ESG INVESTING: A TALE OF TWO PREFERENCES

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A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Finance in the Kenan-Flagler Business School.

Chapel Hill
2023

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ABSTRACT

Paul Yoo: ESG Investing: A Tale of Two Preferences
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What motivates ESG integration? I find both non-pecuniary *and* risk-mitigating preferences explain its prominence. Using widely endorsed ESG ratings, I show each preference induces sizable ESG equity premium identified through option-implied expected returns. Due to unexpectedly persistent demand growth for ESG-conscious assets, realized returns mask true ESG pricing effects, especially those attributable to non-pecuniary preference. Consequently, this paper lends support to recent theoretical frameworks on ESG investing with non-pecuniary preference and reconciles mixed evidence in the empirical literature. In addition, I am able to identify the impact of investors' hedging motives against negative non-pecuniary externalities via option-implied risk-neutral moments.

ACKNOWLEDGEMENTS

I am forever indebted to Jacob Sagi for the support, supervision, and numerous insights along the most important stage of the PhD journey: brainstorming, developing, polishing, and pitching the job market paper. I am extremely grateful to Yasser Boualam for investing tremendous amount of time in me since my second year: from writing papers together to passing on countless tips on how to succeed. I also thank Gregory Brown for his care and encouragement especially during the job market, and thank Christian Lundblad and Olga Hawn for their guidance and support.

I also gratefully acknowledge financial support from the Center for Sustainable Enterprises, the Institute of Private Capital (IPC), and the Kenan Institute of Private Enterprise (KIPE) at UNC Kenan-Flagler Business School. A special measure of gratitude is extended to IPC and KIPE for valuing my research projects on topics in sustainable finance and having me as a research associate that funded my 6th year. I have also benefitted from being surrounded by Finance faculty at Kenan-Flagler Business school. Paolo Fulghieri, Paige Ouimet, Andrei Gonçalves, Jesse Davis, Yunzhi Hu, Andreas Stathopoulos, Gill Segal, Aymeric Bellon, and Donghwa Shin all provided valuable feedback on this dissertation. Special thanks to Christian Lundblad and Paige Ouimet for serving as PhD coordinators and caring about the welfare of me and my PhD colleagues.

Most importantly, this dissertation would not have been possible without the love of God who is the beginning of all wisdom (Proverbs 9:10). I eternally thank Him for adopting me to himself as a son through Jesus Christ to the praise of His glorious grace (Ephesians 1:5-6) and steering me to find my identity in Him through Galatians 2:20. I also thank Him for joining me and my wife, Bora Jin, together whose immeasurable love and support made my sometimes depressive PhD journey enjoyable. Her God-given passion for being a custodian of His creation has solidified my strong sense of love and commitment towards research in sustainable finance. She is and always will be a constant source of inspiration, not just because of her doctorate in statistics from Duke correcting my econometric misapplications but also because of her living out the purpose-driven life alongside me. I will always love her and give myself up for her as Christ loved the church (Ephesians 5:25).

I thank my one and only cohort Spencer Andrews for his friendship and fellowship throughout our PhD journey. I am forever grateful to God for sending him to safeguard my faith in Christ during turbulent times. Without a doubt, having Spencer as my cohort and forever friend is a blessing and I look forward to sharing our lives together in Washington D.C. after we graduate.

Finally, I thank my parents, Kwan Hee Yoo and Qui Hee Kim, for their unconditional love and bottomless giving of prayers and care. Only recently did I come to realize how emotionally and financially tough it would have been for them to support me studying abroad since high school from a distance. Without them, this dissertation was not possible. I also thank my sister Christina Meeyeon Yoo for always being super proud of her little brother and praying for me endlessly. I also thank my in-laws for welcoming me as a family and showing us a model of how to live out the faith in Him.

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CHAPTER 1: ESG INVESTING: A TALE OF TWO PREFERENCES

1.1 Introduction

Over recent two decades, the size of professionally managed capital with environmental, social, and governance (ESG) considerations has grown exponentially in the U.S. and worldwide, as shown in Figure 1.1, and hit $17.1 trillion at the end of 2020 in the U.S. alone.[1] Simultaneously, mutual funds and ETFs that are categorized as sustainable funds have experienced comparable growth in net inflows. Both academics and practitioners have been grappling with the trend to understand what motivates ESG integration, but no consensus has been reached yet. Recent papers built theories to foster discussions on potential drivers, including non-pecuniary benefits (i.e., non-monetary utility from investing in a socially responsible manner) and risk mitigation (e.g., hedging against material ESG risks such as climate or regulatory risks).[2] Empirical literature has provided some evidence for the latter and limited evidence for the former, but has yet to jointly identify the aggregate pricing effects of the two preferences.[3] With only few experimental studies finding investors' willingness to forgo pecuniary rewards for promoting sustainability and empirical evidence for it confronted with endogeneity issues due to persistent capital flows, the theories still lack empirical support for their model implications to be fully appreciated.[4]

To fill the void, this paper empirically examines whether the two major, but inherently distinct, preferences for ESG investing affect asset prices in the U.S. public equity market. In particular,

[1] See US SIF Report and US SIF Fast Facts for more details. The most recent report applies more stringent criteria in computing ESG-integrating AUM for 2022, but it still amounts to $8.4 trillion that is about one-eighth of total US AUM.

[2] Heinkel et al. (2001), Pastor et al. (2021), and Zerbib (2022) focus on modeling non-pecuniary utilities, while Pedersen et al. (2021) feature both non-pecuniary and risk-mitigating preferences.

[3] On the evidence for risk mitigation, see Albuquerque et al. (2019), Hoepner et al. (2022), and Seltzer et al. (2021).

[4] Experimental studies include Riedl and Smeets (2017), Hartzmark and Sussman (2019), Humphrey et al. (2021), Bonnefon et al. (2022), and Heeb et al. (2022). For further discussion of endogeneity concerns on empirical evidence, refer to final paragraphs of this section.

to disentangle the role of non-pecuniary preference from that of pecuniary preference, I use two most widely endorsed firm-level ESG ratings—MSCI's Intangible Value Assessment (IVA) and RepRisk's ESG-risk index (RRI)—to respectively quantify non-pecuniary benefits and downside ESG-risk exposures investors internalize as shareholders.[5] While IVA puts emphasis on evaluating the effectiveness of firms' ESG strategies in place and historical management of previously realized ESG incidents, RRI intentionally confines its scope to gauge firms' exposure to future ESG-related pecuniary risk events. The apparent distinction in rating constructions conduces to IVA and RRI containing information that are more relevant to non-pecuniary and pecuniary ESG considerations, respectively. With this knowledge, I analyze whether investors *ex-ante* require significant equity premium based on each ESG metric. To verify whether each ESG premium is indeed attributable to non-pecuniary or pecuniary preferences, I show that IVA and RRI proxy well for non-pecuniary-based versus risk-based portfolio rebalancing motives of institutional investors, respectively. In addition, I study the time-series dynamic of each ESG premium and cross-sectional variations of option-implied risk-neutral return distributions to shed light on when and how each ESG preference distorts investors' forward-looking perception significantly. In doing so, I not only further validate the ratings as proxies for distinct ESG preferences but also identify the impact of investors' hedging motives against negative non-pecuniary externalities. Finally, I examine the cross-sectional variations of such ESG premia to better understand how differently and strongly each preference manifests itself across firms and investors.

In quantifying ESG equity premia, I use *ex-ante* expected returns of individual stocks recovered from parameter-free options-based measures following Martin and Wagner (2019) and Kadan and Tang (2020) instead of *ex-post* realized returns. As mentioned, the amount of capital with ESG integration has continually soared since the aftermath of 2008 global financial crisis. Such prolonged ESG demand surge marks a period of transition during which realized returns of ESG-(un)friendlier stocks are (downwardly) upwardly biased estimates of expected returns.[6] Concurrently, the number

[5]It is well known that ESG rating providers can disagree substantially on what and how they assess ESG profiles of companies (e.g., Berg et al. (2022b)). Yet, rather than discouraging ESG integration all together, the divergence has resulted in integration of multiple ESG ratings, according to a recent survey conducted by SustainAbility, an ERM Group company.

[6]van der Beck (2021) shows that the outperformance of a representative ESG portfolio over the past decade is primarily flow-driven, based on the quantitatively estimated valuation multiplier for stocks held by ESG funds.

of ESG-rating providers and their coverage of firms expanded. As a result, an empirical study leveraging richer ESG data is constrained to focus on the period exactly when the use of realized returns is most disputable. Indeed, in most recent literature review papers, Coqueret (2021) and Whelan et al. (2021) document that numerous studies using realized returns report mixed results on the association between ESG and equity returns.[7] The main finding, based on option-implied expected returns, is that investors *ex-ante* expect significantly lower returns on firms with better ESG credentials ($ESG^{\Sun} = IVA$) or better ESG-risk hedge ($ESG^{\$} = -RRI$). *Ex-post* realized returns fail to reveal such premia, especially those attributable to the former, while the implied cost of capital (ICC)—an *ex-ante* approach to estimate the market's discount rate of a given firm via equating the firm's stock price to the present value of expected future cash flows—unearths the premia again, reaffirming the bias in realized returns. Because options reflect agents' *ex-ante* perception of risk influenced by both ESG preferences, they can better manifest the equilibrium ESG pricing effects than realized returns amid trending capital flows to ESG-conscious stocks. Moreover, I find $ESG^{\$}$ premium to be counter-cyclical, consistent with counter-cyclical risk-based premia prevalent in the asset-pricing literature. By contrast, $ESG^{\Sun}$ premium is pro-cyclical, suggesting an altogether different mechanism.

As a first pass to test for investors' non-pecuniary ESG considerations, I double-sort S&P 500 stocks based on the level of ESG credentials ($ESG^{\Sun}$) controlling for their ESG-risk hedging quality ($ESG^{\$}$), and vice versa. I follow Martin and Wagner (2019) to back out each stock's expected returns and compute both equal- and value-weighted CAPM-adjusted expected returns of the portfolios. I find that, irrespective of $ESG^{\$}$, higher $ESG^{\Sun}$-rated portfolios are expected to compensate lower returns to investors.[8] Given $ESG^{\Sun}$ gauges investors' non-pecuniary benefit from investment, the result supports the predictions of Pastor et al. (2021) and Pedersen et al. (2021) in which investors are willing to pay more for firms with better ESG credentials. In addition, the negative relationship exhibits strong monotonicity, indicating functional continuity of non-pecuniary utility with respect to ESG credentials, as modeled by the two papers.

[7]For example, Whelan et al. (2021) find that 58%, 13%, and 21% out of more than 1,000 research papers published between 2015 and 2020 report positive, neutral, and mixed associations, respectively. See also, Table 5 in Gillan et al. (2021) for a short summary of selected papers with mixed evidence.

[8]$ESG^{\$}$ portfolios do not exhibit any clear pattern, most likely due to omitted risk factors in this first-pass exercise.

Then, I estimate Fama and MacBeth (1973) regressions to quantify both $ESG^{\sun}$ and $ESG^{\$}$ equity premia more directly and rigorously, controlling for firm characteristics and conventional risk factor exposures. Simultaneous inclusion of both ratings serves two main purposes. First, it alleviates any potential confounding effect due to unobservable links between ESG ratings and firm fundamentals.[9] By doing so, I focus on asset pricing implications that are solely attributable to ESG aspects. Secondly, it corrects for any potential omitted-variable bias due to using single ESG rating that is prevalent in the literature. Although the two ratings are set out to evaluate different ESG aspects, they may at least partially overlap in methodologies and inputs to arrive at final ratings, as shown in Figures 1.2 and 1.3. With MSCI embracing alternative data-driven assessments of material ESG-risk exposures like RepRisk in recent years, separating out non-pecuniary ESG component from $ESG^{\sun}$ to unbiasedly estimate its pricing effects necessitates $ESG^{\$}$ alongside in the regression.[10]

In this comprehensive analysis, I find significantly negative equity premia for both $ESG^{\sun}$ and $ESG^{\$}$. For instance, based on Martin and Wagner (2019) estimate of one-month-ahead expected returns, S&P 500 stocks in the highest $ESG^{\sun}$ ($ESG^{\$}$) quintile are expected to underperform those in the lowest $ESG^{\sun}$ ($ESG^{\$}$) quintile by 0.4% (0.4%) per annum. The result is robust to using Kadan and Tang (2020) estimate of one-month-ahead expected returns with return differentials reaching 0.8% and 0.9% per annum for $ESG^{\sun}$ and $ESG^{\$}$, respectively. Even when the sample expands to include all U.S. stocks, the estimated premia remain as sizable as 2.0% and 3.6% per annum, respectively. Non-pecuniary and risk-hedging preferences can explain the negativity of ESG equity premia. High-$ESG^{\sun}$ companies with better track records of managing and advancing ESG themes enjoy cheaper equity financing as the marginal investor derives higher non-pecuniary utility and consequently requires less pecuniary compensations. High-$ESG^{\$}$ companies insulated from controversies and allegations on ESG issues provide better ESG-risk hedging, and hence, are traded at premium leading to lower returns *ex-ante*. Moreover, pro-cyclical $ESG^{\sun}$ premium suggests its source linked to non-risk considerations while counter-cyclical $ESG^{\$}$ premium suggests

[9]For example, Yang (2021) documents ESG rating inflations for bigger sized firms who have more resources and incentives to greenwash.

[10]See MSCI blog post published in 2019 for details on recent developments in MSCI ESG assessment.

its source concerns risk considerations, given the overwhelming empirical evidence documenting counter-cyclicality of risk-related premia.

Strictly speaking, however, the signs and cyclicalities of $ESG^{\text{☼}}$ and $ESG^{\$}$ equity premia cannot rule out the possibility that they both arise from pecuniary concerns tied to ESG-relevant risks. Because the exact rating methodologies are proprietary, we only superficially know $ESG^{\text{☼}}$ more heavily weighs in non-risk components relative to $ESG^{\$}$, while both encompass material ESG-risk components. In order to directly attribute the respective ESG equity premia to non-pecuniary and risk-mitigating preferences, I examine how each rating update differentially impacts stock turnover decisions of actively managed, equity-focused, mutual funds. In particular, I divide funds into two categories, conventional and ESG funds, whose stated mandates or revealed preferences differ in how they value portfolio alignment with ESG principles. I find that while funds uniformly shift away from stocks experiencing $ESG^{\$}$ downgrades, significantly higher fraction of ESG funds tilt demand towards stocks with $ESG^{\text{☼}}$ upgrades than that of conventional funds. The result provides additional support for the validity of $ESG^{\text{☼}}$ and $ESG^{\$}$ as proxies for non-pecuniary and pecuniary considerations. Observed heterogeneity in reactions to $ESG^{\text{☼}}$ changes signifies that $ESG^{\text{☼}}$ contains information more relevant to ESG-fund managers who professedly commit to weigh in ESG-relevant information more heavily. Contrastingly homogenous responses to $ESG^{\$}$, on the other hand, pertains to funds' shared goal of maximizing risk-adjusted financial returns. In brief, this is a strong evidence that $ESG^{\text{☼}}$ and $ESG^{\$}$ equity premia originate from non-pecuniary and risk-mitigating preferences, respectively.

Armed with the validation of ESG metrics on which ESG preferences they proxy for, I investigate how each preference distorts investors' *ex-ante* risk perception disproportionately across all realizable future events. To this end, I deduce risk-neutral distributions of stock returns from option-implied risk-neutral moments à la Bakshi et al. (2003) and study how the shapes of the distributions vary cross-sectionally with respect to $ESG^{\text{☼}}$ and $ESG^{\$}$. Consistent with non-pecuniary preferences, state prices of the tail outcomes shrink for higher $ESG^{\text{☼}}$-rated firms as investors are effectively less concerned about pecuniary risks. Also, as expected, state prices of the left-tail outcomes deflate for higher $ESG^{\$}$-rated firms due to enhanced downside-risk protections, but interestingly enough, those of the right-side events decrease as well. Put differently, the latter suggests investors desire cashing in on monetary returns of ESG-riskier assets when they perform well. This demonstrates investors seeking for pecuniary protections against negative non-pecuniary ESG externalities, as suggested by Baker et al. (2020), because ESG-riskier firms can outperform in states when ESG-safer stocks fare poorly. As an illustration, during a global energy crisis when the push for renewable energy stalls, oil and gas companies thrive. This imposes negative non-pecuniary externalites on ESG-conscious investors (e.g., environmentalists), and in order to hedge, they rationally load up on lower $ESG^{\$}$ firms, pushing up the Arrow-Debreu prices of such states.

