ESG Didn't Immunize Stocks Against the COVID-19 Market Crash[*]

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August 31st, 2020

Keywords: ESG; COVID-19; Corporate Social Responsibility; Share Price Resilience; Intangible Assets; Out-of-Sample Prediction

JEL Classifications: G01, G11, G32, M14, M41

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[*] Funding for this work was provided by the University of Waterloo's School of Accounting & Finance Research Grant program (Demers), and a CentER scholarship from Tilburg School of Economics and Management (Hendrikse). These funding sources have had no role in the preparation of this manuscript. All errors are the responsibility of the authors. Declarations of interest: none

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Abstract

Environmental, social, and governance ("ESG") scores were widely touted as indicators of share price resilience during the COVID-19 crisis. We present robust evidence that, once the firm's industry affiliation and accounting- and market-based measures of risk have been controlled for, ESG offers no such positive explanatory power for returns during the COVID crisis. Specifically, ESG is insignificant in fully specified returns regressions for the Q1 2020 COVID crisis period, and even in parsimonious models that control for financial flexibility and intangibles. Furthermore, ESG is *negatively* associated with returns during the market's Q2 2020 "recovery". Industry affiliation, market-based proxies for risk, and accounting-based measures of the firm's financial flexibility and investments in intangible assets together dominate the explanatory power of the COVID returns models. We develop parsimonious logit-based models to explain 2008-2009 global financial crisis ("GFC") "winners" and "losers" (i.e., top and bottom deciles of returns), and use these fitted models to predict winners and losers during the COVID crisis. Using ROC curves, we show that our accounting- and market-based models perform well both within-sample for the GFC period, as well as out-of-sample for the COVID crisis, but that ESG does not meaningfully add to the models' performance. Hedge strategies that go long (short) in firms during the COVID crisis that the GFC-based models predict will be winners (losers) yield significant abnormal returns, with ESG offering no enhancement to this investment performance. We conclude that celebrations of ESG as an important resilience factor in times of crisis are, at best, premature.

1. Introduction

The onset of the COVID-19 pandemic led to an unprecedentedly steep and rapid decline in global capital markets during the first quarter of 2020.[1] From its peak on February 19th, 2020, the S&P 500 index had lost 34% by March 23rd, before recovering slightly by the end of the first quarter. In the wake of this pandemic-induced carnage, there have been widespread claims that firms' environmental, social, and governance ("ESG") performance has served as a shield in sparing socially responsible firms the more devastating value destruction experienced by their lesser ESG-performing peers.[2] "Responsible investment" fund managers and ESG data purveyors alike have been perpetuating the reputation of ESG as a resilience factor, with Morningstar even referring to ESG as an "equity vaccine" against the pandemic-induced market selloff (Willis (2020)). For example, for the first quarter of 2020, Blackrock, the largest active investor in the world, reported better risk-adjusted performance across sustainable investment products globally (Blackrock (2020)), Morningstar claimed that 24 of 26 ESG-tilted index funds outperformed their closest conventional counterparts (Hale (2020)), and MSCI boasted that all four of their ESG-oriented indices outperformed a broad market counterpart index (Nagy and Giese (2020)). Following all of this hyping of ESG as downside risk protection, there was no surprise in CNBC's report that the first quarter of 2020 saw record inflows into sustainable funds (Stevens (2020)). Despite this high level of enthusiasm, however, skepticism is beginning to emerge about whether ESG really serves as a returns shield in times of crisis.[3]

Our study undertakes an extensive set of analyses in order to shed light on this debate in the context of U.S. equity share prices. We present robust evidence that ESG is not an "equity vaccine" against declining share prices in times of crisis. Rather, traditional accounting-based measures of the firm's financial flexibility and a stock-based measure of firms' internally developed intangible assets, combined with the firm's industry affiliation and traditional market-

[1] Baker, Bloom, Davis, Kost, Sammon and Viratyosin (2020) establish that no previous infectious disease outbreak, including the Spanish Flu, has impacted the stock market as powerfully as the COVID-19 pandemic.
[2] See, for example, *Fortune*'s "The coronavirus pandemic may be a turning point for responsible business" (Polman (2020)), the *Financial Times*' "ESG funds continue to outperform wider market" (Darbyshire (2020)), or the *Wall Street Journal*'s "ESG Investing Shines in Market Turmoil, With Help From Big Tech" (McCabe (2020)).
[3] For example, the Wall Street Journal recently attributed higher ESG firms' pandemic returns outperformance to luck (Mackintosh (2020)). And a Financial Times article similarly suggested that ESG-tilted bond indices' outperformance during the COVID-19 selloff was not due to ESG per se, but rather because the underlying firms had higher credit ratings and the funds had low exposure to the energy sector that was hit by a contemporaneous crash of historic proportions (Nauman (2020)).

based measures of risk, explain well the within-sample crisis period returns, and offer statistically and economically significant out-of-sample predictions of crisis period winners and losers.

The notion that ESG activities will contribute to stock price resilience during periods of crisis is premised upon the belief that corporate social responsibility activities help to build social capital and trust in the corporation, and that these bonds, in turn, will motivate the company's stakeholders (employees, customers, suppliers, financiers, government, society, etc.) to remain loyal, helping the company to rise above the challenges imposed by a crisis.[4] Several studies of the 2008-2009 global financial crisis ("GFC") period and two early studies related to the COVID pandemic suggest that ESG performance may indeed offer such downside risk protection (Cornett, Erhemjamts and Tehranian (2016); Lins, Servaes and Tamayo (2017); Bouslah, Kryzanowski and Bouchra (2018); Albuquerque, Koskinen, Yang and Zhang (2020); Ding, Levine, Lin and Xie (2020)). By contrast, our findings robustly refute the importance of ESG for U.S. equity securities during the pandemic.[5]

An alternative view of corporate ESG investments suggests that executives may choose to improve their company's ESG scores at the expense of shareholders in order to build their own personal reputations. From this agency theory perspective, ESG investments are at best wasteful, and probably even harmful to shareholders (e.g., by increasing the propensity for management entrenchment). This suggests that not only will ESG scores not be positively associated with share prices, but to the extent that such investments reflect poor management and/or agency problems, such indicators of corporate social responsibility could be a hindrance to a firm's resilience during challenging times. If ESG is irrelevant or even harmful, then more traditional indicators of financial flexibility such as profitability, liquidity, and/or low debt levels are expected to be the key determinants of a firm's resilience to severe economic downturns (Bernanke and Gertler (1989); Bhattacharya, Demers and Joos (2010)). Consistent with this, a

[4] Throughout the paper, we use the terms ESG and corporate social responsibility ("CSR") interchangeably.
[5] As we discuss at greater length in Section 2, the principal difference between our analyses and those of the other studies is that we use more fully specified returns models that control for many additional variables not considered by the other authors, variables that are known to be theoretically and/or empirically correlated with ESG performance (i.e., we do everything possible to mitigate a correlated omitted variables bias). In addition, Ding, et al. (2020) use an international sample of over 6,000 firms from 56 different countries, whereas we focus on a U.S.-only sample (i.e., a market in which there is much talk of, but less practical emphasis on, ESG relative to Europe or other regions in which corporate social responsibility and responsible investing are taken more seriously).

number of studies have documented that firms with weaker balance sheets at the start of the GFC were affected more by that crisis (Kahle and Stulz (2013)), while contemporaneous studies present evidence to suggest that cash and debt levels were important to stock price resilience during the market decline induced by the COVID pandemic (Albuquerque, et al. (2020);Ramelli and Wagner (2020)).

In this study, we undertake a series of analyses designed to uncover whether ESG is an important determinant of COVID period returns either instead of, or incrementally to, more traditional financial statement and market-based measures of risk. We first perform a multiple regression analysis of stock returns during the "crisis" quarter (i.e., January through March 2020). Specifically, we regress buy-and-hold abnormal returns on the firm's ESG scores, after controlling for numerous other factors such as accounting-based measures of financial performance, liquidity, leverage, intangible asset investments, variables capturing institutional investor interest and shareholder orientation, firm age and market share, the firm's industry affiliation, as well as a full array of market-based variables that are known determinants of returns. As expected, our results show that COVID crisis returns are associated with the firm's leverage and cash positions, as well as with industry sector indicators and numerous market-based measures of risk. Contrary to the findings of contemporaneous studies that do not include such a full set of controls (Albuquerque, et al. (2020); Ding, et al. (2020)), as well as to the widespread claims by fund managers, ESG data purveyors, and the financial press who seem to arrive at their conclusions on the basis of simple pairwise correlations, our results provide robust evidence that ESG is not significantly associated with stock market performance during the first quarter of 2020 once the full array of other expected determinants of returns have been controlled for. Interestingly, however, COVID crisis returns are positively associated with the firm's stock of internally-developed intangible assets, even after controlling for the firm's industry affiliation, and this association is both statistically and economically significant. These results suggest that innovation-related assets rather than social capital investments offer the greater immunity to sudden, unanticipated market declines.

To further substantiate the irrelevance of ESG scores in determining crisis period stock price resilience, we undertake an Owen-Shapley decomposition (Huettner and Sunder (2012)) of the explained variation in returns (i.e., the returns regression model's R^2). As shown in Figure 1, the results of these analyses indicate that three groups of explanatory variables offer almost all of the model's explanatory power for returns: market-based risk variables, industry fixed effects, and accounting-based measures capturing the firm's performance, liquidity, leverage, and stock of internally generated intangible assets. Other variables contribute very little to the model's explanatory power, and ESG is responsible for a meagre 1% of the total explained variation.

Notwithstanding ESG's failure to perform in its acclaimed role as a resilience factor during the pandemic-driven market meltdown in Q1 of 2020, we offer corporate social responsibility a second chance to shine. Specifically, we include ESG as an explanatory variable in the same fully specified returns regressions considered for the first quarter analyses, but this time using returns from the COVID "recovery" period, which we define as the second quarter of 2020. The results from this second chance test indicate that firms' ESG scores are significantly *negatively* associated with returns during the market's recovery, while their investments in internally generated innovation-related assets are once again positively associated with returns to an economically significant degree. Taken together, our analyses establish the stunning result that not only did more socially responsible firms not exhibit the alleged greater share price resilience during the highly unexpected COVID-induced market decline, but they actually performed significantly less well when the overall market recovered. By contrast, firms with larger stocks of internally-generated innovation-related intangibles outperformed in both the COVID crisis and recovery periods, even after controlling for their industry affiliation and financial flexibility.

