ESG, Fundamentals, and Stock Returns

Eric Sorensen, Ph.D.
George Mussalli, CFA
Sebastian Lancetti, CFA
Daniel Belanger, CFA

May 2022
*Article pending publishing in JPM Vol 48 Issue 10

Introduction

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.[1]

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 visibly consensus 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 paper introduces evidence of ESG return characteristics and proposes methodology to integrate. It also suggests an optimal approach.

We start with the most basic variable of interest: relative stock return. We 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 to 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.[2] In addition to earnings changes, earnings surprises, and ESG readings, we control for style (growth versus value) and key sectors (energy versus technology).

[1] See Sorensen, Chen and Mussalli [2021] and Chen and Mussalli [2020].

[2] CART was introduced in a book in 1984 by statisticians Breiman, Friedman, Olshen and Stone [1984]. We discuss the merits of CART in the next section.

ESG Research Studies

Long prior the time that 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.[3] Fabozzi *et.al.* [2008], for example, conclude that removing the so-called sin stocks of 20 plus years ago (alcohol, tobacco, fire arms and the like) retarded portfolio returns. More recently, Le Sourd provides a useful and comprehensive review of many such empirical studies.[4] He observes that these analyses, testing the impact of restricting stock choices visa vi ESG, are mixed. In some cases, the research concludes that constraining for social goals lowers returns and/or suppresses diversification, such as the Fabozzi result [2008]. Other studies argue that ESG adherence reduces risk, such as De and Clayman [2015].

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

ESG & Fundamental Earnings

This paper 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 a 1-year horizons for the years 2013 through 2021. The independent variables are 1) ESG ratings at the start of the year; 2) earnings-per-share (EPS) surprise over the 1-year return interval (defined by V below); and 3) EPS change over the 1-year return interval. The ESG scores we test comprise the weighted average MSCI composite rankings for ESG.[5]

$$V_{t0} = \frac{(\text{Reported EPS}_{t0} - \text{Consensus EPS}_{t-1})}{\text{Consensus Standard Deviation}_{t-1}} \quad (1)$$

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 results increases demand, whereas weaker-than-expected results in increases supply. This was first demonstrated by Niederhoffer and Regan [1972], 50 years ago. They simply tested for the unexpected earnings effect among the top 50 stock performers in contrast to the year's bottom 50 performers.

---

[3] See Pedersen *et. al* [2021] for a discussion of altering the Markowitz-type model with ESG constraints.

[4] There are a considerable number of them.

[5] Extensions could include other MSCI data, such pillar rand industry-relative rankings, as well as data from other vendors, such as Sustainalytics. (See Berg, *et. Al.* [2022]).

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."[6] 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 paper, Sorensen and Ghosh [2010] test the importance of end-of-period actual earnings versus the earlier start-of-period consensus expectations in testing equation (1) above. Over a sample of 1991 to 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.[7]

