PORTFOLIO
MANAGEMENT
RESEARCH
By With Intelligence

the journal of PORTFOLIO management

NOVEL RISKS AND SOURCES OF VOLATILITY:
Identification and Measurement Challenges for Portfolio Management

guest co-editor
AHMET K. KARAGOZOGLU

volume **48** *number* **10**

OCTOBER 2022

jpm.pm-research.com

ESG, Fundamentals, and Stock Returns

Eric Sorensen, George Mussalli, Sebastian Lancetti, and Daniel Belanger

PanAgora Asset Management is a quantitative investment manager whose proprietary approach is designed to capitalize on inefficiencies across market cycles and to deliver relative and absolute returns through distinct and innovative equity, multi-asset and risk premia strategies. PanAgora's approach combines the firm's fundamental investment philosophy and original research with an advanced quantitative framework. These elements come together in an open, collaborative environment that builds upon the intellectual versatility of its team and leverages their complementary strengths — essential to serving the evolving objectives of institutional investors worldwide.

PanAgora was founded in 1989 and is based in Boston, MA. Shareholders include the Firm's employees and Great-West Life of Canada, a member of the Power Financial Corporation Group of Companies.

Eric Sorensen, Ph.D., President & Chief Executive Officer

Dr. Sorensen is the President and Chief Executive Officer of PanAgora, and a member of the firm's Board of Directors, Investment, Operating, Risk, Code of Conduct & Ethics, and Directors' Committees. He is responsible for PanAgora's business and investment activities.

He took over leadership of PanAgora in 2004 and established a new research and investment direction for the firm. Prior to joining PanAgora, Dr. Sorensen was Director of Quantitative Research at Putnam Investments, overseeing the activities of several quantitative teams including equity, fixed income, asset allocation and financial engineering. He was also Chief Investment Officer of Structured Equity, which managed institutional portfolios using advanced quantitative approaches.

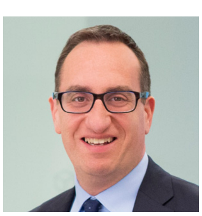
Between 1986 and 2000 Dr. Sorensen was the Global Head of Quantitative Research at Salomon Brothers (now Citigroup). At the end of his 14 years on Wall Street, he led a group of 55 quantitative analysts comprising teams in New York, London, Singapore, Tokyo and Australia. During that time, he published extensively, and consulted with institutional investor clients around the world. His honors include many years on the Institutional Investor All American Research Team, and several Graham and Dodd awards for excellence in financial writing.

Prior to Wall Street, he was a professor with a productive academic career from 1974 to 1986. For a decade he was Professor of Finance and Department Head at the University of Arizona. He has published over 50 journal articles and served on the editorial boards of several academic Finance journals. He is also co-author of the recent book, Quantitative Equity Portfolio Management.

Between 1969 and 1974 he served the country as a United States Air Force Officer and jet pilot. His primary mission was instructor pilot in high-performance jet aircraft.

With over 45 years of quantitative research and investment experience, Dr. Sorensen is a leading expert in the industry. He continues to maintain affiliations in both the industry and academia.

EDUCATION:
University of Oregon, Ph.D.
Oklahoma City University, M.B.A.
University of Oregon, A.B.



George D. Mussalli, CFA, Chief Investment Officer, Equity Investments

Mr. Mussalli is the Head of Equity Research and Chief Investment Officer of Equity Investments at PanAgora. He is responsible for the oversight of the firm's Dynamic and Stock Selector Equity strategies, as well as the Equity Trading & Implementation, Data Science, and Portfolio Strategy teams. He is also a member of the firm's Investment, Operating, Risk, and Directors' and Sustainability Committees.

As the Chief Investment Officer of Equity Investments, Mr. Mussalli directs innovative equity research used in the development of models implemented in PanAgora's equity strategies. Mr. Mussalli's current focus is centered on combining fundamental and quant investing using big data. As a leader in the field, he was appointed to the Editorial Board for The Journal of Financial Data Science as well as the AI and Data Science in Trading Advisory Board, and is further son the advisory board for the Journal of Portfolio Management's ESG Journal.

Prior to becoming the Chief Investment Officer of Equity Investments, Mr. Mussalli served as Head of PanAgora's Stock Selector strategies. His work focuses on combining fundamental insights with sophisticated quantitative techniques to develop proprietary models designed to analyze companies across many dimensions. In addition to overseeing the management of the firm's Stock Selector strategies, he has significantly contributed to the proprietary pool of equity research leveraged across the entire firm during his tenure.

Before joining PanAgora, he was a Portfolio Manager on the Putnam Investments Structured Equity team, where he was responsible for Structured Equity portfolios. He contributed to quantitative research and analysis that supported all equity strategies, including International and Global strategies.

Prior to joining Putnam, Mr. Mussalli worked as a Senior Investment Analyst at John Hancock Funds.

EDUCATION:
Sloan School of Management, Massachusetts Institute of Technology, M.B.A.
Tufts University, B.S.

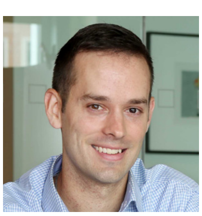
Sebastian Lancetti, CFA, Director, Head of Portfolio Strategy

Mr. Lancetti is a Director at the firm and manages the Equity Portfolio Strategy team. He is responsible for conducting equity research as well as overseeing the marketing and client services product processes for PanAgora's broad suite of equity investment capabilities. Mr. Lancetti's areas of expertise include quantitative strategies, alpha extraction, equity factors and stock market event studies.

Prior to joining PanAgora, Mr. Lancetti was Head of US Equity Quantitative Research at UBS in New York where he developed and marketed global quantitative equity research products to institutional clients. Mr. Lancetti has also worked at UBS UK, Dresdner Kleinwort and Banque de Luxembourg.

Mr. Lancetti is a CFA charterholder.

EDUCATION:
London Business School, Masters in Finance
Università Commercial Luigi Bocconi, Economics



Daniel Belanger, CFA, Analyst, Portfolio Strategy

Mr. Belanger is a quantitative analyst within the Equity Portfolio Strategy team. He helps advance new business initiatives and products, while also contributing to the production of Equity Strategy research and think pieces.

Prior to joining the Portfolio Strategy team, Mr. Belanger was a portfolio associate on the distribution team at PanAgora. Mr. Belanger has previously worked in client service roles at State Street Corporation.

Mr. Belanger is a CFA charterholder.

