can earn higher returns than firms in other industries, Hartzmark and Sussman (2019) show that there is a negative relation between sustainability rating and fund performance, and Bolton and Kacperczyk (2020) find that stocks of firms with higher total CO2 emissions earn higher alphas. However, the time series predictability on the aggregate stock market is unknown.

In this paper, we provide the first aggregate corporate sustainable growth index (thereafter: ESG index) and investigate its forecasting power on the entire stock market. If ESG measures can only forecast stock returns in the cross-section, its role is narrow in the finance literature. However, if it can predict the entire market returns, its role enhances dramatically. As Cochrane (2008) emphasizes, the market risk premium has a far-reaching impact on asset pricing and stock return predictability is one of the central issues in finance. However, the predictive relation between ESG and stock return is not obvious. Pedersen et al. (2020) study the ESG-efficient frontier and find that some ESG information can increase the maximum Sharpe ratio, but others cannot. It indicates that ESG investing has both costs and benefits. On the one hand, involving in ESG activities might increase firms' costs by diverting firms away from their main objective of maximizing shareholders' value, which would indicate a negative or insignificant relation between ESG and stock return. On the other hand, involving in ESG activities might benefit firms through enhancing the improvement of firms' intangibles including reputation, culture and human capital. Firms dedicating to ESG policies such as environmental protections are able to smooth public relations and reduce potential conflicts with local communities. By avoiding potential litigations and reducing risk, firms' contribution to ESG policies might generate net cost savings as well, which in turn suggests a positive relation between ESG and stock return. To date, there is a lack of research that examines various ESG measures collectively. Whether they contain unique information or are able to predict the aggregate stock market at the usual monthly frequency beyond popular return predictors, such as macroeconomic variables, is still an open question.

In this paper, we study a broad range of bottom-up individual ESG measures, and show that their common component matters at the aggregate stock market level. We extract this component by using an information aggregating method, the partial least squares (PLS). In contrast, individual ESG indices have limited power in predicting the market return in- and out-of-sample. Our paper makes three major contributions to the literature. First, we show, for the first time, that ESG index matters at the market level: it can strongly predict the stock market in- and out-of-sample, and is able to yield sizable economic gains to mean-variance investors. Second, the predictive ability that we uncover is distinct from studies on ESG at firm level. The role of ESG becomes much more important than previously thought because now it has an impact on the aggregate market. There are no studies on this issue, and so our paper fills the important gap in the literature. Third, different from macroeconomic predictors of Goyal and Welch (2008), we provide a new firm-level information-based predictor. ESG information and macro information are complementary in the valuation of firms. Pedersen et al. (2020) propose a theory that each stock's environmental, social, and governance (ESG) score provides information about firm fundamentals and affects investor preferences. Our study further provides insights on how ESG components affect the market in the short- and long-term.

In aggregating ESG information, we use the Elastic Net method (Zou and Hastie, 2005) to select 14 individual measures from all 38 individual bottom-up ESG measures as components in order to take out information irrelevant to stock returns. They include five environmental measures: external certification of EMS, participation in carbon disclosure project, carbon intensity, carbon intensity trend, and formal policy or programme on green procurement; four social measures: formal policy on the elimination of discrimination, programmes to increase workforce diversity, employee turnover rate, and scope of social supply chain standards; five governance measures: policy on bribery and corruption, tax transparency, external verification of CSR reporting, executive compensation tied to ESG performance, and policy on political involvement and contributions. Since individual ESG measures are at the firm level, we aggregate them into measures at the market level to assess their overall impact. Although the some of the 14 individual bottom-up ESG aggregates have certain predictive power to forecast market premium in-sample, the degree varies. We can view each of them is a proxy of unobservable ESG index. Due to measure errors, each can perform better or worse than the ESG index. The question is how to extract out the ESG index from them.

We focus on using the PLS. Statistically, we extract the common forecasting information that is related to stock returns from the individual ESG measures by removing all noises of the individual errors irrelevant to stock returns. As shown by Wold (1966), the pioneer of the PLS method, Kelly and Pruitt (2013, 2015), Huang et al. (2015), and Light et al. (2017), among others, PLS is an efficient method to obtain a ESG index from various individual ESG measures. We find that the ESG index can predict the aggregate stock market return remarkably well. Using the PLS ESG index, the monthly in-sample R^2 and out-of-sample R^2_{OS} are 10.25% and 8.52% respectively, with a highly significant slope of 1.10, in the predictive regression of excess stock market return on the PLS ESG index for the period from August 2009 to October 2018. We also aggregate ESG measures in each category: environmental, social, and governance, and find that the PLS ESG index in the environmental category provides the largest in-sample R^2 and out-of-sample R^2_{OS} in three categories, which are 7.84% and 11.39% respectively.

For comparison, we also use volatility-weight and equal-weight approaches to aggregate the different individual ESG information. We find the out-of-sample $R^2_{OS}s$ of the volatility-weight ESG index and the equal-weight ESG index are 5.63% and 8.35%, both at 5% significance level, smaller than the out-of-sample R^2_{OS} (8.52%) of the PLS ESG index. The predictive coefficients of the volatility-weight ESG index and the equal-weight ESG index are 0.87 and 0.62, both at 1% significance level. Similar with the PLS ESG index in the environmental category, the volatility-weight ESG index and equal-weight ESG index provide the largest out-of-sample $R^2_{OS}s$ in three categories, 10.86% and 10.38%, respectively.

For robustness, we use the conservative way to extract the ESG predictive information. We use the Elastic Net method (Zou and Hastie, 2005) and the Lasso method (Tibshirani, 1996) to extract predictive information from all 38 individual ESG measures directly. Although we could include some information irrelevant to future returns, we still find meaningful but smaller out-of-sample $R^2_{OS}s$ than the PLS ESG index. The out-of-sample $R^2_{OS}s$ based on the Elastic Net method and the Lasso method are 6.76% and 3.12%, both at 5% significance level. Consistent with PLS ESG index, volatility-weight ESG index, and equal-weight ESG index, the environmental category in the Elastic Net method and the Lasso method provides the largest out-of-sample predictive power.

We further examine the return predictability of the ESG index in long term performance. In one-year horizon, the PLS ESG index can still significantly forecast stock market returns. In fact, compared to results in the monthly predictive regressions, the magnitude of regression slope and out-of-sample $R^2_{OS}s$ increase to 3.20 and 26.20% in annual predictive horizon. The indices in the social category and the governance category provide the two largest out-of-sample $R^2_{OS}s$ among the three categories, with out-of-sample $R^2_{OS}s$ of 19.23% and 15.76% in one-year horizon, respectively, while the environmental index provides a negative out-of-sample $R^2_{OS}s$ of –1.86% in one-year horizon. It indicates that environmental index can capture short-term (one-month) predictive information whilst aggregate social and governance indices include long-term (one-year) predictive information. Predictive information originated from the environmental, social, and governance categories can be complementary. Therefore, the ESG index exhibits both short-horizon and long-horizon forecasting power.

Furthermore, we compare the predictive power of ESG index with common return predictors, including the 14 macroeconomic variables used by Goyal and Welch (2008), extant uncertainty measures (i.e., economic policy uncertainty, macroeconomic uncertainty, and financial uncertainty), and fundamental growth variables (i.e., aggregate asset growth, fixed investment growth, non-residential investment growth, aggregate consumption growth, industrial production growth, and

GDP growth) used in the literature. We find that the ESG index maintains strong predictability after controlling for them. The results suggest that the ESG index contains unique forecasting information for the stock market, which cannot be explained by the economic fundamentals, uncertainty measures, and fundamental growth.

For portfolios in the cross-section, we find that return predictability of the ESG index is pervasive at the industry portfolio level as well, consistent with our findings at the aggregate market level. Our results demonstrate that the ESG index can significantly predict various industry portfolio returns, with the in-sample R^2s ranging from 2.41% (Utility Industry) to 13.02% (Shop Industry). For international stock markets, we find the ESG index's predictive power is significant to 21 developed markets.[1] Comparing with the out-of-sample R_{OS}^2 (8.52%) performance, ESG index provides the largest out-of-sample R_{OS}^2 in Ireland (20.61%) and the smallest out-of-sample R_{OS}^2 in Australia (4.80%).

In addition to significant predictability of ESG index, whether it can yield sizable economic gains is also an important question. Since a monthly out-of-sample R_{OS}^2 of 0.5% signals substantial economic value (Campbell and Thompson 2008), we show that our ESG index can not only present superior forecasting performances, but also lead to sizable investment gains for a mean-variance investor from an asset allocation perspective. The annualized certainty equivalent return (CER) gains are 4.41% and 3.57% under no transaction cost and 50bps transaction costs, respectively, when the investor allocates investments between the market and risk-free rate. Furthermore, the investment portfolios based on the ESG index have large annualized Sharpe ratios. It generates a Sharpe ratio of 0.44 (no transaction cost) and 0.42 (50bps transaction costs) at the monthly horizon. The volatility-weight ESG index generates a Sharpe ratio of 0.41 (no transaction cost) and 0.38 (50bps transaction costs) at the monthly horizon.

We further examine the ESG portfolio index's predictive power to market returns and ESG index's

[1] 21 developed markets are Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Netherland, New Zealand, Portugal, Singapore, Spain, Sweden, Switzerland, and United Kingdom.

predictive ability to ESG quintile portfolio returns. Lioui (2018) argues that the exposure (beta) of ESG is a risk factor. Dong et al. (2021) finds that the aggregated long-short anomaly portfolio returns can forecast market returns. We argue if the long-short ESG anomaly portfolios reveal systematic risks or market mispricing, they could predict market returns based on Dong et al. (2021)'s findings. First, we obtain 14 individual ESG measures selected from all 38 ESG measures by using the Elastic Net method. Second, we regress each stock returns on one individual ESG measure to obtain that stock's ESG measure's exposures. Third, we sort the ESG exposure to rank stocks and construct the long-short quintile anomaly portfolio. Forth, we can obtain 14 long-short ESG anomaly portfolios. Finally, we use the Partial Least Squares (PLS) method to aggregate 14 long-short ESG anomaly portfolios to the ESG portfolio index. We find ESG portfolio index can forecast market returns, with the out-of-sample R_{OS}^2 of 4.48%, at the 5% significance level. We further find that ESG index can predict the aggregated long-short ESG anomaly portfolio returns and explain almost all ESG quintile anomaly portfolio returns, so we obtain an economic source that ESG index can predict market returns.