Stand-Alone Results

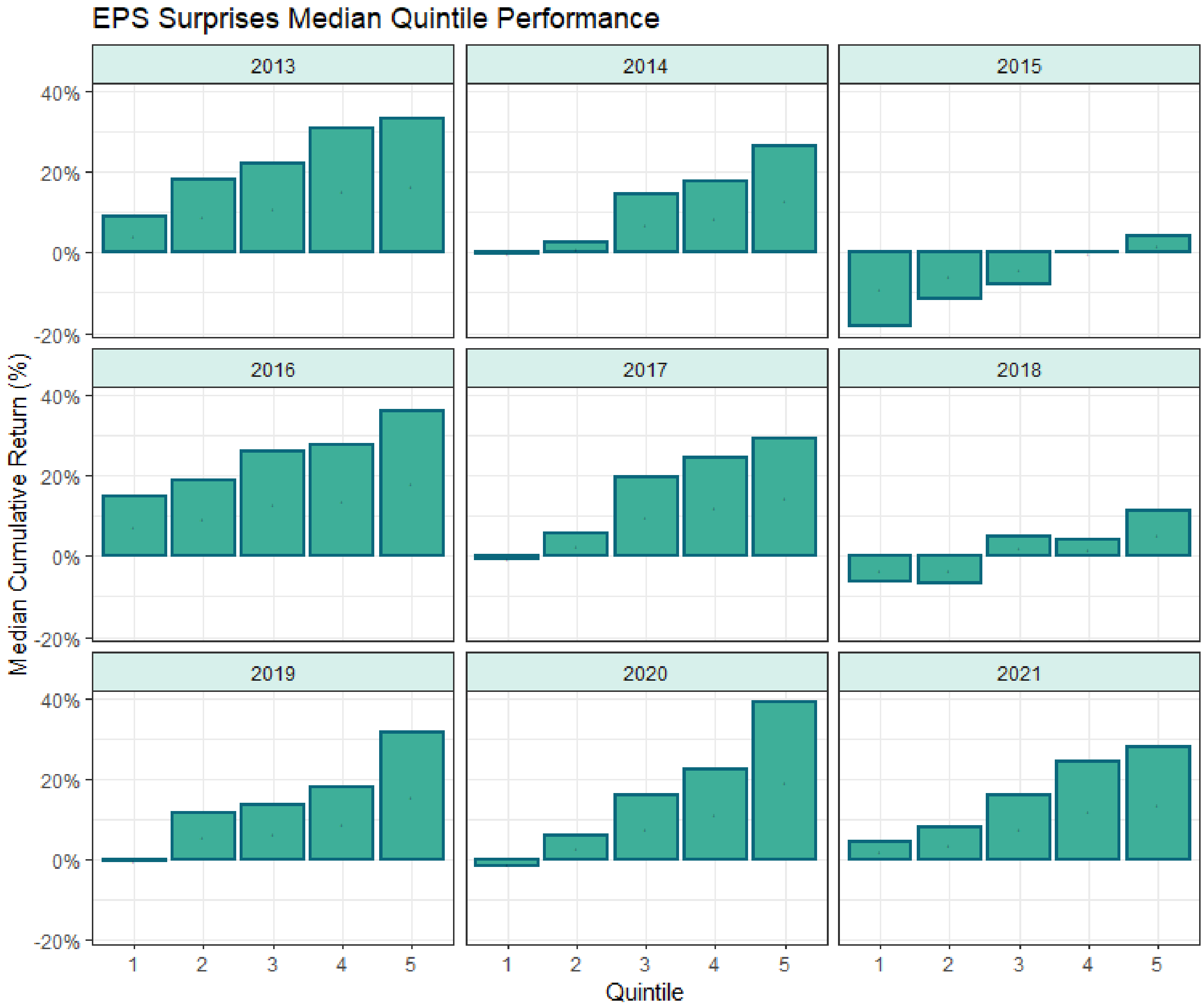
We analyze return data with one-year horizon periods on an annual basis to observe the variable V for the years 2013-2021. The universe is the Russell 1000, and 75% of the sample has a December fiscal year. For example, if a company has a December 2013 fiscal year, V is the difference in the reported 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.[8]

Exhibit 1: Performance of Earnings Surprises split by Quintile

[6] Niederhoffer and Regan [1972] 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% to 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.

[7] 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 vs. Q3 to 14% for Q1 vs. Q2.

[8] 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.



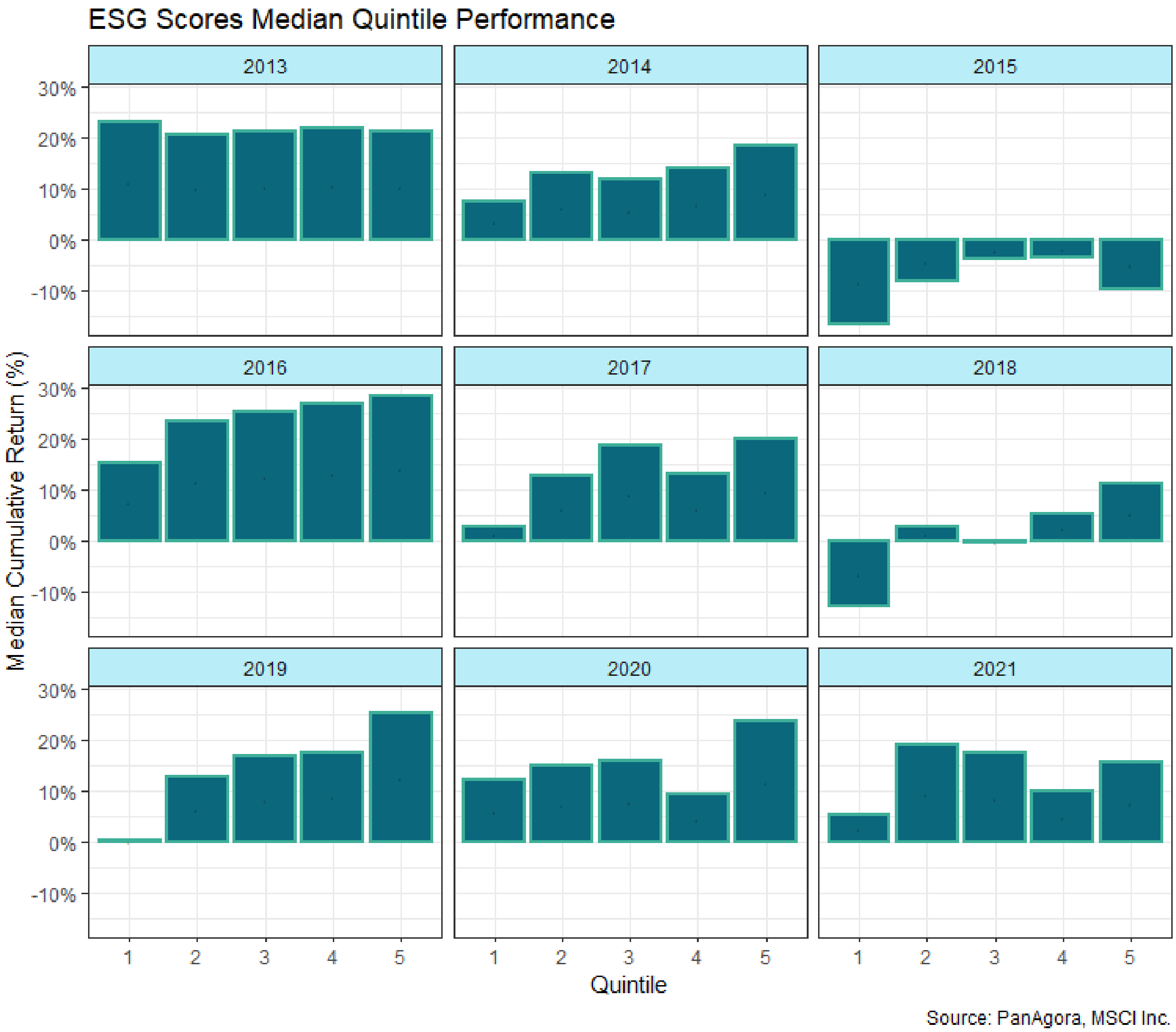
Source: PanAgora, FactSet Accounting Data