EDUCATION:
Suffolk University, BS Economics

ESG, Fundamentals, and Stock Returns

Eric Sorensen, George Mussalli, Sebastian Lancetti, and Daniel Belanger

Eric Sorensen
is the chief executive officer at PanAgora Asset Management in Boston, MA.
esorensen@panagora.com

George Mussalli
is the CIO and head of equities research at PanAgora Asset Management in Boston, MA.
gmussalli@panagora.com

Sebastian Lancetti
is a director and head of strategy at PanAgora Asset Management in Boston, MA.
slancetti@panagora.com

Daniel Belanger
is an analyst on the portfolio strategy team at PanAgora Asset Management in Boston, MA.
dbelanger@panagora.com

KEY FINDINGS

- Earnings outcomes relative to prior expectations continues to be the dominant influence on stock performance during the recent decade and is similar to several prior decades. It is gratifying to observe continued rationality in equilibrium pricing.
- Quintile ESG (environmental, social, and governance) scores between 2013 and 2021 do not demonstrate monotonically higher returns. Years 2016 and 2019, being a slight exception, become relevant using CART (classification and regression trees) modeling showing a hierarchal subordinate role in return discrimination.
- Given an ex ante quantifiable return ranking, CART demonstrates an approach to integrate ESG into a wealth-maximizing objective. The ESG risk budget is optimally implemented where: (1) it conditionally adds return, and (2) does not adversely limit the alpha potential.

ABSTRACT

For decades, modern portfolio theory's function has been delivery of risk-adjusted wealth maximization. For a shorter and more recent period, ESG's (environmental, social, and governance) function has been adherence to social preferences. This article addresses the empirical impact of ESG scores on stock return. It does so with a formal statistical decision tree (classification and regression trees, or CART) to understand the nonlinear and interactive role of ESG scores in an otherwise wealth-maximizing objective. Empirical evidence on stock return from the years 2013–2021 demonstrates that fundamentals (earnings phenomena) consistently dominate relative stock performance. ESG as a stand-alone input plays little or no role; however, in the presence of fundamental drivers, ESG interacts as a subordinate influence on return in some years. This leads to a potential paradigm for joint integration of quantitative fundamentals with ESG scores to achieve higher returns.

Professional money managers are increasingly devoting substantial resources to showcasing the environmental, social, and governance (ESG) profiles of their stocks and portfolios. In earlier research, we presented the challenges of altering the age-old modern portfolio theory (MPT) paradigm in the advent of ESG affinity (see Chen and Mussalli 2020 and Sorensen, Chen, and Mussalli 2021).

ESG begs an empirical question: Does it add to (or detract from) portfolio performance? Historically, the approach to accommodate social preferences was to either slice or season the portfolio. Slicing cuts out complete elements, such as sector or homogeneous sets (tobacco or energy, for example). Seasoning subjectively spikes the holdings with a consensus of visibly ESG-centric names.

Quantitative models enrich the discussion, providing a real solution. Do stocks (portfolios) with higher ESG scores complement or compete with MPT processes? Is a selection process that starts with the ESG score as a filter and then suboptimizes better? If not, where in the process should social preferences enter? We herein address these questions.

The wealth-maximizing investor may seek to marry two objectives: (1) social preferences (ESG adherence), and (2) spending power (monetary return attraction). This article introduces evidence of ESG return characteristics, proposes methodology to integrate, and suggests an optimal approach.

We start with the most basic variable of interest, relative stock return, and then examine whether high (low) ESG scores as a singular input affect stock returns. We analyze how ESG stacks up against attractive (inferior) fundamental corporate earnings. We propose a normative approach for integration of ESG with such fundamentals.

The approach is not a linear, random shuffling of the deck, trading red cards and black cards. The solution is a hierarchical model that captures interactive effects with conditionality. If you are clairvoyant and hold the three stocks with the highest surprise in earnings that are also ESG friendly, then go ahead and retire rich. If not, then build an expert system under uncertain conditions that properly marries your ranking system and the globally accepted metrics of ESG adherence.

We present empirical return evidence for the years 2013–2021. Univariate tests reveal that, on the one hand, earnings phenomena continue to be dominant drivers of relative stock returns across market environments, key sectors, and styles. ESG ratings, on the other hand, add little stand-alone return prediction. Further, we apply a hierarchical tree approach known as classification and regression trees (CART) to assess the ordering and interactions of the inputs.[1] In addition to earnings changes, earnings surprises, and ESG readings, we control for style (growth versus value) and key sectors (energy versus technology).

ESG RESEARCH STUDIES

Long before the term "ESG" crept into the financial literature (circa 2015), researchers began to do empirical work on the impact of constraining portfolios by slicing out possible holdings for social ramifications. In theory, restricting possible diversifying investment choices shifts the efficient frontier.[2] Fabozzi, Ma, and Oliphant (2008), for example, conclude that removing the so-called sin stocks of 20-plus years ago (alcohol, tobacco, firearms, and the like) retarded portfolio returns. More recently, Le Sourd (2022) provides a useful and comprehensive review of many such empirical studies.[3] He observes that these analyses, which test the impact of restricting stock choices vis-à-vis ESG, are mixed. In some cases, the research concludes that constraining for social goals lowers returns and/or suppresses diversification, such as the result of Fabozzi, Ma, and Oliphant (2008). Other research, such as that of De and Clayman (2015), argues that ESG adherence reduces risk.

If the investor seeks social responsibility (however defined) as a primary goal, then the implications for portfolio returns may not be a concern. If return and wealth accumulation are paramount, then the interplay between alpha and ESG accommodation needs to be known.

[1] CART was introduced in Breiman et al. (1984). We discuss the merits of CART in the next section.

[2] See Pedersen, Fitzgibbons, and Pomorski (2021) for a discussion on altering the Markowitz-type model with ESG constraints.

[3] There are a considerable number of them.

ESG AND FUNDAMENTAL EARNINGS

This article seeks to focus on that knowledge. One of the goals of this research is to measure impact of ESG on return. We do this with univariate analyses. In addition, we use CART to analyze a multivariate framework with the intent of controlling for earnings phenomena. We incorporate start-of-period and end-of-period earnings measures. This is not intended as a forecasting variable, per se, but as a control for fundamental change during the period. It offers a more precise estimate of the marginal impact and the interaction effects of ESG. The dependent variable is relative stock return over one-year horizons for the years 2013–2021. The independent variables are: (1) ESG ratings at the start of the year, (2) earnings-per-share (EPS) surprise over the one-year return interval (defined by *V* in Equation 1), and (3) EPS change over the one-year return interval. The ESG scores we test comprise the weighted average MSCI composite rankings for ESG.[4]

$$V_{t0} = \frac{(\text{Reported EPS}_{t0} - \text{Consensus EPS}_{t-1})}{\text{Consensus standard deviation}_{t-1}} \tag{1}$$

The earnings factors control for unanticipated and actual changes in reported earnings over the stock return measuring horizon. Past research demonstrated the power of unexpected earnings results over a given period stimulating the demand for (or supply of) a given stock. Better-than-expected earnings result in increased demand, whereas weaker-than-expected earnings result in increased supply. This was first demonstrated 50 years ago by Niederhoffer and Regan (1972). They simply tested for the unexpected earnings effect among the top 50 stock performers in contrast to the year's bottom 50 performers. Earnings results relative to consensus expectations a year prior dramatically divided winners from losers. They concluded that "an accurate earnings forecast is of enormous value in stock selection."[5] That is probably an understatement over the ensuing 50 years, as rational expectations continued to operate in determining relative stock price equilibria.