We next investigate the extent to which there are common indicators of share price resilience across the two most recent and extreme market crises – the global financial crisis of 2008-2009, and the global humanitarian crisis in 2020. Specifically, we examine whether the experience gleaned from the GFC period can be used to sort ex ante between winners versus losers in the subsequent COVID crisis period. Using a GFC period based logit model for which the dependent variable is set to one if the firm falls into the top decile of returns performance from August 2008 to March 2009 (i.e., "winners") and set to zero if the firm falls into the bottom decile of returns (i.e., "losers"), we regress this indicator on various parsimonious sets of accounting, market, ESG, and other measures of risk in order to obtain a series of within-sample estimated coefficients. We then fit each set of coefficients (i.e., one set from each estimated alternative logit model) to out-of-sample data that was available at the end of 2019 in order to derive predicted Q1 2020 COVID crisis winners and losers. We use receiver operating characteristic ("ROC") curves to evaluate the discriminatory success of each of the accounting-based, market-based, and combined models, and we compare each model's predictive performance to those of an ESG-only and an ESG-accounting-market combined model. Our analyses show that an extremely parsimonious accounting-based model that consists of just two explanatory variables – the firm's liquidity (i.e., cash and short-term investments as a percentage of total assets) and its stock of internally-developed innovation-related assets – actually offers better out-of-sample predictive performance than a more elaborate model consisting of only market-based indicators, and this is despite the market-based model's much better within-sample performance in sorting between GFC period winners and losers. We further find that combining the prediction-relevant accounting- and market-based variables yields a model that outperforms (both within- and out-of-sample) each of the accounting-only or market-only alternatives. Finally, we examine the potential for ESG scores to help in sorting between winners and losers. We find that an ESG-only prediction model does little better than a purely random categorization of winners and losers, and adding ESG offers little improvement to the predictive ability of the combined accounting- and market-based prediction model. Taken together, these analyses establish that a prediction model constructed based upon experience obtained from the global financial crisis can be used to successfully predict winners and losers during the subsequent COVID humanitarian crisis market shock. Given the inherent differences in the nature of the crises, and some knowledgeable experts' claims that the COVID crisis is unlike any that have come before it (Reinhart (2020)), our success in predicting winners and losers across crises is not a trivial feat. Contrary to the current hype, however, ESG plays no meaningful role in this success.

In order to investigate and compare the economic significance of the preceding out-of-sample prediction models, we construct hedge portfolios that go long (short) in firms that the model predicts will be winners (losers). These analyses confirm that the combined accounting- and market-based prediction model is the best performing model (i.e., on both statistical and economic grounds), yielding economically significant abnormal returns of 30% for the Q1 2020 COVID crisis period. Consistent with all our previously reported analyses, ESG offers little to improve the investment success of a hedge strategy relying upon the accounting- and market-based prediction model.

Taken together, our analyses provide robust evidence that, contrary to widespread claims, ESG is not an important determinant of crisis period returns, nor does it offer any meaningful out-of-sample predictive power to help discriminate between crisis period winners and losers. Rather, traditional accounting-based measures of the firm's financial flexibility, such as their liquidity and leverage, are significant in explaining crisis and recovery period returns, as are industry affiliation and the usual market-based measures of risk. Perhaps most surprisingly, a measure of the firm's stock of internally-generated intangible assets (capturing, e.g., R&D, brands, IT, employee training, and specific business processes such as recommendation algorithms) is both statistically and economically significant in explaining both within-sample crisis returns, and in predicting out-of-sample crisis period winners and losers. Furthermore, these results are generalizable across the two most recent, but characteristically very different, global crises. This latter finding is particularly important in light of the increasing threat of catastrophic shocks of various kinds to the global economy (Cambridge Center for Risk Studies (2019)).

The rest of this paper is organized as follows. Section 2 provides a background discussion related to ESG and firm performance, both generally and in times of crisis. Section 3 describes our sample and data. In Section 4 we present our empirical methodologies and results, while Section 5 concludes.

2. Background

The notion that investments in the realm of ESG will enhance shareholder value – i.e., that "doing good is good for business" – in normal times, and even more so in times of crisis, remains a topic of considerable debate. Proponents of ESG claim that such investments help to build social capital for, and trust in, the corporation. They argue that socially and environmentally responsible corporate behavior leads to the creation of important bonds between the firm and its stakeholders (i.e., employees, customers, providers of finance, the communities in which the company serves or operates, suppliers, governmental units, etc.), and that such goodwill will particularly payoff in periods of crisis. This "risk management" view of corporate social responsibility postulates that ESG investments serve as a form of insurance-like protection against downside risk (Godfrey, Merrill and Hansen (2009)).

Several academic studies focusing on the 2008 to 2009 global financial crisis ("GFC") period purport to find evidence to support the case for ESG as a mitigator of downside risk. Cornett, et al. (2016) find that banks appear to be rewarded for being socially responsible, as evidenced by ROE being positively and significantly related to CSR scores. These authors further suggest that post-GFC amplified participation in CSR activities is therefore likely to lead to a lower probability of future crashes. For a sample of U.S. non-financial firms, Bouslah, et al. (2018) find that CSR reduces volatility during the financial crisis, and furthermore that this risk reduction is mainly due to the strengths rather than the concerns component of social performance. Consistent with the bonding and risk mitigation perspective, these authors conclude that CSR strengths act as a risk reduction tool during an adverse economic environment. Lins, et al. (2017) present evidence to suggest that U.S. non-financial firms that had higher social capital (i.e., measured using CSR scores) enjoyed stock returns during the GFC period that were 4% to 7% higher than those with lower social capital, and that high CSR firms also experienced higher profitability, growth, and sales per employee, and that they raised more debt. These authors conclude that the trust between a firm and its stakeholders and shareholders, built through investments in CSR, pays off when the overall level of trust in companies and markets suffers a negative shock.

An alternative view on corporate ESG investments derives from agency theory. This more skeptical perspective suggests that executives may choose to improve their company's ESG scores at the expense of shareholders in order to build their own personal reputations.[6] Because this reputational enhancement leads to a reduced likelihood of turnover, the executive's social capital investments on behalf of the firm form part of the executive's entrenchment strategy (Surroca and Tribó (2008)). To the extent that such ESG-related investments lead to managerial entrenchment and/or are wasteful managerial self-serving expenditures funded from corporate coffers, they could be shareholder value-destroying. Consistent with this, Lys, Naughton and

[6] There are some who question not only the morality, but even the legality (particularly for firms in the state of Delaware) of executives prioritizing any stakeholders other than the company's shareholders (Bebchuk and Tallarita (2020)).

Wang (2015) show that ESG expenditures generate insufficient returns and hence reduce shareholder value. These authors conclude instead that ESG investments appear to be a channel through which a company *communicates* its financial prospects (i.e., the undertaking of CSR initiatives is a signal that the firm's management is anticipating stronger future performance), but that they do not create value for the typical business. In the context of an exogenous and extreme negative shock, the expected informativeness of this signal for the firm's future prospects would surely be revised, and a firm's expenditures on ESG may even be seen as wasteful extravagances that will not help the firm to withstand the challenges of the crisis. Based upon these perspectives, higher investments in ESG may result in socially responsible firms becoming *more* vulnerable in times of crisis.

Several contemporaneous studies have investigated the relation between ESG scores and firms' stock price resilience during the current COVID crisis. Using a global sample of over 6,000 companies from 56 economies, Ding, et al. (2020) purport to find that firms' pandemic-induced share price reductions were decreasing in their 2018 ESG scores. Unlike our tests, their analyses appear to use *raw* rather than *abnormal* returns, and their regressions do not seem to control either for traditional market-based measures of risk, nor for numerous other variables that our data suggest to be highly correlated with returns and firms' ESG scores (i.e., their regressions are likely to suffer from a correlated omitted variables bias). In addition, their results are for a global sample consisting of mostly non-U.S. firms, while ESG is known to have a more positive impact on returns in non-U.S. jurisdictions such as Europe (Amel-Zadeh and Serafeim (2018)). Accordingly, their results are not directly generalizable to the U.S.-only setting that we study.

The primary U.S.-based study that we are aware of that is most closely related to ours is by Albuquerque, et al. (2020). These authors implicitly assume that only the environmental and social capital pillars of the traditional ESG combined score will be relevant for COVID crisis period resilience, but otherwise similarly use Refinitiv's EIKON ESG data to test this claim. They report finding that ES is statistically and economically significant in regressions that contain a small set of accounting-based control variables, together with industry fixed effects. We replicate the findings that they report in their Table 2 and confirm that ES and ESG are each significant in separate specifications that include the same limited set of controls considered by Albuquerque, et al. (2020). By comparison, however, our reported returns regressions include many additional market-based, accounting-based, and other control variables, variables that we find to be significantly correlated with ESG in a very similar sample and dataset to that used by those authors (e.g., we refer the reader to column (2) of our correlation matrix in Table 2B). With the inclusion of these additional controls, some of which our forthcoming regressions reveal to be highly significant determinants of returns, the significance of ES and ESG as a determinant of COVID-19 crisis period returns definitively vanishes. In other words, by avoiding a correlated omitted variables bias, we arrive at opposite conclusions regarding the role of ESG as a share price resilience factor during the COVID crisis.

3. Data, Sample, Variable Measurement, and Descriptive Statistics

3.1 Data and Sample

We obtain accounting information from the Compustat quarterly database and stock market returns data from CRSP and Datastream. Internal control weaknesses are taken from the Audit Analytics dataset, while institutional ownership data is derived from the Thomson Reuters 13f database. Refinitiv's EIKON database is the primary source of our environmental, social, and governance (ESG) scores for the COVID-19 analyses, however because of this database's thin coverage during earlier years, we supplement this with ESG data from MSCI for the period involving the Global Financial Crisis (GFC). I/B/E/S data is the source of our analyst following measure. We also obtain CEO tenure and some governance variables from the BoardEx database for use in some untabulated specification checks. Fama-French factors are obtained from Kenneth French's website.[7] Measures of investor orientation are calculated using data from the Thomson Reuters 13f database merged with investor classification data obtained from Brian Bushee's website.[8] In addition, we manually collected some executive start dates and accounting variables that were identified as missing in order to maximize the available sample.

In order to construct our primary dataset, we begin with all firm-year observations for which an ESG score is available for fiscal 2018, the last annual reporting period included in the database for most firms prior to the onset of the COVID crisis. We restrict our sample to U.S. companies, and we drop all financial and real estate firms from our tests. We also drop all

[7] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[8] https://accounting-faculty.wharton.upenn.edu/bushee/

observations that have an undue influence on the determination of the coefficients in the fully specified returns regression (Model 1 introduced below) for each of the two respective COVID periods.[9] This results in a sample of 1,652 firms for which all requisite data is available for our tests involving the within-sample COVID crisis period (i.e., January to March 2020). Due to bankruptcies, mergers, delistings, lack of Q1 financial statement filings, and the removal of influential observations, our sample declines to 1628 firms for the COVID "recovery" period (i.e., April to June 2020) returns analyses. Further details on the sample determination process are provided in Table 1.

3.3 Descriptive Statistics

Descriptive statistics for our sample firms are provided in Table 2A. As expected, given the relatively large firm bias of some of the databases being used for our analyses (e.g., EIKON and IBES), sample firms tend to be somewhat larger, on average, than the CRSP-Compustat universe. The average (median) firm has been established for 28 (24) years and has nearly 10 (8) analysts providing earnings estimates for it. Nearly 21% of sample firms reported negative earnings for fiscal 2019, while the average (median) firm's intangible investments adjusted ROA for that year was approximately 3.2% (4.4%). The mean (median) overall ESG summary score for sample firms is about 47 (43) out of a theoretical maximum of 100, and the range of this variable for our sample firms is 7 to 95 (untabulated). The average abnormal buy-and-hold (raw) returns during the crisis period were -8.0% (-31.7%), which reverted to a positive 7.5% (34.3%) during the recovery period.