To the best of my knowledge, this paper is the first to acknowledge the duality of ESG preferences and jointly study their asset pricing implications using options-based measures. Prior empirical works have treated ESG preferences simplistically, using a single metric to represent them, and examined its asset-pricing implications via realized returns. For example, Hong and Kacperczyk (2009), Di Giuli and Kostovetsky (2014), and Bolton and Kacperczyk (2021) find the negative ESG-return relationship, whereas Edmans (2011), Dimson et al. (2015), Flammer (2015), Lins et al. (2017), Barko et al. (2022), and Madhavan et al. (2021) find the opposite. Common to all of them is that they examined realized return predictability of a single ESG proxy they adopt.[11] My contribution to this long strand of literature on ESG and cost of capital is to propose a more holistic and refined approach that can reconcile and explain its mixed findings. Better understanding on which component (i.e., non-pecuniary vs. pecuniary) of ESG profiles each paper's proxy represents and checking robustness of their results with *ex-ante* proxies for expected returns may lead to similar conclusions that firms with higher ESG credentials or better ESG-risk hedges should command lower equity cost of capital.

This paper also contributes to the growing literature on non-pecuniary preferences. Recent experimental studies, including Riedl and Smeets (2017), Humphrey et al. (2021), and Bonnefon et al. (2022), have documented subjects' non-pecuniary considerations in investment decisions. Empirical support for investors' non-pecuniary preferences mostly resides in the mutual fund literature focusing on fund flows. Bollen (2007), Renneboog et al. (2011) and Bialkowski and Starks (2016) find net flows to socially responsible investment (SRI) funds are less sensitive to past returns and other fund characteristics than conventional funds. Hartzmark and Sussman (2019)

[11]Instead of realized returns, El Ghoul et al. (2011) and Chava (2014) use implied cost of capital derived from accounting-based models and analysts' earning estimates, respectively, and document negative relationship. Still, they both rely on a single ESG metric.

present causal evidence in which funds attracted significant net inflows upon being categorized as high-sustainability funds unexpectedly. Fund-flow evidence, however, should not be taken at its face value. The papers rely heavily on past realized-return volatility being a rightful statistic for a given fund's underlying future risk profile so that they can attribute positive flows unexplained by past volatility to non-pecuniary considerations. In reality, ESG funds have attracted persistently growing amount of new money, as shown in Figure 1.1, that must non-trivially affect funds' realized return volatility over an extended period of time.[12] Because misrepresenting funds' underlying risk profiles may lead to spuriously associating ESG funds' resilient capital inflows with non-pecuniary preference, evidence based on fund flows are suggestive at best.[13] My paper overcomes such limitations by directly assessing how non-pecuniary preferences influence investors' *ex-ante* forward-looking expectations and perceptions, using flow-immune options-based measures and a non-pecuniary-benefit proxy. Therefore, I complement these studies by identifying sizable pricing effects of non-pecuniary preferences, even after properly accounting for ESG-risk and other well-known risk premia. This empirical evidence establishes a firmer connection with theories modelling non-pecuniary preferences (e.g., Heinkel et al. (2001), Fama and French (2007), Pastor et al. (2021), and Pedersen et al. (2021)) by micro-founding their assumptions.

Lastly, I contribute to the very recent literature on ESG and option prices. Focusing on whether climate risk is priced *ex-ante*, Ilhan et al. (2021) find the cost of protection against left-tail risks is larger for more carbon-intense firms. Cao et al. (2021) broaden the scope to overall ESG and argue investors pay premium for options that offer coverage against volatility, volatility risk, and jump risks of poorer ESG-rated firms.[14] Methodologically, the paper is most closely related to Sautner et al. (2021) in uncovering ESG-related equity premia using options-based expected return measures. In addition to two measures I use, the authors also consider an expected return measure of Chabi-Yo

[12]See Pastor et al. (2022) and van der Beck (2021) on how fund flows could mask true return expectations.

[13]The private-market evidence in Barber et al. (2021) show venture capital investors accept lower pecuniary returns for private impact investing funds than other VC funds, but they also rely on the standard deviation of *ex-post* internal rates of return to control for risks. Jeffers et al. (2021) find no underperformance of impact funds relative to comparable private market strategies when market risk exposure is accounted for based on the approach by Korteweg and Nagel (2016).

[14]Berg et al. (2021a) document a retrospective back-filling issue with Refinitiv ESG data on which the results of Cao et al. (2021) are based.

et al. (2022) in which investors care about higher-moment risks. While it enriches their analyses on time-series variation of risk premium, they focus on quantifying climate-related risk premium rather than a broader ESG-risk premium. More importantly, none of these papers acknowledges the duality of ESG preferences, and hence, do not attempt to further disentangle the option-implied ESG premia for correctly identifying inherently distinct ESG preferences.

The remainder of the paper is organized as follows. Section 1.2 describes the data and provides definitions of key variables. Section 1.3 first quantifies the ESG equity premia of the two ESG proxies using option-implied expected returns, then compares and contrasts the premia with those using realized returns and ICCs. Section 1.4 attributes each premia to non-pecuniary and risk-mitigating preferences, respectively, and investigate how they distort investors' *ex-ante* risk perception differently. Section 1.5 examines cross-sectional variations of ESG equity premia and section 1.6 concludes. All tables and figures are presented in section 1.7.

1.2 Data

In this section, I describe the data, how I collected and processed them, and methodologies to construct new variables that are used to produce results presented in section 1.3 and later.

1.2.1 ESG Metrics

I use two different data providers on firms' ESG assessment: MSCI's Intangible Value Assessment (IVA) rating and RepRisk's Reputational Risk Index (RRI). Out of the list of most frequently used ESG ratings by institutions, IVA and RRI have the longest time series, stretching back to 1999 and 2007, respectively.[15] Sustainalytics, another go-to ESG rating provider now a Morningstar company, was not chosen over MSCI IVA due to its shorter time-series since 2014 and its abrupt methodology change in 2018 to shift focus on measuring companies' ESG-risk exposures.[16]

MSCI IVA Rating With more than 1,700 clients including asset managers, underwriters, etc., MSCI IVA ratings have clearly been one of few leading providers of ESG assessments at the firm

[15] Refinitiv's ESG rating, formerly known as Thomson Reuters Asset4, starts from 2002, but it is of annual frequency. More importantly, according to Berg et al. (2021a), Refinitiv constantly backfills the data, so the rewritten data diverge from what investors actually saw at any given time.

[16] For more information on methodology change, see Morningstar report in 2019.

level.[17] They cover more than 3,800 U.S. firms and 14,000 firms worldwide at the end of 2020. Also, they cover the longest time span starting from 1999 as MSCI acquired RiskMetrics in 2010 who acquired both KLD Research and Analytics (creator of KLD STATS, founded in 1988) and Innovest Strategic Value Advisors (creator of IVA, founded in 1992) in 2009. MSCI discontinued KLD and kept IVA as the core methodology on which MSCI's flagship ESG rating is built and offered to investors.[18]

MSCI collects data from company disclosures to macro data such as academic, government, NGO, and stakeholder datasets. As a descendant of Innovest IVA, MSCI IVA has continued the legacy of evaluating key performance metrics within the key ESG issues listed in figure 1.2 to arrive at overall ESG ratings for companies. Now labeled as ESG management metrics, these performance metrics are designed to assess companies' historical ESG policies and programs. Such emphasis on the track record inevitably leaves backward-looking footprints in IVA rating, despite of adding a dimension to integrate ESG-risk exposure assessment. Because the rating fluctuates based on past ESG performances, it is intuitively linked to investors' non-pecuniary preferences who derive (dis-)utility based on how (mis-)aligned a company's built-in ESG profiles are with their ESG standards.

For all empirical analyses, I use IVA raw score ($ESG^{\text{☼}}$) that aggregates raw E, S, and G pillar scores according to their respective importance weights that vary across GICS Sub-industry level (8-digit) industries.[19] A higher score is assigned if the company has had strong initiatives or track records of oversight on one or more key issues in figure 1.2 that have been deemed particularly important for its industry. IVA industry-adjusted score further adjusts the raw score to represent companies' ranks relative to their global industry peers. Because the paper focuses on US-incorporated firms whose shareholders are predominantly representative of US investors, such additional industry benchmarking may not be desirable in understanding ESG preferences of

[17]According to recent surveys and interviews on investment firms by SustainAbility, an ERM Group company, MSCI IVA is the most often used by investors mainly due to its broad coverage, qualitative reports that accompany scores, and methodology most oriented towards the investment use case. (`https://www.sustainability.com/thinking/rate-the-raters-2020/`)

[18]For details on origins and histories of MSCI ESG rating construction, see Eccles et al. (2019).

[19]It should be noted that the assigned importance weights can be different across companies in the same industry, albeit rarely.

market participants in the U.S.[20] $ESG^{\sun}$ ranges from 0 to 10 and are updated upon arrivals of new and significant information which can be as frequent as monthly. Hence, the data is of monthly frequency spanning from to September 1999 to December 2021.

RepRisk RRI Rating Founded in 2006 originally as a part of the investment bank UBS, RepRisk provides information on firms' exposures to ESG risks to numerous institutional clients, from major hedge funds to large banks, by tracking news of CSR-related incidents of firms. RepRisk adopts machine learning technology to screen over 100,000 information sources on ESG news that are related to one of the 28 predefined incidents listed in figure 1.3. These sources include print and online media (including local, national, and international media), NGOs, government agencies, think tanks, social media, and many other sources.

Unlike MSCI IVA rating, RepRisk's Reputational Risk Index (RRI) is designed to be forward-looking as it only monitors incidents (e.g., allegations, accusations, criticisms) that can have financial impacts on a company in some realizable future states (e.g., regulations, social movements, extreme weather events). It excludes company self-disclosures to further insulate its rating from capturing a company's ESG status quo or credentials. Consistent with this unique approach, Berg et al. (2021b) find that RRI is the least correlated ESG rating with other well-known ESG ratings. Presumably, therefore, $ESG^{\$} = -RRI$ should quantify the level of ESG-risk hedge a given company provides, an information of interest for any risk-averse investors that is potentially distinct from (or only partially overlap with) what $ESG^{\sun}$ captures.

$ESG^{\$}$ which ranges from -100 to 0 and is updated daily from Jan. 2007. $ESG^{\$}$ of -25 to 0 indicates a high ESG-risk hedge where the majority of assessed firms belongs, -49 to -26 a medium ESG-risk hedge, -74 to -50 a low ESG-risk hedge, and -100 to -75 an extremely low ESG-risk hedge. $ESG^{\$}$ of a firm decreases whenever a firm experiences a new ESG incident. How much it decreases depends on the severity and novelty of the incident as well as on the reach and intensity of the news about the incident. $ESG^{\$}$ recovers to -25 within a few months and to 0 within two years if a firm stays free from new incidents over the period. Importantly, $ESG^{\$}$ does not put different importance weights on 28 ESG issues across different sectors, unlike $ESG^{\sun}$. Moreover, most large

[20]Still, all of the results in section 1.3 and onwards are robust to using industry-adjusted $ESG^{\sun}$. See internet appendix Table A.3, for example.

multinationals are expected to rarely stay above -26 due to their global footprint and salience vis-à-vis media and stakeholders.[21]

1.2.2 Options & Equity Markets Data

I obtain daily data on U.S. individual stock options from Ivy DB US OptionMetrics. The dataset includes the daily highest closing bid and lowest closing ask prices, trading volume, open interest, and Cox et al. (1979)'s binomial model-implied volatility of each American-style option whose underlying stock's closing price is also available.

I extract US-listed equity and index options from Jan. 2000 to Dec. 2021 that mature in about a month (within 15 to 45 days-to-maturity) and expire at the end of the third week of the month. To further ensure analyses to be based on actively traded options with minimal data errors, I keep options with positive volumes traded, positive highest closing bid, and positive lowest ask prices.[22] Finally, I remove options with missing values for implied volatility.

Option-implied *Ex-ante* Returns Martin and Wagner (2019) (MW, hereafter) derive an parameter-free formula for the *ex-ante* expected return on an equity market index constituent where the options of a given equity and its index are traded. This theoretically motivated and empirically validated approximation of individual stock's expected return uses option-implied risk-neutral variances of the stock and the index it constitutes. With log-utility investors and using the fact that a typical stock's β on the market return is not too far away from 1, the authors establish

$$\frac{\mathbb{E}_t[R_{i,t+1}] - R_{f,t+1}}{R_{f,t+1}} = SVIX^2_{m,t} + \frac{1}{2}\left(SVIX^2_{i,t} - \bar{SVIX}^2_t\right),$$

where $SVIX_{m,t}$ and $SVIX_{i,t}$ represent risk-neutral variances of the index m and its constituent stock i, and finally $\bar{SVIX}^2_t = \sum_i \omega_{i,t} SVIX^2_{i,t}$ is a value-weighted average of risk-neutral variances of all index constituents.[23] I choose S&P 500 index as the benchmark market index not just because option contracts with wide range of moneyness are actively traded but also because the ESG metrics

[21]See section 1.5.3 for how ESG integration varies across domestic and multinational companies.

[22]Only few options with maturity longer than a month survive after such screening procedure.

[23]More specifically, risk-neutral variances are normalized by risk-free rate so that $SVIX_{i,t} \equiv Var^*_t\left(\frac{R_{i,t+1}}{R_{f,t+1}}\right)$.

have extensive coverage on S&P 500 firms. To identify time-varying S&P 500 constituents and their respective $\omega_{i,t}$, I retrieved time-series of SPDR S&P 500 ETF Trust (ticker: SPY) stock holdings using both Thomson Reuters S12 mutual fund holdings data (until 2010/3) and CRSP Survivor Bias-Free US Mutual Funds portfolio holdings data (from 2010/6).[24] For dates without information about $\omega_{i,t}$ while that about the number of shares held is available, I use stocks' CUSIP identifiers to collect stock prices reported by CRSP Security Files database and impute $\omega_{i,t}$.

Branching out from the same theoretical ground of MW using Martin (2017) approach, Kadan and Tang (2020) (KT, hereafter) provide formula for the lower bounds of individual stocks' expected returns as follows:

$$\mathbb{E}_t[R_{i,t+1}] - R_{f,t+1} \geq \frac{Var_t^*(R_{i,t+1})}{R_{f,t+1}},$$

where $Var_t^*(R_{i,t+1})$ denotes risk-neutral variance of stock i's return. More stringent than MW, KT requires individual stocks to meet Martin (2017)'s *negative correlation condition* (NCC), not just their market index. KT derive sufficient conditions under which NCC holds under a variety of conventional asset pricing models with standard or recursive Epstein and Zin (1989) preferences

$$Cov_t(M_{t,t+1}R_{i,t+1}, R_{i,t+1}) \leq 0, \tag{1.1}$$

where $M_{t,t+1}$ denotes a one-period state-price deflator (SDF) between time t and $t+1$. For different models, the sufficient conditions boil down to an asset i having (i) non-negative correlation with the market return and (ii) assumed relative risk-aversion parameter γ sufficiently high. Hence, depending on the range of acceptable γ, the scope of NCC-satisfying stocks may shrink. Nevertheless, I take a liberal approach and include all S&P 500 stocks, except those that fail to meet (i), as KT document more than 99% of CRSP-listed S&P 500 stocks satisfy NCC under Epstein and Zin (1989) utility specification with γ around 5.

Risk-neutral Moments of Returns Including $SVIX$ measures, this paper requires higher moments of the risk-neutral probability distribution (RND) of a month-ahead returns to understand how the two distinct ESG preferences perturb the distribution both qualitatively and quantitatively. The seminal work by Breeden and Litzenberger (1978) establishes the relation between RND and

[24]The use of two datasets gets away from the reliability issue of CRSP Holdings data on SPY pointed out by WRDS Research.

European call option prices over a continuum of strike prices spanning the possible range of future payoffs. Using their approach, MW define

$$SVIX_{e,t}^2 = \frac{2}{R_{f,t+1} S_{e,t}^2} \left[\int_0^{S_{e,t}} p_e(t, t+1, K) dK + \int_{S_{e,t}}^{\infty} c_e(t, t+1, K) dK \right], \quad e \in \{i, m\},$$

where $R_{f,t+1}$ is the gross risk-free rate from time t to $t+1$, $S_{e,t}$ the underlying equity e's time-t spot price, and $c_e(t, t+1, K)$ and $p_e(t, t+1, K)$ denote call and put prices that expire at time $t+1$ with strike K.

Evidently, the precision of $SVIX$ measures to risk-neutral variance suffers from the lack of far enough out-of-the-money call and put options being traded. Figlewski (2010), among many others, suggested inter- and extrapolation methods on observed implied volatilities to infer option prices over a continuum of strike prices from a smoothed volatility surface.[25] To avoid unnecessary smoothing and overshoots, I interpolate using a piecewise cubic Hermite polynomial with clamped endpoints, following Malz (2014), which avoids violations of no-arbitrage restrictions. Continuum of out-of-the money call and put option prices emerges to compute $SVIX$ measures.