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 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% to 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 1.

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.[9] The average annual returns are shown for each quintile similar to Exhibit 1 EPS surprise quintiles. The ESG quintile 1 through 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.

<u>Exhibit 2: Performance of MSCI ESG Ratings split by Quintile</u>



[9] 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. (Source: MSCI) Previous research papers have discussed the disparity between rating agencies; in particular, the research paper by Berg et.al. [2022].

Conditional Multivariate Results

We believe 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 and others [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.[10] Two independent variables account for the firm's earnings results: 1) the unanticipated change for the year ("EPS Surprise") and 2) the actual percent change for the year ("EPS Change"). [11] These variables are organized as quintiles, with 5 having the highest surprises.[12] The third dependent variable is the ESG quintile rating at the start of the year.[13]

The model recursively iterates through each of the candidate independent variables with the mission to find the one with the greatest explanatory power. 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 the 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, Q5 branching to the right and Q1, 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%, vs 3.6% for lower quintiles (1, 2). However, the model continues to fit subsequent nodes of "if/then" rules. First, it separates out Q5 for EPS Surprise; second, conditioned on that, 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. By comparison, the two nodes to the right have higher returns. 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

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

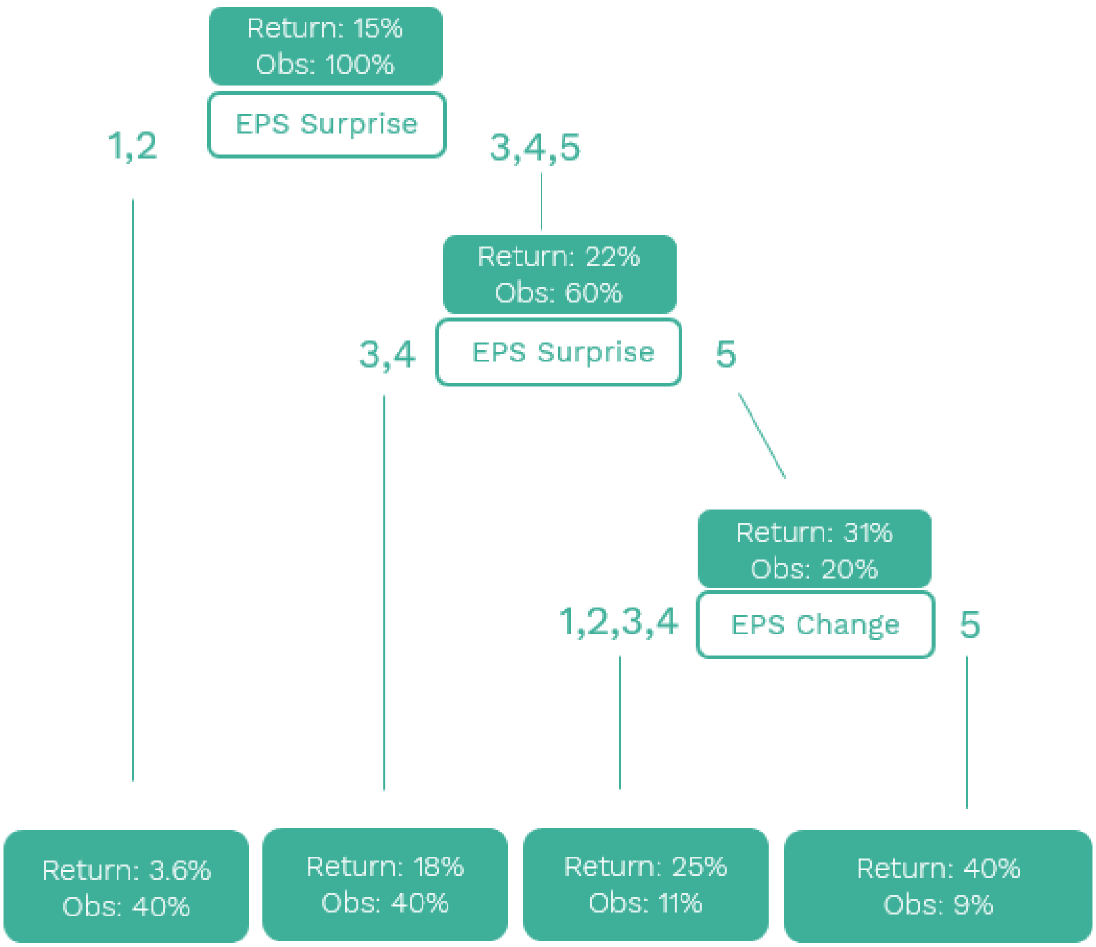
[11] This follows Niederhoffer and Regan [1972], who reported on the actual change and the unanticipated change.