Table 2B presents the pairwise correlations between select regression variables. As shown, *cash* and *RD&SGA_stock* are the two variables that are most significantly correlated with firms' buy-and-hold returns for Q1 2020, while short- and long-term debt are significantly negatively correlated with returns. These simple pairwise correlations confirm our expectations that firms with a lot of liquidity and innovation-based assets are more resilient during the crisis, whereas those with more significant debt burdens are less so. The book-to-market ratio is also significantly negatively correlated with returns, suggesting that firms with better growth prospects and/or unrecognized intangible assets fared better during the first quarter selloff.

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[9] Observations are considered to be unduly influential if the value of their Cook's distance exceeds 0.01.

Firms with more longer-term oriented shareholders (institutional owners) also fared better (worse), and in unreported tabulations (for parsimony) we find that traditional market-based measures of risk are also highly significantly associated with abnormal returns. Consistent with widespread reports that ESG is a resilience factor, Table 2B shows that ESG scores and abnormal returns are positively correlated, albeit not nearly as strongly as the previously mentioned investor orientation, or accounting- and market-based variables. It remains to be seen whether the positive association between ESG and returns will remain significant when ESG competes with these other known risk factors and determinants of returns in a multiple regression analysis. We turn to this next.

4. Empirical Results

4.1 What Explains Returns During the COVID-19 Crisis Period?

In order to investigate the role of ESG as a "resilience" factor that explains returns during the Q1 2020 crisis period, we run a number of variants on the following regression (with only one observation per firm, so firm subscripts are suppressed):

$$
\begin{aligned}
BHAR = \ & \gamma_0 + \gamma_1 ESG + \gamma_2 Cash + \gamma_3 LTDebt + \gamma_4 STDebt + \gamma_5 ROA + \gamma_6 Loss + \gamma_7 InvTurn \\
& + \gamma_8 AcqIntang + \gamma_9 RD\&SGAstock + \gamma_{10} DivPayout + \gamma_{11} MeanAnnSpeed \\
& + \gamma_{12} ICweakness + \gamma_{13} Size + \gamma_{14} MktShare + \gamma_{15} Age + \gamma_{16} Age^2 \\
& + \gamma_{17} Analyst + \gamma_{18} InvestorOrient + \gamma_{19}\, InstOwners + \gamma_{20} lnCEOtenure \\
& + \gamma_{21} BTM + \gamma_{22} BTMneg + \gamma_{23} Momentum + \gamma_{24} IdioRisk + \gamma_{25} MKTRF \\
& + \gamma_{26} SMB + \gamma_{27} HML + \gamma_{28} MOM + \sum_{i=1}^{58} \delta_i\, industry_i + \varepsilon \qquad (1)
\end{aligned}
$$

where *BHAR* are the buy-and-hold abnormal returns for January through March 2020[10] and *ESG* is the EIKON overall summary measure of ESG performance.[11] We control for the firm's liquidity and leverage position with *Cash, LTDebt*, and *STDebt*; for accounting-based performance with *ROA*, the *Loss* indicator variable, and the industry-adjusted inventory turnover ratio (*InvTurn*) measured following the approach suggested by Platt and Platt (1991); as well as for past investments in acquired and internally developed intangible assets with *AcqIntang* and *RD&SGAstock*, respectively.[12] We also include the firm's dividend payout ratio (*DivPayout*), *Size,* market share (*MktShare*), and *Age*, allowing the latter to enter non-linearly with the inclusion of Age^2. We control for the firm's reporting timeliness and quality by including the average earnings announcement speed over the prior four quarters (*MeanAnnSpeed*) as well as a count of internal control weaknesses noted in the most recent fiscal year available prior to the crisis (*ICweakness*). We capture investor horizon (*InvestorOrient*) using the measure proposed by Serafeim (2015), while *InstOwners* is the average percentage of institutional investors in the firm's stock during 2018, the most recent period for which all requisite data is available. *Analyst* is the firm's analyst following, a measure designed to capture the firm's information environment, and *lnCEOtenure* is the natural log of the length of the CEO's tenure with the firm measured in days. Market-based measures of risk and/or growth opportunities include the book-to-market ratio (*BTM*), an indicator set to one if BTM is negative (*BTMneg*), prior stock price momentum (*Momentum*), idiosyncratic risk (*IdioRisk*), as well as the four Fama-French factor loadings (*MKTRF, SMB, HML, MOM*). All specifications also include industry fixed effects

[10] In untabulated specification checks, we alternatively define the COVID crisis period to be February 24th through March 31st, which we establish on the basis that February 24th was the first trading day after Italy recorded its first deaths on Saturday February 22nd, and the Italian government placed more than 50,000 people under strict lockdown on Sunday, February 23rd, which together signaled the extreme significance of COVID-19 to Western countries and their economies (Ramelli and Wagner (2020)). Not surprisingly, given the extreme influence of this period in the determination of Q1 2020 returns, all of our inferences related to ESG and other variables of interest remain unchanged.

[11] In untabulated specification checks, we alternatively use the natural log of (1+BHAR) as the dependent variable. Although this change leads some control variables to become significant in the crisis period regressions, none of our key inferences related to ESG (or *RD&SGAstock*) in either the crisis or recovery period analyses are affected.

[12] Specifically, *RD&SGAstock* is a measure that captures the notion that all R&D expenses and an assumed rate of ⅓ of SG&A expenses represent investments in intangible assets that will have a five-year life. We use the assumed rate of ⅓ of SG&A as a conservative estimate of the "investment" portion of SG&A expenditures, a rate that has been growing over time (see Enache and Srivastava (2018)). We notionally capitalize these expenditures and amortize them linearly over a five-year period, which is also a conservative estimate of the duration of these benefits (see Lev and Sougiannis (1996)). So, for example, *RD&SGA_stock* for fiscal 2019 = FY2019 (R&D+⅓SGA)*100% + FY2018 (R&D+⅓SGA)*80% + FY2017 (R&D+⅓SGA)*60% + FY2016 (R&D+⅓SGA)*40% + FY2015 (R&D+⅓SGA)*20%.

unless indicated otherwise, where industries are defined using 2-digit SIC codes. All variables are winsorized at the top and bottom 1% and each is defined in greater detail in the Appendix.

The results from estimating Model 1 using the abnormal buy-and-hold returns from the first quarter of 2020 as the dependent variable are presented in Table 3. The first specification includes only ESG and industry dummies. Consistent with all the hype, ESG is significantly positively related to returns *in the absence of other controls being included in the regression*. When market-based measures of risk are added to the model as in the second specification, ESG remains significantly positively associated with returns, albeit weakly so. However, *in the more fully specified model* that controls for the accounting-based measures of the firm's financial flexibility, financial performance, and intangible assets, as well as in the complete model that controls for market share, firm age, ownership characteristics, and CEO tenure, *ESG is no longer significant at any conventionally acceptable level.*[13] With a few minor exceptions, the signs and significance of all other variables are generally consistent across models.

With reference to the complete model in column (4), we see that firms with higher levels of institutional ownership performed less well during the market downturn (i.e., *InstOwners* is negative and significant). Not surprisingly, idiosyncratic risk and the four Fama-French factors are all statistically significant in explaining returns, however it is notable that they don't dominate the more fundamental accounting-based measures of the firm's expected resilience. Notably, the firm's profitability (*ROA*) and its level of cash stores (*Cash*) are positive and significant determinants of returns during the crisis period, while the firm's short-term and long-term debt levels are negatively associated with returns. These results suggest that traditional accounting-based measures of the firm's financial performance and financial flexibility are all important indicators of a company's share price resilience during this period of unexpected global crisis. *RD_SGA_stock,* a measure of the firm's stock of innovative assets (i.e., the unamortized portion of the capitalized internally-developed R&D- and SG&A-related intangible assets) is also statistically and economically significant. The results from model (4) suggest that a one standard deviation increase in the stock of internally developed intangible assets is associated with an approximately 2% increase in abnormal returns during the Q1 2020 crisis

[13] In untabulated specification checks, we also consider just the combined ES component of ESG that has been used in some prior studies. Our results are consistent – ES is not significantly associated with COVID-19 crisis period returns, even when separate governance-related controls are excluded from the model.

period.[14] Finally, we emphasize that our results clearly demonstrate that, contrary to widespread claims during the early months of the COVID-19 pandemic that ESG performance was a "resilience" factor, in appropriately specified regressions such as those in columns (3) and (4) of Table 3, the summary ESG performance score is not statistically significant in explaining the crisis period returns.[15]

In order to gain a better understanding of the relative importance of accounting, market, industry membership, and other variables in explaining crisis period returns, we undertake an Owen-Shapley decomposition as explained by Huettner and Sunder (2012).[16] Using this approach, we are able to estimate the proportion of the explanatory power for returns that each set of variables contributes. Table 3 reports that our most complete regression model (4) explains approximately 40% of the overall cross-sectional variation in the COVID crisis period returns for the firms in our sample. Figure 1 presents a pie chart depicting the proportion of this 40% that is explained by each group of variables. As shown, the set of market-based measures contributes the most to the overall R^2, with about 39% of the explained variation being due to these variables. Industry membership is a close second, accounting for 36% of the explained variation. Profitability performance, liquidity, debt, and measures of intangibles investments derived from the firm's financial statements combined with measures of the firm's reporting system quality together account for 20% of the explained variation in stock returns, while other variables (e.g., ownership characteristics, market share, and firm age) contribute just 3% of the overall explanatory power. Notably, the ESG summary score is the least important category, contributing a measly 1% of the total explained variation in returns during the COVID crisis.

Taken together, our results from the regression analyses and Owen-Shapley decomposition suggest that classic market-based determinants of returns, industry fixed effects,

[14] This is calculated as .12027261 * .161635 = 1.94%. Following the recommendation of Mummolo and Peterson (2018), we calculate the standard deviation of 0.12027261 after isolating the residual variation in *RD_SGA_stock* with respect to the industry fixed effects by regressing *RD_SGA_stock* on the set of industry dummy variables.
[15] In untabulated specification checks, we also investigate EIKON's "ESG controversies" score both as an *alternative* measure of ESG performance, and as an *incremental* measure of ESG performance. We find that the ESG controversies score is *negatively associated with COVID crisis period returns* when separately or incrementally included in columns (1) and (2) of Table 3. Inclusion of the controversies score attenuates the coefficient on ESG, however our inferences (including those related to *RD&SGAstock* and financial flexibility) remain unchanged. The controversies variable is insignificant in the more fully specified models (3) and (4), and all other inferences remain unchanged.
[16] In order to undertake these analyses, we also make use of the rego Stata module made freely available by one of the authors on his website: http://www.marco-sunder.de/stata/rego.html.

as well as financial statement variables that capture the firm's liquidity, leverage, and investments in intangibles are all important in explaining COVID crisis period stock returns. By contrast, ESG does not meaningfully contribute to the explanation of returns during the pandemic crisis.

4.2 Determinants of Returns During the COVID "Recovery" Period

Table 4 presents the results of the regressions from variants of Model 1 using the abnormal buy-and-hold returns from the second calendar quarter of 2020 (i.e., the COVID "recovery" period) as the dependent variable. For these regressions, the market-based explanatory variables are updated to include Q1 2020 realizations, the annual accounting variables are from fiscal 2019 (i.e., identical to those used in the Table 3 regressions), and we also include the difference between the firm's intangibles-adjusted ROA from the first quarter of 2020 and the first quarter of 2019 (*delta_ROA_Q1*) in order to capture the Q1 2020 COVID-19 shock to the firm's operations. The overall explanatory power of the most complete model for this recovery period is approximately 20%, which is considerably below the 40% of explained variation documented for the crisis period in Table 3.