For higher risk-neutral moments, I follow the model-free derivations of Bakshi et al. (2003). In particular, the τ-period risk-neutral return skewness and kurtosis at time t are given by

$$\begin{aligned} SKEW(t,\tau) &= \frac{e^{r_f \tau} W(t,\tau) - 3\mu(t,\tau) e^{r_f \tau} V(t,\tau) + 2\mu(t,\tau)^3}{[e^{r_f \tau} V(t,\tau) - \mu(t,\tau)^2]^{3/2}}, \\ KURT(t,\tau) &= \frac{e^{r_f \tau} X(t,\tau) - 4\mu(t,\tau) e^{r_f \tau} W(t,\tau) + 6 e^{r_f \tau} \mu(t,\tau)^2 V(t,\tau) - 3\mu(t,\tau)^4}{[e^{r_f \tau} V(t,\tau) - \mu(t,\tau)^2]^2}, \end{aligned}$$

where $V(t,\tau)$, $W(t,\tau)$, and $X(t,\tau)$ are prices of the volatility, cubic, and quartic contracts, respectively; $\mu(t,\tau)$ is the risk-neutral expectation of the log return over the period τ; and r_f is the time-t prevailing risk-free rate.[26] As with $SVIX$ measures, $SKEW(t,\tau)$ and $KURT(t,\tau)$ critically depend on the availability of out-of-the-money call and put option prices. I follow the same procedure as outlined earlier to populate them over wide range of strike prices to approximate these moments.

[25] Following Aramonte et al. (2021), if implied volatilities of both a call and a put option with the same strike price K are available, I compute the volume-weighted implied volatility for the given moneyness to better incorporate relative liquidity of the two options.

[26] See Theorem 1 and its proof in Bakshi et al. (2003) for details. Also, see appendix A.1 for how $\mu(t,\tau)$ differs from the risk-neutral mean imputation of Bakshi et al. (2003).

Because the focus of the paper is on U.S. stocks and their options traded on American exchanges, individual stock and market index options are of American style. To reconcile it with above European style option-implied measures, I use binomial option pricing model à la Cox et al. (1979) to account for early exercise premia when pricing options with their corresponding inter- or extrapolated implied volatilities. Because OptionMetrics provided volatility surfaces of American options based on the same binomial-tree model, all of inter- or extrapolated elements in the formulae are effectively European-equivalents, following Carr and Wu (2009) among others. Hence, the above risk-neutral moment identities are applicable to U.S. stocks.

Equity Prices & Fundamentals Daily stock returns, price, trading volumes, and shares outstanding are obtained from the Center for Research on Security Prices (CRSP). The accounting data are collected from Compustat. I focus on individual common stocks (CRSP share codes of 10 and 11) that primarily trade on AMEX, NASDAQ, or NYSE (CRSP primary exchange codes of 'A', 'Q', or 'N', respectively). The daily Fama-French factors and risk-free rates are from Kenneth French's data library. The details of all of the control variables constructed from these datasets are presented in Table 1.1.

1.2.3 Final Panel

For the sample period from January 2007 to December 2021, I merge all data sources to construct a monthly panel of firms with ESG metrics, *ex-ante* expected monthly stock returns, option-implied risk-neutral moments, stock prices and company fundamentals.[27] The date of each month is the last trading day of the third week, which is the most popular, hence actively traded, option expiration date. CRSP, Compustat, and OptionMetrics data are merged using CRSP/Compustat Merged (CCM) and OptionMetrics-CRSP linking tables available on Wharton Research Data Services (WRDS). MSCI IVA rating identifies firms with both ISINs and CUSIPs while RepRisk RRI rating does with ISINs only. To match each unique publicly traded firm, represented by a CRSP identifier *permco* that tracks historical CUSIPs of the same firm, with its corresponding ESG metrics, I use the Refinitiv Eikon database to construct a linking table that amasses all ISINs and CUSIPs ever assigned to securities issued by every unique firm in the sample. This only leaves very few firms

[27]For backward looking variables such as past 12-month return volatility and 36-month rolling CAPM-β, the data prior to January 2007 is used.

with more than one matched ESG ratings, mostly due to ESG data providers either (i) treating different identifiers for the same firm separately or (ii) lagging consolidation (severance) of ratings at the time of mergers (spin-offs). For these firms, I manually choose the most time-consistent ESG rating.[28] Finally, I exclude financial sector stocks (i.e., $6000 \leq SIC$ Code ≤ 6999) and observations when previous stock prices were below 1.[29]

Tables 1.2 and 1.3 provide summary statistics of the final panel from January 2007 to December 2021 when both $ESG^{☼} = IVA$ and $ESG^{\$} = -RRI$ data are available. Almost all S&P 500 stocks are assigned with both $ESG^{☼}$ and $ESG^{\$}$ ratings during the sample period, while roughly less than half of CRSP stocks carried both during the same time period. Not surprisingly, S&P 500 stocks are on average bigger in size and assets, more growth-oriented, lower in leverage, and higher in earnings. They are much more liquid and their prices are less volatile. Interestingly, in both samples, the average time-series correlations of the two proxies $Corr(ESG_t^{☼}, ESG_t^{\$})$ are close to 0 with only few companies having $|Corr(ESG_t^{☼}, ESG_t^{\$})| \geq 0.5$. Given that $ESG_t^{☼}$ is quite persistent and rarely jumps for any given firm, such low Pearson correlation coefficient highlights the dissimilarity between the two. If one proxy is specialized in gauging non-pecuniary ESG aspects while the other calibrates the degree of material ESG-risk hedge, then we should expect $Corr(ESG_t^{☼}, ESG_t^{\$}) \approx 0$ on average.

1.2.4 Mutual Funds Holdings Data

In section 1.4, I look at how mutual funds adjust portfolio holdings to firm-level $ESG^{☼}$ and $ESG^{\$}$ updates to examine their validity as proxies for non-pecuniary and risk-mitigating preferences, respectively. To this end, I retrieve monthly (with gaps) mutual fund characteristics and holdings data from CRSP Survivor Bias-Free Mutual Fund Database from Jan. 2003 to Dec. 2020.[30] The same CRSP *portno* is assigned to funds with multiple share classes, so they are treated as a single fund. Also, I restrict the sample to actively managed U.S. domestic equity funds by omitting index

[28]Majority of such cases have ESG ratings identical when rounded up to nearest decimal.

[29]All of the results in section 1.3 and onwards are robust to (i) using NAICS 2-digit code to exclude financial sector, (ii) additionally excluding utility sectors ($4900 \leq SIC$ Code ≤ 4949) or (iii) not excluding any sectors.

[30]As Lettau et al. (2021) point out, CRSP provides the most comprehensive data on mutual fund holdings since 2002. Thomson Reuters s12 database is important for the pre-2002 periods.

funds and ETFs. I drop observations on dates when funds (i) held less than 90% of total net assets (TNA) invested in CRSP stocks (i.e., stocks with CRSP-assigned *permnos*), (ii) held less than 100 unique CRSP stocks, or (iii) managed less than $1 million TNA.[31] Finally, I keep funds with tenure of 2 years or longer (i.e., portfolio holdings data available for more than 2 years). Using *permnos* (and corresponding *permcos*) of portfolio holdings, Compustat-based firm-level fundamentals and ESG proxies are merged in.

1.3 ***Ex-ante*** **ESG Integration**

As shown in figure 1.1, the size of professionally managed assets with ESG analysis and strategies in the United States has been growing exponentially in the recent decade, hitting $17.1 trillion at the end of 2020. This survey-based identification of ESG-focused AUM practices by all money managers is backed up by concurrent and comparable growth in net flows to sustainable funds.[32] During such prolonged demand shift diverges the gap between *ex-ante* expected returns and *ex-post* realized returns to the extent that the latter no longer unbiasedly estimate the former.[33]

In this section, I address the challenge directly and compute parameter-free *ex-ante* expected returns by MW, as described in section 1.2.2, to identify equity premia associated with variations in ESG metrics $ESG^{\text{☼}}$ and $ESG^{\$}$. Also, I use KT's expected return lower bound estimates to leverage its applicability to equities that do not constitute major market indices.[34] Both measures, as theoretically shown in appendix A.1, should reflect not only investors' pecuniary risk considerations but also their non-pecuniary preferences, if exist. More importantly, they should be unaffected by trending ESG capital flows. Even if investors form expectations of continuing capital inflows to ESG-friendly assets, risk-neutral variances of such assets would hardly change because consequent

[31] Kacperczyk et al. (2008) used 80% of TNA as their threshold to define an equity-focused funds. Chen et al. (2021) and Chen et al. (2004) screen out funds with less than $5 and $15 million, respectively. Results in section 1.4 are robust to these screening variations.

[32] Morningstar estimates flows for 315 open-end and exchange-traded funds that it defines to have ESG focus. This includes equity, fixed-income, allocation, and alternative funds, in which the first two has attracted the majority of the capital poured in.

[33] See Elton (1999) and Pastor et al. (2022), for example.

[34] Chabi-Yo et al. (2022) generalize the expected return estimate to reflect higher order moments, but necessitate an additional restrictions on the prudence parameter (i.e., skewness preferences), unlike MW or KT.

depreciation (appreciation) of out-of-the-money put (call) option prices only perturbs the first moment. Relatively more susceptible to flow-induced biases are *ex-post* realized returns and ICC measures, and I investigate whether using them leads to the same conclusion.

The main goal is to examine how and to what extent $ESG^{\text{☼}}$ and $ESG^{\$}$ are integrated in investment decisions *ex-ante*. As described in section 1.2.1, $ESG^{\text{☼}}$ and $ESG^{\$}$ are quantities based on distinct rating methodologies and information sets, albeit not completely unrelated. In particular, $ESG^{\$}$ weighs in the breadth and depth of media coverage on ESG-risk incidents above all. Furthermore, $ESG^{\$}$ intentionally disregards voluntarily reported company disclosures, unlike $ESG^{\text{☼}}$ which relies on them for company-specific information. Specific to $ESG^{\text{☼}}$ is evaluating the track records of companies' performance in managing key ESG issues within their industries and awarding ESG-promoting commitments and policies.[35] Therefore, $ESG^{\text{☼}}$ is likely to reflect historical ESG performances and pledges much more so than $ESG^{\$}$ that aims at measuring preparedness for future negative ESG incidents. Naturally, ESG-conscious investors would integrate the two metrics separately if each metric is deemed informative on its own. Moreover, if such investors have been controlling a significant fraction of market participants' total wealth, equilibrium equity prices must adjust to cross-sectional variations in $ESG^{\text{☼}}$ and $ESG^{\$}$ over time.

1.3.1 ESG Equity Premia

First, I use a conventional portfolio sort as a first pass to probe equity premia associated with $ESG^{\text{☼}}$ and $ESG^{\$}$. More specifically, I divide stocks into 25 (5×5) quintile portfolios based on the levels of $ESG^{\text{☼}}$ and $ESG^{\$}$. In each month t, I sort stocks into 5 groups according to $ESG^{\text{☼}}$. Within each $ESG^{\text{☼}}$ group, I further sort stocks into 5 groups according to $ESG^{\$}$. For each portfolio, I compute both value-weighted and equal-weighted expected returns, net of market risk premium estimated through 36-month rolling market β of each portfolio, and rebalance it in month $t+1$.[36] Also, I construct zero-cost trading strategies LMH in which an investor takes long positions in the lowest $ESG^{\text{☼}}$ ($ESG^{\$}$) quintile and short positions in the highest $ESG^{\text{☼}}$ ($ESG^{\$}$) quintile within each of 5 levels of $ESG^{\$}$ ($ESG^{\text{☼}}$) to assess equity premia in each dimension. Finally, I compute

[35] For the actual rating changes based on such criteria, see this Bloomberg article.

[36] I avoid netting out other factor risk premia as it involves estimation of portfolio-level factor exposures that is known to exacerbate errors-in-variables concern.

expected return of a "long low-$ESG^{☼}$-low-$ESG^{\$}$ and short high-$ESG^{☼}$-high-$ESG^{\$}$" portfolio **in bold red**.

Panels A and B of Table 1.4 report value-weighted and equal-weighted MW expected returns, respectively.[37] Because I only adjust for the market risk premium, the tabulated expected returns of portfolios are mostly positive and significant. Even with these crude measures that are likely to comprise other risk premia, high-$ESG^{☼}$ stocks have been consistently associated with significantly lower *ex-ante* premia than low-$ESG^{☼}$ stocks, suggesting $ESG^{☼}$ premium is largely orthogonal to risk premia and arises from non-risk considerations. Conditional on ESG-risk hedge level, both value-weighted and equal-weighted expected returns monotonically decrease by and large as $ESG^{☼}$ increases. Moreover, unconditional to ESG-risk hedge level, investors expect the $ESG^{☼}$ LMH portfolios to generate significant monthly excess returns of at least 1.2% per annum. Much less obvious is the pricing implication of $ESG^{\$}$. First of all, given $ESG^{☼}$, no discernible relation between expected returns and $ESG^{\$}$ exists. Also, $ESG^{\$}$ LMH portfolio returns in Panel A and B contradict in which the former (latter) suggests positive (negative) ESG-risk hedge premium. The fact that bigger sized firms are more prone to ESG controversies (Glossner (2021)) and that investors command lower premia from them in general can partially reconcile this divergence and side with negative $ESG^{\$}$ premium. However, it requires further investigation as other omitted pricing factors most likely confound the results.

To identify and quantify ESG equity premia more precisely, I estimate the following Fama and MacBeth (1973) regressions

$$\begin{aligned}
\mathbb{E}_t[R^{ex}_{i,t+1}] &= \alpha_i + \lambda_1 ESG^{☼}_{i,t} + \lambda_2 ESG^{\$}_{i,t} + \boldsymbol{\zeta}'\boldsymbol{X}_{i,t} + \varepsilon_{i,t+1}, \\
\mathbb{E}_t[R^{ex}_{i,t+1}] &= \alpha_i + \lambda_1 ESG^{☼}_{i,t} + \mu_1 \mathbb{1}(ESG^{☼}_{i,t} < 2) + \tilde{\lambda}_1 ESG^{☼}_{i,t} \times \mathbb{1}(ESG^{☼}_{i,t} < 2) \\
&\quad + \lambda_2 ESG^{\$}_{i,t} + \mu_2 \mathbb{1}(ESG^{\$}_{i,t} < -40) + \tilde{\lambda}_2 ESG^{\$}_{i,t} \times \mathbb{1}(ESG^{\$}_{i,t} < -40) + \boldsymbol{\zeta}'\boldsymbol{X}_{i,t} + \varepsilon_{i,t+1},
\end{aligned} \tag{1.2}$$

where $\mathbb{1}(ESG^{☼}_{i,t} < 2)$ and $\mathbb{1}(ESG^{\$}_{i,t} < -40)$ are dummy variables that equal 1 if $ESG^{☼}_{i,t}$ is in the lowest quintile and if $ESG^{\$}_{i,t}$ falls below -40 to be in the lowest quintile, respectively, and 0

[37]The results are robust to 3×3 and 7×7 portfolio sorts. Moreover, using KT expected returns, which expand the universe of stocks to all CRSP-listed stocks, also exhibit similar trends.

otherwise.[38] At each month, the regressors are winsorized at the top and bottom 5% only for the level variables, except for $ESG_t^{☼}$ and $ESG_t^{\$}$, not the logarithm variables.[39] All regressors, except for factor β's, are standardized to mean 0 and standard deviation 1 at each month.

Because $ESG_{i,t}^{☼}$ and $ESG_{i,t}^{\$}$ can be correlated over time at the stock level, I intentionally include both in the regression to alleviate omitted variable biases that may arise if both meaningfully explain expected-return variations. The vector $\boldsymbol{X}$ stacks potential pricing factors, including 36-month rolling market beta, firm market value, book-to-market ratio, past 6-month momentum, past 6-month average turnover, leverage, investment, and earnings per share.[40] The parameter λ's are of interest that estimate pricing effects of both ESG proxies and detect non-linearities, if any.

Table 1.5 tabulates the results, with the first 6 columns for MW expected-return measure $\mathbb{E}_t^{MW}[R_{i,t+1}]$ and the last 6 columns for KT expected-return measure $\mathbb{E}_t^{KT}[R_{i,t+1}]$. Under MW measure, I confirm significantly negative equity premia for both $ESG^{☼}$ and $ESG^{\$}$ at the 5% and 1% significance levels, respectively, based on Newey and West (1987) autocorrelation corrected standard errors in empirical specifications with different sets of pricing factors. All else equal, in the richest set-up controlling for well known pricing factors, 1 standard deviation increase in $ESG^{☼}$ is associated with about 12 basis points (b.p.) per annum drop of one-month-ahead returns expected by shareholders. This is tantamount to 0.36% decrease in expected returns per annum for firms moving from the lowest to highest $ESG^{☼}$ quintile. For $ESG^{\$}$, 1 standard deviation increase results in 14 b.p. decrease in one-month-ahead expected returns per annum on average, which is equivalent to around 0.43% decrease in expected returns due to being less vulnerable to material ESG controversies that puts firms from the lowest to highest $ESG^{\$}$ quintile.