In a more recent article, Sorensen and Ghosh (2010) tested the importance of end-of-period actual earnings versus the earlier start-of-period consensus expectations in testing Equation 1. Over a sample of 1991–2008, they found a dramatic and consistent result. The earlier in time the investor can predict future earnings results, the better the returns. In addition, for forecast horizons of 3, 6, 9, 12, and 15 months, the stock returns monotonically increase for each quintile of earnings surprise.[6]

---

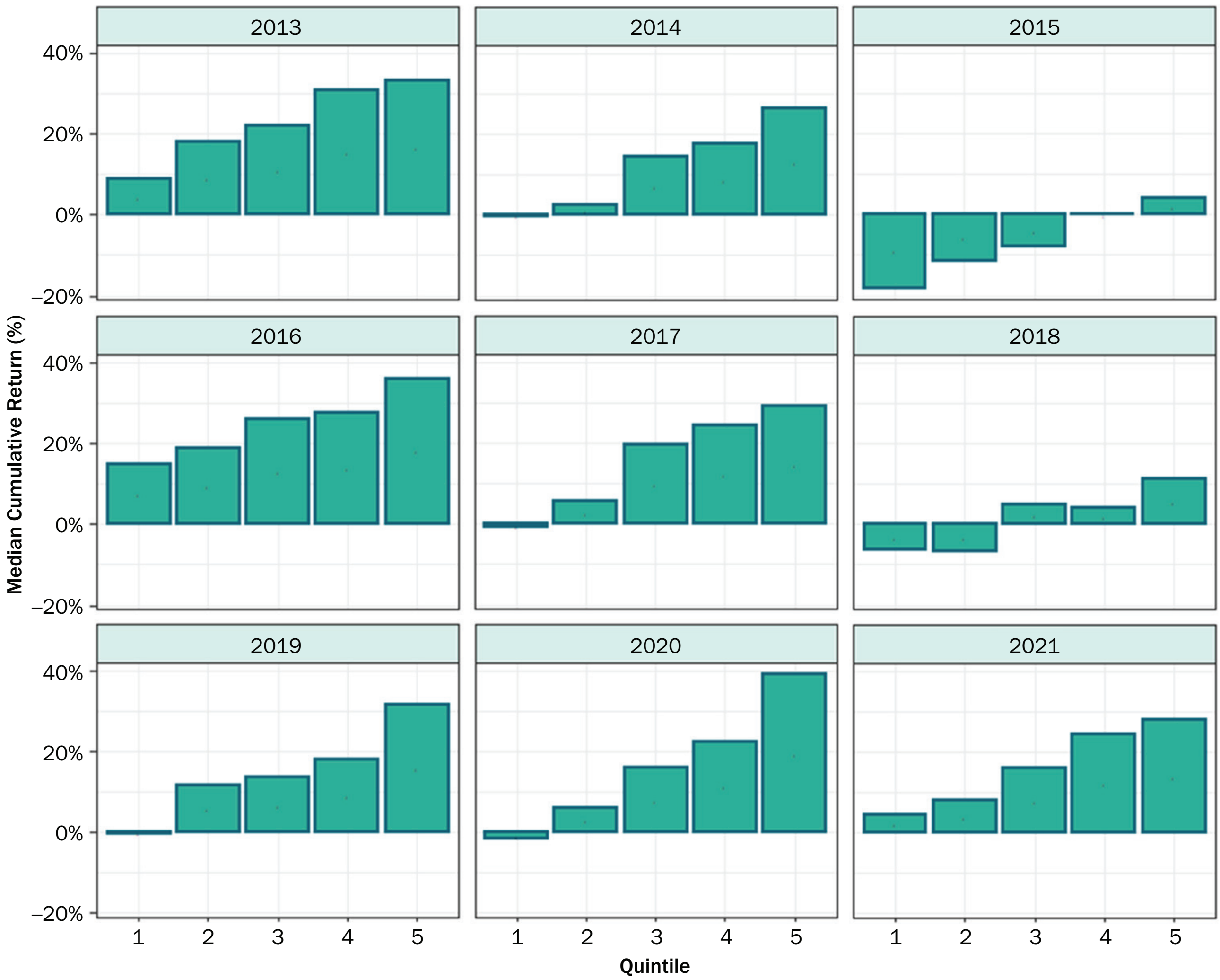
[4] Extensions could include other MSCI data, such as pillar rand industry-relative rankings, as well as data from other vendors, such as Sustainalytics (see Berg, Kölbel, and Rigobon 2022).

[5] They observed that, during the calendar year 1970, of the 1,253 NYSE-listed stocks, almost half posted gains or losses in excess of 20%. They analyzed the earnings data of the top 50 stock return performers in comparison to the bottom 50 performers. Using actual 1969 reported earnings, actual 1970 reported earnings, and 1970 earnings estimates measured as of early 1970, they observed two general tendencies: (1) Predictably, the top 50 stocks (up 27%–125%) tended to have year-over-year earnings increases compared to the bottom 50 (down –49% to –78%), which tended to have big earnings declines; and (2) most important, it was the firm-specific earnings outcomes for 1970 measured against the prior-year expectations that drove a wedge between superior and inferior returns. When forecasts underestimated the earnings results by 4% or more, the odds were 14 to 1 that the stock ended up a top 50 member; in contrast, when forecasts overestimated by 8% or greater, the odds were 17 to 1 for a bottom 50 type.

[6] For the entire sample, the 12-month Q5–Q1 spread averages 48.5%, with a high of 70.2% in 1991 and a low of 26.4% in 2001. Moreover, it is more than just discriminating in the top/bottom quintile extremes: The average spread between each quintile is uncannily systematic, ranging from 11.4% for Q2 versus Q3 to 14% for Q1 versus Q2.

EXHIBIT 1

Performance of Earnings Surprises (split by quintile), 2013–2021



SOURCES: PanAgora, FactSet Accounting Data.

STAND-ALONE RESULTS

We analyze return data with one-year horizon periods on an annual basis to observe the variable *V* for the years 2013–2021. The universe is the Russell 1000, and 75% of the sample has a December fiscal year. For example, if a company has a December 2013 fiscal year, *V* is the difference in the reported earnings in December 2013 and the consensus forecast 12 months prior (December 2012) scaled by the variation in those forecasts. For stocks with fiscal years other than December, the calculation is taken from 12 months prior to the fiscal month and included in the tests for the closest calendar year.[7]

Exhibit 1 presents the average returns for each of the earnings surprise (*V*) quintiles for 2013 through 2021. The results are consistent over time. In each calendar year, the stock returns for all 12-month horizons are monotonically increasing with the surprise quintile. For the entire sample period, the median spread between Q5 and Q1

[7] For example, if a company reports in March 2019, *V* uses the horizon of March 2018 to March 2019, and the result is used for the 2018 calendar sample.

is +24.2%, with a high of +40.6% in 2020 and a low of +17.8% in 2018. The median spread between each quintile is systematic, ranging from a median of 5.7%–8.0%. The median difference between quintiles 1 and 2 is 5.7%, between 2 and 3 is 8%, and so on. The numeric calculations from Exhibit 1 are presented in Appendix, Exhibit A1.