We also explore the economic driving force of the predictive power of the ESG index. First, if ESG activities' growth increases firms' costs and decreases shareholders' value, ESG index reveals one dimension of systematic risks; If ESG activities' growth raises firms' intangible values and reduces potential conflicts, ESG index indicates one dimension of good information. Second, we ask whether the predictability comes primarily from time variations in cash flows or discount rates. Specifically, we use the Campbell (1991) and Campbell and Ammer (1993) vector auto-regression (VAR) approach and the information contained in popular economic predictors to decompose total stock market return into three components: the expected return, discount rate news, and cash flow news. We find that the ability of ESG index to predict future stock market return results from its ability to predict both future cash flow news and discount rate news while the latter channel contributes as a more economically important source.

Our empirical findings are essential for three reasons. First, we show that ESG index matters to the aggregate stock market both statistically and economically, highlighting its unrecognized significant role in asset pricing. Second, we find that environmental index has short-term predictive information while social and governance indices have long-term predictive information. Third, relying on any individual ESG measure, the true predictive power of ESG index is likely to be understated. Instead, our ESG index uses individual ESG measures collectively via the efficient aggregating method of PLS. The ESG index summarizes the most relevant forecasting information in individual measures, and therefore, they outperform the extant individual ESG measures.

The remainder of the paper is organized as follows. Section 2 describes the data and methodology to construct the ESG index. Section 3 shows the empirical results. Section 4 studies the economic source of the predictability. Section 5 concludes.

2. Data and ESG construction

2.1. Individual ESG measures

We use corporate sustainable growth (ESG) measures from Morningstar Sustainalytics, a leading corporate ESG ratings database in the world.[2] Morningstar Sustainalytics provides the monthly firm-level ESG scores beginning in August 2009. It covers three-layer ratings, the overall ESG scores, Environmental, Social, and Governance three category scores, and 38 sub-category scores (indicators) across Environmental, Social, and Governance categories.[3] Morningstar Sustainalytics ESG Ratings measure how well companies proactively manage the environmental, social, and governance issues that are the most material to their business. Based on a structured, objective and transparent methodology, Morningstar Sustainalytics ESG Ratings provide an assessment on companies' ability to mitigate risks and capitalize on opportunities.

The Morningstar Sustainalytics research process for producing a company ESG rating follows six stages. The process starts with the collection of company data via its own disclosure, media and NGO reporting to analyze information according to the indicator and controversy framework. This is followed by a robust peer review and quality assurance process. The research itself is conducted

[2] Sustainalytics works with hundreds of the world's leading asset managers and pension funds who incorporate ESG and corporate governance information and assessments into their investment processes. Sustainalytics also works with hundreds of companies and their financial intermediaries to help them consider sustainability in policies, practices and capital projects. With 16 offices globally, Sustainalytics has more than 800 staff members, including more than 350 analysts with varied multidisciplinary expertise across more than 40 industry groups.

[3] Sustainalytics ESG data is also used by Cao et al. (2020), Engle et al. (2020), Hartzmark and Sussman (2019), and Starks et al. (2020).

at the indicator level, where a comprehensive set of generic and industry-specific metrics is analyzed, scored and weighted to determine a company's overall ESG performance. For every indicator, analysts evaluate the degree to which a company meets relevant best practice standards. On this basis, a raw score out of 100 is assigned to every indicator, based on a set of detailed and well-documented internal criteria.

We calculate the ESG index from original ESG measures and use the Elastic Net method (Zou and Hastie, 2005) to select 14 individual ESG measures from all 38 ESG measures. Five environmental measures: external certification of EMS, participation in carbon disclosure project, carbon intensity, carbon intensity trend, and formal policy or programme on green procurement; four social measures: formal policy on the elimination of discrimination, programmes to increase workforce diversity, employee turnover rate, and scope of social supply chain standards; five governance measures: policy on bribery and corruption, tax transparency, external verification of CSR reporting, executive compensation tied to ESG performance, and policy on political involvement and contributions.

We use the equal-weight method in aggregating the firm-level ESG measures to the market-level ESG index. This equal-weight aggregation method is also used by Rapach et al. (2016), Jondeau et al. (2019), and Chen et al. (2021), among others. The reason is that equal-weight method is likely more informative than the value-weight method that places more emphasis on large cap firms and ignores more effects from the great majority of small cap firms. Therefore, in order to reduce of bias from concentration of large cap stocks, we adopt the equal-weight approach to aggregate the firm-level ESG measure to the market level.

Table 1 reports the means, standard deviations, first-order autocorrelation coefficients $\rho(1)$, skewness, kurtosis, minimum values, and maximum values of the 14 individual ESG measures. As Table 1 shows, the values of mean vary from –0.74% for growth in carbon intensity to 6.62% for growth in employee turnover rate. Not only growth in external certification of EMS, but also growths in carbon intensity, carbon intensity trend, and policy on bribery and corruption have negative mean values. The average value of growth in aggregated firm-level participation in carbon disclosure project is about 0.35% per month with standard deviation of 6.28. The average value of growth in external verification of CSR reporting is 1.51% with minimum value of –6.95% and maximum value of 39.93%. Moreover, most of the measures are positive skewed with relatively high kurtosis. The first-order autocorrelation coefficients reflect these measures are quite persistent.

[Insert Table 1 about here]

Table 2 presents pairwise correlations between individual ESG measures. We observe that most individual ESG measures are positively correlated, with several exceptions that have negative values. Table 2 indicates that extant measures capture both the common and different aspects of individual ESG measures. The correlation coefficients range from –0.47 to 0.87, suggesting that these 14 individual ESG measures capture both common and different aspects of ESG, and hence, using a specific proxy is unlikely to be complete in terms of the aggregate effect of ESG on the stock market.

[Insert Table 2 about here]

2.2. ESG index

In this subsection, we tend to use the individual ESG measures collectively. The ESG index is an unobservable variable and any of the 14 individual ESG measures is simply a proxy of the unobservable variable. Then, we aim to extract the common component of individual ESG measures by removing noises.

2.2.1. Forecasting model

The forecasting model is based on ESG measures,

$$r_{t+1} = a + b \times ESG_t^* + \varepsilon_{t+1}, \quad (1)$$

where r_{t+1} is realized excess stock market return at time $t+1$, ESG_t^* is the unobservable ESG index at time t, and ε_{t+1} is a noise term that is unforecastable and irrelevant to ESG_t^*. Model (1) indicates that ESG_t^* is related to the subsequent stock market return.

Then, we assume a linear factor structure for the individual ESG measures. Let $ESG_t = (ESG_{1,t}, \dots, ESG_{N,t})'$ denote an $N \times 1$ vector of individual ESG measures at period t, N is the number of individual measures. The model of $ESG_{i,t}$ $(i = 1, \dots N)$ is given by

$$ESG_{i,t} = \eta_{i,0} + \eta_{i,1} \times ESG_t^* + \eta_{i,2} \times Error_t + e_{i,t}, \tag{2}$$

where ESG_t^* is the unobservable ESG index in model (1), $\eta_{i,1}$ is the factor loading that summarizes the sensitivity of individual ESG measure $ESG_{i,t}$ to the unobservable ESG index ESG_t^*, $Error_t$ is the common approximation error component of all individual ESG measures that are unrelated to stock market returns, and $e_{i,t}$ is the idiosyncratic noise associated with measure i.

To determine the unique role of ESG index in the stock market, we aim to efficiently estimate ESG_t^*, the collective contribution to the unobservable ESG index. The key idea here is to impose the factor structure (2) on individual ESG measures to estimate ESG_t^*, and at the same time, to remove their common approximation error $Error_t$ and the idiosyncratic noise $e_{i,t}$ from the estimation process. We consider one common aggregation approach: PLS. Thus, we have the estimated ESG index, ESG^{PLS}. To avoid the estimation errors and show the robustness of our measures, we also consider two alternative aggregation methods: volatility-weight and equal-weight.

2.2.2. Partial least square (PLS)

The PLS approach extracts ESG_t^* from the individual ESG measures based on its covariance with future stock market returns and uses a linear combination of the individual ESG measures to predict returns. PLS is implemented in the following two steps of ordinary least squares (OLS) regressions. The first step is a time-series regression of each individual ESG measure at month t on the future realized excess stock market return (as a proxy for expected excess returns), r_{t+1},

$$ESG_{i,t} = \pi_0 + \pi_i \, r_{t+1} + u_{i,t}, \tag{3}$$

where $ESG_{i,t}$ is the i-th individual ESG measure. The coefficient of π_i in the first-step time-series regression (3) captures the sensitivity of the individual ESG measure $ESG_{i,t}$ to the unobservable ESG index ESG_t^* instrumented by future stock market return r_{t+1}. Because the future stock market return r_{t+1} is driven by ESG_t^*, as shown in model (1), individual ESG measures are related to the predictable component of stock returns and are uncorrelated with the unforecastable errors. Therefore, the coefficient π_i approximately represents how each individual ESG measure depends on the unobservable ESG index ESG_t^*.

The second-step regression is a cross-sectional regression for each time period t,

$$ESG_{i,t} = c_t + ESG_t^{PLS}\,\hat{\pi}_i + v_{i,t}, \tag{4}$$

where $\hat{\pi}_i$ is the regression loading in regression (3) and ESG_t^{PLS}, the regression slope, is the PLS ESG index at time t. In the regression (4), the first-step loading estimated becomes the independent variable, and ESG_t^{PLS} is the regression slope to be estimated.

PLS exploits the factor nature of the joint system, Equations (1) and (2), to infer the relevant ESG factor ESG_t^{PLS} . If the true factor loading π_i were known, we could consistently estimate ESG_t^{PLS} by simply running cross-sectional regressions of $ESG_{i,t}$ on π_i period by period. However, since π_i is unknown, the first-stage regression slopes provide an approximate estimation of how $ESG_{i,t}$ depends on ESG_t^{PLS}. In other words, PLS applies time $t+1$ stock market returns to discipline the dimension reduction to extract ESG_t^* relevant for predicting, and eliminates the common and idiosyncratic components, e.g., $Error_t$ and $\varepsilon_{i,t}$, irrelevant for predicting.