In fact, the magnitudes based on MW measure are possibly underestimates. It is important to note that MW derive an exact formula for expected returns of any stocks that constitute the market, assuming log-utility preference for investors. Given the assumption is not too far-fetched, MW measure must inherit the cross-sectional and time-series variations of the actual expected returns,

[38]Note $ESG_{i,t}^{\$}$ rarely falls below -60.

[39]All regression specifications of this paper winsorize regressors in this way with an only exception of R_t^{ex} when used as a regressor. All results are robust to 1% winsorization.

[40]The results are robust to using the illiquidity measure of Amihud (2002), capital expenditure, and gross-profitability measure of Novy-Marx (2013) (or return-on-equity), instead of turnover, investment, and earnings per share, respectively. Details of these alternative variables are provided in Table 1.1.

and hence ideal for accurately pinning down the signs of λ's. We know, however, CAPM with relative risk-aversion parameter $\gamma = 1$ severely underestimates the observed equity premium. This suggests the true magnitudes of ESG pricing effects could be higher, while the estimated (negative) signs of λ's are presumably accurate.

In contrast, KT measure applies no such restriction on γ. In turn, it only manages to specify a lower bound on expected returns of stocks that meet sufficient conditions to ensure (1.1). Nevertheless, if the lower bound co-moves with the actual expected returns at least partially, then it could be an improved proxy for expected returns to uncover the magnitudes of λ's more precisely. Indeed, the estimated pricing effects of $ESG^{\text{☼}}$ and $ESG^{\$}$ approximately double under the KT measure, as shown in latter 6 columns of Table 1.5. Firms with lowest quintile $ESG^{\text{☼}}$ ratings are expected to compensate about 0.76% per annum higher in one-month-ahead returns than those with highest quintile $ESG^{\text{☼}}$ ratings, while firms with lowest quintile $ESG^{\$}$ ratings are expected to compensate about 0.9% per annum higher in one-month-ahead returns than those with highest quintile $ESG^{\$}$ ratings. Admittedly, the relative crudeness of KT measure may misconstrue the actual magnitude of ESG pricing effects. Nonetheless, that the results are robust to using KT measure is particularly convincing, considering it is constructed to only partially capture the true variations of equity premia.

Moreover, I find similar results in an expanded sample of stocks including non S&P 500 companies, as shown in Table 1.6. The inclusion arguably injects unexplainable randomness that hampers statistical power. Yet, the same directionality of ESG pricing effects persists and the size of the effects multiplies across empirically reasonable range of γ and beyond.[41] I perform an additional robustness check, running another Fama and MacBeth (1973) regression using estimated factor exposures (i.e., β's) identified in Carhart (1997) and Fama and French (2017) as $X_{i,t}$ in equation (1.2), instead of firm fundamentals. Although Kim (1995) points out this framework suffers from the well-known errors-in-variables problem and may overestimate the magnitudes and explanatory powers of non-factor coefficients, Table 1.7 reports extremely high t-statistics for λ_1

[41]KT first-order approximates sufficient conditions for (1.1) to hold for individual stocks with $\delta_{i,t} = \frac{Var_t(R_{i,t})}{Cov_t(R_{i,t}, R_{m,t})}$. More specifically, KT measure is a legitimate lower bound of expected returns for stocks that meet (i) $Cov(R_{i,t}, R_{m,t}) > 0$ and (ii) $\delta_{i,t} \leq \gamma$ for the previous 12 months.

(significant at 1%) and λ_2 (significant at 1% or 5%) across all specifications, alleviating the concern of spurious inference.[42]

Throughout the analyses, I have examined potential non-linearities of ESG pricing effects and negative screenings, motivated by recent papers including Hartzmark and Sussman (2019) and Humphrey et al. (2021). The predominance of negative screenings in socially responsible investing practice would predict stronger pricing effects and larger equity premia in the tails—the lowest $ESG^{\sun}$ and lowest $ESG^{\$}$ firms—because of the lack of risk sharing among investors who end up holding more of these tail assets than they desire.[43] Interestingly, however, I fail to reject the null that the overall $ESG^{\sun}$ effect is quantitatively similar near the tails in all cases. More action occurs within the lowest quintile $ESG^{\$}$ stocks in both S&P 500 and all CRSP samples. As shown in Tables 1.5 and 1.6, extremely poor ESG-risk hedges seem to carry a non-negligible markup ($\tilde{\lambda}_2$) in expected returns per additional revelation of material ESG liabilities. This indicates negative-screening practices mostly pertain to attenuating downside pecuniary ESG-risk exposures. Interestingly enough, however, extremely poor ESG-risk hedges do seem to be valued at a premium on average with lower expected returns (i.e., negative μ_2). I provide a rationale for it in relation to ESG-conscious investors' hedging demand in section 1.4.4. Determining why there lacks evidence for non-pecuniary-based screening is out of the scope of this paper. Yet, the facts that (1) investors do not necessarily exclude assets based on aggregated ESG profile but laboriously assess each element in E, S, and G categories and (2) U.S. money managers are not as actively excluding ESG-sin assets as Europe (see figure 1.4) may render plausibility to it.

1.3.2 Realized Returns

Recovering *ex-ante* returns requires assumptions. Although both MW and KT measures rely on arguably benign assumptions on the degree of investor risk aversion, they inevitably have limitations as estimates. Nevertheless, they should better manifest *ex-ante* perception of investors than *ex-post* realized returns, especially when unanticipated shocks persist long enough for the latter to belie

[42]The baseline regression that includes estimated market β's is not immune to the problem, but there is no evidence to suggest any systematic correlation between the two ratings and estimated market β's at the firm level, which is the source that causes biases.

[43]See Heinkel et al. (2001) for the theoretical rationale behind such prediction.

investors' *ex-ante* ESG integration. In other words, if investors expected persistent demand surge for ESG products and efficiently priced such information in, then the same analyses using realized returns should reveal comparable pricing effects of both $ESG^{\sun}$ and $ESG^{\$}$.

I start by examining CAPM-adjusted realized excess returns of the double sorted ESG portfolios based on the levels of $ESG^{\sun}$ and $ESG^{\$}$. Table 1.8 fails to identify any meaningful pattern across the two dimensions in either of value-weighted or equal-weighted portfolio returns. The arbitrariness contrasts with Table 1.4 that exhibits clear patterns in the ranks of $ESG^{\sun}$, and this discernible divergence between the two hints that unexpected and non-random positive demand shocks for high-$ESG^{\sun}$ stocks have lingered over the sample period affecting realized returns non-trivially.

Table 1.9 zooms in on ESG pricing effects more comprehensively by estimating (1.2) via Fama and MacBeth (1973) regression, replacing $\mathbb{E}_t[R^{ex}_{i,t+1}]$ with $R^{ex}_{i,t+1}$. Almost all $ESG^{\$}$ coefficients are not statistically significant for the samples with and without non S&P 500 stocks. Interestingly enough, the $ESG^{\sun}$ coefficients turn positive, albeit insignificantly, for both samples. Juxtaposing these estimates with significantly negative estimates of λ_1 and λ_2 in Tables 1.5 & 1.6 underlines a considerable wedge between expected and realized returns.

Because realized returns of individual stocks exhibit idiosyncracies more markedly than expected returns by nature, I run a cross-sectional return predicability regression that controls for both time and industry fixed effects. Namely, I estimate the following regression for any realized return of a stock i in an industry j of Fama-French 49-industry classifications at time $t+1$

$$\begin{aligned} R^{ex}_{i,t+1} = \alpha + \theta_j + \nu_q + \lambda_1 ESG^{\sun}_{i,t} + \mu_1 \mathbb{1}(ESG^{\sun}_{i,t} < 2) + \tilde{\lambda}_1 ESG^{\sun}_{i,t} \times \mathbb{1}(ESG^{\sun}_{i,t} < 2) \\ + \lambda_2 ESG^{\$}_{i,t} + \mu_2 \mathbb{1}(ESG^{\$}_{i,t} < -40) + \tilde{\lambda}_2 ESG^{\$}_{i,t} \times \mathbb{1}(ESG^{\$}_{i,t} < -40) + \boldsymbol{\zeta}' \boldsymbol{X}_{i,t} + \varepsilon_{i,t+1}, \end{aligned} \tag{1.3}$$

where q denotes the calendar quarter at month t, θ_j and ν_q denote industry and quarter fixed effects, respectively.[44] They absorb any unobservable industry- and time-specific trends that influence *ex-post* stock returns and potentially confound the ESG pricing effects. Table 1.10 reports the re-estimated coefficients and t-statistics based on clustered standard errors at the stock level. One noticeable change occurs to the $ESG^{\$}$ coefficients λ_2's that are significantly negative for both samples and more so for non-S&P 500 stocks. Although the effect is concentrated for extremely

[44]Results are robust to using 2-digit or 3-digit NAICS industry fixed effects.

poor ESG-risk hedge within S&P 500 stocks, the overall association between realized returns and $ESG^{\$}$ is consistently strong to infer negative ESG-risk hedge premium. Lowest $ESG^{\$}$ quintile S&P 500 firms outperform the highest $ESG^{\$}$ quintile S&P 500 firms by about a sizable 7.4% per annum over next month *ex-post*, all else equal, in the richest specification.

While the re-estimated λ_2 suggests alignment of expected and realized returns, the re-estimated $ESG^{\Sun}$ coefficients consistently suggest otherwise. Similar to the results in Table 1.9, negative $ESG^{\Sun}$ premium vanishes and now turns significantly positive throughout the specifications in both samples of S&P 500 stocks and all CRSP stocks, consistent with higher-$ESG^{\Sun}$ stocks experiencing unexpected capital inflows that elevate *ex-post* returns. This echoes not only the meta-analysis result of Friede et al. (2015) who document 90% of academic studies prior to 2015 find non-negative (and mostly positive) relation between ESG profiles and returns but also the practitioners' rhetoric of "doing well by doing good."[45] Also, notice the signs (or statistical significance) of momentum and earnings-per-share coefficients flip using realized returns as a dependent variable. Taken together, the results based on realized returns affirm quantitatively important differences between expected and realized returns over the sample period. That the empirical literature has produced mixed results using realized returns in various time horizons calls for improved proxy for expected returns.[46]

1.3.3 Implied Cost of Capital

Another well-known *ex-ante* approach to improve upon the weaknesses of using realized returns as a proxy for expected returns is the implied cost of capital (ICC) measure. Accounting literature has proposed a number of approaches in estimating future cash flows of a firm, including Gebhardt et al. (2001) (GLS, hereafter), from which the discount rate that equates the present value of such future cash flows with the underlying stock's current price is computed. Therefore, ICCs as discount rates must vary according to how investors *ex-ante* integrate non-pecuniary and pecuniary ESG information, as these ESG preferences move current stock prices.

Nevertheless, ICCs are not as flow-immune as option-implied expected returns to the extent that current prices of ESG-(un)friendlier stocks adjust non-trivially to investors' expectations of

[45] `https://www.ishares.com/us/strategies/sustainable-investing`

[46] See Table 5 of Gillan et al. (2021) for the summary of recent papers with mixed results relating ESG and financial performance.

continuing capital inflows (outflows) in the future. For example, an ESG-insensitive, but rational, investor would long ESG-friendly stocks in expectation of surging prices due to trending ESG capital, thereby elevating their current prices. Notice, this effect, if exist, is on top of how actual ESG preferences would affect the prices *ex-ante*, and hence, can cause overstating the ESG equity premia associated with $ESG^{\text{☼}}$ and $ESG^{\$}$. Still, examining how the results based on ICCs are comparable to those based on MW and KT and distinguishable from those based on realized returns can reassure us about the unexpectedness of ESG capital flows and in which specific dimension ($ESG^{\text{☼}}$ or $ESG^{\$}$) is the unexpectedness concentrated.

In estimating annual ICCs in each month t, I strictly follow the approach of Hou et al. (2012) (HVZ, hereafter), which builds on the classic framework of GLS but replaces analysts' earnings forecasts with regression-based forecasts.[47] I choose regression-based GLS as the ICC method because Lee et al. (2021) show it produces the most precise expected return estimates in the cross section out of several popular methods.[48] Table 1.11 tabulates the estimates of equation (1.2) where the ICC is the new proxy for $\mathbb{E}_t[R^{ex}_{i,t+1}]$ with the first and last 4 columns use S&P 500 and all CRSP stocks as samples, respectively. Similar to the results based on MW and KT, both λ_1 and λ_2 are significantly negative, even for the expanded samples of all CRSP stocks including those without actively traded options. The robustness of the signs and statistical significance with ICC not only validates MW and KT as proxies for expected returns but also underscores investors' integration of ESG information contained in $ESG^{\text{☼}}$ or $ESG^{\$}$. Furthermore, consistent with potential overstatement of statistical significance using ICC, the t-statistics for the coefficients are much higher than those of Table 1.5 for S&P 500 stocks. Finally, the result backs up the interpretation that the increasing amount of capital flowing into higher $ESG^{\text{☼}}$-rated firms has been largely unexpected.

1.4 Sources of ESG Equity Premia

With considerable ESG equity premia identified, equally important is to study the mechanism by which they materialize. Because each ESG proxy is importantly associated with equity premia

[47]See section 2 and Table A1 of HVZ for further details. The minimum solution accuracy to be included in the sample is set at 1e−5.

[48]The results are robust to other methods discussed in HVZ as shown in table A.1.

in and of itself, it is unlikely $ESG^{\text{☼}}$ and $ESG^{\$}$ equity premia arise from the same cause.[49] To determine plausible sources of the two distinct ESG premia, I investigate *how* investors integrate $ESG^{\text{☼}}$ and $ESG^{\$}$ information differently. First, I construct hypotheses about the sources based on findings of recent papers and present a couple of supporting evidence. To directly test them, I examine the changes in stock holdings of equity-focused mutual funds upon their portfolio firms' $ESG^{\text{☼}}$ and/or $ESG^{\$}$ rating updates. Recognizing the discrepancies in stated ESG mandates or revealed ESG preferences across funds and analyzing how differently they adjust holdings upon $ESG^{\text{☼}}$ and $ESG^{\$}$ updates should uncover how each proxy is perceived and affects asset prices. Furthermore, inferring from parameter-free risk-neutral moments à la Bakshi et al. (2003), I recover aggregated *ex-ante* perception of investors on all realizable future states of individual stock returns (i.e., risk-neutral distributions) to investigate if and how each dimension of ESG profiles distorts the risk perception.

1.4.1 Material Risk vs. Non-Pecuniary Channels

As described in section 1.2.1, both MSCI and RepRisk claim their respective ESG ratings, IVA and RRI, are calibrated to quantify material ESG-risk exposures. In fact, RRI measures nothing but the degree of exposures to downside ESG-related risks, whereas IVA bakes in the assessment of a given firm's ESG opportunities and conducts as well. Recent papers, including Glossner (2021) and Yang (2021), test whether both ESG metrics are forward-looking and indeed reflect the magnitude of firms' ESG-risk exposures. Both papers document RRI predicts higher future corporate bad news, regulatory penalties, and litigations, while the latter surprisingly finds higher IVA also predicts *more* of those within 'E' dimension and does not predict less of them in 'S' dimension. Therefore, I can hypothesize that the negative $ESG^{\$} = -RRI$ equity premium mainly stems from investors' pecuniary concern to mitigate non-hedgeable ESG risks, whereas the negative $ESG^{\text{☼}}$ equity premium arises through non-pecuniary considerations.

If the hypothesis on $ESG^{\$}$ is true, one should expect to correctly identify its negative equity premium even with *ex-post* returns. As long as $ESG^{\$}$ measures the quality of ESG-risk hedge,

[49]In the internet appendix Table A.4 to Table A.7, I further show the robustness of results when $ESG^{\text{☼}}$ and $ESG^{\$}$ are orthogonalized from each other to attenuate any biases stemming from the two ratings themselves being correlated. This indicates the ratings capture mutually exclusive (non-pecuniary vs. pecuniary) ESG aspects of firms.

risk-averse investors with or without any inclination for sustainablility must require less pecuniary compensations for funnelling capital to high-$ESG^{\$}$ firms. That is, the unexpectedly prolonged ESG-investing boom that has elevated appreciation for ESG-friendly stocks would hardly alter investors' attitude towards mitigating material risks. Indeed, in both samples with and without S&P 500 stocks, higher $ESG^{\$}$ predicts lower *ex-post* returns over next month—an estimated λ_2 or $\lambda_2 + \tilde{\lambda}_2$ of (1.3) is significantly negative, as shown in Table 1.10.