Similar to the crisis period, as shown in column (1) of Table 4, ESG is highly significant in the recovery returns regression when it is the only explanatory variable in the model (together with industry fixed effects). During the recovery period, however, ESG is *negatively* associated with abnormal returns, indicating that high ESG firms performed *worse* than their less socially responsible counterparts. Furthermore, the negative association between ESG and recovery period returns is evident across all models, and it remains significant when the full set of controls are included as in column (4).[17] Unlike in the crisis period, analyst following and *BTM* are both positively significantly associated with recovery period returns, whereas most of the other market-based measures of risk are not significant in the complete model. By contrast, *Cash* maintains a positive association with returns and the stock measure of internal investments in intangibles, *RD&SGA_stock,* is also once again very significantly positively associated with recovery period returns. A one standard deviation increase in *RD&SGA_stock* results in an 4.5% increase in returns (.11939058 * .372395 ≈ 4.5%, again calculated using the industry-

[17] A review of the variance inflation factors (VIFs) makes clear that the opposite-signed coefficient on ESG is not due to multicollinearity problems.

orthogonalized standard deviation of *RD&SGA_stock*) during Q2 of 2020, even after controlling for industry fixed effects. Firm age, the dividend payout ratio, and the industry-adjusted inventory turnover ratio are all negatively associated with returns. The year-over-year change in adjusted first-quarter ROA, which provides an early indication of the firm's operational sensitivity to the COVID-19 crisis, is positive and highly significantly associated with returns. In other words, and not surprisingly, firms whose earnings were less hard hit at the start of the crisis enjoyed better second quarter stock returns. Long-term debt is positively associated with returns, suggesting that more heavily leveraged firms were oversold during the first quarter crisis period and experienced a recovery in the second quarter. The negative association between momentum and returns is also consistent with stocks that were over-beaten during the crisis period having recovered more in the second quarter.

One of the most important takeaways from Table 4 is that firms with higher ESG scores *underperformed* their less socially responsible counterparts. Furthermore, the stock return underperformance of socially responsible firms is economically significant; a one standard deviation increase in the ESG score leads to a *decrease* in abnormal returns of approximately 3% (= 16.692222 * -0.001749; calculated using the variation in ESG after orthogonalizing the industry fixed effects) during the second quarter of 2020, even while the overall market was experiencing a significant recovery.[18]

In order to understand the importance of each set of variables in explaining market returns during the recovery period, we once again undertake an Owen-Shapley decomposition of the approximately 20% explained variation in recovery period returns. Figure 2 depicts the results of this analysis. As shown, the general magnitudes of the explanatory contribution of each group of variables are broadly similar to those previously documented for the COVID crisis period. Specifically, for the recovery period, traditional market-based measures of the firm's riskiness and growth potential are responsible for 34% of the explanatory power of the model (versus 39% for the COVID crisis period), while industry indicators contribute 35% to the R^2 (versus 36% for the crisis period). Variables derived from the company's financial reporting system are responsible for 20% of the explanatory power of the model in both periods, and other

[18] In untabulated specification checks, we find that EIKON's ESG controversies score is insignificant in all recovery period regressions when included as an incremental or alternative measure of ESG performance. All other inferences remain unchanged.

factors explain 8% (versus 3%) of the explained recovery (crisis) period returns. Notably, despite its significance in the regression, ESG is nevertheless once again a relatively negligible explanatory variable, contributing just a 3% fraction of the already modest 20% overall explanatory power of the model.

The combined results from the first two quarters of 2020 presented here provide robust evidence that firms that are perceived to be "doing (more) good" than others do not have share prices that are more resilient during the COVID returns crisis in Q1 of 2020 once industry affiliation and known accounting- and market-based determinants of returns have been controlled for, and furthermore these firms' share prices performed significantly less well, both statistically and economically, than those of less socially responsible firms during the market recovery of Q2 2020.

4.3 Crisis-to-Crisis Out-of-Sample Predictions

COVID-19 is the second crisis to affect global stock markets in a little over 10 years, following the Global Financial Crisis (GFC) that ended in early 2009.[19] Our next set of analyses examines the extent to which there are common indicators of share price resilience across the two crises such that the experience from the GFC period can be used to predict winners and losers in the subsequent COVID crisis. Finding such commonality is a non-trivial endeavor as the crises, one financial and one humanitarian, are characteristically different. Indeed, Reinhart (2020) suggests that the COVID-19 pandemic is unlike any other crisis that has preceded it.

To begin our analyses, we rank the GFC period abnormal returns for all 1690 non-financial firms for which the requisite regression variables are available, and we use these ranks to create an indicator variable, *Winner,* that is set to one for firms whose returns are in the top decile, and set to zero for firms that are in the bottom decile ("losers").[20] Using these top and bottom 10% firms, we estimate several parsimonious logit prediction models that are variants of Model 1 except that they use the dichotomous *Winner* as the dependent variable. The alternative

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[19] Following Lins, et al. (2017), for the analyses presented in this section, we define the GFC period to be August 2008 to March 2009, inclusive.
[20] In untabulated results, we alternatively set the *Winner* indicator to one (zero) for firms that are in the top (bottom) quartile of returns performance. The results from these analyses are substantively similar to those reported, and none of our key inferences are affected.

specifications are chosen based upon the importance of each independent variable's contribution to explaining winners in a more fully specified model, or for comparisons across groups of explanatory variables such as accounting-only or market-only models. We use the estimated coefficients from each of these respective logit regressions derived from the GFC data to predict over-/under-performers during the subsequent COVID crisis period in the first quarter of 2020.

The results of several first-stage predictive regressions are presented in Table 5.[21] As shown in the first column, an extremely parsimonious model consisting only of accounting-based proxies for liquidity (*Cash*) and the firm's stock of internally developed intangibles (*RD&SGA_stock*) yields a count within-sample pseudo-R^2 of 72%. Thus, consistent with the considerable significance of these variables in explaining COVID crisis returns, they also do a great job in sorting between winners and losers during the prior global financial crisis. The second column presents the results from a more fully specified accounting-only model in which only the industry-adjusted turnover is incrementally significant to cash and intangibles, and the model actually yields a slightly inferior count pseudo-R^2 of 70%.

Column (3) presents the results of a market-only model. All of the explanatory variables are significant, and the model yields an astonishing within-sample count pseudo-R^2 of 92%. The combined model in Column (4), which includes all significant accounting- and market-based variables, yields an even more astounding count pseudo-R^2 of 95%.[22] In untabulated analyses, we also include investor orientation, institutional ownership, firm age, and other non-accounting and non-market-based variables, however none of these variables are significant and they are therefore not retained for the tabulated parsimonious models that will be used for out-of-sample predictions.

The models in columns (5) and (6) demonstrate the within-sample explanatory power (or lack thereof) of ESG for GFC period winners and losers. Broadly consistent with prior studies investigating corporate social responsibility as a determinant of GFC period share price resilience, our results also suggest that ESG is significant in explaining GFC returns winners and

[21] These logit regressions use only the top and bottom 10% of GFC period returns firms, reducing the estimation sample to 338 observations.
[22] Although HML is weakly significant in Model (3), it loses significance when included in the combined Model (4). We therefore drop this variable as the fitted coefficients from Model (4) will be used for out-of-sample predictions, and the inclusion of an insignificant variable in this fitting process is inappropriate.

losers, albeit modestly so, and *only when it is the only explanatory variable in the model.* The within -sample discriminatory power of ESG for sorting between GFC winners and losers is nevertheless very modest, yielding a count pseudo-R^2 of approximately 54%. This is little better than what would be obtained by chance (i.e., a random assignment into winner versus loser categories). Consistent with ESG's relatively low discriminatory power as a stand-alone variable, when it is combined with the more informative market- and accounting-based variables as in column (6), ESG loses all significance. These results make clear that, similar to the previously documented insignificance of ESG for explaining COVID crisis returns, ESG is also irrelevant for discerning between GFC period winners and losers when forced to compete with more informative accounting- and market-based indicators of resilience.

In order to assess each of the previous models' respective within-sample GFC estimation success, as well as its out-of-sample success in predicting winners and losers during the COVID crisis period, we adopt a receiver operator characteristic ("ROC") curve methodology that provides an intuitive summary representation of classification accuracy Hosmer and Lemeshow (2000). The ROC curve is a graphical plot of the sensitivity versus (1 − specificity) of a binary classification system, which in our setting is the logit-based winner versus loser predictions. The best possible prediction model yields a graph with a point in the upper left corner of the ROC space, indicating 100% sensitivity (i.e., all winners are accurately predicted) and 100% specificity (i.e., no winners are predicted to be losers).[23]

An example of such ROC curves is provided in Figure 3A, which shows the within-sample GFC period classification success of winners versus losers for each of the accounting-only, market-only, and ESG-only logit models, respectively. The 45-degree line indicates the "curve" that would result from a purely random assignment of firms into winners and losers, with the area under this curve obviously being equal to 50% (i.e., random chance). As is evident from the figure, and consistent with the previously reported count pseudo-R^2 measures of model performance, the market-based model lies well above and to the left of the accounting-based and ESG-based models, indicating that the market-based model is much better within-sample at discriminating between winners and losers. The area under the market-only ROC curve is an

[23] Further details regarding the derivation of the ROC curves is available in the Appendix to Demers and Joos (2007) or in Hosmer and Lemeshow (2000).

astounding 98%, whereas that under the accounting-only model is an inferior, but still very respectable, 77%. By contrast, the ESG-based model's ROC curve lies just above and to the left of the "random chance" 45-degree line, consistent with the measured area under this curve of just 55.5% (i.e., slightly better than what would be generated from random assignments).

In Table 6 we report the ROC scores for the previous logit-based models estimated within-sample during the GFC period, as well as the ROC scores obtained from using the GFC-fitted models as out-of-sample predictions for COVID winners and losers. Of greatest interest are the respective models' out-of-sample predictive success, so our discussion focuses on the COVID prediction column. In contrast to the previously reported dominance of the market-based model for discriminating within-sample winners versus losers (i.e., as depicted in Figure 3A), the accounting-only models both actually outperform the market-based model on an *out-of-sample* basis, as reflected by the ROC scores of the accounting-based Models 1 and 2 of 79% and 77%, respectively, versus just 72% for the market-based model. Indeed, the fitted coefficients on just two accounting variables, cash and the firm's stock of internally developed intangible assets (*RD&SGA_stock*), estimated from the GFC period and projected into the COVID crisis period, can be used to outperform a more elaborate accounting-only or market-only prediction model. Intuitively, these crisis-to-crisis prediction results suggest that cash and innovation-based assets are indicators of the firm's resilience during a major global crisis, regardless of the nature of that crisis (i.e., whether financial or humanitarian). By contrast, differences in market conditions prior to the onset of each crisis led to different within-crisis returns responses to the market-based variables. Alternatively stated, the extremely high level of GFC period within-sample performance of the market-only model results in part from an over-fitting to that particular sample period such that the coefficient estimates do not provide great out-of-sample predictions of winners versus losers during the subsequent crisis.