[12] The correlation between the one-year change and the one-year surprise is relatively low. Correlations average .16 over the nine-year period, with a low of .02 in 2020 and a high of .52 in 2015. (In 2015 the average stock return was minus 5.7%, an anomaly year in a decade of mostly upward stock market moves.) In the CART analyses below, we restrict the sample for the years to 2016 to 2021. During this period, the earnings surprise and actual earnings change correlations averaged less than 10%.

[13] 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.

period, stocks with high growth (actual earnings changes) and high unanticipated components are identified as major winners.

Exhibit 3: Classification and Regression Trees (CART) Analysis from 2016 - 2021



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

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 above 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.[14] 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 above 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.[15] 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. 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.

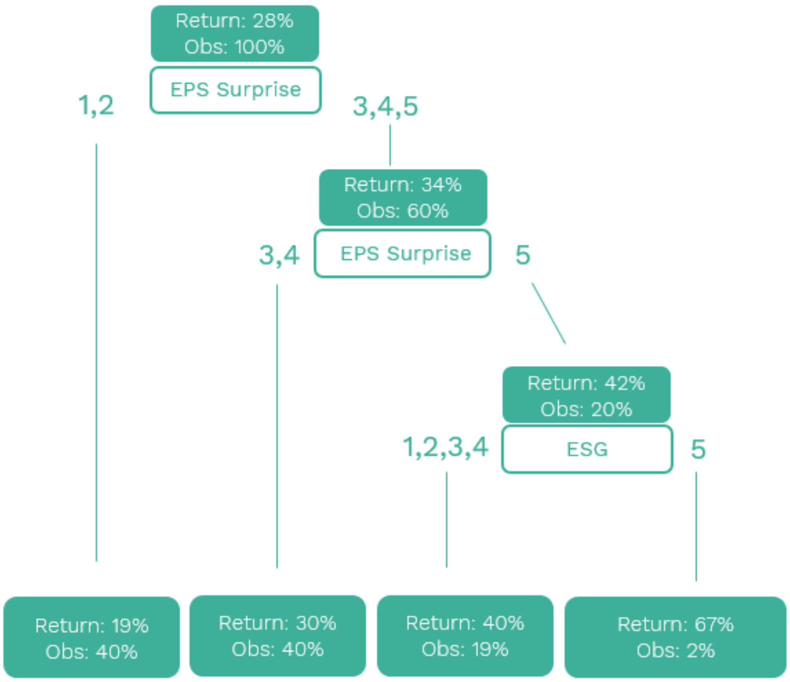
In 2016, ESG splits the data on the right subordinately to the top Earnings Surprise quintile. If a stock has top-level earnings surprise and the ESG rating is top quintile, the average performance is 67%—more than double that of the typical stock for the year. These constituents make up only 2% of cases, 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 splits 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 2 quintiles of ESG have average returns of 16%. In contrast, the lower 3 quintile ESG names have 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.