Since the proxies could be measured with noise, the first-stage regression takes an errors-in-variables form and the second-stage regression produces an estimate for a latent factor's unique but unknown rotation (Kelly and Pruitt, 2015). However, because the relevant factor space is spanned by the proxies' common component, the realized returns' predictive regression of on the estimated PLS factor delivers consistent forecasts of expected returns driven by the latent factor.

2.2.3. Alternative aggregation methods

We also use two alternative aggregation ESG measures: ESG^{Vol} and ESG^{Equ}. The volatility-weight is the reciprocal of the volatility of each ESG measure. Less volatile individual ESG measure will be given larger weights. The equal-weight treats the ESG measures equally.

[Insert Figure 1 about here]

Figure 1 displays the time series of the three ESG indices, ESG^{PLS}, ESG^{Vol}, and ESG^{Equ}, from August 2009 to October 2018. We observe that the ESG indices, measured by PLS, volatility-weight, and equal-weight, are time varying for our sample from August 2009 to October 2018.

2.2.4. In-sample performance

We consider the following predictive regression based on ESG indices,

$$R_{t+1} = \alpha + \beta \times X_t + \varepsilon_{t+1}, \tag{5}$$

where R_{t+1} is the stock market excess return in month $t+1$, and X_t refers to one of the estimated ESG indices, ${X_t}^{PLS}$, ${X_t}^{Vol}$, and ${X_t}^{Equ}$, constructed by the PLS, volatility-weight, and equal-weight methods, respectively. Model (1) indicates that X_t is related to the subsequent stock return. We test the in-sample predictive ability of X_t by estimating the regression (5) from August 2009 to October 2018. Specifically, we inspect the estimate of β ($\hat{\beta}$) in regression (5). The null hypothesis is that X_t has no predictive ability; that is, $\beta = 0$, and regression (5) reduces to the constant expected return model ($R_{t+1} = \alpha + \varepsilon_{t+1}$). Under the alternative hypothesis, β is different from zero, and X_t is informative for predicting R_{t+1}. A time-varying expected stock return model uses. We use the Newey and West (1987) standard error to compute the *t*-statistic corresponding to $\hat{\beta}$.

2.2.5. Out-of-sample performance

The in-sample analysis gives parameter estimates that are more efficient and more precise return forecasts by using all available data, but Goyal and Welch (2008) argue that out-of-sample tests could be more relevant for assessing genuine return predictability in the practice.

We start with an initialization period to estimate the predictive regression (6) based on the ESG index to produce the first out-of-sample forecast. The forecast return is

$$\hat{R}_{t+h} = \hat{\alpha}_t + \hat{\beta}_t \times X_t, \tag{6}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of regression (5). We recursively estimate regression (5) and repeatedly construct the monthly out-of-sample forecasts based on Equation (6) for the following periods, until we reach the end of the sample period. Furthermore, we impose an economic restriction in predicting stock returns, that the expected risk premium must be positive to be consistent with theory of Campbell and Thompson (2008) and Pettenuzzo et al. (2014).

In the implementation, we use the first seven years as the initial training period and the rest as the out-of-sample forecast evaluation period. We choose the length of the initial in-sample estimation period so that the observations are enough to precisely estimate the initial parameters. Then, we formulate the monthly ESG index $({X_t}^{PLS},\ {X_t}^{Vol}, or\ {X_t}^{Equ})$ using the available data observed no later than current month to predict following month return out-of-sample.

To evaluate the out-of-sample performance, we use the R^2_{OS} of Campbell and Thompson (2008) and the *MSFE-adjusted* statistic test of Clark and West (2007). The R^2_{OS} measures the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast vis-$\acute{a}$-vis the benchmark forecast. When R^2_{OS} > 0, the predictive regression forecast outperforms the benchmark forecast in terms of MSFE. The popular benchmark is the average excess return from the beginning of the sample through month *t*. This forecast corresponds to the constant expected excess return model, Equation (5) with $\beta = 0$, and indicates that stock returns cannot be forecastable, as in the random walk process with drift model for the log of stock prices. To uncover whether the predictive regression forecast produces a statistically significant improvement in MSFE, we utilize Clark and West (2007)'s MSFE-adjusted statistic to test the null hypothesis that the historical average MSFE is not more than that of the predictive regression forecast against the alternative hypothesis that the historical average MSFE is greater than that of the predictive regression forecast, corresponding to $H_0: R_{OS}^2 \leq 0$ against $H_A: R_{OS}^2 > 0$.

3. Empirical results

3.1. Forecasting stock market returns with individual ESG measures

In this section, we explore the forecasting power of individual ESG measures for the stock market excess return, defined as the difference between the value-weight aggregate stock return and T-bill rate from the CRSP database. The univariate predictive regression is

$$R_{t+1} = \alpha + \beta \times Ind\_ESG_t + \varepsilon_{t+1}, \tag{7}$$

where R_{t+1} is the stock market excess return in month $t+1$, and Ind_ESG_t is one of the 14 individual ESG measures. We test the in-sample predictive ability of Ind_ESG_t by estimating the regression (7) from August 2009 to October 2018. Specifically, we inspect the estimate of β ($\hat{\beta}$) in regression (7). The null hypothesis is that Ind_ESG_t has no predictive ability; that is, $\beta = 0$, and regression (7) reduces to the constant expected return model ($R_{t+1} = \alpha + \varepsilon_{t+1}$). Under the alternative hypothesis, β is different from zero, and Ind_ESG_t contains information useful for predicting R_{t+1}. We use the Newey and West (1987) standard error to compute the *t*-statistic corresponding to $\hat{\beta}$.

[Insert Table 3 about here]

Table 3 presents the regression slope β, Newey-West t-value, the in-sample R^2, and the out-of-sample R_{os}^2 of predicting future market return with individual ESG measures. Predictors in Panel A, B and C are individual ESG measures in environmental, social, and governance category, respectively. The sample spans the period from Aug 2009 to Oct 2018. Statistical significance for R_{os}^2 is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing $H_0: R_{os}^2 \leq 0$ against $H_A: R_{os}^2 > 0$. For the environmental category, 4 out of 5 measures have positive forecasting signs, among which, formal policy or programme on green procurement exhibits the highest predictive β of 0.57, and the t-statistic reaches 2.64. Moreover, external certification of EMS shows a negative predictive β of –0.26 with a weak t-value of –1.56. It is worth noting that 3 out of 5 environmental growth measures reveal positive and significant out-sample R_{os}^2 at 10% level, which are carbon intensity, carbon intensity trend, and formal policy or programme on green procurement. Panels B and C of Table 2 present differentiated results as Panel A when the predictors are extended to social category or governance category. Apparently, most of these 9 measures perform a positive predictive β with quite high t-value. However, none of the out-of-sample R_{os}^2 displays statistical significance. Especially, 3 out of 4 social growth measures in Panel B have negative R_{os}^2 without statistical significance. Similarly, 3 out of 5 governance growth measures in Panel C exhibit negative insignificant R_{os}^2 at 10% level. Overall, Table 3 shows that while the extant individual ESG measures may have certain time-series forecasting power, only individual ESG measures in the environmental group are more able to predict market returns in general, especially for the out-of-sample forecasting.

3.2. Forecasting stock market returns with ESG indices

In this section, we explore the forecasting power of ESG indices for the stock market excess return. The univariate predictive regression is

$$R_{t+1} = \alpha + \beta \times Agg\_ESG_t + \varepsilon_{t+1}, \tag{8}$$

where R_{t+1} is the stock market excess return in month $t+1$, and Agg_ESG_t is one of the estimated ESG indices, Agg_ESG^{PLS} , Agg_ESG^{Vol}, and Agg_ESG^{Equ} constructed by the PLS, volatility-weight, and equal-weight methods, respectively. We test the in-sample predictive ability of Agg_ESG_t by estimating the regression (8) from August 2009 to October 2018. Specifically, we inspect the estimate of β ($\hat{\beta}$) in regression (8). The null hypothesis is that Agg_ESG_t has no predictive ability; that is, $\beta = 0$, and regression (8) reduces to the constant expected return model ($R_{t+1} = \alpha + \varepsilon_{t+1}$). Under the alternative hypothesis, β is different from zero, and Agg_ESG_t contains information useful for predicting R_{t+1}. We use the Newey and West (1987) standard error to compute the *t*-statistic corresponding to $\hat{\beta}$.

[Insert Table 4 about here]

We construct the ESG indices based on selected individual ESG predictors using the PLS method. Table 4 reports the regression slope, Newey-West t-value, the in-sample $R^2(\%)$, and the out-of-sample $R^2_{os}(\%)$ of predicting future market return with these aggregate measures. In Panel A, the regression coefficient β using the PLS method is 1.10%, suggesting that a one-standard deviation increase in the PLS ESG index leads to a 1.10% increase in the next month's expected stock market return. The in-sample $R^2(\%)$ and the out-of-sample $R^2_{os}(\%)$ are 10.25 and 8.52, respectively. In Panels B-D, we report performances by ESG indices in different subcategories. For the aggregation in environmental category using the PLS method, the predictive β is 0.97, which is economically sizeable. The corresponding R^2_{os} is 11.39, and its significance level reaches 1%. Panels C and D show results when the predictor is extended to social category or governance category. It is worth noting that the significance level for Panel C and Panel D is weaker than that for Panel B, especially for Panel D, which remains insignificant out-of-sample by PLS method. To some degree, the empirical evidence proves that the predicting power of ESG indices for market return stems more from environmental growth.

3.3. Forecasting market return over longer horizon with ESG indices

In this section, we investigate the long horizon forecasting performance by using ESG indices.

[Insert Table 5 about here]

The table reports the regression slope, Newey-West t-value, the in-sample $R^2(\%)$, and the out-of-sample $R^2_{os}(\%)$ of predicting future cumulative market return over one-year horizon with ESG indices. Panel A of Table 5 reports the PLS ESG index's predicting results. The predicting coefficient β in one-year is 3.20%, which is roughly three times larger than the predicting slope β (1.10%) in one-month. The out-of-sample R^2_{os} increases from 8.52% (one-month forecasting) to 26.20% (one-year forecasting). Panels B, C, and D report one-year horizon forecasting results by using the environmental, social, and governance indices, respectively. It is interesting to note that the PLS environmental index does not have significant predictive power for market returns.