The results for earnings phenomenon here are encouraging in that the fundamental MPT proposition is intact. The average spreads are a bit lower than the earlier study by Sorensen and Ghosh (2010). The slightly lower spreads could be due to the extraordinary monetary stimulus of the entire period, which created falling rates and rising stock prices in general. It is nevertheless gratifying to observe a continued rationality in equilibrium pricing. The more accurate the earnings forecast, the more dramatic the returns relative to other competitors.

Exhibit 2 shows the MSCI ESG ratings, in quintiles, at the start of each year beginning in 2013.[8] The average annual returns are shown for each quintile similar to the Exhibit 1 EPS surprise quintiles. The ESG quintile 1–5 return patterns are not as suggestive of monotonically higher returns as they are for earnings surprise (Exhibit 1). This is to be expected because earnings drive stock prices, and we are measuring the unanticipated portion.

CONDITIONAL MULTIVARIATE RESULTS

We believe that CART is an ideal model for estimating the ordering of stock factors' significance with interaction effects in explaining periodic relative stock returns. This nonlinear approach, developed by Breiman et al. (1984), does not require any traditional statistical assumptions about the distributions of the input variables. Because stock attribute data are often abnormal with outliers, we use categorical classification (e.g., quintile membership or binary membership) as opposed to continuous regression inputs. Classification trees (as opposed to regression trees) are much easier to interpret and much less susceptible to spurious overfitting.

The target or dependent variable is the one-year total return for each stock in the Russell 1000, with three explanatory variables.[9] Two independent variables account for the firm's earnings results: (1) the unanticipated change for the year ("EPS Surprise"), and (2) the actual percentage change for the year ("EPS Change").[10] These variables are organized as quintiles, with five having the highest surprises.[11] The third dependent variable is the ESG quintile rating at the start of the year.[12]

The model recursively iterates through each of the candidate independent variables with the mission to find the one with the greatest explanatory power.

[8] MSCI's weighted average ESG score is a normalized score for each company. Its calculation is based on the weighted average of the scores from all the key issues that fall under each of the ESG pillars. Each pillar is organized by underlying themes. Scores are ranked from 0 to 10 where 0 is very poor and 10 is very good (MSCI; https://www.msci.com/our-solutions/esg-investing/esg-ratings). Previous research papers have discussed the disparity between rating agencies, in particular, the research paper by Berg, Kölbel, and Rigobon (2022).

[9] The yearly samples are slightly less than 1,000 because of missing observations for the MSCI rating history.

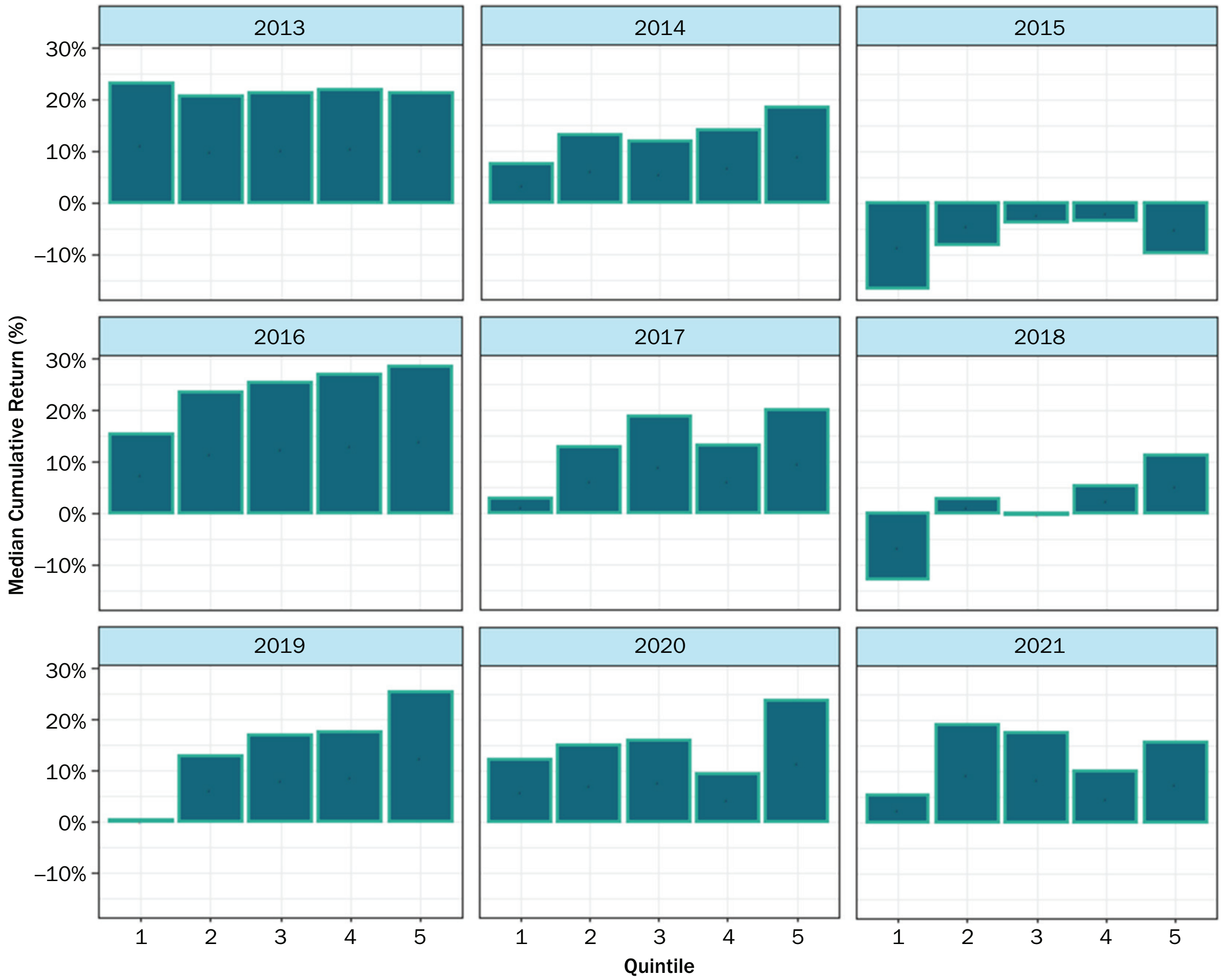
[10] This follows Niederhoffer and Regan (1972), who reported on the actual change and the unanticipated change.