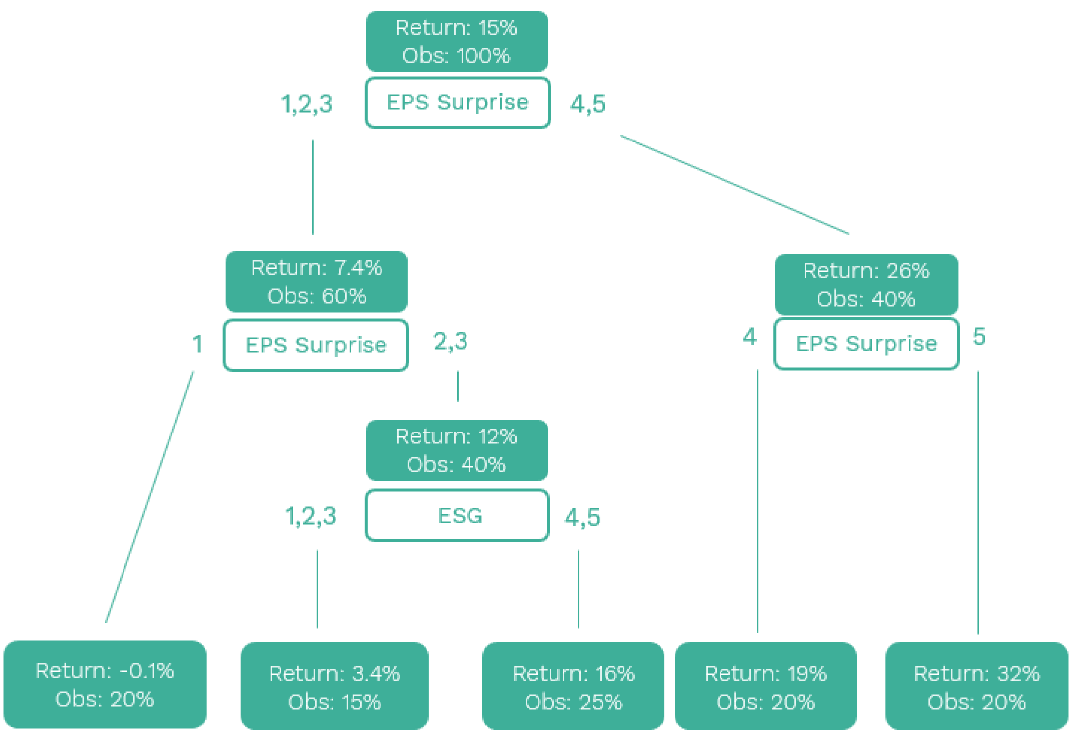
[14] The exception is when the actual earnings change is at the top of the tree in one instance.
[15] Other years are available on request.

Exhibit 4: Classification and Regression Trees (CART) Analysis: 2016



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

Exhibit 5: Classification and Regression Trees (CART) Analysis: 2019



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

Controlling for Sector & Style

There is some evidence that the ESG numeric ranking creates conditional demand for stocks at the margin. Clearly the CART models we estimate 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 depends on the origin of the rating. (MSCI has a comprehensive description of its process[16].) 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.[17]

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.

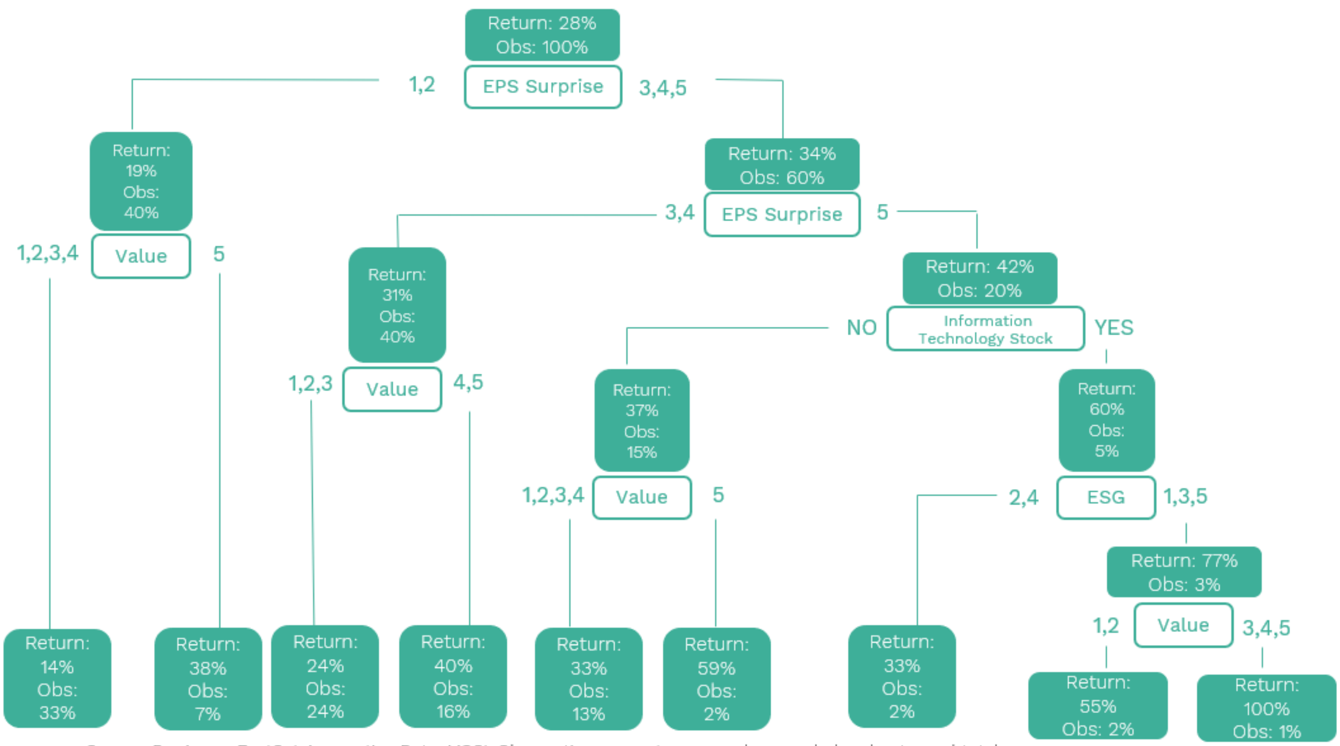
Exhibits 6 and 7 both have the full contingent of explanatory variables. Exhibit 6 (2016) leads to some interesting observations. First, after Earnings Surprise, which is dominant at the top, value appears in all terminal nodes. On the left, after cases are conditioned on lower quintiles of surprise, 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 all together. In this year, energy and technology both played roles, which likely reduced the significance of the ESG ranking per se.[18]