Contrastingly, $ESG^{\text{☼}}$ coefficients of (1.3) diverge both qualitatively and quantitatively from those of (1.2). In fact, $ESG^{\text{☼}}$ positively predicts *ex-post* returns for all U.S. firms. This suggests the information contained in $ESG^{\text{☼}}$, particularly those that are orthogonal to $ESG^{\$}$, is less relevant to pecuniary risks but rather embeds non-pecuniary aspects of firms to which increasing amount of capital has become attentive. That a prolonged escalation of capital with non-pecuniary considerations can elevate realized returns of high-$ESG^{\text{☼}}$ stocks and widen the wedge between their expected and realized returns conforms with the hypothesis that $ESG^{\text{☼}}$ equity premium arises from non-pecuniary considerations.

1.4.2 Cyclicality of ESG Equity Premia

Including a seminal paper by Fama and French (1989), there exists a large empirical literature documenting counter-cyclical risk premia on various asset markets.[50] As Cochrane (2011) concludes, theoretical controversies about the formation of time-varying discount rates are largely unresolved. Still, they all focus on innovations that perturb agents' pecuniary considerations.[51] Therefore, if $ESG^{\$}$ measures the quality of ESG-risk hedge, then one should expect the magnitude of $ESG^{\$}$ premium to be counter-cyclical. Also, if $ESG^{\text{☼}}$ premium does not exhibit counter-cyclicality, then it must be less relevant to pecuniary risks.

Figure 1.5 plots the time-series dynamics of the ESG premia calculated from the sample of S&P 500 stocks over a rolling window of past 3 years. Top (bottom) panels are using MW and KT expected return measures in which the solid lines are negated values of $ESG^{\text{☼}}$ ($ESG^{\$}$) λ estimates

[50]For example, see Gilchrist et al. (2009) for stocks and corporate bonds, Ludvigson and Ng (2009) for Treasury bonds, and Lustig et al. (2014) for currencies.

[51]E.g., Campbell and Cochrane (1999), Bansal and Yaron (2004), and Wachter (2013) for habit-formation, long-run risk, and disaster risk models, respectively.

of the first regression in (1.2) and surrounding dashed lines represent 95% confidence intervals. Notice, the $ESG^{\$}$ premium, based on both MW and KT measures, was higher during the 3-year window that mostly overlaps with the Great Recession. As the economy entered into the recovery phase, the premium slowly subsided and even became negligible before turning significantly large at the onset of COVID-19 recession. In contrast to counter-cyclicality of $ESG^{\$}$ premium, I find $ESG^{\text{☼}}$ premium to be pro-cyclical which hardly sides with the risk-related interpretation. During the Great Recession, the premium was negligible, and only after the recession does it become significant when ESG integration picked up its pace (see Figure 1.1).

In fact, exactly when $ESG^{\text{☼}}$ premium arises do realized returns diverge from expected returns in estimating the $ESG^{\text{☼}}$ premium. Figure 1.6 overlays the λ's and their 95% confidence bands estimated from (1.3) on Figure 1.5. For comparability, all variables, including expected- and realized-return variables, are standardized in both (1.2) and (1.3) regression models. The discrepancies between estimated $ESG^{\text{☼}}$ premium (top panels) using option-based *ex-ante* returns and *ex-post* realized returns for the sample of S&P 500 stocks start to enlarge from mid-2010s and remain statistically significant until the end of the sample period. On the other hand, no significant divergence is observed in $ESG^{\$}$ dimension as the dynamics of the point-estimates based on two return measures resemble each other and their confidence bands overlap throughout. This suggests the flow-induced bias in realized returns over the last decade was mostly due to market participants awakening to ESG non-pecuniary benefits or developing preferences toward them over the period. Such contrasting trends between the two ESG premia remain even when expanding the rolling window to past 4 or 5 years or when the sample composites all CRSP stocks.[52] All these evidence rationalize the interpretation that $ESG^{\text{☼}}$ and $ESG^{\$}$ premia stem from investors' non-pecuniary and pecuniary considerations, respectively.

1.4.3 Evidence from Mutual Fund Stock Holdings

On top of the evidence so far that suggest the aforementioned hypotheses are true, this section examines mutual funds' turnover decisions upon ESG-rating events in order to test the hypotheses more directly and conclusively. More specifically, I examine how the cross-section of actively managed equity-focused mutual funds adjusts stock holdings upon ESG rating updates. Active fund managers

[52] See Figure A.1 and A.2 for the result with all CRSP stocks.

proactively reassess and rebalance funds' security holdings to be aligned with professed investment strategies and styles. Hence, portfolio holdings adjustments reflect managers' due diligence and, therefore, reveal their preferences. In all likelihood, revealed preferences and prospectuses would be heterogenous across different funds and fund managers. For example, ESG funds that elect or mandate to integrate companies' ESG practices and records would respond more sensitively to news about portfolio companies' ESG policies, such as public commitments and actions to promote societal goals, than traditional funds would.

Still, all active mutual funds share the common goal of outperforming the benchmark or peer indices in a risk-adjusted sense. As they strive for maximizing Sharpe ratios within their constraints, any incidents in portfolio companies heightening overall risk exposures of the portfolio should cause rather homogenous reactions across mutual funds. Namely, in the ESG context, mutual funds would tilt towards stocks providing more protections from future ESG-risk events. Therefore, mutual funds provide an ideal setting to test whether $ESG^{\text{☼}}$ and $ESG^{\$}$ proxy for non-pecuniary and risk-mitigating preferences, respectively. If the aforementioned hypotheses on $ESG^{\text{☼}}$ and $ESG^{\$}$ equity premia are true, then only ESG funds should increase/decrease portfolio weights on firms underwent meaningful $ESG^{\text{☼}}$ upgrades/downgrades while all mutual funds increase/decrease portfolio weights on firms whose $ESG^{\$}$ notably improves/deteriorates. Moreover, $ESG^{\text{☼}}$ and $ESG^{\$}$ rating updates are arguably exogenous in that both ESG raters exhibit periodicity and that it is unlikely for mutual fund holdings change to have any significant repercussions on third-party ESG ratings.[53]

To assess mutual funds' sensitivity to portfolio companies' $ESG^{\text{☼}}$ and $ESG^{\$}$ updates, I first apply moderate screens enumerated in section 1.2.4 on all CRSP-listed mutual to ensure funds in the final sample are not unsophisticated noise traders and have enough skin in the game to act in accordance with generating superior risk-adjusted returns in the long-run. Then, I assess $ESG^{\text{☼}}$ and $ESG^{\$}$ sensitivities in a two-staged regression. In the first stage, I estimate the following

[53]Tang et al. (2022) find significant ESG rating inflations of MSCI "sister firms" who hold ownership stake in MSCI, but it only poses a minimal concern because I examine all incidents of $ESG^{\text{☼}}$ changes of all CRSP mutual fund constituents with $ESG^{\text{☼}}$ ratings.

regression for each mutual fund i,

$$\Delta\omega_{i,h,t} = a_i + z_i\omega_{i,h,t-1} + \zeta_{i,\beta}\Delta\beta^m_{i,h,t} + \boldsymbol{\zeta}_{i,X}\Delta\boldsymbol{X}_{i,h,t} + \eta_{i,h,t}, \tag{1.4}$$

where Δ denotes the first difference over 3 months, $\omega_{i,h,t}$ the value weight of a mutual fund i on a stock holding h at time t, $\beta^m_{i,h,t}$ a stock h's 36-month rolling market beta, and a vector $\boldsymbol{X}_{i,h,t}$ stacks firm fundamentals.[54] I exclude financial sector stocks and holdings with $\omega_{i,h,t} < 0.1\%$ or $\omega_{i,h,t-1} < 0.1\%$ from the analysis. Even stocks without $ESG^{\sun}$ or $ESG^{\$}$ rating are included in the first stage to more precisely estimate all coefficients of the regressors. This effectively disciplines the estimated residual variation of $\hat{\eta}_{i,h,t}$ unexplained by the traditional risk factors.

In the second stage, I regress the recovered residual $\Delta\hat{\omega}_{i,h,t} \equiv \hat{\eta}_{i,h,t}$ on changes to $ESG^{\sun}$ and $ESG^{\$}$. Specifically, I estimate

$$\begin{aligned} \Delta\hat{\omega}_{i,h,t} &= \tilde{a}^{\sun}_i + b^{\sun}_i \Delta ESG^{\sun}_{i,h,t} \times \mathbb{1}_{|\Delta ESG^{\sun}_{i,h,t}| \geq 0.1} + \epsilon^{\sun}_{i,h,t}, \\ \Delta\hat{\omega}_{i,h,t} &= \tilde{a}^{\$}_i + b^{\$}_i \Delta ESG^{\$}_{i,h,t} \times \mathbb{1}_{\Delta ESG^{\$}_{i,h,t} < 0} + \epsilon^{\$}_{i,h,t}, \end{aligned} \tag{1.5}$$

where $\mathbb{1}_{|\Delta ESG^{\sun}_{i,h,t}| \geq 0.1}$ and $\mathbb{1}_{\Delta ESG^{\$}_{i,h,t} < 0}$ are indicators that equal 1 if the absolute changes in $ESG^{\sun}$ and the change in $ESG^{\$}$ ratings are greater or equal to 0.1 and less than 0, respectively, and equal 0 otherwise. These thresholds are chosen so that $b^{\sun}_i$ and $b^{\$}_i$ capture sensitivities to meaningful, non-mechanical, changes to $ESG^{\sun}$ and $ESG^{\$}$.[55] Then, I count up the number of mutual funds with $ESG^{\sun}$ and $ESG^{\$}$ coefficients being significantly different from zero out of (i) all funds in the sample, (ii) traditional funds, and (iii) ESG funds. I categorize funds as ESG funds if they received 4 or above "globes" from Morningstar's sustainability rating at the end of 2021; otherwise, they are labeled as traditional funds.

To add statistical context to the mutual fund counts, I set a null hypothesis under which each mutual fund's sensitivity to $ESG^{\sun}$ or $ESG^{\$}$ updates is predominantly negligible and assumed

[54] $\omega_{i,h,t}$'s are as of at the last day of month t, while other regressors (i.e., $\beta^m_{i,h,t}$, $\boldsymbol{X}_{i,h,t}$, $ESG^{\sun}_{i,h,t}$, and $ESG^{\$}_{i,h,t}$) are as of at the end of third week of the same month t. Changes in these regressors, therefore, always precede weight adjustments.

[55] For $ESG^{\$}$, an ESG incident shoots down $ESG^{\$}$, after which it slowly appreciates over time under RepRisk's discretion as described in 1.2.1. Hence, I restrict to occurrences of $\Delta ESG^{\$}_{i,h,t} < 0$.

to be randomly drawn. That is, under the null, each sensitivity coefficient b_i follows a Bernoulli distribution that equals 0 with probability $1-p$ or non-zero with probability p for every mutual fund i. Plausibly assuming positive correlation across mutual funds' turnover decisions, if the null hypothesis is true, then the counts of b_i's significantly away from zero converges in distribution to

$$\#(b_i^{esg} \neq 0) \xrightarrow{d} N(np, np(1-p)(1+\rho(n-1))), \qquad esg \in \{ESG^{\text{☼}}, ESG^{\$}\}$$

using normal approximation to the binomial where n and $\rho > 0$ denote the number of distinct mutual funds in the sample and the pairwise correlation in stock turnovers, respectively.[56] I estimate ρ by averaging pairwise stock turnover correlations of all possible mutual fund pairs that have commonly held stocks at any given time. Namely, I compute Pearson's pairwise linear correlation coefficient on $(\Delta\omega_{i,h,t}, \Delta\omega_{i',h,t})$ for all $i \neq i'$. Pairs with less than 50 commonly held stocks or correlation coefficient not significantly different from zero at 10% level are dropped.

Panel A of Table 1.12 tabulates the counts of significantly non-zero $b^{\text{☼}}$ and $b^{\$}$ of (1.5) at a two-tailed 10%, 5%, and 1% significance levels, corresponding to $p = 0.05$, 0.025, and 0.005 of the null hypothesis, respectively, for counts of either $b_i^{esg} > 0$ or < 0. Column numbers (1), (2), and (3) correspond to cases where I include 36-month market β, Carhart 4-factor β's, or firm-characteristic variables used in (5) in Table 1.5 in the first-stage regression, respectively. Using the above normal approximation, I can reject the null at 10%, 5%, or 1% significance levels if the cumulative distribution function evaluated at the observed counts exceeds 0.9, 0.95, or 0.99, respectively. Superscripts *, **, and *** are attached to the observed counts accordingly. First of all, based on the counts of funds with $b_i^{\text{☼}} < 0$ or $b_i^{\$} < 0$ out of all mutual funds, I fail to reject the null hypothesis for $b_i^{\text{☼}}$ or $b_i^{\$}$. However, I reject it at 1% significance level for $b_i^{\$}$ based on the counts of $b_i^{\$} > 0$. A large number of mutual funds immediately and markedly increase the fraction of wealth allocated to firms experiencing $ESG^{\$}$ improvements. Price appreciation of such stocks must follow, vindicating the negative $ESG^{\$}$ equity premium. Interestingly, $ESG^{\$}$-induced demand tilts are largely universal across fund ESG categories. The perceived homogeneity in mutual fund responses to $ESG^{\$}$ changes suggests it proxies for the level of pecuniary hedge against ESG-relevant

[56]For a detailed derivation of the normal approximation to the correlated binomial, see Theorem 1 of Diniz et al. (2010).

risks which should be of interest to all mutual funds who are to mitigate material risk exposures per their fiduciary duty.

Unlike $ESG^{\$}$, the counts of $b_i^{\text{☼}} > 0$ feature heterogeneity across fund ESG categories. While ESG funds show signs of non-negligible demand tilt towards stocks with $ESG^{\text{☼}}$ upgrades, traditional funds' responses seem muted. ESG funds consciously put more importance weights on non-pecuniary ESG factors, be they portfolio companies' ESG management track record or credentials, than traditional funds. Naturally, they attract and cater to a group of clienteles who value these attributes. Therefore, disproportionately more powerful rejection of the null hypothesis with ESG funds than with traditional funds implies $ESG^{\text{☼}}$ appraises non-pecuniary ESG factors and the $ESG^{\text{☼}}$ equity premium is mainly driven by agents who value them. This result attenuates a concern that $ESG^{\text{☼}}$ equity premium originates from a different type of risk (for example, a longer-run ESG risk) or a resilience to ESG risks in general.

Panel B of Table 1.12 reports the same counts as panel A, but relies on an empirical distribution of counts for inference. More specifically, at each time t, I jumble up all stock-level ESG-proxy pairs and randomly assign them back to stocks without replacement. In brief, for every stock h, its ESG-proxy pair $(\Delta ESG^{\text{☼}}_{h,t}, \Delta ESG^{\$}_{h,t})$ is reassigned to a randomly drawn stock h', followed by reassignment of $(\Delta ESG^{\text{☼}}_{h',t}, \Delta ESG^{\$}_{h',t})$ to randomly drawn stock h'', and so forth. Everything else remains intact so that the random reassignments of ESG-proxy pairs preserves turnover correlations across all fund pairs ($\rho_{i,i'}$, $\forall i \neq i'$) and error distributions of (1.4), among others. In effect, re-counting of significantly non-zero $b^{\text{☼}}$ and $b^{\$}$ of (1.5) after the random reassignments produces an empirical distribution of counts under the null hypothesis. Not relying on a debatable assumption of $\rho_{i,i'} = \rho > 0 \ \forall i \neq i'$ should further discipline the inference and yield more conclusive evidence. Empirical p-values are computed after $2,000$ iterations and superscripts *, **, and *** denote p-values less than 0.1, 0.05, and 0.01, respectively.

Strong homogeneity in mutual fund responses to $ESG^{\$}$ changes remain across fund ESG categories as shown by Panel B of Table 1.12. In fact, every count of $b^{\$} > 0$ is still significant at 1% level, demonstrating a unanimous tilting towards stocks with $ESG^{\$}$ increases. More importantly, there exists a clearer distinction in $ESG^{\text{☼}}$ sensitivities between traditional and ESG funds. Significantly higher fraction of ESG funds react positively and strongly to $ESG^{\text{☼}}$ improvements than that of traditional funds, causing sizable fraction of all funds significantly up-weighting in stocks with

$ESG^{\Sun}$ inflations.[57] Because the sample focuses on long-lasting mutual funds with large AUM, prices of these stocks would endogenously appreciate for an extended period of time. Therefore, mutual funds' substantial, yet heterogenous, $ESG^{\Sun}$ sensitivities not only parallels with negative $ESG^{\Sun}$ equity premium documented in section 1.3 but also shows the premium is mainly driven by investors with non-pecuniary preferences.[58]

1.4.4 Risk-neutral Distribution: Non-pecuniary Preference & Hedging Demand

Analyzing risk-neutral distribution (RND) of stock returns is another avenue for understanding how investors perceive information contained in $ESG^{\Sun}$ and $ESG^{\$}$ differently. Based on option-implied risk-neutral moments à la Bakshi et al. (2003), the probability density on all realizable future states can be recovered, uncovering investor *ex-ante* risk perception across all future states. Therefore, cross-sectional variations in the shape of RND with respect to $ESG^{\Sun}$ and $ESG^{\$}$ must inform on the mechanisms through which the two ESG information are priced in.