[11] The correlation between the one-year change and the one-year surprise is relatively low. Correlations average 0.16 over the nine-year period, with a low of 0.02 in 2020 and a high of 0.52 in 2015. (In 2015 the average stock return was –5.7%, an anomaly year in a decade of mostly upward stock market moves.) In the following CART analyses, we restrict the sample for the years 2013–2021. During this period, the earnings surprise and actual earnings change correlations averaged less than 10%.

[12] We also tested the one-year change in the rating over the return period. This added little insight because the ratings are very slow moving. In addition, it did not appear to affect the results by using snapshots of the ratings after the beginning of each year, say midyear, for example.

EXHIBIT 2

Performance of MSCI ESG Ratings (split by quintile), 2013–2021



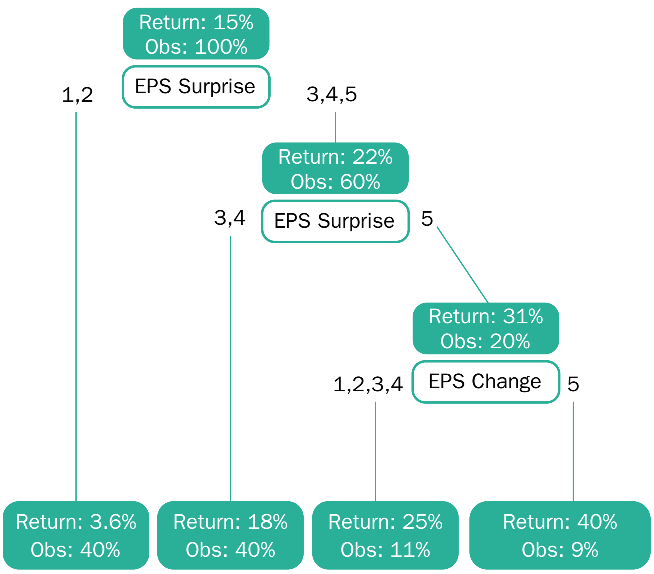
SOURCES: PanAgora, MSCI Inc.

Each variable is tested for each potential split (Q1 and Q2 versus the higher quintiles, for example). The sum of squared errors in the forecast is the test statistic for each iteration. The most predictive variable is chosen, and the precise split is determined in the data that minimize the errors.

Exhibit 3 is a model estimate for all years' data between 2016 and 2021. The node (box) at the top reading "15%" and "100%" indicates the mean annual stock return of 15% for the entire sample (100%). In the first split level of the tree (top), we see the EPS surprise (earnings surprise). The maximum explanatory power associated with return is found to be a split of Q3, Q4, and Q5 branching to the right and Q1 and Q2 branching to the left. To the left there are no further splits. If the tree were to terminate at this second node, it would conclude that the higher quintiles (3, 4, 5) of EPS surprise led to returns of 22% versus 3.6% for lower quintiles (1, 2), but the model continues to fit subsequent nodes of "if/then" rules. First, it separates out Q5 for EPS surprise; second, conditioned on that, it separates out Q5 for EPS change. The four terminal nodes at the bottom moving from left to right represent increasing returns. The two left nodes account for 80% of the cases, with average returns of 3.6% and 18%, respectively. In comparison, the two nodes to the right have higher returns.

EXHIBIT 3

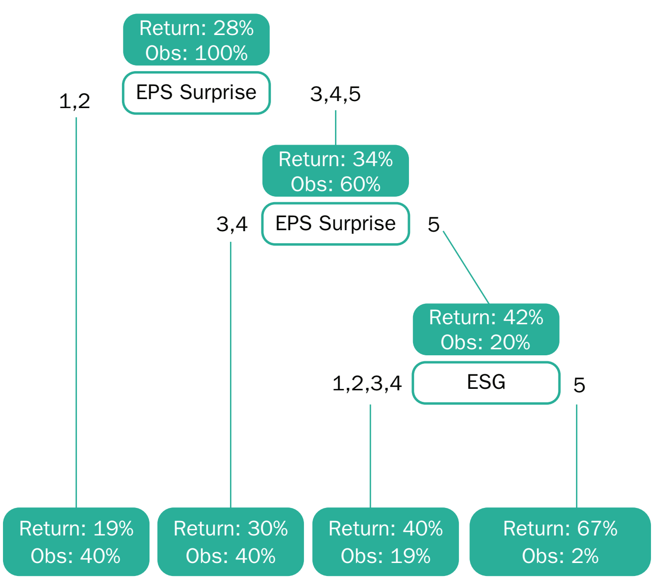
CART Analysis from 2016–2021



SOURCES: PanAgora, FactSet Accounting Data, MSCI. Observation percentages may be rounded and not equal total.

EXHIBIT 4

CART Analysis: 2016



SOURCES: PanAgora, FactSet Accounting Data, MSCI. Observation percentages may be rounded and not equal total sum.

In particular, the 9% of the cases at the far right (top in both EPS surprise and EPS change) indicate mean returns of 40%. Over the sample period, stocks with high growth (actual earnings changes) and high unanticipated components are identified as major winners.

Exhibit 3 lends itself to important observations. First, all the nodes and splitting results are as expected. Higher earnings surprise and upward-moving earnings elevate returns. In fact, all the trees produced over the sample years with the three variables reveal hierarchic ordering and directional returns completely consistent with logic and our priors.

Second is the key dominance of earnings surprise. The return patterns associated with unanticipated earnings results (as we saw earlier in Exhibit 1) are also evidenced in the CART modeling. In this 2016–2021 pooled example, a single splitting node separates all the Russell 1000 stocks between relative winners and losers. In the single-year CART models, the dominant first split is on EPS surprise in almost all years.[13] In several of the trees produced, we observe EPS surprise creating nodes at multiple levels. (Below we present a summary table of the relative importance of all the variables by year.)

The influence of earnings surprise is to be expected. Earnings-per-share changes for a company are a major determinant of price changes, ceteris paribus. This is the strongest possible fundamental variable we could use as a control in observing the impact of ESG ratings. In a later section, for a decision-making application, we suggest using more observable inputs with no foresight, such as a manager's ex ante alpha scores.