[16] See footnote 7.

[17] 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 to 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.

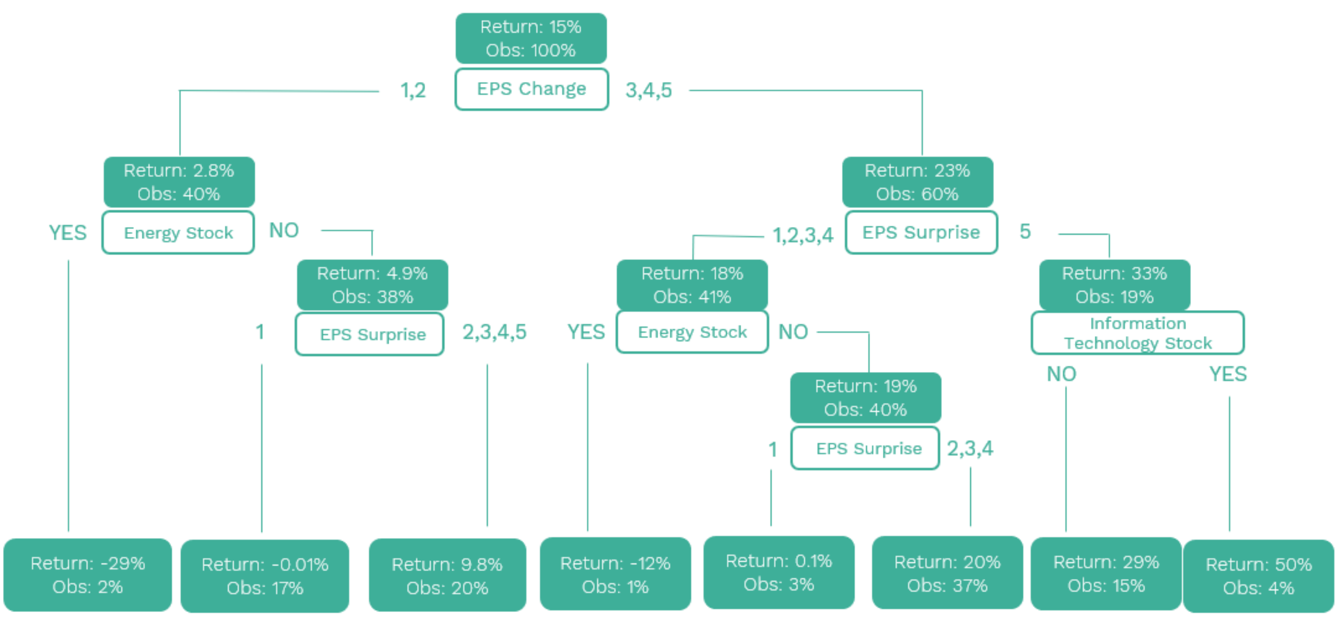
[18] Energy returns were negative unless they had mid-range EPS Surprise. Additionally, technology stocks that had top EPS Surprise soared.

Exhibit 6: Classification and Regression Trees (CART) Analysis - Full Contingency of Variables: 2016



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

Exhibit 7: Classification and Regression Trees (CART) Analysis - Full Contingency of Variables: 2019



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

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.

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**

Source: PanAgora, Barra, FactSet Accounting Data, MSCI

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 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. However, many active managers claim and/or demonstrate that they capture part of these future unknown fundamental return drivers.[19] In addition, active managers use differing criteria for selecting stocks as well for forming portfolios. The research results here provide a potential path forward for the integration of proprietary alpha and ESG. It suggests a tree structure. However, the tree is quite different than 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.