Building on the evidence from mutual funds, if $ESG^{\Sun}$ proxies for non-pecuniary benefit, then investors should effectively be less risk-averse towards investing in stocks with higher $ESG^{\Sun}$ ratings. Unconditional utility gain from holding higher-$ESG^{\Sun}$ stocks hedges against uncertain pecuniary outcomes, and hence, the prices of Arrow-Debreu securities that pay out upon tail events should be lower. If $ESG^{\$}$ captures downside ESG-risk protection, then state prices of left-tail events should be lower for higher $ESG^{\$}$ stocks.

To test such predictions, I first estimate the relationship between risk-neutral moments and ESG metrics by simply replacing the dependent variable in (1.3) with Bakshi et al. (2003) parameter-free estimates of centralized risk-neutral moments. In addition to including quarter and industry fixed effects, I control for return volatility of past 12 months to prevent unobserved firm-specific idiosyncracies from confounding the true relationship. First of all, Table 1.13 shows that risk-neutral

[57] Results are robust to different definitions of ESG funds (e.g., MSCI fund ratings above A or funds with Morningstar-identified ESG mandates) and to inclusion of funds with more than 80% of TNA on CRSP equities.

[58] Chen et al. (2021) find mutual funds allocate higher capital to stocks with favorable TruValue Labs ESG rating on average. Berg et al. (2022a) also find mutual funds with a dedicated ESG strategy adjust their stock ownership in response to MSCI IVA rating up- and downgrades. My result confirms and extends their main finding by implementing a two-staged regression that recovered $b^{\Sun}$ more accurately by netting out other well-known risk-based sensitivities.

volatility decreases with $ESG^{\sun}$ and $ESG^{\$}$ for S&P 500 stocks. The relation cannot serve as a litmus test, but can be explained by non-pecuniary and risk-mitigating preferences, respectively. The higher non-pecuniary utility an investor enjoys from owning an equity claim, the less pecuniary compensation she requires from it in all future states, pushing down its risk-neutral volatility. Also, improved protections from non-hedgeable downside risks should reduce the risk-neutral volatility, as they comfort risk-averse investors and attenuate risk-neutral densities around the left tail. Meanwhile, this result on risk-neutral volatility shows robustness of the findings in section 1.3. Recall, MW and KT expected return measures are based on risk-neutral variances, so finding a directionally identical result from a cross-sectional regression with Bakshi et al. (2003) risk-neutral volatility estimates further corroborates the findings of ESG equity premia.[59]

Next, the results on higher moments, presented in and Table 1.14, paint a more complete picture on how $ESG^{\sun}$ and $ESG^{\$}$ alter the overall shape of RND. As expected, the risk-neutral skewness increases with $ESG^{\$}$ for all CRSP stocks on average. However, such relationship is almost entirely driven by lowest $ESG^{\$}$ quintile stocks. Still, the fact that risk-neutral volatility decreases with $ESG^{\$}$ across entire $ESG^{\$}$ domain implies diminished concern for downside realizations of higher $ESG^{\$}$ stocks. Decreasing risk-neutral kurtosis with $ESG^{\$}$ supports this interpretation as it indicates fatter, but shorter, tails. On the other hand, $ESG^{\sun}$ has negligible effects on risk-neutral skewness and kurtosis. With decreasing risk-neutral volatility, one can suspect the flattening of tails, consistent with non-pecuniary utilities suppressing state prices around the tails.

Because the actual shape of RND is non-linearly associated with higher moments, I use the skew-t distribution of Theodossiou (1998) to infer the shape as accurately as possible by choosing parameters that replicate the observed moments in Tables 1.13 and 1.14.[60] It is particularly useful to condense more complex distributional dynamics at the lowest $ESG^{\$}$ quintile, as shown in Table 1.14. As a base, I pick a set of parameters $(\sigma, \lambda, \eta, \psi)$ that matches unconditional averages of risk neutral volatility, skewness, and kurtosis for S&P 500 stocks.[61] Figure 1.7 plots the probability density in a

[59] Weaker statistical significance of $ESG^{\sun}$ coefficients with all CRSP stocks does not pose Statistically weaker result

[60] Skew-t distribution is widely used and shown to model stock return dynamics well in the empirical finance research including Aramonte et al. (2021).

[61] For details on the probability density function and what each parameter controls, see section 2 of Theodossiou (1998) where $\eta = k$ and $\psi = n$ in his notations.

solid black line. Then, I calculate changes to the moments corresponding to the lowest-to-highest quintile $ESG^{\text{☼}}$ change and the lowest-to-highest quintile $ESG^{\$}$ change and overlay new RNDs in a blue and red dashed lines in the top and bottom subplots, respectively.

The top subplot confirms the reduction in state prices near the tails as a result of sizable $ESG^{\text{☼}}$ improvements. The enlarged graphs around the tails clearly illustrate such effect with blue dashed lines situating below black solid lines. The effect is statistically significant based on the Kolmogorov-Smirnov test statistic k that strongly rejects the null hypothesis under which two RNDs are from the same probability distribution. A significant improvement in $ESG^{\$}$ can also transform investors' risk perception, as the bottom subplot and its test statistic k suggest. As predicted, investors are less concerned about the downturns of higher $ESG^{\$}$ stocks as they are deemed improbable or less systematic.

More interestingly, as implied by significantly negative μ_2 coefficient, sufficiently high $ESG^{\$}$ improvement that brings up firms into the highest $ESG^{\$}$-quintile seems to deflate the state prices around the right outcomes. One plausible explanation is investors' hedging motives against negative ESG externalities that are subdued exactly in these states. To illustrate, consider the states of the economy when the public's attention to ESG issues is low. We know the attention on each element of ESG can intensify and subside around major events (e.g., climate change (Paris Agreement), human rights abuses (Me-Too movement), and worker safety & supply chain management (COVID-19)). We also know that ESG-conscious firms tend to outperform ESG-unconscious firms during times with heightened attention.[62] This entails the latter stocks faring well on low-attention states, exactly when coordinated actions to promote ESG abate. Such states impose negative non-pecuniary externalities to ESG-conscious investors, the likes of environmentalists and social activists for example, who therefore have the strongest desire to hedge against the negative externalities by loading on ESG-unconscious stocks, as highlighted by Baker et al. (2020). Accordingly, the hedging demand can significantly raise the Arrow-Debreu prices around the right outcomes, most notably for the lowest $ESG^{\$}$ quintile stocks. This finding sits well with negative μ_2 estimates in Tables 1.5 and 1.6 under the richest empirical specifications. RNDs show hedging demand weakens for the

[62] Choi et al. (2020) and Albuquerque et al. (2020) document outperformance of low carbon-intensive companies during months with abnormally warm temperature and that of environmentally and socially friendlier firms during the first quarter of 2020 when COVID-19 shock was realized, respectively.

highest $ESG^{\$}$ quintile firms, so the offsetting effect on positive $ESG^{\$}$ equity premia should appear on these stocks, if any. Finally, as shown by the latter columns of Tables 1.13 and 1.14, the $ESG^{☼}$ and $ESG^{\$}$-induced RND distortions are largely present for non S&P 500 stocks as well, despite of additional idiosyncracies possibly confounding the estimates.

1.5 Cross-sectional Implications

So far, I have shown the importance of average investors' non-pecuniary and pecuniary ESG preferences via sizable ESG equity premia over the past decade and a half. This section examines whether ESG premia are explained by other factors or exhibit any meaningful cross-sectional variations. In particular, I focus on three dimensions—industry, institutional ownership, and multi-nationality—to not only reject a possibility of their systematic associations with ESG ratings confounding the main finding but also study how differently each preference manifest itself across their cross-sections.

1.5.1 Industry

As noted in section 1.2.1, $ESG^{☼}$ adjusts importance weights on its ESG criteria across different industries while $ESG^{\$}$ does not. It is not readily clear whether any industry adjustments enhance or undermine ESG rating comparability across industries. Moreover, not all ESG credentials or incidents are bound to have same ramifications or receive same amount of investor attention across industries. If majority of cross-sectional variations in ESG metrics stems from industry-specific components, then $ESG^{☼}$ and $ESG^{\$}$ can be more or less explaining industry premia rather than ESG premia. To test such alternative explanation, Table 1.15 reports cross-sectional return predictability regression results of (1.3) where I use MW or KT expected-return measures and include Fama-French 49 or NAICS 2-digit industry fixed effects within the sample of S&P 500 stocks. The industry-controlled ESG equity premia estimates are largely comparable to those in Table 1.5 in terms of their magnitudes. The statistical significance increases to 5% or 10% level in the time windows when ESG preferences strengthen (see Figure 1.5). Such observations alleviate the aforementioned concern and substantiate the findings of previous sections.

Armed with this finding, I examine how the pricing effects of non-pecuniary and pecuniary ESG preferences vary across industries by interacting both $ESG^{\text{☼}}$ and $ESG^{\$}$ with the industry dummies. Instead of introducing all industry-interacted variables at once, I add one industry-interacted variable and an industry dummy at a time to preserve statistical power of the regression. Should the intensities of the two preferences in a given industry significantly differ from other industries, the interaction-term coefficients must be significantly away from 0. Therefore, the sum of coefficients on each ESG metric and its industry-interacted term represent the intensity of each preference in a given industry. Table 1.16 ranks Fama-French 49 industries based on the intensity of each ESG preference. "Mining", "Tobacco", "Accommodation", "Oil & Gas" industries exhibit very high non-pecuniary ESG premia because of their operational immediacy to both environmental and societal externalities.[63] More interestingly, the rankings of non-pecuniary and pecuniary preference intensities do not align for most industries. Not only does this imply that marginal improvements in ESG credentials or ESG-risk hedge have been appreciated in differing degrees across industries but it also demonstrates the two ratings capture distinct ESG characteristics.

1.5.2 Institutional Ownership

Out of all capital with ESG considerations in 2020, the amount that caters to individual or retail investors consists of more than a quarter, according to the breakdown by US SIF Report (see Figure 1.8), but it is predominantly of institutional capital. Globally, the number of institutional signatories to UN Principles of Responsible Investing has surpassed 4,000 recently.[64] Despite of growing survey-based evidence showing persistent growth in ESG-integrating institutional capital, we still lack knowledge on whether or not it is truly institution-driven phenomenon.

To shed light on this, Table 1.17 reports results of the following Fama and MacBeth (1973) regression

[63]Despite of the apparent differences between Fama-French and NAICS industry classification systems, Table A.8 shows comparable industry rankings of non-pecuniary-preference intensities.

[64]See UN PRI Article for details.

$$\mathbb{E}_t[R^{ex}_{i,t+1}] = \alpha_i + \lambda_1 ESG^{☼}_{i,t} + \tilde{\lambda}_1 ESG^{☼}_{i,t} \times \mathbb{1}_{IO_{i,t} \leq 60\%}$$
$$+ \lambda_2 ESG^{\$}_{i,t} + \tilde{\lambda}_2 ESG^{\$}_{i,t} \times \mathbb{1}_{IO_{i,t} \leq 60\%} + \mu_1 \mathbb{1}_{IO_{i,t} \leq 60\%} + \mu_2 IO_{i,t} + \boldsymbol{\zeta}' \boldsymbol{X}_{i,t} + \varepsilon_{i,t+1}, \tag{1.6}$$

where $\mathbb{1}_{IO_{i,t} \leq 60\%}$ denotes a dummy variable that equals 1 if stock i's institutional ownership share is below 60%. Roughly speaking, slightly less than 10% of S&P 500 stocks and slightly less than 50% of all CRSP stocks have lower than 60% of institutional ownership.[65] If both non-pecuniary and pecuniary ESG integrations are mainly driven by institutions than by retail investors, then $ESG^{☼}$ and $ESG^{\$}$ should be less relevant in explaining variations of expected returns of stocks with lower institutional ownership.

Firstly, the weakly significant and negative coefficients of $\tilde{\lambda}_1$'s under various samples with different compositions of stocks indicates that even within stocks with least institutional presence, significant equity premium linked to non-pecuniary preference robustly exists. Presumably, equilibrium expected returns of such stocks should weigh in preferences of retail investors more heavily. Hence, the result hints that retail investors have been deriving non-pecuniary utilities by investing in equities according to their ESG credentials. It challenges the idea that ESG integration has been solely driven by institutions with ESG preferences, at least for those accredited to non-pecuniary preference, and may even suggest the opposite in which institutions are catering to non-pecuniary preference of retail investors.

In contrast, when it comes to material ESG-risk hedge consideration, retail investors seem to be less efficient. In most samples, estimated $\tilde{\lambda}_2$'s are significantly positive to the extent that $\lambda_2 + \tilde{\lambda}_2$ becomes positive. This could be due to retail investors' portfolio being suboptimally diversified—and hence requiring higher *ex-ante* compensation in general ($\mu_1 > 0$)—which constrains them from efficiently integrating information about stocks' benefit as ESG-risk hedges. Lack of supply to short sell, proxied by low institutional ownership, may also contribute to observed inefficiency as investors cannot easily construct arbitrage shorts on low-$ESG^{\$}$ rated stocks.[66] Interestingly, these potential

[65]Results are robust to different thresholds such as 50% and 70%.

[66]For the validity of institutional ownership as a proxy for short supply, see D'Avolio (2002) and Nagel (2005).

constraints fail to overpower non-pecuniary consideration, hinting at its intensity and its irrelevance to the constraints.

1.5.3 Domestic vs. Multinational Companies

Companies, despite of their equity claims being traded in major U.S. stock exchanges, may operate in foreign soils and rely non-trivially on the production and sales of goods or services not just in the U.S. On the one hand, multinationals' ESG efforts are expected to be less concentrated in the U.S. while being exposed to expanded catalogue of ESG risks that are unique to foreign jurisdictions. On the other hand, any particular ESG pursuit by a multinational can carry broader implications than by a domestic company while being better insulated from country-specific ESG risks. However, unless the marginal investor participating in the U.S. equity market actively internalizes non-US ESG externalities and is geographically well-diversified, the former should dominate the latter.

Using a flag that codes whether firm fundamental variables are constructed from both domestic and international sources as a proxy for companies' operational footprints in foreign soils, I run the following Fama and MacBeth (1973) regression

$$\begin{aligned}\mathbb{E}_t[R^{ex}_{i,t+1}] = \alpha_i + \lambda_1 ESG^{☼}_{i,t} + \tilde{\lambda}_1 ESG^{☼}_{i,t} \times \mathbb{1}_{Mult_{i,t}} \\ + \lambda_2 ESG^{\$}_{i,t} + \tilde{\lambda}_2 ESG^{\$}_{i,t} \times \mathbb{1}_{Mult_{i,t}} + \mu \mathbb{1}_{Mult_{i,t}} + \boldsymbol{\zeta}' \boldsymbol{X}_{i,t} + \varepsilon_{i,t+1},\end{aligned} \tag{1.7}$$

where $\mathbb{1}_{Mult_{i,t}}$ denotes a dummy variable that equals 1 if stock i's Compustat variables come from both domestic and international reports at month t. Table 1.18 reports the results and confirms the prediction. US equity market participants are shown to hardly internalize any non-pecuniary efforts by multinational companies as $\lambda_1 + \tilde{\lambda}_1 \approx 0$. By contrast, the intensity of ESG-risk hedge consideration intensifies for multinationals whose global footprints expose them to various country-specific ESG regulatory standards.

Several studies have shown that ESG integration has been Europe-led in which economic agents are found to be more responsive to ESG-relevant events. Whether it be due to civil-law regulations pushing for stakeholder orientation (Liang and Renneboog (2017)) or genuine devotion to social responsibility (Gibson et al. (2021)), non-US developed economies have espoused ESG integrations for long. Naturally, the implications of any changes to ESG profiles would be enlarged for firms whose stakeholders consist of ESG advocates in other countries. For example, Dai et al. (2021) show customers in high ESG standard countries influence suppliers operating in similarly high standard countries more strongly to address ESG issues. This is consistent with intensified $ESG^{\$}$ premium for multinationals whose controversial ESG practices are more likely to face material consequences (e.g., more stringent regulations) affecting shareholders in the U.S.

A new insight Table 1.18 uncovers is that such spillover pricing effect due to firms' international exposure realizes mainly through pecuniary ESG preferences of US investors. Even though any given ESG pursuit that a multinational company has been pledging to may create global non-pecuniary externalities, US investors seem to discount its non-pecuniary value, suggesting near-sightedness of their non-pecuniary ESG preferences. It is also possible that a given firm's ESG policies do not necessarily apply uniformly across boarders. The systematic disjoint may cause domestic investors to disregard ESG credentials built up outside of U.S. All in all, provided that the variable $Mult_{i,t}$ reasonably captures companies' degree of international exposure, the result hints at two-speed immediacy of foreign-born non-pecuniary externalities and pecuniary risks to domestic investors with ESG preferences.