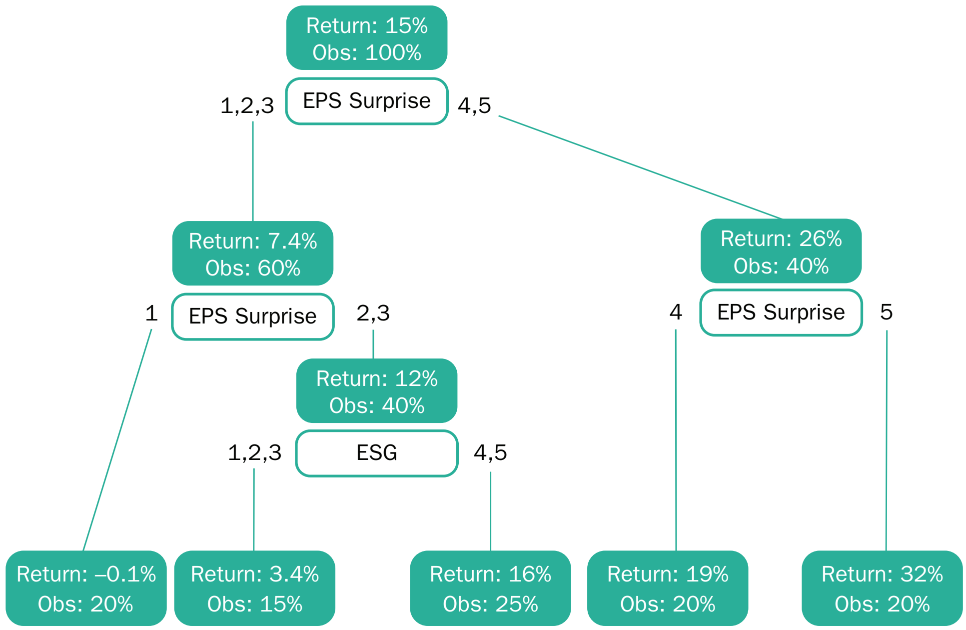
Third, there is the noticeable absence of ESG as a discriminator after accounting for the two fundamental earnings variables in the pooled sample. If univariate tests for the data from Exhibit 2 were to show ESG significance, it is washed out in the presence of earnings surprise and earnings change. In Exhibit 2, we noted that ESG seems more influential in the years 2016 and 2019, the two years for which the yearly CART models result with a significant presence of ESG as an explanatory return variable.

SINGLE-YEAR MULTIVARIATE TESTS

We present the model results in years 2016 and 2019.[14] Exhibit 4 shows that the average stock return for 2016 is 28%. Exhibit 5 has a 15% average stock return for 2019. EPS surprise is again the dominant discriminator variable. It enters in both trees as the first node and again as the second split level.

[13] The exception is when the actual earnings change is at the top of the tree in one instance.
[14] Other years are available on request.

EXHIBIT 5
CART Analysis: 2019



SOURCES: PanAgora, FactSet Accounting Data, MSCI. Observation percentages may be rounded and not equal total sum.

In both cases, the top quintile of earnings surprise separates to the far right. In addition, the terminal nodes have increasing returns moving from left to right. Both years do indicate significance of ESG at the third level. Interestingly, it enters at different sides of the tree, with differing implications of how it exerts influence.

In 2016, ESG splits the data on the right subordinately to the top earnings surprise quintile. If a stock has top-level earnings surprise and the ESG rating is top quintile, the average performance is 67%—more than double that of the typical stock for the year. These constituents make up only 2% of cases, which is approximately 20 names. In this tree, the model concludes that ESG is highly supportive of stock return at the margin after accounting for earnings, but only in a relatively small set of cases.

In 2019, ESG split the data toward the left, subordinate to lower earnings surprise quintiles 2 and 3. The separating influence comes within the set of lower earnings surprise names. Stocks with below-average fundamental surprise (earnings surprise = 2 or 3) but within top two quintiles of ESG have average returns of 16%. In contrast, the lower three quintile ESG names average returns of only 3.4%.

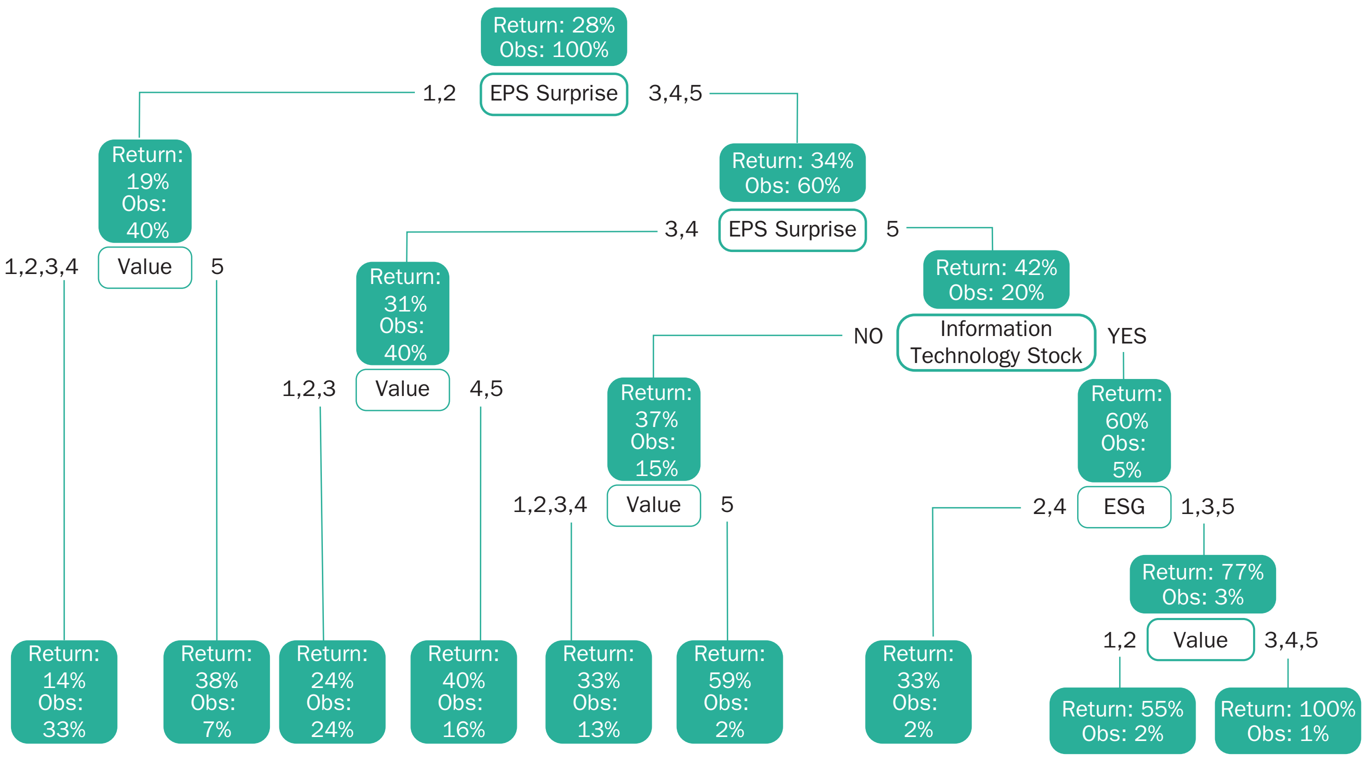
It is important to appreciate that ESG can be a return-enhancing input to an otherwise pure alpha process. In the tests here, we are using an alpha that is impossible to attain in a competitive investment arena. It is logical that ESG may be a stronger candidate for forming return-oriented portfolios gleaned from a tree structure with more realistic inputs. We discuss this in the last section.