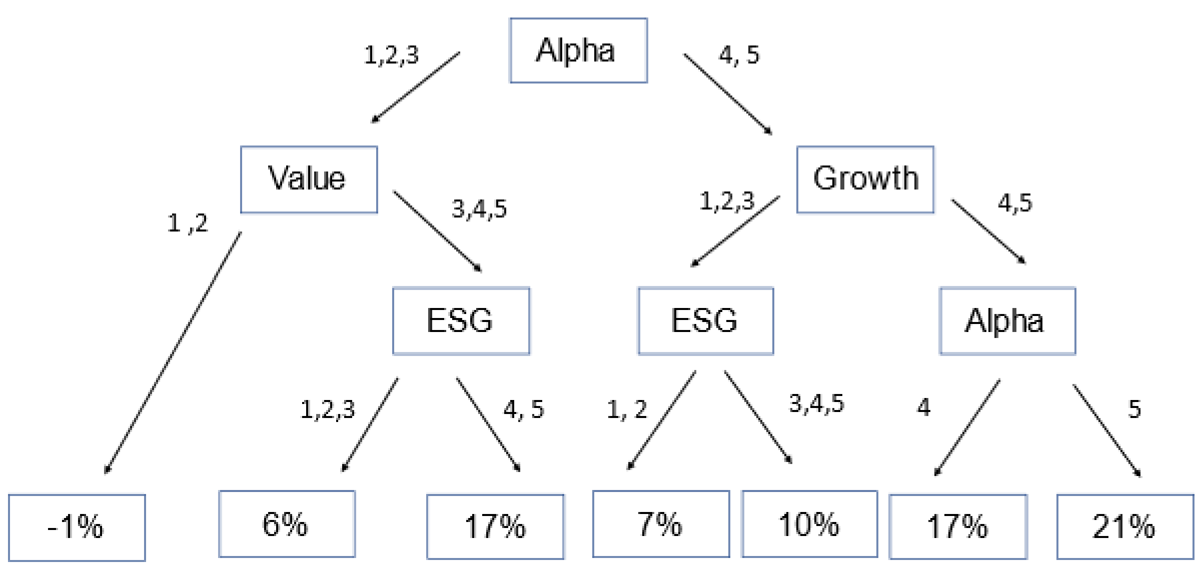
We propose an alternative. Estimate the parameters of tree with inputs similar to exhibits 7 and 8, but replace the earnings variables with the ex-ante alpha ranking actually used by the manager. This

[19]Prior research demonstrates that a small amount of prediction skill leads to portfolio superiority if constructed properly. Sorensen, Alonso, Lancetti, and Belanger [2022].

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 at the same time 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 below, 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 mid-level 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 to 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



Source: PanAgora. The above chart is a hypothetical example provided for illustrative purposes only.

Appendix 1: Table of 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%

Source: PanAgora, FactSet

Q1 = lowest surprise; Q5 = highest surprise

References

Bloomberg News. "JPMorgan Analyst Says War Sows Client Doubts of Worth of ESG." March 21, 2022.

Berg, F., J. Kölbel, and R. Rigobon, "Aggregate Confusion: The Divergence of ESG Ratings" (revised April 22, 2022). SSRN: https://ssrn.com/abstract=3438533 or http://dx.doi.org/10.2139/ssrn.3438533

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

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." *Journal of Investing* 24 (4): 49-72.

Fabozzi, F.J., K. C. Ma and B. J. Oliphant. 2008. "Sin Stock Returns." *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 K. Pomorski. 2021. "Responsible Investing: The ESG-efficient Frontier. *Journal of Financial Economics,* 142(2): 572-597.

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

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., 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.

Disclosures

This material is solely for informational purposes and shall not constitute an offer to sell or the solicitation to buy securities. The opinions expressed herein represent the current, good faith views of the author(s) at the time of publication and are provided for limited purposes, are not definitive investment advice, and should not be relied on as such. The information presented in this article has been developed internally and/or obtained from sources believed to be reliable; however, PanAgora Asset Management, Inc. ("PanAgora") does not guarantee the accuracy, adequacy, or completeness of such information. Predictions, opinions, and other information contained in this article are subject to change continually and without notice of any kind and may no longer be true after the date indicated. Any forward-looking statements speak only as of the date they are made, and PanAgora assumes no duty to and does not undertake to update forward-looking statements. Forward-looking statements are subject to numerous assumptions, risks, and uncertainties, which change over time. Actual results could differ materially from those anticipated in forward-looking statements. Equities may decline in value due to both real and perceived general market, economic, and industry conditions. There is no guarantee that any investment strategy will achieve its investment objective or avoid incurring substantial losses.