1.6 Conclusion

Social preferences have taken the center stage in recent discussions on ESG investing and stakeholder capitalism. For businesses, it is ever more important to understand their value implications, as setting out and committing to social objectives can be deemed costly at the outset. Contrary to such prior, I show the efforts to build up ESG credentials will not go unnoticed and be rewarded with cheaper equity financing. Over the past decade and a half, average public market investors have exhibited preferences for non-pecuniary benefits who require significantly less pecuniary compensation from firms with higher ESG credentials, all else equal. Also important for firms is to stay vigilant in managing and fortifying against impending ESG risks (e.g., transitional, regulatory, litigation, reputational risks). With continuously growing awareness of ESG issues, availability of third-party metrics to rank firms, and global initiatives to mandate disclosures on ESG profiles, the already sizable pricing effects of the two ESG preferences are likely underestimations of what lies ahead.

For investors, my results caution against "doing-well-by-doing-good" rhetoric. Echoing Pastor et al. (2022), unexpectedly persistent growth in ESG-conscious money can sustain higher realized returns of firms with better ESG credentials, masking their equilibrium expected returns. This paper responds to the authors' explicit call for an improved expected-return estimate by using options-based measures and, in turn, disproves the rhetoric. When the economy converges to the new normal with the level of ESG integrations at its steady state, I expect (negative) non-pecuniary ESG equity premium to be more readily observable for researchers to form consensus around it more easily. In the meantime, my paper could serve a rationale for firms to promote ESG alignment and walk the ESG talk.

1.7 Tables and Figures

Table 1.1: Variable Definitions

Variable	**Definition**	**Source**
$\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$	Martin and Wagner (2019)'s estimate of S&P 500 stocks' expected returns	OptionMetrics
$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$	Kadan and Tang (2020)'s estimate of CRSP stocks' expected returns	OptionMetrics
$\mathbb{E}_t[R_{t+1}^{GLS}]$	Implied cost of capital of Gebhardt et al. (2001) estimated following Hou et al. (2012)	CRSP/Compustat
R_t^{ex}	The monthly gross excess return from the month-end date $t-1$ to t	CRSP
$Log(Vol(R_{t-11:t}))$	The logarithm of past year's gross return volatility	CRSP
β_t^{mkt}	The 36-month rolling average of the regression coefficient in which the monthly market return is regressed on monthly stock returns	Kenneth French's Data Library
$Log(Size_t)$	The logarithm of monthly market cap	CRSP
$Log(BTM_t)$	The logarithm of monthly book-to-market ratio (TEQQ / Size)	CRSP/Compustat
MOM_t	The past 6-month net excess return	CRSP
$Log(Turn_t)$	The logarithm of daily share turnover (Volume / Total Shares Outstanding) averaged over the past 6 months	CRSP
$Log(Illiq_t)$	The logarithm of daily Amihud (2002)'s stock illiquidity measure averaged over the past 6 months	CRSP
$Log(LEV_t)$	The logarithm of monthly market leverage (LTQ / Size)	CRSP/Compustat
EPS_t	The quarterly earnings-per-share (EPSPXQ)	Compustat
ROE_t	The quarterly return-on-equity (NIQ / TEQQ)	Compustat
Gross Profitability$_t$	The quarterly Novy-Marx (2013) gross profitability measure	Compustat
Inv_t	The quarterly investment measure (ΔATQ / ATQ) of Hou et al. (2015)	Compustat
$Log\left(\frac{Capex_t}{Asset_t}\right)$	The logarithm of quarterly capital expenditure (PPENTQ / ATQ)	Compustat
ΔGDP_t	Computed monthly real GDP changes from $t-1$ to t	IHS Markit
IO_t	The monthly percentage of outstanding shares held by SEC 13-F institutions	Thomson Reuters SEC 13-F
$\mathbb{1}_{Mult_t}$	Equals 1 if Compustat data is based on both domestic and international source	Compustat

**Note: The month-end dates are at the last trading days of the third week of each month which is the most popular (and actively traded) option expiration dates. Compustat variables are of quarterly frequencies, so the most recent observations from any given month t are used to construct monthly company-specific variables. SEQQ replaces TEQQ if TEQQ is missing. All level variables, except for $\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$, $\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$, $\mathbb{E}_t[R_{t+1}^{GLS}]$, R_t^{ex}, ΔGDP_t, and IO_t, are winsorized at the top and bottom 5%.

Table 1.2: Summary Statistics (S&P 500 Stocks)

	N	Mean	SD	Min	p10	p25	p50	p75	p90	Max
$ESG_t^{☼}$	63,368	4.87	1.23	0.00	3.32	4.07	4.86	5.62	6.45	9.24
$ESG_t^{\$}$	50,982	-18.94	13.95	-76.00	-36.00	-25.00	-20.00	-8.00	0.00	0.00
$Corr(ESG_t^{☼}, ESG_t^{\$})$	421	0.07	0.32	-0.76	-0.36	-0.15	0.08	0.30	0.49	0.84
$\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$	64,445	0.56	0.84	-0.68	0.07	0.17	0.34	0.64	1.19	15.35
$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$	64,445	1.27	1.77	0.13	0.33	0.49	0.80	1.38	2.42	45.16
$\mathbb{E}_t[R_{t+1}^{GLS}]$	62,208	0.66	0.52	0.00	0.22	0.35	0.55	0.82	1.18	14.87
R_t^{ex}	64,420	1.12	9.89	-77.67	-9.04	-3.48	1.28	5.90	11.02	145.48
$Log(Vol(R_{t-11:t}))$	63,916	2.03	0.49	-0.07	1.42	1.68	2.00	2.34	2.69	4.81
β_t^{mkt}	60,804	1.06	0.50	-0.12	0.42	0.72	1.04	1.35	1.69	3.01
$Log(Size_t)$	64,445	23.62	1.13	19.08	22.27	22.87	23.49	24.26	25.19	28.66
$Log(BTM_t)$	62,167	-1.23	0.90	-9.08	-2.32	-1.68	-1.14	-0.64	-0.26	2.75
MOM_t	62,032	6.64	23.61	-84.58	-19.97	-6.14	6.32	18.41	32.20	352.46
$Log(Turn_t)$	64,243	2.20	0.57	-2.49	1.54	1.82	2.15	2.53	2.94	5.23
$Log(Illiq_t)$	64,243	-9.43	1.06	-14.04	-10.80	-10.03	-9.37	-8.79	-8.18	-1.73
$Log(LEV_t)$	64,371	-0.76	1.02	-5.37	-2.04	-1.39	-0.76	-0.07	0.50	4.35
EPS_t	62,157	0.75	0.72	-4.16	0.02	0.35	0.71	1.18	1.61	3.42
ROE_t	62,155	0.04	0.08	-0.80	-0.01	0.02	0.04	0.07	0.12	0.29
Gross Profitability$_t$	62,082	0.08	0.05	-0.11	0.02	0.04	0.07	0.11	0.16	0.24
Inv_t	62,070	0.02	0.06	-0.27	-0.04	-0.01	0.01	0.03	0.07	0.92
$Log\left(\frac{CAPEX_t}{ASSET_t}\right)$	64,054	-1.66	0.99	-6.87	-2.94	-2.35	-1.65	-0.78	-0.37	-0.04
IO_t	64,445	0.79	0.16	0.00	0.62	0.72	0.82	0.90	0.96	1.00
$Log(Asset_t)$	64,371	9.59	1.16	6.17	8.14	8.73	9.53	10.40	11.09	13.65
$\mathbb{1}_{Mult_t}$	64,386	0.42	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00

**Note: The sample consists of S&P 500 firms and spans from 2007/1 to 2021/12 during which both $ESG^{☼}$ and $ESG^{\$}$ data are available. Return measures are in %. See Table 1.1 for detailed definitions of each variable.

Table 1.3: Summary Statistics (All CRSP Stocks)

	N	Mean	SD	Min	p10	p25	p50	p75	p90	Max
$ESG_t^{\text{☼}}$	259,123	4.50	1.09	0.00	3.12	3.80	4.50	5.20	5.80	9.29
$ESG_t^{\$}$	213,766	-8.89	12.04	-76.00	-24.00	-18.00	0.00	0.00	0.00	0.00
$Corr(ESG_t^{\text{☼}}, ESG_t^{\$})$	1,258	0.02	0.33	-0.99	-0.43	-0.21	0.02	0.27	0.47	0.91
$\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$	64,445	0.56	0.84	-0.68	0.07	0.17	0.34	0.64	1.19	15.35
$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$	337,987	3.49	4.95	0.13	0.53	0.92	1.80	3.80	8.02	58.64
$\mathbb{E}_t[R_{t+1}^{GLS}]$	503,263	0.99	1.35	0.00	0.17	0.39	0.71	1.21	1.97	146.76
R_t^{ex}	542,773	0.90	18.35	-97.05	-16.07	-6.71	0.45	7.49	16.91	2,827.42
$Log(Vol(R_{t-11:t}))$	506,033	2.47	0.60	-1.47	1.73	2.07	2.46	2.86	3.23	6.71
β_t^{mkt}	343,651	1.21	0.64	-0.23	0.41	0.76	1.16	1.62	2.12	3.01
$Log(Size_t)$	546,296	20.29	2.06	11.19	17.64	18.82	20.23	21.68	23.02	28.66
$Log(BTM_t)$	513,987	-0.84	1.01	-11.65	-2.06	-1.39	-0.78	-0.23	0.25	5.92
MOM_t	410,329	6.68	37.92	-84.58	-34.84	-16.15	3.02	23.26	49.98	352.46
$Log(Turn_t)$	526,867	1.87	1.08	-6.35	0.52	1.35	1.97	2.51	3.03	10.39
$Log(Illiq_t)$	525,760	-4.97	3.31	-14.04	-8.95	-7.39	-5.38	-2.91	-0.39	8.73
$Log(LEV_t)$	538,064	-0.89	1.48	-9.79	-2.77	-1.82	-0.86	0.05	0.91	6.41
EPS_t	421,865	0.21	0.65	-4.16	-0.46	-0.12	0.11	0.51	1.07	3.42
ROE_t	421,672	-0.01	0.12	-0.80	-0.17	-0.03	0.02	0.04	0.09	0.29
Gross Profitability$_t$	413,883	0.08	0.07	-0.11	0.00	0.03	0.07	0.11	0.17	0.24
Inv_t	413,934	0.02	0.10	-0.27	-0.08	-0.03	0.01	0.04	0.11	0.92
$Log\left(\frac{CAPEX_t}{ASSET_t}\right)$	531,362	-2.11	1.38	-12.12	-3.88	-2.87	-1.94	-1.08	-0.44	-0.01
IO_t	546,545	0.60	0.33	0.00	0.06	0.32	0.70	0.89	0.99	1.00
$Log(Asset_t)$	538,314	6.46	2.09	-4.71	3.74	4.96	6.43	7.89	9.17	13.65
$\mathbb{1}_{Mult_t}$	538,767	0.13	0.34	0.00	0.00	0.00	0.00	0.00	1.00	1.00

**Note: The sample consists of all CRSP firms and spans from 2007/1 to 2021/12 during which both $ESG^{\text{☼}}$ and $ESG^{\$}$ data are available. Return measures are in % and Martin and Wagner (2019) expected returns cover S&P 500 stocks only. See Table 1.1 for detailed definitions of each variable.

Table 1.4: Expected Returns of Double-sorted ESG Portfolios

Panel A: Value-weighted Expected Return

ESG Credentials ($ESG^{\sun}$)	ESG-risk Hedge ($ESG^{\$}$) Low	2	3	4	High	LMH
Low	0.236***	0.218***	0.253***	0.252***	0.264***	0.028
	(3.67)	(4.51)	(3.85)	(4.42)	(4.89)	(1.17)
2	0.186***	0.220***	0.236***	0.243***	0.245***	0.058*
	(4.49)	(4.52)	(4.35)	(4.09)	(3.67)	(1.73)
3	0.179***	0.205***	0.208***	0.204***	0.222***	0.042**
	(3.66)	(4.73)	(4.24)	(3.88)	(4.85)	(2.17)
4	0.184***	0.161***	0.161***	0.197***	0.231***	0.048
	(4.12)	(3.54)	(4.04)	(4.15)	(3.53)	(1.17)
High	0.151***	0.152***	0.162***	0.167***	0.177***	0.026
	(3.40)	(3.57)	(4.21)	(4.43)	(3.55)	(1.32)
LMH	0.085***	0.066***	0.092**	0.085***	0.087***	**0.059****
	(3.08)	(3.45)	(2.33)	(2.91)	(3.57)	**(2.36)**

Panel B: Equal-weighted Expected Return

ESG Credentials ($ESG^{\sun}$)	ESG-risk Hedge ($ESG^{\$}$) Low	2	3	4	High	LMH
Low	0.346**	0.309***	0.294***	0.281***	0.257***	−0.090*
	(3.37)	(4.12)	(3.34)	(3.49)	(3.68)	(−1.81)
2	0.266***	0.243**	0.261***	0.267***	0.235***	−0.031
	(3.83)	(3.69)	(3.92)	(3.67)	(3.16)	(−1.28)
3	0.237***	0.226***	0.225***	0.199***	0.210***	−0.028
	(3.03)	(3.47)	(3.50)	(2.99)	(3.71)	(−0.81)
4	0.147***	0.166**	0.142***	0.170**	0.222**	0.074*
	(2.63)	(2.16)	(2.83)	(2.36)	(2.55)	(1.67)
High	0.143***	0.189***	0.180***	0.188***	0.128**	−0.015
	(2.84)	(2.81)	(2.68)	(3.54)	(2.12)	(−0.69)
LMH	0.203***	0.120***	0.114***	0.093*	0.128***	**0.218*****
	(3.60)	(2.75)	(3.07)	(1.87)	(3.47)	**(4.27)**

Note: The sample consists of S&P 500 index constituents during 2007/1 $\sim$ 2021/12 whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. First, at each month t, stocks are sorted into quintiles based on $ESG^{\sun}$. Then, within each $ESG^{\sun}$ quintile, stocks are further sorted into quintiles based on $ESG^{\$}$ to construct a total of 25 portfolios that are monthly rebalanced. Each portfolio is treated as a separate asset and each cell represents Martin and Wagner (2019) value-weighted (Panel A) or equal-weighted (Panel B) expected excess return that is unexplained by the market factor in the Fama and MacBeth (1973) regression. Number in red indicates expected return of long Low-$ESG^{\sun}$-Low-$ESG^{\$}$ & short High-$ESG^{\sun}$-High-$ESG^{\$}$ portfolio. During the sample period, each portfolio consists of about 7 to 13 stocks. In parentheses report Newey and West (1987) t-statistics and *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.5: ESG *Ex-ante* Equity Premia (S&P 500 Stocks)