CONTROLLING FOR SECTOR AND STYLE

There is some evidence that the ESG numeric ranking creates conditional demand for stocks at the margin. Clearly, the CART models we estimated offer only scant evidence that ESG stimulates returns. One issue is the inputs that determine the proprietary rating result. Where does the ESG rating land for a particular stock? This

EXHIBIT 6

CART Analysis: Full Contingency of Variables, 2016



SOURCES: PanAgora, FactSet Accounting Data, MSCI. Observation percentages may be rounded and not equal total sum.

depends on the origin of the rating. (MSCI has a comprehensive description of its process.[15]) Other processes may differ. For example, PanAgora Asset Management has used certain proprietary ESG inputs as potential alpha sources for two decades. It may be that, in the case of MSCI ratings, there is overlap with certain sectors as well as the growth/value characteristics of stocks.[16]

In the next two exhibits, we replicate the trees for 2016 and 2019 but with added explanatory variables that may correlate with ESG ratings. We introduce two style variables (by quintile): growth and value (using Barra measures). In addition, we add two dummy (0–1) variables for the two sectors purported to be populated with high or low ESG scores: technology and energy. High ESG scores are associated with tech and lower with energy, for example.

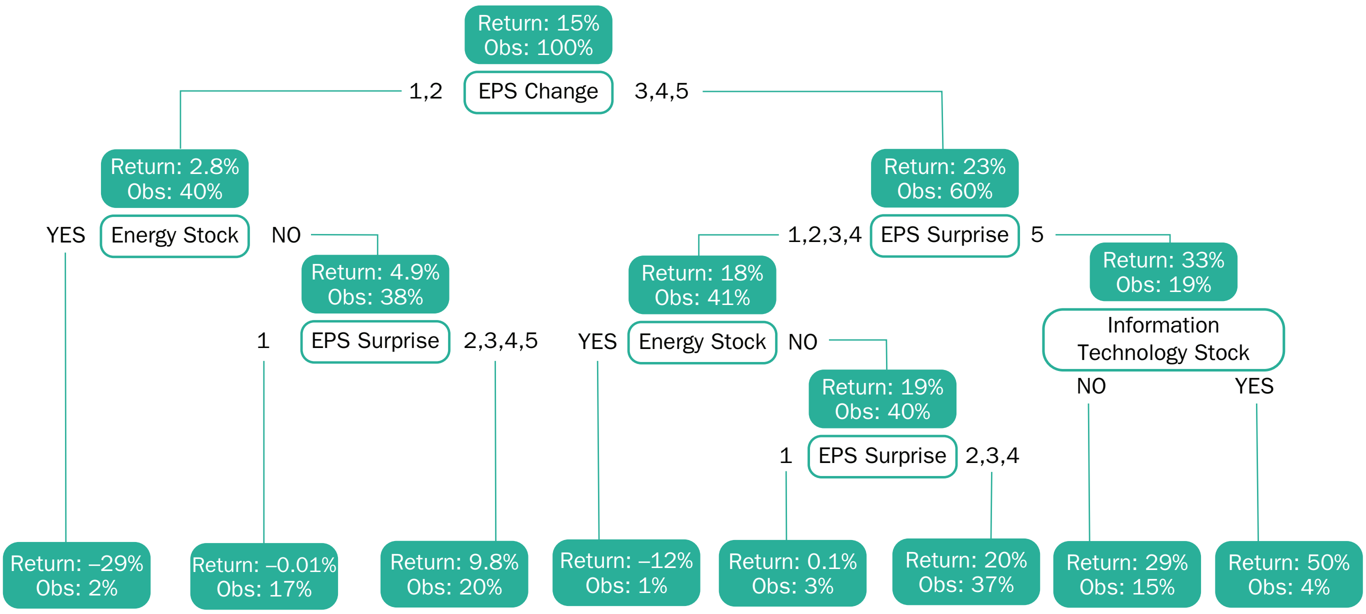
Exhibits 6 and 7 both have the full contingent of explanatory variables. Exhibit 6 (2016) leads to some interesting observations. First, after earnings surprise, which is dominant at the top, value appears in all terminal nodes. On the left, after cases are conditioned on lower quintiles of surprise, the most attractive value quintile (5) generates very large returns. Across the board for bottom nodes, value stocks perform better. This is even true for technology stocks to the right of the tree. Second, ESG appears to be overridden by the technology influence on return. The one ESG split is ambiguous or spurious due to: (1) a 1–3–5 versus 2–4 quintile separation, and (2) relatively few cases. In Exhibit 7 (2019), ESG disappears altogether. In this

[15] See footnote 6.

[16] The average pairwise correlation between MSCI's Weighted Average ESG Score and Barra Value (Book-to-Price, GEMLT model) is approximately –0.13 from 2013–2021 for the companies within our sample. For Barra Growth (GEMLT model) over the same sample period, the average pairwise correlation is approximately –0.06.

EXHIBIT 7

CART Analysis: Full Contingency of Variables, 2019



SOURCES: PanAgora, FactSet Accounting Data, MSCI. Observation percentages may be rounded and not equal total sum.

year, energy and technology both played roles, which likely reduced the significance of the ESG ranking per se.[17]

SUMMARY OF RETURN IMPACT

Exhibit 8 is a summary table of the relative importance of CART input variables. For reasons we have stated, EPS surprise and EPS change rank high at the left of the table. Moving toward the right of the table, the categorical impact declines with value, growth, technology, energy, and ESG, respectively.

ACTIVE MANAGEMENT WITH ESG

Active managers seek to outperform. On the one hand, our results suggest that incorporating ESG into the process may not support this goal. On the other hand, we have not run econometrics here that include an active manager's ex ante alpha ranking process, be it quantitative or fundamental. What we have done is include a clairvoyant ex post alpha surrogate—future earnings surprise.

It is unrealistic to assume that we know the precise future fundamental changes. Markets are far too competitive and variable for that. Despite this, many active managers claim and/or demonstrate that they capture part of these future unknown fundamental return drivers.[18] In addition, active managers use differing criteria for selecting stocks as well for forming portfolios. The research results here provide a

[17] Energy returns were negative unless they had midrange EPS surprise. Additionally, technology stocks that had top EPS surprise soared.

[18] Prior research demonstrates that a small amount of prediction skill leads to portfolio superiority if constructed properly (Sorensen et al. 2022).

EXHIBIT 8
Rank in Variable Importance

Rank in Variable Importance							
Year	EPS Surprise	Actual EPS Growth	Value	Growth	Info. Tech Security	Energy Security	ESG
2013	1	2	3	4	6	7	5
2014	1	3	5	4	7	2	6
2015	1	3	7	4	5	2	6
2016	2	3	1	6	5	7	4
2017	1	2	3	4	5	7	6
2018	1	2	4	6	3	7	5
2019	2	1	6	5	4	3	7
2020	2	1	4	3	6	7	5
2021	1	5	2	3	4	7	6
Average Rank	**1.3**	**2.4**	**3.9**	**4.3**	**5.0**	**5.4**	**5.6**

SOURCES: PanAgora, Barra, FactSet Accounting Data, MSCI.