Forecasts, estimates, and certain information contained herein are based upon proprietary research and should not be considered as investment advice or a recommendation of any particular security, strategy, or investment product. Statements concerning financial market trends are based on current market conditions, which will fluctuate. There is no guarantee that these investment strategies will work under all market conditions, and each investor should evaluate their ability to invest for the long-term, especially during periods of downturn in the market. Outlook and strategies are subject to change without notice. This material contains the current opinions of the manager, and such opinions are subject to change without notice. This communication is not a public offer and should not be deemed to be a contractual commitment or undertaking between the intended recipient of this communication and PanAgora, but as an indication of what services may be offered subject to a legally binding contract between the parties, and therefore no reliance should be placed on this document or its content. Opinions, estimates, and recommendations offered constitute our judgment and are subject to change without notice, as are statements of financial market trends, which are based on current market conditions. This communication and its content represent confidential information. This material has been prepared for informational purposes only and is not intended to provide, and should not be relied on for, accounting, legal, or tax advice. You should consult your tax or legal adviser regarding such matters.

Hypothetical (Simulated) Performance: The hypothetical performance included in this report does not represent the performance of actual client portfolios. The performance is shown for illustrative purposes only.

Historical or Simulated performance presented herein is purely theoretical and involves the application of PanAgora quantitative strategies to historical financial data to show what decisions would have been made if the strategy were employed. These back-tested performance results are shown for illustrative purposes only and do not represent actual trading or the impact of material economic and market factors on PanAgora's decision-making process for an actual PanAgora client account. Back-tested performance results were achieved by means of a retroactive application of a model designed with the benefit of hindsight.

HYPOTHETICAL PERFORMANCE RESULTS HAVE MANY INHERENT LIMITATIONS, SOME OF WHICH ARE DESCRIBED BELOW. NO REPRESENTATION IS BEING MADE THAT ANY ACCOUNT WILL OR IS LIKELY TO ACHIEVE PROFITS OR LOSSES SIMILAR TO THOSE SHOWN. IN FACT, THERE ARE FREQUENTLY SHARP DIFFERENCES BETWEEN HYPOTHETICAL PERFORMANCE RESULTS AND THE ACTUAL RESULTS SUBSEQUENTLY ACHIEVED BY ANY PARTICULAR INVESTMENT PROGRAM. ONE OF THE LIMITATIONS OF HYPOTHETICAL PERFORMANCE RESULTS IS THAT THEY ARE GENERALLY PREPARED WITH THE BENEFIT OF HINDSIGHT. IN ADDITION, HYPOTHETICAL TRADING DOES NOT INVOLVE FINANCIAL RISK, AND NO HYPOTHETICAL TRADING RECORD CAN COMPLETELY ACCOUNT FOR THE IMPACT OF FINANCIAL RISK IN ACTUAL TRADING. FOR EXAMPLE, THE ABILITY TO WITHSTAND LOSSES OR TO ADHERE TO A PARTICULAR INVESTMENT PROGRAM IN SPITE OF TRADING LOSSES ARE MATERIAL POINTS WHICH CAN ALSO ADVERSELY AFFECT ACTUAL TRADING RESULTS. THERE ARE NUMEROUS OTHER FACTORS RELATED TO THE MARKETS IN GENERAL OR TO THE IMPLEMENTATION OF ANY SPECIFIC INVESTMENT PROGRAM WHICH CANNOT BE FULLY ACCOUNTED FOR IN THE PREPARATION OF HYPOTHETICAL PERFORMANCE RESULTS AND ALL OF WHICH CAN ADVERSELY AFFECT ACTUAL TRADING RESULTS.

This document is the property of PanAgora and is not intended for distribution or dissemination, directly or indirectly, to any other persons than those to which it has been addressed exclusively for their personal use. It is being supplied to you solely for your information and may not be reproduced, modified, forwarded to any other person, or published, in whole or in part, for any purpose without the prior written consent of PanAgora.

Information Barrier:

The information contained herein is not, and should not be considered to be, nonpublic information regarding securities transactions by, or portfolio holdings of, any client of, or fund sponsored or managed by PanAgora.

Australian Disclosure:
PanAgora is exempt from the requirement to hold an Australian financial services license under the Corporations Act 2001 in respect of the financial services. PanAgora is regulated by the SEC under U.S. laws, which differ from Australian laws.

Index Disclosures

The Russell 1000® Index measures the performance of the large-cap segment of the US equity universe. It is a subset of the Russell 3000® Index and includes approximately 1,000 of the largest securities based on a combination of their market cap and current index membership. The Russell 1000 represents approximately 93% of the US market.

Certain information included herein is derived by PanAgora Asset Management, Inc in part from MSCI's Index (the "Index Data"). However, MSCI has not reviewed this product or report, and does not endorse or express any opinion regarding this product or report or any analysis or other information contained herein or the author or source of any such information or analysis. Neither MSCI nor any third party involved in or related to the computing or compiling of the Index Data makes any express or implied warranties, representations or guarantees concerning the Index Data or any information or data derived there from, and in no event will MSCI or any third party have any liability for any direct, indirect, special, punitive, consequential or any other damages (including lost profits) relating to any use of this information. Any use of MSCI data requires a license from MSCI.

Not intended for public distribution.

*A peer-reviewed version of this article is forthcoming in The Journal of Portfolio Management Novel Risks Special Issue Vol 48 Issue 10