As is evident from Table 6, the best out-of-sample predictions are obtained from a model that incorporates all the significant accounting- and market-based variable (as determined from the previous within-sample GFC period analyses, so without the use of hindsight). This model (4) yields an ROC score of 81%, indicating a highly successful rate of out-of-sample prediction success. In other words, despite claims that the COVID pandemic is unlike anything that the markets have seen before (Reinhart (2020)), our results show that a model estimated on accounting and market data from the last great financial crisis can be used to successfully predict winners and losers in the current humanitarian crisis.

Returning to our investigation of the utility of ESG scores as a COVID crisis resilience factor, we assess the performance of a simple prediction model that projects that firms falling into the top (bottom) decile of ESG performance in 2018 (i.e., the most recent measure available prior to the onset of the pandemic), will be stock return winners (losers). As shown in Table 6, the ROC score computed from this prediction model is just 56%, which is marginally better than the 50% ROC score that would result from chance (i.e., a random assignment of top and bottom ESG firms into the expected winner versus loser categories). Finally, we include the firm's ESG rank as an incremental variable in the top-performing accounting- and market-based model and present these results in column (6).[24] As shown, this model yields an out-of-sample ROC score of 81%, which is identical (when rounded) to that of the combined model (4) that omits ESG, indicating that *ESG offers no incremental contribution to the model's prediction success*.

These results are also summarized graphically in Figure 3B. Consistent with the ROC scores reported in Table 6, the graph shows that the accounting-based model (2) is superior to the market-based model (3) (i.e., it is generally to the left and above the market model), although not dramatically so, and that each of these models clearly dominates the ESG-only model. Similar to the previously reported within-sample performance of ESG, the ROC curve generated from the out-of-sample ESG-only prediction model hovers feebly around the 45-degree line, a performance result that would be obtained by random classification of winners and losers. Not shown for the sake of parsimony, the ROC curve from the combined model (4) that slightly outperforms the accounting-only model on the basis of ROC score should be understood to lie slightly above and to the left of the curve associated with the accounting-only model (2).

Overall, the results in this section establish that a GFC-based estimation model consisting of just two accounting variables performs much better than a market-only model, and nearly as

[24] EIKON has such thin coverage of ESG scores during the GFC period that we would be left with only 300 usable observations for the GFC-based prediction model if we were to rely upon this data source. MSCI has much greater coverage during these earlier years, however we do not currently have access to the corresponding MSCI ESG data for the most recent period, and the MSCI and EIKON ESG scores are computed quite differently. In order to make use of the maximum amount of observations for this test, we therefore use the ranks of the MSCI ESG scores in the GFC period estimation model, which we then fit to the ranks of the EIKON ESG scores in the COVID period prediction model.

well as a combined accounting- and market-based model, in predicting out-of-sample COVID crisis winners versus losers. The finding of predictive success from one characteristically different crisis to another is particularly important in light of the expected increasing rate of catastrophic market shocks arising from diverse causes (e.g., extreme weather, environmental disasters, etc.) (World Economic Forum (2019)). Furthermore, consistent with the meagre within-sample contribution of ESG to the explanatory power for returns during both the COVID crisis and recovery periods, the results in this section show that ESG also adds little to accounting and market variables for purposes of out-of-sample prediction of crisis winners and losers.

4.4 Hedge Portfolio Returns

The previous ROC-based analyses suggest that several logit models estimated on GFC data perform statistically well out-of-sample in predicting winners and losers during the COVID crisis period. In order to assess the economic significance of these alternative models, we compute the returns from a simple hedge portfolio strategy of going long (short) in the firms that each model predicts to be winners (losers). In Table 7 we report the returns from this strategy for each of the models estimated in Table 5 and whose ROC-based out-of-sample performance was previously reported in Table 6. For the sake of completion, we also table the returns to firms that were not predicted to have extreme performance (i.e., those that fall into deciles 2 through 8 when the GFC-estimated model is fitted to all available sample firms from the COVID crisis period).

As shown in Table 7, each of the prediction models leads to significant returns from a hedge strategy of going long (short) in predicted winners (losers) during the COVID crisis period. Furthermore, the investment performance ranking of the models parallels that of their previously reported ROC-based statistical performance. For example, the two-factor accounting-based model (1) yields significant hedge abnormal returns of 25% during the COVID crisis, which is slightly better than the to 23% returns generated from the more elaborate accounting-only model (2). The market-only model (3) under-performs each of the accounting models, yielding hedge returns of 19%. Consistent with its better out-of-sample statistical performance, the accounting- and market-combined model (4) also yields a better economic performance, generating abnormal hedge returns of nearly 28% for the first quarter of 2020. In addition to the highly statistically and economically significant extreme decile hedge strategy performance, it is worth noting that the returns reported for each predicted decile for each of these four models are generally monotonically increasing when moving from the predicted bottom through the predicted top 10% performers. In other words, the models are doing a good job of predicting firm return performance across performance levels, not just at categorizing the extreme tails of performance returns. Furthermore, abnormal positive returns are available from the predicted winners (i.e., the top decile) across models, suggesting that even a long-only strategy would be profitable.

The models reported in columns (5) and (6) provide evidence related to the out-of-sample returns-relevance of ESG scores. Consistent with the statistical mediocrity of the ESG-only prediction model, the abnormal returns available from model (5) are modest in comparison with the yields from models (1) through (4), coming in at just 6.1%. Furthermore, the returns are not monotonically increasing across the predicted low to high deciles, and unlike each of the previous models, the returns associated with the highest decile (i.e., the predicted "winners") of the ESG-only model are *negative*. Notably, however, the returns to an ESG-only top-bottom decile hedge strategy are nevertheless positive and significant in the absence of any other considerations, which is perhaps what helps to fuel claims that ESG firms are more resilient during the crisis. It is notable, however, that the combined accounting, market, and ESG model (6) yields returns that are essentially identical to those of the combined model (4) that excludes ESG as a predictive variable (i.e., 27.8% compared to 27.7%). In summary, predictions based upon ESG on its own yield small (but still positive and significant) abnormal returns, however these are grossly inferior to those available from accounting- and market-based models. Furthermore, ESG adds nothing to the hedge return performance when it is used in conjunction with the more prediction-informative accounting and market variables.

Finally, in order to benchmark the previous GFC-based and ESG-based prediction models, we present in columns (7) through (9) the investment success of predictions model premised upon prior returns performance. Specifically, we compute the one-, two-, and three-year pre-COVID returns (e.g., calendar year 2019 for one-year prior returns, years 2018 through 2019 for two-year returns, etc.). We then predict that during the COVID crisis, each firm will land in its prior returns decile. As shown, the top-bottom long-short hedge strategy from this simple prediction model yields significant abnormal returns when implemented using the one- and three-year prior returns intervals, but insignificant returns for the 2-year interval. Specifically, the returns are 7.3% using one-year pre-pandemic (i.e., calendar 2019) returns, 12.2% using 3-year pre-pandemic period returns, and an insignificant 5.1% using the prior two-year performance. Even for the significant one-year- and three-year-based strategies, however, the returns are far from monotonic through the deciles. More importantly, the simple one-year and three-year prior returns-based strategies yield returns that are grossly inferior to those obtainable from any of the crisis-to-crisis prediction models (1) through (4), yet they are notably higher than the returns generated from the ESG-only model (5).

Overall, we conclude from our analyses that a parsimonious accounting- and market-based logit model estimated on GFC period data leads to statistically and economically significant out-of-sample predictions for COVID crisis period winners versus losers. Consistent with the findings from the previously reported within-sample analyses, ESG scores add little, either statistically or economically, to out-of-sample prediction success.

5. Summary and Conclusion

Despite the dramatic increase in responsible investing in recent years, the question as to whether ESG pays off for shareholders – i.e., whether doing good is good for business – remains the subject of considerable debate. Proponents of corporate social responsibility claim that it is particularly valuable as a risk mitigation strategy, offering the prospect of significant downside protection in periods of crisis. Consistent with this, fund managers and ESG data purveyors, as well as financial journalists, have been trumpeting the value of ESG as a "vaccine" against the pandemic-induced market turmoil of the current COVID crisis. The extensive analyses presented in this study suggest that the celebration of ESG as a resilience factor in times of unexpected crisis is, at best, premature, or at worst, misplaced.

While our results don't speak to the longer-term shareholder value creation of responsible corporate citizenship, an approach to doing business that we generally support and advocate for, they do provide robust evidence that firms with higher ESG scores do not experience superior returns (i.e., smaller losses) during the pandemic-induced selloff in the first quarter of 2020 once industry affiliation, and accounting- and market-based determinants of returns have been properly controlled for. Furthermore, our findings show that ESG scores are negatively associated with returns during the COVID recovery period in Q2 of 2020. By contrast, traditional balance-sheet based measures of liquidity and leverage are significantly associated with share price robustness during the crisis, consistent with a long line of finance research suggesting that financial flexibility is important to a firm's performance in the face of unexpected negative shocks. Not surprisingly, industry affiliation and traditional market-based measures of risk are also shown to be highly significantly associated with returns. Most interestingly, we find that a measure of the firm's stock of investments in internally-generated intangible assets is very significant in explaining returns during each of the COVID-19 crisis and recovery periods, suggesting that the flexibility that derives from a large stock of innovative assets is as important as financial flexibility to firms' prospects during this global pandemic.

Our key findings – that the flexibility derived from each of the firm's capital structure and its stock of internally-developed innovation-related assets are positive indicators of the firm's prospects while ESG investments are not – are generalizable across crises. This result itself is important in light of the unprecedented rate at which the planet is being destroyed combined with the increasing interconnectedness of the global economy, trends that most experts predict will lead to more frequently recurring global crises in the years to come. Our crisis-to-crisis analyses show that a parsimonious prediction model estimated on the GFC period can be used to successfully predict winners and losers during the subsequent humanitarian crisis currently affecting global capital markets. A combined model that relies on both accounting- and market-based measures yields highly significant hedge returns, while ESG does little to improve the investment model.

Overall, our study provides robust evidence to refute the widespread claim that ESG is a significant share price resilience factor during the COVID-19 global crisis.

Appendix

Variable Definitions

AcqIntang	=	Goodwill + other intangibles / total assets. Goodwill and other intangibles set to zero if missing. Compustat 2019 items (GDWL + INTANO) / AT. Capitalized and unamortized R&D and 1/3SG&A added to total assets.
Age	=	Firm age measured as years of data available before 2020 in Compustat annual.
Analyst	=	Number of analyst estimates for the next fiscal period, keeping the last available observation in 2019. I/B/E/S item numest. Set to zero if missing.
BHAR	=	Abnormal buy-and-hold returns estimated using the market model. Betas are estimated using a 60-month estimation window before the start of the return period and requiring at least 12 months of return data availability.
BTM	=	Book value of equity / market value of equity. Compustat 2019 items CEQ/(PRCC_C * CSHO).
BTMneg	=	A dummy variable taking the value of one if BTM is negative.
Cash	=	Cash and short-term investments / total assets. Compustat 2019 items CHE/AT. Capitalized and unamortized R&D and 1/3SG&A added to total assets.
Delta_ROA_Q1	=	The change in ROA for Q1 2020. Calculated as ROA_Q1_2020 - ROA_Q1_2019. See ROA for more details. Calculated using Compustat quarterly and subtracting ¼ * RDSGA_amort for FY2019 in the numerator.
DivPayout	=	The dividend payout ratio defined as dividends / net income. Compustat 2019 items DV / NI. Set to zero if missing.
ESG	=	Refinitiv's EIKON ESGScore for FY2018.
HML	=	The factor loading on Kenneth French's high minus low factor for US firms. The factor loadings are obtained by regressing firm specific returns on French's four factors. We use a 60-month estimation window before the start of the return period and require at least 12 months of return data availability for each firm.
ICWeakness	=	Number of internal control weaknesses in the most recent fiscal year with data availability. Audit Analytics SOX 404 internal controls file. Data item count_weak. Set to zero if missing.
IdioRisk	=	The firm-specific root mean squared error of the market model regression estimations.