However, the PLS social index and PLS governance index contain significant forecasting information. R^2_{os}s of social index and governance index using the PLS method are 19.23% at 10% significant level and 15.76% at 5% significant level. The results of Table 4 and Table 5 reflect the different forecasting patterns of environmental, social, and governance indices. Environmental index captures short-term forecasting power while social index and governance index contain the long-term predicting information. The comprehensive PLS ESG index can forecast market returns in both short and long horizons.

3.4. Controlling for economic variables

Our compelling evidence shows the strong predictability of ESG indices. We further examine whether the forecasting information comes from the business cycle-related fundamentals. To address this issue, we control for a set of economic variables commonly used in the forecasting literature. The predictive regression is,

$$R_{t+1} = \alpha + \beta \times Agg\_ESG_t + \psi Z_t + \varepsilon_{t+1}, \tag{9}$$

where R_{t+1} is the stock market excess return in month $t+1$, Agg_ESG_t is Agg_ESG^{PLS} in month *t*, and Z_t is one of the 14 economic predictors from Goyal and Welch (2008).[4]

[Insert Table 6 about here]

Panel A of Table 6 reports that the two economic predictors, dividend price ratio (DP) and dividend yield ratio (DY), display significant positive predictive power for the market return among these economic indicators. Panel B reports that the regression slopes on Agg_ESG^{PLS} remain statistically significant after controlling for the economic variables, suggesting that the impact of ESG index on aggregate stock market cannot be explained by the economic fundamentals. In addition, the coefficient estimates are large in magnitude. For example, the β estimates of Agg_ESG^{PLS} keep around 1.10%, indicating the economic significance after controlling one of 14

[4] The data is available from Amit Goyal's website, http://www.hec.unil.ch/agoyal/.

economic predictors. ESG index generates strong forecasting power for the aggregate stock market beyond economic predictors.

3.5. Controlling for uncertainty variables

In the section, we investigate whether uncertainty measures can digest the forecasting power of ESG index. Specifically, we employ three uncertainty measures, including macroeconomic uncertainty (Jurado et al., 2015), financial uncertainty (Jurado et al., 2015), and economic policy uncertainty (Baker et al., 2016).

[Insert Table 7 about here]

Panel A of Table 7 reports three uncertainty measures' forecasting results. None of the three measures can provide significant predictive power for the market return. Panel B reports the results of forecasting market return with ESG index after controlling one of the three uncertainty variables. The ESG index can significantly predict the market premium, with the coefficient of roughly 1.10%.

3.6. Controlling for fundamental growth variables

In the section, we investigate whether fundamental growth measures can digest the forecasting power of ESG index. Specifically, we make use of aggregate asset growth, fixed investment growth, non-residential investment growth, aggregate consumption growth, industrial production growth, and GDP growth.

[Insert Table 8 about here]

Panel A of Table 8 reports six fundamental growth measures' forecasting results. None of the six measures can provide significant predictive power for the market return. Panel B reports the results of forecasting market return with ESG index after controlling one of the six fundamental growth variables. The ESG index can still significantly predict the market premium.

3.7. Forecasting industry portfolio returns with ESG index

We examine whether ESG index can predict the excess returns of 12 industry portfolios. The 12 industries are defined from Ken French data library.[5] We find ESG index can significantly predict all 12 industry portfolio returns. The in-sample R^2(%) ranges from 2.41 (Utility Industry) to 13.02 (Shop Industry). The environmental index and social index can significantly predict 11 industry portfolio returns except the excess returns of utility industry. The governance index can predict 10 industry portfolio returns except the excess returns of utility and health industries.

[Insert Table 9 about here]

3.8. Forecasting international market returns with U.S. ESG index

In this section, we examine whether the U.S. ESG index can forecast returns of international markets. We study 21 developed markets, including Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Netherland, New Zealand, Portugal, Singapore, Spain, Sweden, Switzerland, and United Kingdom. The 21 developed market returns are available from AQR data sets.[6] Rapach et al. (2013) find that lagged U.S. market returns significantly forecast market returns in 10 developed countries. If the U.S. ESG index is a predictor to U.S. market returns, it may predict other developed countries' market returns. We find that U.S. ESG index can predict all 21 developed markets' returns. The predictive coefficients of 21 developed markets are economically and statistically significant, ranging from 0.61 (Japan) to 1.76 (Greece). The in-sample R^2(%) ranges from 1.62 (Spain) to 6.83 (Hong Kong) and the out-of-sample R_{os}^2(%) ranges from 4.80 (Australia) to 20.61 (Ireland).

[Insert Table 10 about here]

3.9. ESG indices using alternative methods

In this section, we construct ESG indices using volatility-weight and equal-weight methods. Table 11 reports the regression slope, Newey-West t-value, the in-sample R^2(%), and the out-of-sample R_{os}^2(%) of predicting future market return with these indices. In Panel A, the regression coefficient

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[5] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[6] See https://www.aqr.com/Insights/Datasets.

β using the volatility-weight method is 0.87% and using the equal-weight method is 0.62%. The out-of-samples $R^2_{os}s(\%)$ of volatility-weight method and equal-weight method are 5.63 and 8.35, which are smaller than the out-of-sample $R^2_{os}(\%)$ of PLS method, 8.52. In Panels B-D, we report performances by ESG indices in different subcategories. The out-of-samples $R^2_{os}s(\%)$ of the volatility-weight environmental index and the equal-weight environmental index are 10.86 and 10.38, which are slightly smaller than the out-of-sample $R^2_{os}(\%)$ of PLS method, 11.39. However, the out-of-samples $R^2_{os}s(\%)$ of the volatility-weight social index and the equal-weight social index are 5.97 and 5.34, which are larger than the out-of-sample $R^2_{os}(\%)$ of PLS method, 4.44. Finally, the out-of-samples $R^2_{os}s(\%)$ of the volatility-weight governance index and the equal-weight governance index are also not significant as the PLS method.

[Insert Table 11 about here]

3.10. Asset allocation analysis

In this section, we assess the economic value of forecasting stock market returns with the ESG index from the investing perspective. Following Kandel and Stambaugh (1996), Campbell and Thompson (2008), and Ferreira and Santa-Clara (2011), we explore the certainty equivalent return (CER) gain and Sharpe ratio. The higher the CER gain and Sharpe ratio, the larger the risk-rewarded returns by using the ESG index.

Suppose a mean-variance investor allocates his wealth between the stock market and the one-month T-bill rate. At the start of each month, he invests a proportion of w_t to the stock market to maximize his next one-month expected utility,

$$U(R_p) = E(R_p) - \frac{\gamma}{2} Var(R_p), \tag{10}$$

where R_p is the return of the investor's portfolio, $E(R_p)$ and $Var(R_p)$ are the mean and variance of the market returns, and γ is the investor's risk aversion.

Let R_{t+1} and $R_{f,t+1}$ be the market return and T-bill rate. The investor's portfolio return at the end of each month is

$$R_{p,t+1} = w_t R_{t+1} + R_{f,t+1}, \tag{11}$$

where $R_{f,t+1}$ is known at t. With a simple calculation, the optimal portfolio weight is

$$w_t = \frac{1}{\gamma} \frac{\hat{R}_{t+1}}{\hat{\sigma}_{t+1}^2}, \tag{12}$$

where $\hat{R}_{t+1}$ and $\hat{\sigma}_{t+1}^2$ are the investor's estimates on the mean and variance of the market returns based on $t+1$ information up to time t.

The CER of the portfolio is

$$\text{CER} = \hat{\mu}_p - \frac{\gamma}{2} \hat{\sigma}_p^2, \tag{13}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ are the mean and variance of the investor's portfolio over the out-of-sample evaluation period. The CER can be interpreted as the compensation to the investor for holding the stock market. The difference between the CERs for the investor using the predictive regression based on ESG index and the historical return mean is naturally an economic measure of return predictability significance.

[Insert Table 12 about here]

Table 12 reports portfolio gains of a mean-variance investor with risk-aversion $\gamma = 5$ for predicting future market return with ESG indices constructed based on individual ESG predictors using PLS, volatility-weight, and equal-weight methods. When there is no transaction cost, the annualized CER gain by using the PLS (volatility, equal) ESG index is 4.41% (2.74%, 1.60%), suggesting that investing with the PLS (volatility, equal) ESG index forecast can generate 4.41%

(2.74%, 1.60%) more risk-adjusted return relative to the historical return mean. The monthly Sharpe ratio is 0.44 (0.41, 0.38). When there is a transaction cost of 50 basis points, the CER gain by using the PLS (volatility, equal) ESG index is 3.57% (1.38%, 0.38%), which is still economically sizeable. The corresponding Sharpe ratio is 0.42 (0.38, 0.36).

In summary, there are potentially large investment profits based on ESG index, suggesting substantial economic values for mean-variance investors. This analysis emphasizes the important role of ESG index on the aggregate stock market from an investing perspective.

3.11. Forecasting market return with ESG portfolio index

Dong et al. (2021) find that aggregated long-short financial anomaly portfolio returns evince statistically and economically significant out-of-sample predictive ability for the market excess return. Lioui (2018) argues that the exposure (beta) of ESG is a risk factor. In this section, we examine whether the aggregated long-short ESG anomaly portfolio returns can significantly forecast market returns. First, we obtain 14 individual ESG measures selected from all 38 ESG measures by using the Elastic Net method. Second, we regress each stock returns on one individual ESG measure to obtain that stock's ESG measure's exposures. Third, we sort the ESG exposure to rank stocks and construct the long-short quintile anomaly portfolio. Forth, we can obtain 14 long-short ESG anomaly portfolios. Finally, we use the Partial Least Squares (PLS) method to aggregate 14 long-short ESG anomaly portfolios to the ESG portfolio index.

[Insert Table 13 about here]

Table 13 shows the regression slope, Newey-West t-value, the in-sample $R^2(\%)$, and the out-of-sample $R_{os}^2(\%)$ of predicting future market return with the ESG portfolio indices. Panel A represents the predictive performance from ESG portfolio index which covers three categories: environmental, social, and governance. The in-sample $R^2(\%)$ of ESG portfolio index is 14.00, that is larger than the in-sample $R^2(\%)$ of 10.25 of ESG index in Table 4. But the out-of-sample $R_{os}^2(\%)$ of ESG portfolio index is 4.48, at 5% significance level, that is smaller than the out-of-sample $R_{os}^2(\%)$ of 8.52 of ESG index in Table 4. Although ESG portfolio index's predictive ability is weaker than ESG index, ESG portfolio index can still provide significant out-of-sample predictive power for the market excess return. Panel B, C, and D shows the predictive performances from ESG portfolio indices in environmental, social, and governance category, respectively. We find only environmental portfolio index has significant out-of-sample predictive power.