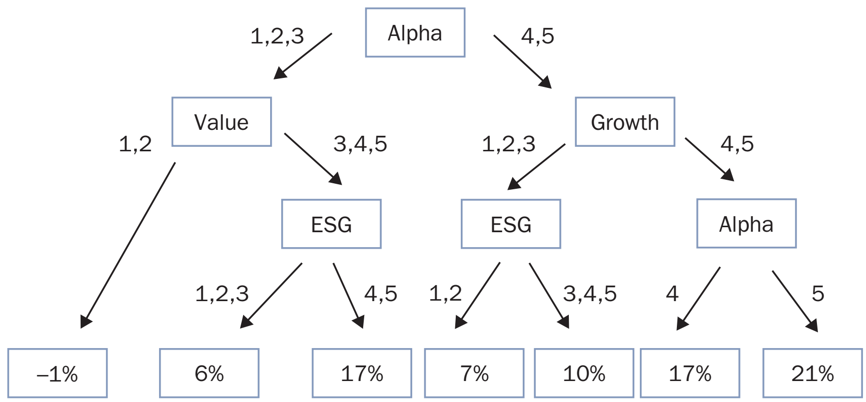
potential path forward for the integration of proprietary alpha and ESG. It suggests a tree structure. The tree is quite different from what devout ESG managers might implement. Managers that offer strict adherence to ESG are likely too restrictive in that they implicitly invoke a tree structure that has ESG criteria arbitrarily at the top. The evidence here is that, in seeking higher returns, the rating of ESG should not sit on the top of the tree. Such an approach is the type of slicing exercise we described in our introduction.

We propose an alternative. Estimate the parameters of the tree with inputs similar to Exhibits 7 and 8, but replace the earnings variables with the ex ante alpha ranking actually used by the manager. This proprietary input is likely subject to considerable error but contains elements of successful forecasting. The alpha scores are added to other exogenous ingredients to include the ESG metric. All inputs are put on a level playing field, with readings taken both simultaneously and through time. If done properly, the ESG influence in the resulting selection process can be: (1) dialed up or down, and (2) integrated with the other factors (alpha, sector, style, risk partitions, etc.). The resulting CART estimation will suggest spending the ESG risk budget in places where it adheres to social partialities, optimally while limiting and controlling any alpha dilution. One of many outcomes is spending the ESG budget where the manager's alpha confidence is weaker. In this way, ESG exposures may be accomplished where they count the most net of erosion of expected monetary return. ESG interplay may suggest use in value stocks, growth stocks, certain sectors, and risk segments about which the alpha model is more uncertain. In addition, the static results may evolve over time, suggesting using random forests that adapt through time.

As an example, consider the hypothetical tree structure in Exhibit 9, in which the nodes of the tree provide heuristics for a multifactor weighting scheme. The hierarchical structure is a conditioning system that is input to a more formal portfolio construction process to jointly and optimally achieve targets for alpha and ESG. Exhibit 9's CART tree renders seven terminal nodes. ESG enters in two nodes at level three. For relatively low alpha and high value stocks, ESG weighs in. ESG also conditions on high alpha and stocks that have midlevel growth. There are alternate ways to implement the tree results in a construction process. One uses the seven terminal nodes and assigns constituents a composite rank that correlates with the mean return parsed by the tree. In addition, trees can exist within sectors, within style, within risk segments, and so on.

EXHIBIT 9

Active Management Example of Heuristic ESG Integration



NOTE: This exhibit is a hypothetical example provided for illustrative purposes only.

SOURCE: PanAgora.

APPENDIX

EXHIBIT A1

EPS Calculations

Returns by Earnings Surprises One-Year Horizon Foresight (by quintile)					
YEAR	Q1	Q2	Q3	Q4	Q5
2013	8.88%	18.19%	21.94%	30.67%	33.13%
2014	–0.11%	2.43%	14.52%	17.47%	26.54%
2015	–18.01%	–11.47%	–7.97%	0.26%	4.03%
2016	14.87%	18.74%	25.96%	27.53%	36.12%
2017	–0.60%	5.66%	19.58%	24.36%	29.27%
2018	–6.37%	–6.61%	4.85%	4.17%	11.39%
2019	–0.39%	11.52%	13.60%	18.01%	31.41%
2020	–1.44%	6.18%	15.91%	22.57%	39.18%
2021	4.29%	8.08%	16.01%	24.29%	27.80%
Median	0.12%	5.86%	13.82%	18.81%	26.54%

NOTE: Q1 = lowest surprise; Q5 = highest surprise.

SOURCES: PanAgora, FactSet.

REFERENCES

Berg, F., J. Kölbel, and R. Rigobon. 2022. “Aggregate Confusion: The Divergence of ESG Ratings.” SSRN 3438533.

Breiman, L., J. H. Friedman, J. R. Olshen, and C. Stone. *Classification and Regression Trees*. New York: Wadsworth Statistics/Probability Series, 1984.

Chen, M., and G. Mussalli. 2020. “An Integrated Approach to Quantitative ESG Investing.” *The Journal of Portfolio Management* 46 (3): 65–74.

De, I., and M. R. Clayman. 2015. “The Benefits of Socially Responsible Investing: An Active Manager’s Perspective.” *The Journal of Investing* 24 (4): 49–72.

Fabozzi, F. J., K. C. Ma, and B. J. Oliphant. 2008. "Sin Stock Returns." *The Journal of Portfolio Management* 35 (1): 82–94.

Le Sourd, V. 2022. "Does ESG Investing Generate Outperformance?" *A Supplement to Pension & Investments* 1 (29): 28–30.

Niederhoffer, V., and P. J. Regan. 1972. "Earnings Changes, Analysts' Forecasts, and Stock Prices." *Financial Analysts Journal* 28 (3): 65–71.

Pedersen, L. H., S. Fitzgibbons, and L. Pomorski. 2021. "Responsible Investing: The ESG-Efficient Frontier." *Journal of Financial Economics* 142 (2): 572–597.

Sorensen, E., N. Alonso, S. Lancetti, and D. Belanger. 2022. "Active vs. Passive: Old Wine in New Wine Skins." *The Journal of Portfolio Management* 48 (3): 3–18.

Sorensen, E., M. Chen, and G. Mussalli. 2021. "The Quantitative Approach for Sustainable Investing." *The Journal of Portfolio Management* 47 (8): 38–49.

Sorensen, E., and S. Ghosh. 2010. "Rewarding Fundamentals." *The Journal of Portfolio Management* 36 (4): 71–76.

Disclosures