InstOwners	=	Shares held by institutional investors as a percentage of total shares outstanding for FY2018. Calculated using Thomson Reuters 13f database. Truncated at 100% (Gompers and Metrick (2001)). Set to zero if missing.
InvestorOrient	=	Percentage dedicated holders – percentage transient investors for FY2018. Calculated using Thomson Reuters 13f and Bushee's institutional investor classification data (Bushee (1998)). Set to zero if missing.
InvTurn	=	Industry-adjusted inventory turnover ratio. Compustat items COGS/INVT. Dividing the firm-specific inventory turnover ratio by the average 2-digit SIC industry inventory turnover for FY2019. Set to zero if missing.
lnCEOtenure	=	The natural log of the number of days since the CEO was appointed before January 2020. Set to zero if there was a CEO change in the first month of the return period (i.e. in January 2020). BoardEx organizational composition item datestartrole.
Loss	=	A dummy variable taking the value of one if ROA, adjusted for one-off items and R&D + 1/3SG&A capitalization and amortization, is negative.
LTDebt	=	Long-term debt. Compustat 2019 DLTT / AT. Capitalized and unamortized R&D and 1/3SG&A added to total assets. Set to zero if missing.
MeanAnnSpeed	=	The average quarterly earnings announcement speed over fiscal year 2019. Compustat quarterly items (RDQ - APDEDATEQ) / 365 * (- 1).
MKTRF	=	The factor loading on Kenneth French's market factor for US firms. The factor loadings are obtained by regressing firm specific returns on French's four factors. We use a 60-month estimation window before the start of the return period and require at least 12 months of return data availability for each firm.
MktShare	=	Sales / total industry sales. Compustat 2019 SALE / sum(SALE_i) where i = all firms in 2-digit SIC.
MOM	=	The factor loading on Kenneth French's momentum factor for US firms. The factor loadings are obtained by regressing firm specific returns on French's four factors. We use a 60-month estimation window before the start of the return period and require at least 12 months of return data availability for each firm.
Momentum	=	Raw buy-and-hold return in the 12-month period before the start of the return period.

RD&SGAstock	=	Stock-transformed R&D + 1/3*SG&A for FY2019 using a 5-year amortization period. See footnote 12 for a detailed example. Compustat items XRD + 1/3*XSGA. Scaled by total assets. Capitalized and unamortized R&D and 1/3SG&A added to total assets. XRD and XSGA set to zero if missing. In case of insufficient data availability, we retain the assumption of a 5-year amortization period and assume the last available R&D and SG&A expense to be constant for the prior years.
ROA	=	Return on assets specified as (net income – one-off items + R&D + 1/3*SG&A – (R&D and 1/3*SG&A amortization)) / total assets. Compustat 2019 items (NI – SPI – DO + XRD + XSGA – RDSGA_amort) / AT. Capitalized and unamortized R&D and 1/3SG&A added to total assets. RDSGA_amort calculated assuming 20% annual amortization, assuming the last available R&D and SG&A expense to be constant for prior years in case of insufficient data availability. Special items, discontinued operations, R&D and SG&A set to zero if missing.
Size	=	Log-transformed market cap. Compustat 2019 items CSHO * PRCC.
SMB	=	The factor loading on Kenneth French's small minus big factor for US firms. The factor loadings are obtained by regressing firm specific returns on French's four factors. We use a 60-month estimation window before the start of the return period and require at least 12 months of return data availability for each firm.
STDebt	=	Short-term debt. Compustat 2019 items DLC/AT. Capitalized and unamortized R&D and 1/3SG&A added to total assets. Set to zero if missing.

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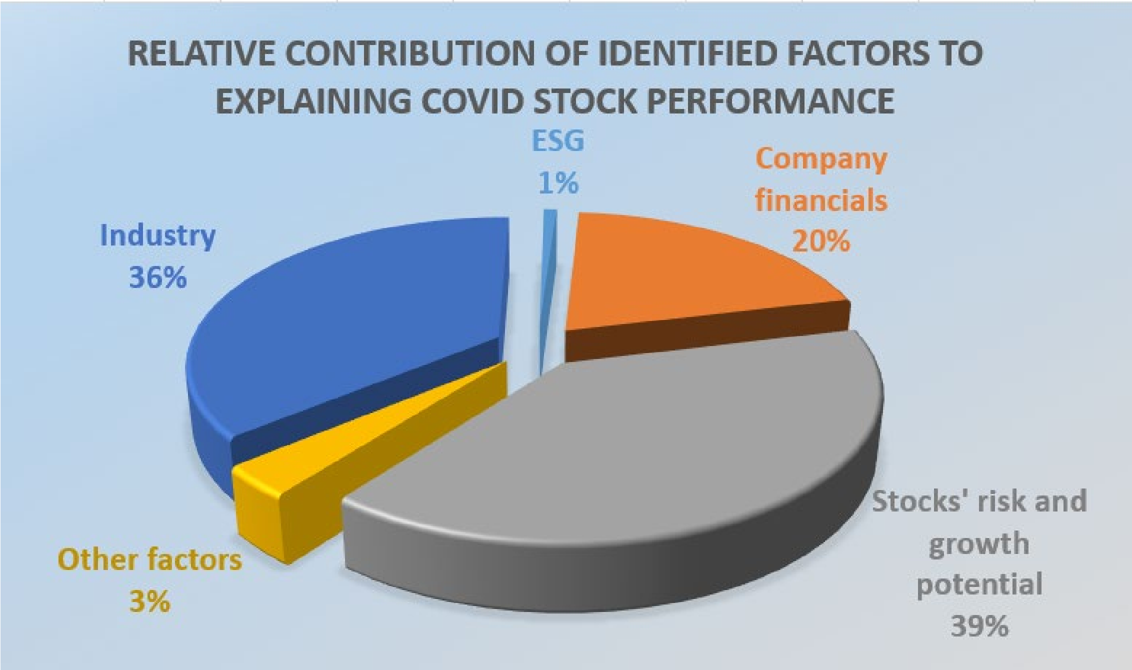
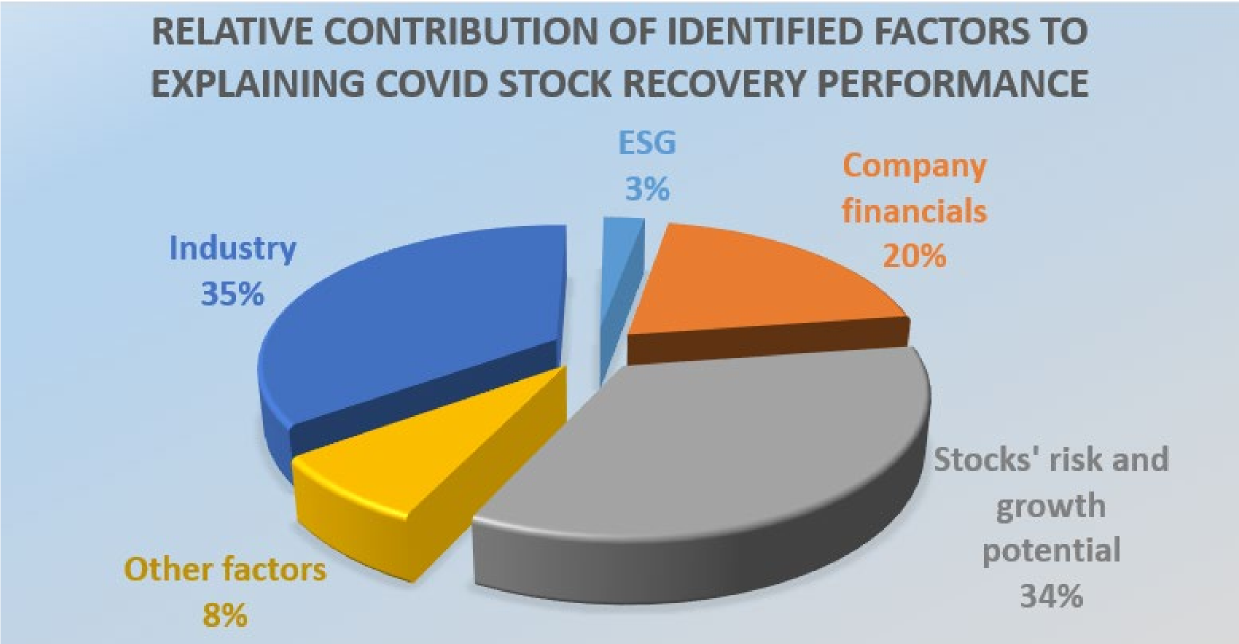
Figure 1: Owen-Shapley R^2 Decomposition Analysis Covid Crisis Period



The pie chart in Figure 1 represents the contribution of ESG, company financials, stocks' risk and growth potential, industry, and other factors to our Covid Crisis period model R^2 (Table 3) . Company financials consists of: Cash, LTDebt, STDebt, ROA, Loss, InvTurn, RD_SGAstock, AcqIntang, DivPayout, ICWeakness, MeanAnnSpeed, Size. Stocks'risk and growth potential consists of: Analyst, BTM, BTMNeg, Momentum, IdioRisk, MKTRF, HML, SMB, MOM. Other factors consist of: Mktshare, Age, InvestorOrient, InstOwners, lnCEOtenure. All percentages rounded to the nearest integer.