3.12. Explaining and Forecasting ESG portfolios with ESG index

In this section, we examine whether ESG index can predict the aggregated long-short ESG anomaly portfolio returns and can explain all ESG quintile anomaly portfolio returns. This study not only helps to strengthen our previous findings for aggregate stock market predictability, but also helps to enhance our understanding for the economic sources of return predictability.

[Insert Table 14 about here]

Table 14 shows that ESG index can explain all ESG quintile anomaly portfolio returns contemporaneously. All of the regression slope estimates are positive. Table 15 shows that ESG index can predict the aggregated long-short ESG anomaly portfolio returns. The t-value and in-sample $R^2(\%)$ and are 2.53 and 6.38. Based on the results of Table 14 and Table 15, we provide an economic source that ESG index can predict market returns.

[Insert Table 15 about here]

3.13. Out-of-sample performance of forecasting market return based on the Elastic Net, the Lasso, and the PCA methods

In the previous sections, we have shown that market returns can be significantly forecasted by ESG indices by any of the three methods, PLS, volatility-weight, or equal-weight. This section tests conservative way to extract the ESG predictive information. Specifically, we use the Elastic Net method (Zou and Hastie, 2005), the Lasso method (Tibshirani, 1996), and the PCA method to extract predictive information from all 38 individual ESG measures directly. The Elastic Net method and the Lasso method can deal with highly correlated predictors and has been successfully used in Rapach et al. (2013) and Kozak et al. (2020) for time series and cross-sectional return predictability.

Although we could include some information irrelevant to future returns, we still find meaningful but smaller out-of-samples R_{OS}^2s of one-month horizon and one-year horizon than the PLS ESG index.

The PCA method extracts the first principal component of $ESG_{i,t}$ as the aggregate ESG measure that has the maximum representation of the total variations of the 38 individual ESG measures and has been widely used in the literature on stock return predictability, such as in studies by Baker and Wurgler (2006), Ludvigson and Ng (2007), and Neely et al. (2014), among many others. However, the major shortcoming of the PCA is that it may fail to eliminate the common measurement or observation errors ($Error_t$) unrelated to the stock returns in individual ESG measures. In fact, it captures only the maximum common variations of predictors, and thus, incorporates the $Error_t$ into the estimation process as well.

[Insert Table 16 about here]

Table 16 reports the out-of-sample R_{OS}^2s of predicting future market return with ESG measures constructed based on all available individual ESG measures using the Elastic Net method, the Lasso method, and the PCA method. The ESG measure in (1) covers all three groups of individual ESG measures: environmental, social, and governance groups. The ESG measure in (2), (3), and (4) involves the environmental group, the social group, and the governance group, respectively.

In one-month horizon, the out-of-sample R_{OS}^2 of the PLS ESG index is 8.52%, shown in Table 4. The out-of-samples R_{OS}^2s of the Elastic Net and the Lasso in ESG measures are 6.76% and 3.12%, at 5% significance level, which reflects that ESG measure has strong out-of-sample forecasting power. But the out-of-sample R_{OS}^2 of the PCA in ESG measures is negative. In three sub-groups, only the out-of-sample R_{OS}^2 of the Elastic Net and the Lasso in environmental measures shows significant out-of-sample forecasting power at 5% level. The results suggest that the PCA cannot extract the short-term forecasting information and the short-term predicting power of ESG measure for market return primarily stems from environmental measures.

In one-year horizon, the out-of-sample R_{OS}^2 of the PLS ESG index is 26.20%, shown in Table 5. The out-of-samples $R_{OS}^2 s$ of the Elastic Net and the Lasso in ESG measures is 10.11% and 17.54% and are statistically significant. But the out-of-sample R_{OS}^2 of the PCA in ESG measures is still negative. In three sub-groups, the out-of-samples $R_{OS}^2 s$ of the Elastic Net and the Lasso in environmental measures are negative (–17.76% and –23.59%). The out-of-samples $R_{OS}^2 s$ of the Elastic Net and the Lasso in social measures are 10.08% (significant at 10% level) and 3.50% (not significant) and the out-of-samples $R_{OS}^2 s$ of the Elastic Net and the Lasso in governance measures are 14.52% and 13.44%, both at 5% significance level. The results indicate that the PCA fails to extract the long-term predictive information and the long-term forecasting information of ESG measure for market excess return is mainly from social measures and governance measures, while the governance measures contribute as more economically important sources.

4. Economic explanation

The section examines the economic driving force of the predictive power of ESG index, whether it is from the cash flow channel or discount rate channel or both, where we measure the news components using the VAR methodology of Campbell (1991) and Campbell and Ammer (1993).

Based on Campbell (1991), the total market return can be decomposed into three components,

$$R_{t+1} = E_t(R_{t+1}) + \eta_{t+1}^{CF} - \eta_{t+1}^{DR}, \tag{14}$$

Where $E_t(R_{t+1})$ is the expected return, η_{t+1}^{CF} is the cash flow news and η_{t+1}^{DR} is the discount rate news. Following Cochrane (2011), when running the three components of (14) on the composite ESG index,

$$E_t(R_{t+1}) = \alpha + \beta_E D_t + \varepsilon_{t+1}^{E},$$
$$\eta_{t+1}^{CF} = \beta_{CF} D_t + \varepsilon_{t+1}^{CF},$$
$$\eta_{t+1}^{DR} = \beta_{DR} D_t + \varepsilon_{t+1}^{DR}$$

one can obtain

$$\beta = \beta_E + \beta_{CF} - \beta_{DR}, \tag{15}$$

where β is the regression slope in (8). Then, by comparing the estimated slope coefficients, we can ascertain the extent to which the ESG index's ability to predict the total market returns relates to its ability to predict the three components in (14).

The results are reported in Table 17, where the cash flow news and discount rate news are estimated based on VARs comprising the total market return, dividend-price ratio, and one of the rest 13 macroeconomic predictors explored in Goyal and Welch (2008). We always include the dividend-price ratio in the VARs because Engsted et al. (2012) show that it is important to include this variable to properly estimate the cash flow and discount news components. In the last row of Table 17, we also consider the decomposition based on VAR comprising the total market return, dividend-price ratio, and the first three principal components extracted from the 14 macroeconomic predictors.

[Insert Table 17 about here]

According to Cochrane (2011), a variable that predicts market return must predict its cash flow news or discount rate news or both. Table 17 confirms this argument. Over the 2009:8–2018:10 sample period, the ESG index is significantly related with the cash flow component and discount rate component of the total market return, while the index is insignificantly related with the expected returns. Also, the regression slope on the discount rate news is always much larger in absolute value than that on the cash flow news. For example, when the VAR is based on the total market return and the dividend-price ratio, the regression slope is –0.85 on the discount rate news, 0.33 on the cash flow news, and –0.08 on the expected return. The sum of the three regression slopes in the right-had side of (15) is –0.08 + 0.33 + 0.85 = 1.10, equal to the value using log excess return as the dependent variable in (8). Thus, we conclude that the ability of ESG index in predicting market returns is likely to operate via both cash flow and discount rate channels, and the latter might be the more economically important source.

5. Conclusion

We investigate the predictive power of ESG indices for the aggregate stock market. We aggregate individual ESG measures by using PLS, volatility-weight, and equal-weight. We find that the ESG indices predict the subsequent monthly stock market returns positively and significantly in short and long horizons. In contrast, individual ESG measures have limited return predictability. Additionally, we show that ESG indices main capture short-term forecasting power while social indices and governance indices can capture long-term predicting information. The predictive power of ESG index is greater than that using fundamental return predictors and still exists after controlling for economic, uncertainty, and fundamental measures. Moreover, the strong predictability exists out-of-sample and delivers sizable economic value for mean-variance investors in asset allocation.

Our study highlights the important role of ESG information in the stock market and in finance in general. We identify both cash flow and discount rate channels as the driving forces of the return predictability of ESG. Future research may explore some open issues. First, it will be valuable to explore ESG information in other assets or developing markets. Second, it would be useful to investigate how its predictive power could be further improved with other new methods.

Appendix A. Detailed Description of Economic Variables

In the robustness check, we control for the following 14 economic variables of Goyal and Welch (2008).

- Dividend–price ratio (log), DP: log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index).
- Dividend yield (log), DY: log of a 12-month moving sum of dividends minus the log of lagged stock prices.
- Earnings–price ratio (log), EP: log of a 12-month moving sum of earnings on the S&P 500 index minus the log of stock prices.
- Dividend–payout ratio (log), DE: log of a 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings.
- Stock return variance, SVAR: sum of squared daily returns on the S&P 500 index.
- Book-to-market ratio, BM: ratio of book value to market value for the Dow Jones Industrial Average.[7]
- Net equity expansion, NTIS: ratio of a 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
- Treasury bill rate, TBL: interest rate on a 3-month Treasury bill (secondary market).
- Long-term yield, LTY: long-term government bond yield.
- Long-term return, LTR: return on long-term government bonds.
- Term spread, TMS: long-term yield minus the Treasury bill rate.
- Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.
- Default return spread, DFR: long-term corporate bond return minus the long-term government bond return.
- Inflation, INFL: calculated from the consumer price inflation (CPI) for all urban consumers; we use lagged 2-month inflation in the regression to account for the delay in CPI releases.

[7] We compute the logarithm of the book-to-market ratio in the empirical analysis.

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Figure 1. Time series of ESG indices

This figure plots the time series of ESG indices based on three weighting methods: *PLS*, *Vol* and *Equ*. All indices are standardized. The sample spans the period from Aug 2009 to Oct 2018.

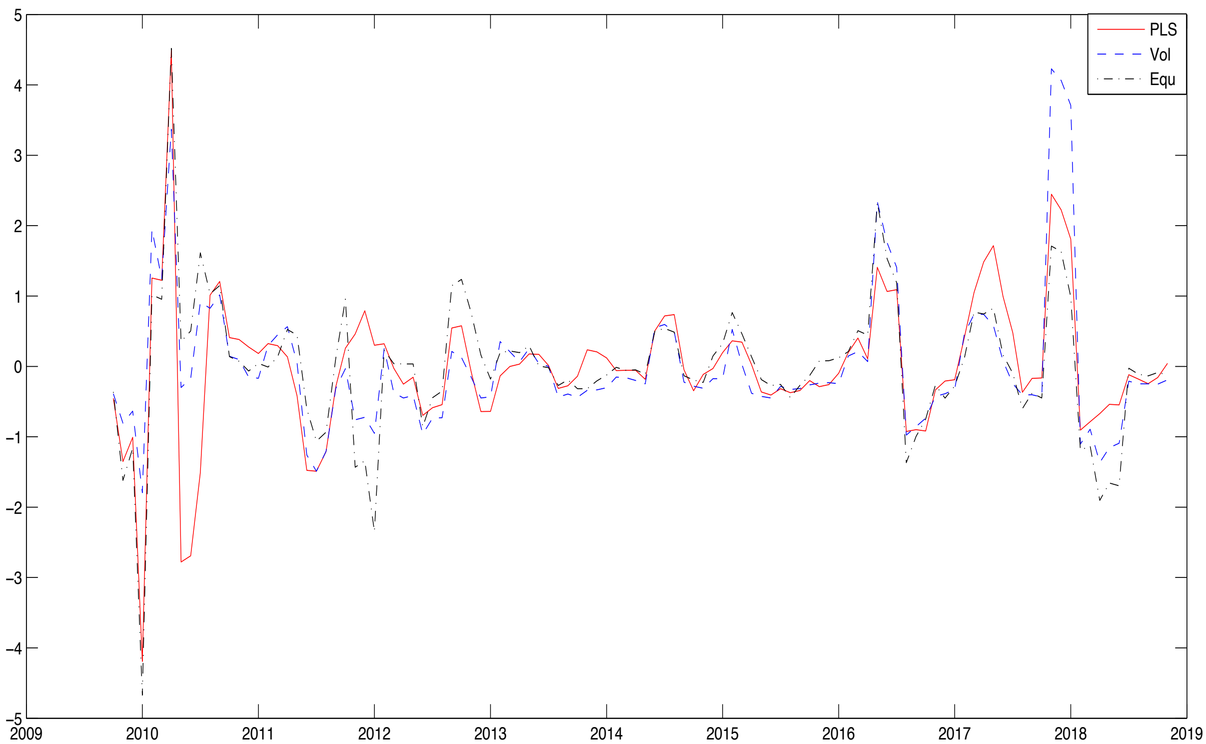

Table 1: Summary statistics of individual ESG predictors

The table reports summary statistics of individual ESG predictors studied in this paper. Individual ESG predictors in Panel A, Panel B and Panel C are individual ESG measures in the environmental group, the social group, and the governance group, respectively, and are transformed in percentage level of growth rate. The sample spans the period from Aug 2009 to Oct 2018.

individual ESG measures	mean	std	$\rho(1)$	skew	kurt	min	max
Panel A: Environmental							
External Certification of EMS	-0.24	1.27	0.53	-0.46	5.91	-5.67	3.43
Participation in Carbon Disclosure Project	0.35	6.28	0.63	3.53	20.29	-11.22	35.00
Carbon Intensity	-0.74	5.01	0.70	-1.05	8.50	-19.96	14.80
Carbon Intensity Trend	-0.41	7.64	0.72	-0.20	7.48	-25.26	24.80
Formal Policy or Programme on Green Procurement	0.47	1.19	0.60	-0.71	8.85	-5.35	4.03
Panel B: Social							
Formal Policy on the Elimination of Discrimination	0.35	2.17	0.69	3.87	19.59	-2.58	11.46
Programmes to Increase Workforce Diversity	0.72	2.05	0.52	0.39	6.61	-7.25	7.99
Employee Turnover Rate	6.62	30.52	0.65	5.20	29.64	-10.93	181.46
Scope of Social Supply Chain Standards	0.61	1.96	0.49	0.46	8.85	-6.95	8.43
Panel C: Governance							
Policy on Bribery and Corruption	-0.01	0.89	0.73	0.97	9.53	-2.65	3.65
Tax Transparency	0.36	2.02	0.36	1.95	19.07	-8.32	13.09
External Verification of CSR Reporting	1.51	6.47	0.72	4.41	24.73	-6.95	39.93
Executive Compensation Tied to ESG Performance	1.42	5.53	0.36	4.01	31.64	-19.58	41.69
Policy on Political Involvement and Contributions	0.08	2.01	0.75	-0.04	9.10	-6.56	7.91

Table 2: Correlations of individual ESG predictors

The table reports the pairwise correlations of individual ESG predictors: External Certification of EMS (E1), Participation in Carbon Disclosure Project (E2), Carbon Intensity (E3), Carbon Intensity Trend (E4), Formal Policy or Programme on Green Procurement (E5), Formal Policy on the Elimination of Discrimination (S1), Programmes to Increase Workforce Diversity (S2), Employee Turnover Rate (S3), Scope of Social Supply Chain Standards (S4), Policy on Bribery and Corruption (G1), Tax Transparency (G2), External Verification of CSR Reporting (G3), Executive Compensation Tied to ESG Performance (G4), Policy on Political Involvement and Contributions (G5). The sample spans the period from Aug 2009 to Oct 2018.

corr	E1	E2	E3	E4	E5	S1	S2	S3	S4	G1	G2	G3	G4	G5
E1	1.00													
E2	0.19	1.00												
E3	0.09	0.08	1.00											
E4	0.10	0.14	0.77	1.00										
E5	0.10	0.00	-0.14	-0.15	1.00									
S1	0.10	0.08	0.15	0.08	-0.05	1.00								
S2	0.20	0.02	0.18	0.19	0.40	0.09	1.00							
S3	-0.13	0.00	0.53	0.35	0.04	0.10	0.02	1.00						
S4	0.16	-0.05	0.03	0.06	0.46	0.02	0.87	0.11	1.00					
G1	0.35	0.10	0.30	0.21	-0.20	0.83	0.14	0.07	0.04	1.00				
G2	0.01	0.05	-0.06	-0.10	0.42	0.09	0.17	0.29	0.22	-0.05	1.00			
G3	-0.36	-0.14	-0.39	-0.40	0.43	-0.11	-0.19	-0.11	-0.12	-0.38	0.34	1.00		
G4	0.24	0.05	0.04	-0.02	0.43	0.13	0.45	-0.02	0.46	0.16	0.63	-0.06	1.00	
G5	0.20	0.13	0.28	0.23	0.03	0.18	0.53	-0.04	0.33	0.39	-0.12	-0.47	0.17	1.00

Table 3: Forecasting market return with individual ESG predictors

The table reports the regression slope, Newey-West t-value, in-sample $R^2(\%)$, and out-of-sample $R^2_{os}(\%)$ of predicting future market return with individual ESG predictors:

$$R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$$

where R_{t+1} is market excess return in month t+1 and predictors X_t in Panel A, B and C are individual ESG predictors in environmental, social and governance category, respectively. Individual ESG predictors are selected among all available individual ESG measures based on elastic net method during a training sample. Statistical significance for R^2_{os} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{os} \leq 0$ against H_A: $R^2_{os} > 0$. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

Predictor	β	t-value	$R^2(\%)$	$R^2_{os}(\%)$
Panel A: Environmental				
External Certification of EMS	-0.26	-1.56	0.56	1.05
Participation in Carbon Disclosure Project	0.46	1.95	1.77	0.18
Carbon Intensity	0.51	2.18	2.19	6.47*
Carbon Intensity Trend	0.47	1.95	1.83	6.10**
Formal Policy or Programme on Green Procurement	0.57	2.64	2.77	7.98*
Panel B: Social				
Formal Policy on the Elimination of Discrimination	-0.40	-1.41	1.37	-1.41
Programmes to Increase Workforce Diversity	0.47	2.31	1.89	-2.72
Employee Turnover Rate	0.45	4.54	1.71	-11.35
Scope of Social Supply Chain Standards	0.50	2.30	2.09	0.67
Panel C: Governance				
Policy on Bribery and Corruption	-0.30	-1.17	0.76	-2.84
Tax Transparency	0.50	2.46	2.10	3.35
External Verification of CSR Reporting	0.27	2.22	0.63	0.63
Executive Compensation Tied to ESG Performance	0.51	4.78	2.15	-0.98
Policy on Political Involvement and Contributions	-0.04	-0.25	0.01	-0.91

Table 4: Forecasting market return with ESG index
The table reports the regression slope, Newey-West t-value, in-sample $R^2(\%)$, and out-of-sample $R^2_{os}(\%)$ of predicting future market return with ESG index:

$$R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$$

where R_{t+1} is market excess return in month t+1, predictor X_t in Panel A is the ESG index which covers three categories: environmental, social and governance, and predictor X_t in Panel B, C and D is the ESG index in environmental, social and governance category, respectively. In each panel, we construct the ESG index by aggregating information from individual ESG predictors using partial least squares (*PLS*) approach. Individual ESG predictors are selected among all available individual ESG measures based on elastic net method during a training sample. Statistical significance for R^2_{os} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{os} \leq 0$ against H_A: $R^2_{os} > 0$. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

β	t-value	$R^2(\%)$	$R^2_{os}(\%)$
Panel A: Environmental, Social and Governance			
1.10	5.18	10.25	8.52**
Panel B: Environmental			
0.97	4.07	7.84	11.39***
Panel C: Social			
0.76	4.00	4.80	4.44*
Panel D: Governance			
0.64	3.70	3.41	1.28

Table 5: Forecasting market return over longer horizon with ESG index

The table reports the regression slope, Newey-West t-value, in-sample $R^2(\%)$, and out-of-sample $R^2_{os}(\%)$ of predicting future cumulative market return over 1-year horizon with ESG index:

$$R_{t+h} = \alpha + \beta X_t + \varepsilon_{t+1}$$

where R_{t+h} is cumulative market excess return between month t and month t+12, predictor X_t in Panel A is the ESG index which covers three categories: environmental, social and governance, and predictor X_t in Panel B, C and D is the ESG index in environmental, social and governance category, respectively. In each panel, we construct the ESG index by aggregating information from individual ESG predictors using partial least squares (*PLS*) approach. Individual ESG predictors are selected among all available individual ESG measures based on elastic net method during a training sample. Statistical significance for R^2_{os} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{os} \leq 0$ against H_A: $R^2_{os} > 0$. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