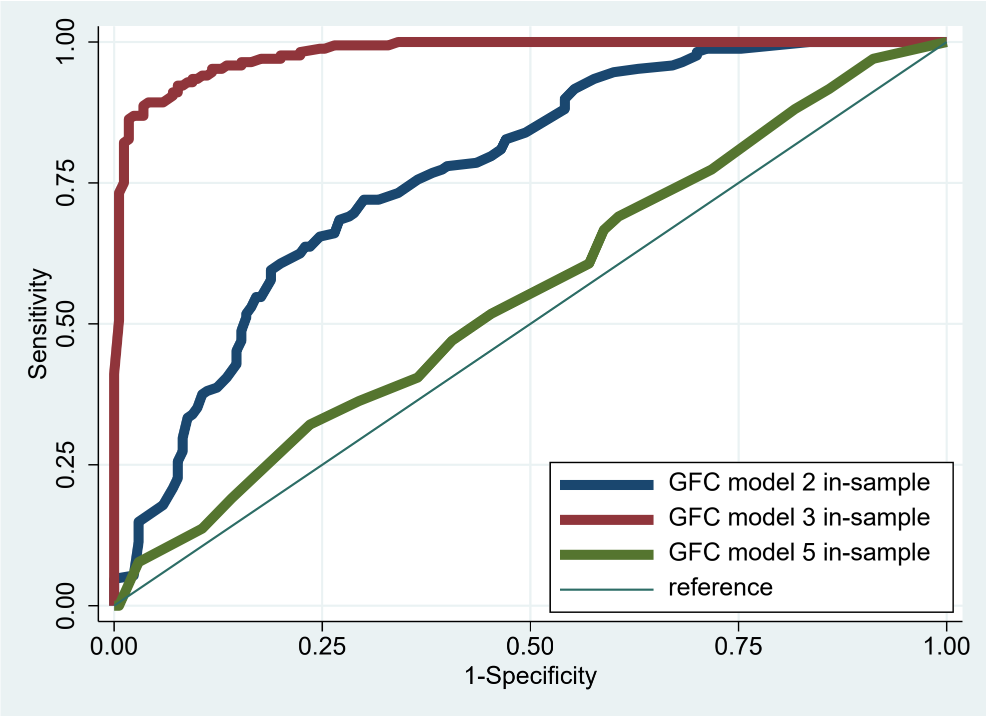
Figure 2: Owen-Shapley R^2 Decomposition Analysis Covid Recovery Period



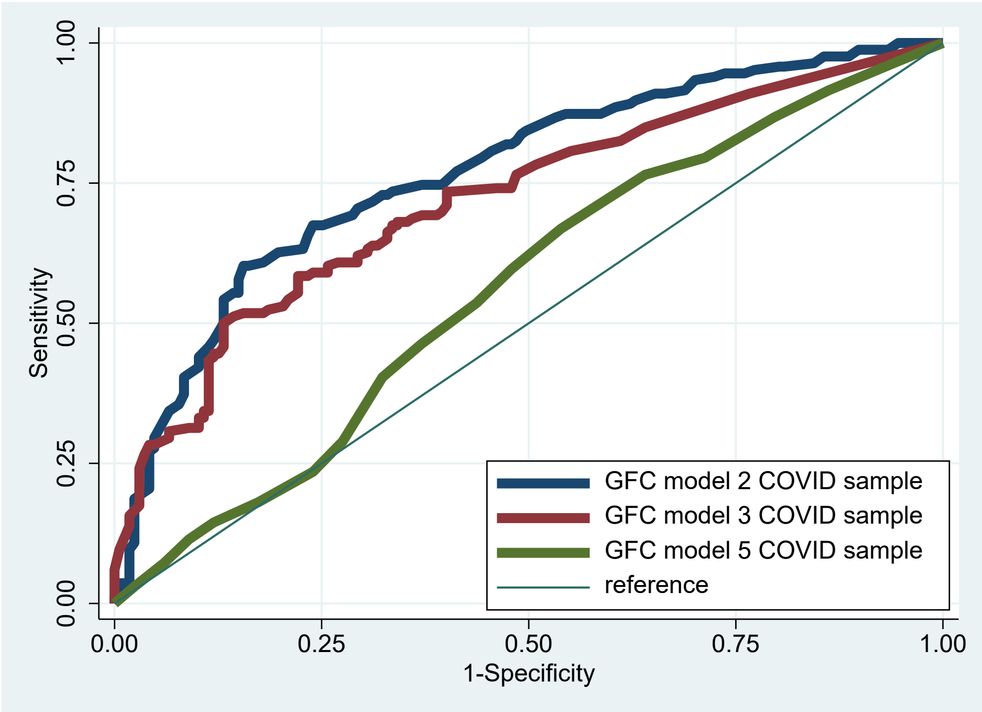
The pie chart in Figure 2 represents the contribution of ESG, company financials, stocks' risk and growth potential, industry, and other factors to our Covid Recovery period model R^2 (Table 4) . Company financials consists of: Cash, LTDebt, STDebt, ROA, delta_ROA_Q1, Loss, InvTurn, RD_SGAstock, AcqIntang, DivPayout, ICWeakness, MeanAnnSpeed, Size. Stocks'risk and growth potential consists of: Analyst, BTM, BTMNeg, Momentum, IdioRisk, MKTRF, HML, SMB, MOM. Other factors consist of: Mktshare, Age, InvestorOrient, InstOwners, lnCEOtenure. All percentages rounded to the nearest integer.

Figure 3: Receiver Operating Curve (ROC) graphical analysis of GFC logistic models

Figure 3 compares the predictive performance of three GFC sample-based logistic regressions predicting winners versus losers (top vs bottom 10% crisis returns) from table 5 with ROC lines: model 2 (accounting-based), model 3 (market-based) and model 5 (ESG). The 45-degree reference line represents the zero-performance model. ROC lines closer to the reference have worse performance.



Panel A: GFC in-sample prediction performance



Panel B: COVID sample prediction performance

Table 1: Sample Determination

Refinitiv EIKON ESG Data	
Number of observations for FY 2018	2,312
Dropping:	
Non-US firms	-42
Duplicates	-1
Unavailable Compustat Data	-26
SIC Code 6000 - 6999	-568
Insufficient or missing return data	-10
Missing BTM	-2
Influential observations cooksd > 0.01	-11
Number of sample firms	1652

Table 2: Summary Statistics and Correlation Matrix

Panel A: Summary statistics Covid-19 January-March crisis period.

	N	Mean	Std. Dev.	p25	Median	p75
BHAR	1652	-.08	.233	-.23	-.08	.052
RawReturn	1652	-.317	.236	-.476	-.315	-.161
ESG	1652	46.661	17.317	33.519	43.372	58.158
Cash	1652	.134	.144	.028	.079	.184
LTDebt	1652	.24	.181	.09	.225	.35
STDebt	1652	.024	.038	.004	.011	.031
ROA	1652	.032	.087	.011	.044	.077
Loss	1652	.209	.407	0	0	0
InvTurn	1652	.642	1.029	0	.393	.781
RD SGAstock	1652	.214	.162	.082	.185	.313
AcqIntang	1652	.194	.193	.018	.136	.331
DivPayout	1652	.154	.606	0	0	.308
ICweakness	1652	.125	.515	0	0	0
MeanAnnSpeed	1652	-.099	.02	-.114	-.101	-.086
Size	1652	7.889	1.655	6.709	7.767	8.92
Analyst	1652	9.711	7.42	4	8	14
BTM	1652	.416	.486	.147	.308	.541
BTMneg	1652	.057	.232	0	0	0
Momentum	1652	.245	.473	-.033	.208	.462
IdioRisk	1652	.111	.062	.065	.094	.138
MKTRF	1652	1.064	.623	.668	1.042	1.397
SMB	1652	.778	.995	.156	.629	1.265
HML	1652	-.008	1.008	-.457	.064	.545
MOM	1652	-.073	.69	-.392	-.045	.283
MktShare	1652	.026	.062	.001	.004	.018
Age	1652	27.912	19.927	10	24	38
Age Sqrd	1652	1175.916	1475.729	100	576	1444
InvestorOrient	1652	-1.696	8.108	-5.653	-.66	2.917
InstOwners	1652	67.714	21.523	59.407	72.391	81.541
lnCEOtenure	1652	6.698	1.664	6.184	7.028	7.682

All variables are as defined in the Appendix. Institutional ownership is truncated at 100% and all other continuous variables are winsorized at the 1% and 99% level.

Panel B: Correlation Matrix Covid-19 January-March crisis period

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) BHAR	1.00																		
(2) ESG	0.07***	1.00																	
(3) Cash	0.26***	-0.19***	1.00																
(4) LTDebt	-0.24***	0.11***	-0.40***	1.00															
(5) STDebt	-0.11***	0.07***	-0.17***	0.10***	1.00														
(6) ROA	-0.01	0.18***	-0.22***	0.04	0.01	1.00													
(7) InvTurn	-0.02	0.05**	-0.06**	0.09***	0.03	-0.02	1.00												
(8) RD_SGAstock	0.27***	-0.13***	0.44***	-0.45***	-0.12***	-0.33***	-0.06**	1.00											
(9) AcqIntang	-0.01	0.08***	-0.37***	0.27***	-0.05*	0.22***	-0.05**	-0.29***	1.00										
(10) MeanAnnSpeed	0.05**	0.40***	-0.22***	0.01	0.10***	0.39***	0.03	-0.15***	0.06**	1.00									
(11) Size	0.10***	0.58***	-0.14***	0.10***	0.05**	0.47***	0.01	-0.25***	0.22***	0.54***	1.00								
(12) Analyst	0.08***	0.49***	-0.05*	0.10***	0.05**	0.23***	0.00	-0.06***	0.06***	0.42***	0.73***	1.00							
(13) BTM	-0.18***	-0.07***	-0.24***	-0.05*	0.00	-0.18***	-0.03	-0.27***	-0.06**	-0.09***	-0.31***	-0.16***	1.00						
(14) Momentum	0.12***	-0.02	0.11***	-0.04*	-0.04	0.16***	0.00	0.00	0.05**	0.09***	0.29***	0.09***	-0.35***	1.00					
(15) IdioRisk	0.06**	-0.35***	0.44***	-0.15***	-0.08***	-0.52***	-0.04	0.43***	-0.32***	-0.51***	-0.56***	-0.28***	0.10***	-0.04	1.00				
(16) MktShare	-0.06**	0.34***	-0.18***	0.14***	0.11***	0.14***	0.10***	-0.19***	0.05*	0.26***	0.37***	0.31***	0.00	0.03	-0.23***	1.00			
(17) Age	-0.06**	0.40***	-0.33***	0.07***	0.10***	0.21***	0.05**	-0.30***	0.05**	0.37***	0.35***	0.11***	0.02	-0.02	-0.45***	0.23***	1.00		
(18) InstOwners	-0.07***	0.16***	-0.13***	0.12***	0.03	0.17***	0.00	-0.12***	0.12***	0.16***	0.15***	0.20***	0.02	0.03	-0.24***	0.04*	0.02	1.00	
(19) InvestorOrient	0.11***	0.22***	-0.07***	-0.03	0.00	0.02	0.00	-0.07***	0.09***	0.16***	0.22***	0.09***	-0.02	0.03	-0.19***	0.08***	0.23***	-0.08***	1.00

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

Table 3: COVID-19 January-March Crisis Period Within Sample Regressions

Table 3 shows results from regressing buy-and-hold abnormal returns on our independent variables for the January-March 2020 Covid Crisis period. In column (1), we regress BHAR on Refinitiv's ESGScore, in column (2) we add market and return related variables, in column (3) we add accounting variables, and in column (4) we regress BHAR on our complete model. Industry dummies included. Robust standard errors reported in parentheses. Institutional ownership truncated at 100. All other continuous variables winsorized at the 1 and 99% level. We remove 11 influential observations. All variables are as defined in the Appendix.