β	t-value	$R^2(\%)$	$R^2_{os}(\%)$
Panel A: Environmental, Social and Governance			
3.20	5.47	17.17	26.20**
Panel B: Environmental			
1.15	0.99	2.21	-1.86
Panel C: Social			
2.56	5.54	11.00	19.23*
Panel D: Governance			
3.04	5.47	15.48	15.76**

Table 6: Controlling for economic variables
Panel A reports the results of predicting market return as

$$R_{t+1} = \alpha + \psi Z_t + \varepsilon_{t+1}$$

where Z_t is either the first principle component of the 14 economic variables in Welch and Goyal (2008) or one of the 14 economic variables. Panel B reports the results of forecasting market return with ESG index and economic predictor as

$$R_{t+1} = \alpha + \beta X_t + \psi Z_t + \varepsilon_{t+1}$$

where X_t is the ESG index constructed by aggregating information from individual ESG predictors using partial least squares (*PLS*) approach. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

Panel A: Univariate			Panel B: Bivariate		
Predictor	ψ	$R^2(\%)$	β	ψ	$R^2(\%)$
ECON	0.00	0.00	1.11***	0.02	10.26
DP	1.02***	8.83	1.16***	1.09***	20.19
DY	0.83***	5.83	1.05***	0.76***	15.14
EP	0.33	0.92	1.10***	0.32	11.10
DE	-0.06	0.03	1.10***	-0.04	10.27
RVOL	0.05	0.02	1.15***	0.25	10.75
BM	0.25	0.52	1.10***	0.24	10.76
NTIS	-0.10	0.08	1.10***	-0.02	10.26
TBL	-0.17	0.23	1.12***	-0.23	10.70
LTY	-0.39*	1.28	1.07***	-0.22	10.66
LTR	0.41	1.39	1.09***	0.37	11.38
TMS	-0.20	0.35	1.10***	-0.04	10.27
DFY	0.15	0.20	1.13***	0.26	10.84
DFR	0.02	0.00	1.11***	-0.03	10.26
INFL	-0.27	0.62	1.09***	-0.23	10.69

Table 7: Controlling for uncertainty variables

Panel A reports the results of predicting market return as

$$R_{t+1} = \alpha + \psi Z_t + \varepsilon_{t+1}$$

where Z_t represents economic policy uncertainty (EPU_t), macroeconomic uncertainty measure ($MacroU_t$), and financial uncertainty measure ($FinU_t$), respectively. Panel B reports the results of forecasting market return with ESG index and one of the three uncertainty variables as

$$R_{t+1} = \alpha + \beta X_t + \psi Z_t + \varepsilon_{t+1}$$

where X_t is the ESG index constructed by aggregating information from individual ESG predictors using partial least squares (PLS) approach. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

Panel A: Univariate			Panel B: Bivariate		
Predictor	ψ	$R^2(\%)$	β	ψ	$R^2(\%)$
EPU	0.46	1.76	1.09***	0.42	11.75
$MacroU$	-0.25	0.53	1.09***	-0.09	10.32
$FinU$	-0.15	0.19	1.11***	0.05	10.28

Table 8: Controlling for fundamental growth variables

Panel A reports the results of predicting market return as

$$R_{t+1} = \alpha + \psi Z_t + \varepsilon_{t+1}$$

where Z_t represents aggregate asset growth (AG_t), fixed investment growth ($FINVG_t$), non-residential investment growth (NRG_t), aggregate consumption growth ($CONG_t$), industrial production growth (IPG_t), and GDP growth ($GDPG_t$), respectively. Panel B reports the results of forecasting market return with ESG index and one of the six fundamental growth variables as

$$R_{t+1} = \alpha + \beta X_t + \psi Z_t + \varepsilon_{t+1}$$

where X_t is the ESG index constructed by aggregating information from individual ESG predictors using partial least squares (PLS) approach. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

Panel A: Univariate			Panel B: Bivariate		
Predictor	ψ	$R^2(\%)$	β	ψ	$R^2(\%)$
AG	0.22	0.43	1.08***	0.20	10.32
$FINVG$	-0.31	0.79	1.09***	-0.08	10.30
NRG	-0.25	0.53	1.09***	-0.11	10.36
$CONG$	0.31	0.81	1.08***	0.15	10.44
IPG	-0.14	0.15	1.12***	-0.22	10.66
$GDPG$	0.02	0.00	1.12***	0.12	10.38

Table 9: Forecasting industry portfolio returns with ESG index

The table reports the regression slope, Newey-West t-value, and in-sample $R^2(\%)$ of predicting future industry returns with ESG index:

$$R^i_{t+1} = \alpha^i + \beta^i X_t + \varepsilon_{t+1}$$

where R^i_{t+1} is monthly excess return of industry i in month t+1, predictor X_t is the ESG index constructed by aggregating information from individual ESG predictors which cover three categories: environmental, social and governance, using the *PLS* method, and predictor X_t in Panel B, C and D is the ESG index constructed by aggregating information from individual ESG predictors in environmental, social and governance category, respectively. The sample spans the period from Aug 2009 to Oct 2018.

Industry	β^i	t-value	$R^2(\%)$	Industry	β^i	t-value	$R^2(\%)$
Panel A: Environmental, Social and Governance							
NoDur	0.70	3.92	5.56	Telcm	1.23	4.72	10.03
Durbl	1.48	2.97	6.06	Utils	0.49	1.70	2.41
Manuf	1.49	4.90	9.94	Shops	1.30	5.54	13.02
Enrgy	1.27	3.26	5.12	Hlth	0.78	2.22	4.14
Chems	0.77	3.56	4.73	Money	1.08	3.21	5.30
BusEq	1.34	5.58	9.54	Other	1.28	4.40	9.43
Panel B: Environmental							
NoDur	0.72	3.83	5.92	Telcm	1.00	2.70	6.62
Durbl	1.43	2.42	5.66	Utils	0.46	1.48	2.08
Manuf	1.25	3.71	7.06	Shops	1.12	4.28	9.59
Enrgy	1.00	2.06	3.17	Hlth	0.80	3.16	4.37
Chems	0.73	2.94	4.28	Money	0.88	2.37	3.54
BusEq	1.13	4.21	6.80	Other	1.04	3.04	6.28
Panel C: Social							
NoDur	0.47	2.44	2.53	Telcm	0.79	2.97	4.13
Durbl	0.71	2.09	1.41	Utils	0.33	1.15	1.07
Manuf	0.87	3.34	3.43	Shops	0.97	4.02	7.15
Enrgy	0.71	2.00	1.59	Hlth	0.64	4.27	2.83
Chems	0.41	2.40	1.31	Money	0.83	2.75	3.16
BusEq	0.90	3.48	4.31	Other	0.79	2.94	3.60
Panel D: Governance							
NoDur	0.29	2.42	0.97	Telcm	0.85	3.15	4.73
Durbl	1.03	2.44	2.90	Utils	0.26	1.19	0.69
Manuf	1.06	4.62	5.03	Shops	0.69	3.72	3.70
Enrgy	1.02	3.57	3.31	Hlth	0.20	0.94	0.28
Chems	0.51	4.31	2.07	Money	0.59	3.09	1.57
BusEq	0.83	2.59	3.67	Other	0.90	3.63	4.74

Table 10: Forecasting international market returns with ESG index

The table reports the regression slope, Newey-West t-value, in-sample $R^2(\%)$, and out-of-sample $R^2_{os}(\%)$ of predicting future international market returns with ESG index:

$$R^i_{t+1} = \alpha^i + \beta^i X_t + \varepsilon_{t+1}$$

where R^i_{t+1} is market excess return for country i in month t+1, predictor X_t is the ESG index in the United States, which is constructed by aggregating information from individual ESG predictors using partial least squares (*PLS*) approach. Statistical significance for R^2_{os} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{os} \leq 0$ against H_A: $R^2_{os} > 0$. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

β^i	t-value	$R^2(\%)$	$R^2_{os}(\%)$	β^i	t-value	$R^2(\%)$	$R^2_{os}(\%)$
		Australia				Italy	
1.35	4.90	5.74	4.80*	0.99	2.00	2.22	6.50***
		Austria				Japan	
1.45	3.92	5.93	19.25***	0.61	3.40	2.87	8.07***
		Belgium				Netherland	
0.69	1.95	2.22	6.51**	1.21	3.77	5.96	15.48***
		Denmark				New Zealand	
1.17	2.64	5.60	12.40***	1.28	6.95	6.73	15.79***
		Finland				Portugal	
0.94	1.82	2.63	12.87**	0.77	1.59	1.65	7.03**
		France				Singapore	
1.05	3.12	3.88	12.77**	1.00	5.09	4.84	8.26***
		Germany				Spain	
1.16	3.35	5.01	15.12***	0.87	2.20	1.62	7.43***
		Greece				Sweden	
1.76	1.82	2.65	13.91***	1.16	2.91	4.39	6.97*
		Hong Kong				Switzerland	
1.33	3.60	6.83	14.38***	0.85	2.12	4.17	16.59***
		Ireland				United Kingdom	
1.71	3.88	2.97	20.61**	0.88	3.45	3.92	13.11***
		Israel					
0.98	1.71	4.11	13.53***				

Table 11: Forecasting market return with ESG index using alternative methods

The table reports the regression slope, Newey-West t-value, in-sample $R^2(\%)$, and out-of-sample $R^2_{os}(\%)$ of predicting future market return with ESG index using alternative methods:

$$R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$$

where R_{t+1} is market excess return in month t+1, predictor X_t in Panel A is the ESG index which covers three categories: environmental, social and governance, and predictor X_t in Panel B, C and D is the ESG index in environmental, social and governance category, respectively. In each panel, we construct the ESG index by aggregating information from individual ESG predictors using alternative weighting methods: *Vol* and *Equ*. Individual ESG predictors are selected among all available individual ESG measures based on elastic net method during a training sample. Statistical significance for R^2_{os} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{os} \leq 0$ against H_A: $R^2_{os} > 0$. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