	(1) BHAR	(2) BHAR	(3) BHAR	(4) BHAR
ESG	.001392***	.000612*	.000405	.00046
	(.000287)	(.000339)	(.000353)	(.000359)
Analyst		.001109	-.001035	-.000366
		(.000815)	(.001051)	(.001082)
BTM		-.033008**	-.009371	-.008472
		(.015406)	(.016214)	(.016348)
BTMneg		-.032588	.020464	.01764
		(.026191)	(.026593)	(.026397)
Momentum		-.017353	-.021256	-.019937
		(.015103)	(.015162)	(.015357)
IdioRisk		-.456138***	-.551213***	-.593019***
		(.151765)	(.183061)	(.191464)
MKTRF		.151236***	.161821***	.162141***
		(.011518)	(.011267)	(.011278)
SMB		.018516**	.021417***	.022237***
		(.008088)	(.00811)	(.008163)
HML		-.038558***	-.028214***	-.030544***
		(.008745)	(.008981)	(.009227)
MOM		-.024104**	-.047122***	-.045262***
		(.011064)	(.011535)	(.011639)
Cash			.184953***	.188322***
			(.056054)	(.055938)
LTDebt			-.170099***	-.15897***
			(.040882)	(.041528)
STDebt			-.225173*	-.217725*
			(.127508)	(.127244)
ROA			.161916	.189142*
			(.110414)	(.111941)
Loss			.013763	.014121
			(.02201)	(.02214)
InvTurn			.008418*	.008283*
			(.005002)	(.004974)
RD_SGAstock			.167242***	.161635***
			(.059324)	(.058646)
AcqIntang			.017954	.018048
			(.032467)	(.032531)
DivPayout			.005658	.002294
			(.008536)	(.00861)
ICweakness			.010924	.011941
			(.00996)	(.009935)
MeanAnnSpeed			.754658**	.721644**
			(.339702)	(.346952)
Size			.012814*	.009221
			(.007236)	(.007958)
MktShare				.007059
				(.077561)

Age				.000919
				(.001092)
Age_Sqrd				-.000014
				(.000013)
InvestorOrient				.001142
				(.000721)
InstOwners				-.000638**
				(.000277)
lnCEOtenure				-.000679
				(.002606)
_cons	-.262773***	-.308083***	-.349971***	-.292999***
	(.056666)	(.053357)	(.084013)	(.092884)
Observations	1652	1652	1652	1652
R-squared	.23761	.357692	.400499	.405482
Industry Dummies	YES	YES	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 4: COVID-19 April-June Recovery Period Within Sample Regressions

Table 4 shows results from regressing buy-and-hold abnormal returns on our independent variables for the April-June 2020 Covid Recovery period. In column (1), we regress BHAR on Refinitiv's ESGScore, in column (2) we add market and return related variables, in column (3) we add accounting variables, and in column (4) we regress BHAR on our complete model. Industry dummies included. Robust standard errors reported in parentheses. Institutional ownership truncated at 100. All other continuous variables winsorized at the 1 and 99% level. We remove 20 influential observations. All variables are as defined in the Appendix.

	(1)	(2)	(3)	(4)
	BHAR	BHAR	BHAR	BHAR
ESG	-.002031***	-.002307***	-.002293***	-.001749***
	(.000465)	(.000573)	(.000642)	(.000663)
Analyst		.007963***	.00879***	.008254***
		(.001358)	(.001939)	(.002002)
BTM		.107736***	.134861***	.138683***
		(.040736)	(.042923)	(.042483)
BTMneg		.067859	.008057	.01932
		(.054283)	(.056095)	(.055776)
Momentum		-.154867***	-.116623**	-.114743**
		(.048099)	(.04703)	(.046817)
IdioRisk		.573157**	.009476	-.161567
		(.280361)	(.327293)	(.332023)
MKTRF		-.058337**	-.060668**	-.059382**
		(.02547)	(.025881)	(.026163)
SMB		.011776	.009476	.009968
		(.01527)	(.015066)	(.014989)
HML		.008643	.027892	.029885
		(.021537)	(.021739)	(.021745)
MOM		.021388	.01479	.011801
		(.025328)	(.026731)	(.026763)
Cash			.063561	.023486
			(.099324)	(.099366)
LTDebt			.246129***	.229017***
			(.077103)	(.077272)
STDebt			-.20973	-.211467
			(.305307)	(.302685)
ROA			.063568	.055156
			(.234602)	(.237692)
delta_ROA_Q1			1.591269***	1.512087***
			(.564379)	(.563367)
Loss			.065122	.065736
			(.043632)	(.043305)
InvTurn			-.018581*	-.019639**
			(.009749)	(.00979)
RD_SGAstock			.393917***	.372395***
			(.110443)	(.110399)
AcqIntang			-.000949	-.012046
			(.05851)	(.060288)
DivPayout			-.028499**	-.026304*
			(.013788)	(.013642)
ICweakness			-.00165	-.002982
			(.018998)	(.018926)
MeanAnnSpeed			-.13793	.185101
			(.611201)	(.604498)
Size			-.005514	-.00204
			(.014402)	(.015804)
MktShare				-.179782

				(.136011)
Age				-.004592**
				(.002137)
Age_Sqrd				.000043*
				(.000026)
InvestorOrient				6.000e-06
				(.001426)
InstOwners				-.000561
				(.00056)
lnCEOtenure				.000437
				(.005061)
_cons	.196726***	.033711	-.055762	.075406
	(.037809)	(.056975)	(.154479)	(.173852)
Observations	1628	1628	1628	1628
R-squared	.100749	.155907	.189623	.195624
Industry Dummies	YES	YES	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 5: Logistic Regression GFC period

Table 5 shows the results from the logistic regression models estimated in the GFC period to explain top 10% winners versus bottom 10% losers, based on the crisis returns in the period Aug 2008-March 2009. Model 1 represents an extremely parsimonious accounting-based model with 2 factors, Model 2 is a more fully specified accounting-only model, Model 3 shows a market-only model, Model 4 combines the significant accounting and market variables from Models 2 and 3, Model 5 includes the ESG rank as the only variable, and finally Model 6 combines Model 4 and the ESG rank. All variables are defined in the Appendix.

	(1) Winner	(2) Winner	(3) Winner	(4) Winner	(5) Winner	(6) Winner
Cash	2.851***	3.566***		5.276**		5.345**
	(0.843)	(0.999)		(2.319)		(2.337)
RD_SGAstock	4.742***	5.009***		6.728***		6.755***
	(0.902)	(1.032)		(2.115)		(2.142)
STDebt		-2.349				
		(3.554)				
LTDebt		0.372				
		(0.835)				
ROA		1.526				
		(2.575)				
Size		-0.029				
		(0.122)				
Loss		-0.086				
		(0.563)				
DivPayout		0.182				
		(0.183)				
MeanAnnSpeed		2.409				
		(3.547)				
AcqIntang		0.548				
		(0.865)				
InvTurn		0.539***		0.893**		0.909**
		(0.199)		(0.380)		(0.380)
BTM			-4.160***	-3.413***		-3.442***
			(1.179)	(1.284)		(1.274)
BTMneg			-4.381***	-5.427***		-5.347***
			(1.597)	(1.815)		(1.826)
Momentum			-4.866***	-5.044***		-4.967***
			(0.840)	(0.955)		(0.937)
IdioRisk			-34.738***	-44.910***		-46.162***
			(7.706)	(10.028)		(10.081)
MKTRF			5.136***	5.411***		5.518***
			(0.717)	(0.797)		(0.814)
SMB			1.217***	1.251***		1.274***
			(0.256)	(0.292)		(0.291)
HML			0.404*			
			(0.217)			
MOM			-1.911***	-1.263***		-1.283***
			(0.392)	(0.403)		(0.407)
ESGrank					0.707*	1.064
					(0.399)	(0.986)
constant	-1.387***	-1.581	-0.642	-2.510*	-0.334	-2.999**
	(0.216)	(1.092)	(1.004)	(1.289)	(0.215)	(1.374)
Observations	339	339	339	339	339	339
Count Pseudo R^2	0.720	0.704	0.923	0.950	0.537	0.953

Standard errors are in parenthesis
*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 6: GFC Logistic Regression and COVID Performance Prediction Success

Table 6 presents the area under the Receiver Operating Curve (ROC area) of the logit-based models estimated in the GFC period, as presented in table 5. In addition, column (2) shows the ROC areas obtained from using the GFC-fitted models as out-of-sample predictions for COVID winners and losers. Standard errors of the ROC areas are in parentheses.

GFC Winner Prediction model (top versus bottom 10%)	(1) ROC area In-sample GFC period	(2) ROC area Out-of-sample COVID period
Model 1	0.766	0.787
Cash, RD_SGAStock	(0.026)	(0.025)
Model 2	0.770	0.769
Cash, RD_SGAStock, STDebt, LTDebt, ROA, Size, Loss, DivPayout, MeanAnnSpeed, AcqIntang, InvTurn	(0.025)	(0.026)
Model 3	0.981	0.719
BTM, BTMneg, Momentum, IdioRisk, MKTRF, SMB, HML, MOM	(0.006)	(0.028)
Model 4	0.986	0.810
Cash, RD_SGAStock, InvTurn, BTM, BTMneg, Momentum, IdioRisk, MKTRF, SMB, MOM	(0.004)	(0.024)
Model 5	0.555	0.559
ESG rank	(0.031)	(0.032)
Model 6		
Cash, RD_SGAStock, InvTurn, BTM, BTMneg, Momentum, IdioRisk, MKTRF, SMB, MOM, ESG rank	0.986 (0.005)	0.810 (0.024)

Table 7: Predicted COVID Performance: Hedge Returns Analysis

Table 7 presents the portfolio COVID crisis returns obtained from ranking firms before the COVID crisis period according to several methods. Column (1) to (6) refer to the portfolio assignment based on the GFC winners prediction Model 1 to 6 in table 5 applied to the COVID sample. Column (1) is based on a parsimonious 2-factor accounting model; column (2) refers to a more extended accounting model; column (3) refers to a market-only model; column (4) is a combination of parsimonious accounting and market-factor model; column (5) is based on the ESG only ranking in 2018; column (6) is based on a combined accounting, market and ESG rank model; columns (7) to (9) refer to rankings based on pre-Covid historical stock performance: one year, resp. two year, resp. three year. The COVID period hedge return is obtained from going long in the highest portfolio and short in the lowest portfolio.

	(1) GFC Model 1	(2) GFC Model 2	(3) GFC Model 3	(4) GFC Model 4	(5) GFC Model 5	(6) GFC Model 6	(7) 1 year past returns	(8) 2 years past returns	(9) 3 years past returns
Predicted COVID portfolio	Average portfolio return during COVID crisis period								
1	-0.185	-0.191	-0.174	-0.186	-0.117	-0.193	-0.120	-0.073	-0.119
2	-0.151	-0.152	-0.122	-0.163	-0.096	-0.177	-0.114	-0.140	-0.148
3	-0.137	-0.127	-0.122	-0.152	-0.102	-0.116	-0.095	-0.118	-0.099
4	-0.109	-0.089	-0.106	-0.135	-0.074	-0.155	-0.089	-0.093	-0.084
5	-0.091	-0.084	-0.076	-0.086	-0.070	-0.071	-0.104	-0.087	-0.076
6	-0.059	-0.091	-0.078	-0.063	-0.067	-0.089	-0.066	-0.088	-0.088
7	-0.124	-0.073	-0.066	-0.058	-0.045	-0.034	-0.067	-0.053	-0.081
8	0.005	-0.037	-0.026	-0.009	-0.095	-0.024	-0.052	-0.071	-0.052
9	0.008	0.029	-0.019	-0.014	-0.054	-0.002	-0.022	-0.039	-0.024
10	0.068	0.038	0.014	0.091	-0.055	0.085	-0.047	-0.022	0.003
highest minus lowest	0.254	0.229	0.188	0.277	0.061	0.278	0.073	0.051	0.122
t-value	[9.00]	[8.36]	[6.96]	[10.03]	[2.53]	[9.95]	[2.33]	[1.59]	[3.70]