Method	β	t-value	$R^2(\%)$	$R^2_{os}(\%)$
Panel A: Environmental, Social and Governance				
Vol	0.87	4.11	6.30	5.63**
Equ	0.62	3.41	3.22	8.35**
Panel B: Environmental				
Vol	0.77	2.81	4.93	10.86***
Equ	0.65	2.21	3.52	10.38***
Panel C: Social				
Vol	0.53	4.96	2.36	5.97**
Equ	0.40	2.93	1.36	5.34**
Panel D: Governance				
Vol	0.59	4.08	2.93	3.72
Equ	0.38	2.56	1.19	1.09

Table 12: Asset allocation results

The table reports portfolio gains of a mean-variance investor with risk-aversion $\gamma = 5$ for predicting future market return with ESG index aggregated based on individual ESG predictors using different weighting methods: *PLS*, *Vol* and *Equ*. The investor allocates her wealth monthly among the stock market and the risk-free asset by applying the out-of-sample forecast based on the ESG index. CER gain is the annualized certainty equivalent return difference between applying an ESG index forecast and applying the historical return mean forecast. Sharpe ratio is the monthly average portfolio excess return divided by its standard deviation. The portfolio weight is estimated recursively using data available at the forecast formation month t. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

	No transaction cost		50 bps transaction costs	
Method	CER gain (%)	Sharp ratio	CER gain (%)	Sharp ratio
PLS	4.41	0.44	3.57	0.42
Vol	2.74	0.41	1.38	0.38
Equ	1.60	0.38	0.38	0.36

Table 13: Forecasting market return with ESG portfolio index

The table reports the regression slope, Newey-West t-value, in-sample $R^2(\%)$, and out-of-sample $R^2_{os}(\%)$ of predicting future market return with ESG portfolio index:

$$R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$$

where R_{t+1} is market excess return in month t+1, predictor X_t in Panel A represents the ESG portfolio index which covers three categories: environmental, social and governance, and predictor X_t in Panel B, C and D represents the ESG portfolio index in environmental, social and governance category, respectively. In each panel, we employ partial least squares (*PLS*) approach to extract predictive signal in long-short ESG portfolio returns as the ESG portfolio index. The ESG portfolios are constructed based on stocks' exposures to individual ESG predictors. Individual ESG predictors are selected among all available individual ESG measures based on elastic net method during a training sample. Statistical significance for R^2_{os} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{os} \leq 0$ against H_A: $R^2_{os} > 0$. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

β	t-value	$R^2(\%)$	$R^2_{os}(\%)$
	Panel A: Environmental, Social and Governance		
1.07	4.22	14.00	4.48**
	Panel B: Environmental		
0.98	4.21	11.86	6.51*
	Panel C: Social		
0.96	4.26	11.35	7.99
	Panel D: Governance		
0.83	3.45	8.42	-6.29

Table 14: ESG index and ESG portfolio returns

The table reports the regression slope, Newey-West t-value, and in-sample $R^2(\%)$ of explaining ESG portfolio returns with ESG index:

$$R_t^i = \alpha^i + \beta^i X_t + \varepsilon_{t+1}$$

where R_t^i is monthly excess return of ESG portfolio i, predictor X_t is the ESG index constructed by aggregating information from individual ESG predictors which cover three categories: environmental, social and governance, based on the *PLS* method. The ESG portfolios are constructed based on stocks' exposures to individual ESG predictors. Individual ESG predictors are selected among all available individual ESG measures based on elastic net method during a training sample. The sample spans the period from Aug 2009 to Oct 2018.

	β^i	t-value	$R^2(\%)$	β^i	t-value	$R^2(\%)$
		Panel A: E1			Panel B: E2	
Low	0.88	3.01	3.86	0.82	2.33	2.95
2	0.65	3.23	3.80	0.50	2.04	1.83
3	0.55	2.59	2.79	0.66	2.98	3.94
4	0.52	1.99	2.04	0.57	2.46	2.91
High	0.81	2.13	2.84	0.85	2.73	3.97
		Panel C: E3			Panel D: E4	
Low	0.78	3.09	3.73	0.71	2.62	2.87
2	0.48	2.20	2.08	0.46	2.06	1.87
3	0.57	2.69	2.82	0.62	2.89	3.53
4	0.58	2.18	2.35	0.60	2.45	2.54
High	1.00	2.35	3.93	1.01	2.49	4.35
		Panel E: E5			Panel F: S1	
Low	0.84	3.01	3.89	0.95	2.35	3.44
2	0.50	2.29	2.23	0.63	2.19	2.96
3	0.59	2.60	3.10	0.48	2.17	2.10
4	0.70	2.67	3.34	0.53	2.66	2.52
High	0.78	2.09	2.70	0.82	3.28	3.99
		Panel G: S2			Panel H: S3	
Low	0.77	2.50	2.90	0.73	2.08	2.55
2	0.57	2.37	2.69	0.41	1.81	1.39
3	0.56	2.47	2.78	0.63	2.68	3.33
4	0.66	2.79	3.42	0.66	2.71	3.60
High	0.84	2.38	3.50	0.97	3.23	4.60

	β^i	t-value	$R^2(\%)$	β^i	t-value	$R^2(\%)$
		Panel I: S4			Panel J: G1	
Low	0.69	2.58	2.63	0.95	2.32	3.69
2	0.58	2.54	2.89	0.59	2.16	2.67
3	0.58	2.64	2.94	0.49	2.10	2.13
4	0.61	2.28	2.83	0.56	2.88	2.85
High	0.94	2.52	3.73	0.82	3.20	3.66
		Panel K: G2			Panel L: G3	
Low	0.85	2.64	4.01	1.00	3.30	5.29
2	0.57	2.46	2.89	0.63	2.88	3.69
3	0.53	2.57	2.36	0.50	2.07	2.26
4	0.64	2.66	3.04	0.52	2.22	1.96
High	0.81	2.32	3.04	0.75	2.12	2.50
		Panel M: G4			Panel N: G5	
Low	0.67	2.13	2.41	0.95	2.35	3.44
2	0.52	2.11	2.28	0.63	2.19	2.96
3	0.59	2.65	3.03	0.48	2.17	2.10
4	0.66	2.76	3.13	0.53	2.66	2.52
High	0.96	2.93	4.38	0.82	3.28	3.99

Table 15: ESG index and ESG portfolio index

The table reports the regression slope, Newey-West t-value, and $R^2(\%)$ of predicting ESG portfolio index with ESG index. The ESG index is constructed by aggregating information from individual ESG predictors using partial least squares (*PLS*) approach. Individual ESG predictors are selected among all available individual ESG measures based on elastic net method during a training sample. The sample spans the period from Aug 2009 to Oct 2018.

β	t-stat	$R^2(\%)$
0.25	2.53	6.38

Table 16: Out-of-sample $R^2_{os}(\%)$s of forecasting market return based on alternative methods
Panel A and Panel B report the out-of-sample $R^2_{os}(\%)$s of predicting 1-month (1M) ahead and 1-year (1Y) ahead market returns with ESG index constructed based on all available individual ESG measures using alternative methods: principal component analysis (*PCA*), least absolute shrinkage and selection operator (*LASSO*), and elastic net (*ENet*). The ESG index in (1) covers all three groups of individual ESG measures: environmental, social and governance. The ESG index in (2), (3) and (4) involves the environmental group, the social group, and the governance group, respectively. Statistical significance for R^2_{os} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{os} \leq 0$ against H_A: $R^2_{os} > 0$. $***$, $**$, and $*$ indicate significance at 1%, 5%. 10% levels, respectively. The sample spans the period from Aug 2009 to Oct 2018.

$R^2_{os}(\%)$	PCA	LASSO	ENet
		Panel A: 1M	
(1)	-0.09	3.12**	6.76**
(2)	0.49	5.31**	5.71**
(3)	-0.56	-0.21	2.58
(4)	0.76	-0.83	-0.71
		Panel B: 1Y	
(1)	-0.52	17.54*	10.11**
(2)	1.66	-23.59	-17.76
(3)	-3.39	3.50	10.08*
(4)	-1.71	13.44**	14.52**

Table 17: Forecasting channel

This table reports the estimation results for the predictive regression

$$Y_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$$

where X_t is the ESG index constructed by aggregating information from individual ESG predictors based on *PLS* method, Y_t is one of three estimated components of the S&P 500 log return for month t. The three estimated components of the S&P 500 log return are the expected return ($\hat{E}r_{t+1}$), cash flow news ($\hat{\eta}^{CF}_{t+1}$), and discount rate news ($\hat{\eta}^{DR}_{t+1}$), corresponding to $\hat{\beta}_{\hat{E}}$, $\hat{\beta}_{CF}$, and $\hat{\beta}_{DR}$. The components are estimated based on a VAR comprised of the variables in the 1st column: the S&P 500 log return (”r”), 14 representative macroeconomic variables, and the first three components extracted from the 14 representative macroeconomic variables (”PC”). We report the regression slopes and Newey-West t-statistics. The sample spans the period from 2009 to 2018.

VAR variables	$\hat{\beta}_{\hat{E}}$	t-stat	$\hat{\beta}_{CF}$	t-stat	$\hat{\beta}_{DR}$	t-stat
r, DP	-0.08	-0.86	0.33	2.90	-0.85	-4.04
r, DP, DY	-0.10	-0.84	0.33	3.13	-0.87	-4.24
r, DP, EP	-0.06	-0.62	0.06	0.77	-1.10	-4.40
r, DP, DE	-0.06	-0.62	0.06	0.77	-1.10	-4.40
$r, DP, RVOL$	-0.06	-0.69	0.32	2.92	-0.85	-3.91
r, DP, BM	-0.08	-0.87	0.37	3.21	-0.81	-3.42
$r, DP, NTIS$	-0.09	-0.94	0.36	3.10	-0.83	-3.81
r, DP, TBL	-0.06	-0.60	0.35	3.08	-0.82	-4.02
r, DP, LTY	-0.07	-0.80	0.42	5.03	-0.75	-3.18
r, DP, LTR	-0.05	-0.51	0.33	3.01	-0.82	-3.81
r, DP, TMS	-0.05	-0.51	0.47	6.03	-0.69	-3.05
r, DP, DFY	-0.02	-0.19	0.32	2.73	-0.80	-3.81
r, DP, DFR	-0.10	-1.14	0.34	2.94	-0.87	-4.25
$r, DP, INFL$	-0.08	-0.85	0.34	2.94	-0.84	-4.02
r, DP, PC	-0.03	-0.27	0.25	2.38	-0.88	-4.08