	$\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$						$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$ESG_t^{☼}$	-0.019***	-0.017**	-0.010**	-0.007	-0.010**	-0.008	-0.037***	-0.035**	-0.021**	-0.015	-0.021**	-0.015
	(-2.87)	(-2.44)	(-2.28)	(-1.43)	(-2.24)	(-1.44)	(-2.87)	(-2.44)	(-2.28)	(-1.43)	(-2.24)	(-1.44)
$\mathbb{1}_{ESG_t^{☼}<2}$		-1.542		-1.312		-1.300		-3.083		-2.624		-2.601
		(-0.91)		(-0.87)		(-0.85)		(-0.91)		(-0.87)		(-0.85)
$ESG_t^{☼} \times \mathbb{1}_{ESG_t^{☼}<2}$		-0.613		-0.554		-0.550		-1.226		-1.107		-1.101
		(-0.87)		(-0.88)		(-0.87)		(-0.87)		(-0.88)		(-0.87)
$ESG_t^{\$}$	-0.054***	-0.052***	-0.013***	-0.007	-0.012***	-0.007	-0.109***	-0.104***	-0.026***	-0.015	-0.025***	-0.013
	(-6.01)	(-5.17)	(-3.27)	(-1.43)	(-3.21)	(-1.35)	(-6.01)	(-5.17)	(-3.27)	(-1.43)	(-3.21)	(-1.35)
$\mathbb{1}_{ESG_t^{\$}\leq-40}$		-0.139**		-0.151**		-0.149**		-0.278**		-0.302**		-0.298**
		(-2.59)		(-2.43)		(-2.38)		(-2.59)		(-2.43)		(-2.38)
$ESG_t^{\$} \times \mathbb{1}_{ESG_t^{\$}\leq-40}$		-0.063***		-0.074***		-0.073***		-0.125***		-0.149***		-0.146***
		(-2.71)		(-2.74)		(-2.68)		(-2.71)		(-2.74)		(-2.68)
β_t^{mkt}	0.415***	0.416***	0.239***	0.238***	0.240***	0.239***	0.830***	0.831***	0.477***	0.476***	0.480***	0.478***
	(8.02)	(8.04)	(6.19)	(6.18)	(6.21)	(6.19)	(8.02)	(8.04)	(6.19)	(6.18)	(6.21)	(6.19)
$Log(Size_t)$	-0.105***	-0.107***	0.029***	0.027***	0.030***	0.028***	-0.210***	-0.214***	0.058***	0.054***	0.059***	0.056***
	(-8.90)	(-8.96)	(4.48)	(4.13)	(4.49)	(4.18)	(-8.91)	(-8.96)	(4.48)	(4.13)	(4.49)	(4.18)
$Log(BTM_t)$	0.028***	0.029***	0.010**	0.011**	0.010**	0.011**	0.055***	0.057***	0.020**	0.022**	0.020**	0.022**
	(3.29)	(3.32)	(2.37)	(2.45)	(2.29)	(2.38)	(3.29)	(3.32)	(2.37)	(2.46)	(2.29)	(2.38)
MOM_t	-0.080***	-0.078***	-0.074***	-0.072***	-0.074***	-0.072***	-0.160***	-0.156***	-0.147***	-0.144***	-0.147***	-0.144***
	(-4.00)	(-4.02)	(-4.10)	(-4.09)	(-4.13)	(-4.13)	(-4.00)	(-4.02)	(-4.10)	(-4.09)	(-4.13)	(-4.13)
$Log(Turn_t)$			0.205***	0.207***	0.204***	0.206***			0.410***	0.414***	0.408***	0.412***
			(14.00)	(14.20)	(13.80)	(14.05)			(14.00)	(14.20)	(13.80)	(14.05)
$Log(LEV_t)$			0.037**	0.038**	0.037**	0.039**			0.074**	0.076**	0.075**	0.077**
			(2.41)	(2.47)	(2.43)	(2.49)			(2.41)	(2.47)	(2.43)	(2.49)
EPS_t			-0.089***	-0.087***	-0.088***	-0.086***			-0.178***	-0.174***	-0.176***	-0.171***
			(-7.57)	(-7.48)	(-7.79)	(-7.70)			(-7.57)	(-7.48)	(-7.79)	(-7.70)
Inv_t					-0.004	-0.005					-0.009	-0.010
					(-0.98)	(-1.14)					(-0.98)	(-1.14)
Constant	0.133***	0.132***	0.314***	0.313***	0.313***	0.311***	0.392***	0.390***	0.755***	0.751***	0.751***	0.748***
	(5.09)	(5.03)	(9.87)	(9.77)	(9.87)	(9.77)	(9.17)	(9.08)	(12.79)	(12.78)	(12.77)	(12.77)
N	46725	46725	46715	46715	46705	46705	46725	46725	46715	46715	46705	46705
Adj. R^2	0.324	0.323	0.477	0.478	0.478	0.480	0.324	0.323	0.477	0.478	0.478	0.480

Note: The first and last 6 columns report Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using Martin and Wagner (2019) and Kadan and Tang (2020) expected excess returns as dependant variables, respectively. The sample consists of S&P 500 index constituents during 2007/1 $\sim$ 2021/12 whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of $ESG^{☼}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.6: ESG *Ex-ante* Equity Premia (All Stocks)

	$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$							
	$\gamma = 4$		$\gamma = 5$		$\gamma = 6$		$\gamma = 7$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ESG_t^{☼}$	-0.041***	-0.034***	-0.046***	-0.038***	-0.052***	-0.044***	-0.056***	-0.048***
	(-4.68)	(-4.39)	(-4.52)	(-3.97)	(-4.99)	(-4.75)	(-4.94)	(-4.65)
$\mathbb{1}_{ESG_t^{☼}<2}$		-7.497		-6.875		-6.913		-6.566
		(-1.59)		(-1.49)		(-1.56)		(-1.49)
$ESG_t^{☼} \times \mathbb{1}_{ESG_t^{☼}<2}$		-3.472		-3.166		-3.215		-3.078
		(-1.61)		(-1.52)		(-1.62)		(-1.56)
$ESG_t^{\$}$	-0.074***	-0.049***	-0.084***	-0.054***	-0.092***	-0.060***	-0.101***	-0.066***
	(-4.41)	(-3.39)	(-4.58)	(-3.43)	(-4.64)	(-3.48)	(-4.95)	(-3.74)
$\mathbb{1}_{ESG_t^{\$}\leq -40}$		-0.743***		-0.902***		-0.975***		-1.036***
		(-3.14)		(-3.70)		(-3.61)		(-3.71)
$ESG_t^{\$} \times \mathbb{1}_{ESG_t^{\$}\leq -40}$		-0.278***		-0.329***		-0.356***		-0.385***
		(-3.55)		(-4.15)		(-4.14)		(-4.27)
Constant	0.970***	0.987***	1.077***	1.091***	1.130***	1.144***	1.194***	1.207***
	(7.90)	(7.97)	(8.08)	(8.11)	(8.01)	(8.06)	(7.95)	(7.99)
N	49458	49458	58221	58221	64136	64136	68427	68427
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.386	0.382	0.391	0.391	0.387	0.389	0.395	0.396

Note: Each pair of columns reports Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using Kadan and Tang (2020) expected excess returns as dependant variables for the sample of CRSP stocks that satisfy the following two conditions: (i) $Cov(R_{i,t}, R_{m,t}) \leq 0$ and (ii) $\frac{Var(R_{i,t})}{Cov(R_{i,t}, R_{m,t})} \leq \gamma$ for the previous 12 months. Meeting both (i) and (ii) is a sufficient condition for Kadan and Tang (2020) expected returns to be legitimate lower bounds of actual expected returns, given the acceptable range of relative risk aversion parameter value is lower than γ. The sample period is from 2007/1 to 2021/12 and I further restrict to stocks whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of $ESG^{☼}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All columns include the most rich set of control variables (i.e., control variables in (5), (6), (11), or (12) in Table 1.5. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.7: ESG *Ex-ante* Equity Premia alongside Factor Risk Premia (S&P 500 Stocks)

	$\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$						$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$ESG_t^{☼}$	-0.035***	-0.036***	-0.031***	-0.032***	-0.034***	-0.035***	-0.070***	-0.072***	-0.063***	-0.065***	-0.069***	-0.070***
	(-4.05)	(-3.86)	(-4.24)	(-4.05)	(-4.81)	(-4.63)	(-4.05)	(-3.86)	(-4.23)	(-4.05)	(-4.81)	(-4.63)
$\mathbb{1}_{ESG_t^{☼}<2}$		-1.508		-1.601		-1.303		-3.016		-3.203		-2.605
		(-0.90)		(-0.94)		(-0.94)		(-0.90)		(-0.94)		(-0.94)
$ESG_t^{☼} \times \mathbb{1}_{ESG_t^{☼}<2}$		-0.588		-0.624		-0.502		-1.176		-1.248		-1.004
		(-0.85)		(-0.89)		(-0.88)		(-0.85)		(-0.89)		(-0.88)
$ESG_t^{\$}$	-0.012*	-0.021**	-0.016**	-0.024***	-0.023***	-0.029***	-0.024*	-0.042**	-0.033**	-0.047***	-0.046***	-0.057***
	(-1.72)	(-2.47)	(-2.18)	(-2.70)	(-2.78)	(-3.09)	(-1.72)	(-2.47)	(-2.18)	(-2.70)	(-2.78)	(-3.09)
$\mathbb{1}_{ESG_t^{\$}\leq -40}$		0.065		0.058		0.053		0.130		0.116		0.107
		(0.71)		(0.68)		(0.59)		(0.71)		(0.68)		(0.59)
$ESG_t^{\$} \times \mathbb{1}_{ESG_t^{\$}\leq -40}$		0.046		0.041		0.038		0.093		0.082		0.076
		(1.26)		(1.16)		(1.04)		(1.26)		(1.16)		(1.04)
cons	0.028	0.033	0.054*	0.059*	0.053	0.057*	0.182***	0.192***	0.235***	0.243***	0.232***	0.239***
	(0.94)	(1.16)	(1.71)	(1.88)	(1.58)	(1.71)	(3.46)	(3.87)	(4.35)	(4.61)	(4.12)	(4.33)
N	48333	48333	48333	48333	48333	48333	48333	48333	48333	48333	48333	48333
β's	FF3	FF3	FFC	FFC	FF6	FF6	FF3	FF3	FFC	FFC	FF6	FF6
Adj. R^2	0.292	0.292	0.318	0.319	0.344	0.344	0.292	0.292	0.318	0.319	0.344	0.344

Note: The first and last 6 columns report Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using Martin and Wagner (2019) and Kadan and Tang (2020) expected excess returns as dependant variables, respectively, where each pair of columns regresses on the estimated 36-month rolling factor exposures to risk factors of Fama and French (1993) (FF3), Carhart (1997) (FFC), and Fama and French (2017) (FF6). The sample consists of S&P 500 index constituents during 2007/1 $\sim$ 2021/12 whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of $ESG^{☼}$ and $ESG^{\$}$ are presented in section 1.2.1. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.8: Realized Excess Returns of Double-sorted ESG Portfolios

Panel A: Value-weighted CAPM-α (2007/01 $\sim$ 2021/12)						
ESG Credentials ($ESG^{\text{☼}}$)	ESG-risk Hedge ($ESG^{\$}$)					
	Low	2	3	4	High	LMH
Low	-0.222	-0.527	-0.314	-0.196	-0.583	-0.361
	(-0.53)	(-1.12)	(-0.66)	(-0.34)	(-1.11)	(-1.28)
2	-0.276	-0.216	-0.435	-0.806	-0.701	-0.425
	(-0.70)	(-0.51)	(-0.98)	(-1.59)	(-1.38)	(-1.51)
3	0.134	-0.286	-0.451	-0.346	-0.547	-0.682^{***}
	(0.38)	(-0.77)	(-0.95)	(-0.74)	(-1.23)	(-2.82)
4	-0.073	-0.149	-0.448	-0.150	-0.250	-0.176
	(-0.22)	(-0.40)	(-1.11)	(-0.35)	(-0.50)	(-0.54)
High	-0.011	-0.263	-0.043	-0.281	-0.416	-0.404
	(-0.03)	(-0.74)	(-0.12)	(-0.72)	(-0.92)	(-1.50)
LMH	-0.211	-0.264	-0.271	0.085	-0.168	**0.193**
	(-0.86)	(-0.88)	(-1.02)	(0.26)	(-0.58)	**(0.77)**

Panel B: Equal-weighted CAPM-α (2007/01 $\sim$ 2021/12)						
ESG Credentials ($ESG^{\text{☼}}$)	ESG-risk Hedge ($ESG^{\$}$)					
	Low	2	3	4	High	LMH
Low	-0.184	-0.035	-0.185	0.111	-0.410	-0.226
	(-0.32)	(-0.06)	(-0.33)	(0.17)	(-0.70)	(-0.76)
2	-0.256	-0.107	-0.099	-0.751	-0.294	-0.038
	(-0.46)	(-0.21)	(-0.19)	(-1.30)	(-0.49)	(-0.12)
3	0.066	0.041	-0.363	-0.139	-0.181	-0.247
	(0.14)	(0.09)	(-0.66)	(-0.26)	(-0.31)	(-1.07)
4	-0.009	-0.189	-0.396	0.417	-0.015	-0.006
	(-0.02)	(-0.39)	(-0.75)	(0.76)	(-0.03)	(-0.03)
High	0.021	-0.206	-0.153	-0.091	-0.286	-0.307
	(0.06)	(-0.49)	(-0.40)	(-0.20)	(-0.55)	(-1.26)
LMH	-0.205	0.171	-0.032	0.202	-0.124	**0.102**
	(-0.69)	(0.56)	(-0.09)	(0.64)	(-0.57)	**(0.37)**

**Note: The sample consists of all CRSP stocks during 2007/1 $\sim$ 2021/12. First, at each month t, stocks are sorted into quintiles based on $ESG^{\text{☼}}$. Then, within each $ESG^{\text{☼}}$ quintile, stocks are further sorted into quintiles based on $ESG^{\$}$ to construct a total of 25 portfolios that are monthly rebalanced. Each portfolio is treated as a separate asset and each cell represents *ex-post* value-weighted (Panel A) or equal-weighted (Panel B) realized excess return that is unexplained by the market factor in the Fama and MacBeth (1973) regression. Number in red indicates expected return of long Low-$ESG^{\text{☼}}$-Low-$ESG^{\$}$ & short High-$ESG^{\text{☼}}$-High-$ESG^{\$}$ portfolio. During the sample period, each portfolio consists of about 13 to 55 stocks. The result is robust with the sample restricted to S&P 500 stocks only. In parentheses report Newey and West (1987) t-statistics and *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.9: ESG *Ex-post* Equity Premia

	R_{t+1}^{ex}							
	S&P 500 Stocks				All Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ESG_t^{\text{☼}}$	0.052	0.047	0.071	0.062	0.053	0.049	0.058	0.057
	(0.96)	(0.84)	(1.39)	(1.17)	(1.04)	(0.93)	(1.22)	(1.12)
$\mathbb{1}_{ESG_t^{\text{☼}}<2}$		1.687		1.196		0.242		0.739
		(0.46)		(0.34)		(0.18)		(0.50)
$ESG_t^{\text{☼}} \times \mathbb{1}_{ESG_t^{\text{☼}}<2}$		0.785		0.596		0.189		0.275
		(0.51)		(0.40)		(0.53)		(0.74)
$ESG_t^{\$}$	-0.029	0.038	-0.024	0.046	-0.096	-0.046	-0.090	-0.033
	(-0.53)	(0.61)	(-0.50)	(0.82)	(-1.54)	(-0.81)	(-1.48)	(-0.67)
$\mathbb{1}_{ESG_t^{\$}\leq -40}$		-0.708		-0.406		0.255		0.248
		(-1.13)		(-0.63)		(0.13)		(0.12)
$ESG_t^{\$} \times \mathbb{1}_{ESG_t^{\$}\leq -40}$		-0.410*		-0.295		0.030		0.021
		(-1.91)		(-1.35)		(0.05)		(0.03)
R_t^{ex}	-0.016	-0.016	-0.015	-0.015	-0.019**	-0.018**	-0.020**	-0.019**
	(-1.58)	(-1.58)	(-1.53)	(-1.54)	(-2.14)	(-2.11)	(-2.40)	(-2.37)
β_t^{mkt}	0.410	0.400	0.246	0.234	0.212	0.216	0.245	0.242
	(1.12)	(1.09)	(0.75)	(0.72)	(0.64)	(0.66)	(0.85)	(0.85)
$Log(Size_t)$	-0.009	-0.017	0.023	0.021	-0.226	-0.226	-0.386**	-0.387**
	(-0.10)	(-0.18)	(0.28)	(0.26)	(-1.29)	(-1.30)	(-2.44)	(-2.47)
$Log(BTM_t)$	-0.077	-0.080	-0.017	-0.028	0.060	0.059	0.037	0.031
	(-1.11)	(-1.16)	(-0.34)	(-0.56)	(0.73)	(0.73)	(0.50)	(0.41)
MOM_t	-0.083	-0.082	-0.091	-0.089	0.151	0.154	0.125	0.129
	(-0.87)	(-0.87)	(-0.99)	(-0.96)	(0.98)	(0.99)	(0.89)	(0.91)
$Log(Turn_t)$			0.195**	0.199**			0.053	0.061
			(2.30)	(2.35)			(0.44)	(0.50)
$Log(LEV_t)$			-0.086	-0.072			0.049	0.064
			(-0.92)	(-0.75)			(0.40)	(0.54)
EPS_t			0.226***	0.230***			0.390***	0.391***
			(4.28)	(4.37)			(6.70)	(6.65)
Inv_t			-0.062	-0.058			-0.075	-0.069
			(-1.31)	(-1.24)			(-1.12)	(-1.02)
Constant	0.536*	0.517*	0.701**	0.683**	0.846**	0.846**	0.734*	0.736*
	(1.77)	(1.71)	(2.42)	(2.35)	(2.12)	(2.12)	(1.86)	(1.87)
N	47755	47755	47733	47733	130422	130422	130337	130337
Adj. R^2	0.136	0.133	0.164	0.161	0.101	0.100	0.121	0.121

Note: The first and last 4 columns report Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using realized excess returns as dependant variables for S&P 500 stocks and for all CRSP stocks, respectively. The sample period is from 2007/1 to 2021/12. Details of $ESG^{\text{☼}}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. On average, standard deviations of $ESG^{\text{☼}}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.10: ESG *Ex-post* Return Predictability

	R^{ex}_{t+1}							
	S&P 500 Stocks				All Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ESG^{☼}_t$	0.050	0.057	0.065	0.072*	0.065**	0.065*	0.070**	0.075**
	(1.20)	(1.36)	(1.55)	(1.70)	(2.08)	(1.95)	(2.17)	(2.18)
$\mathbb{1}_{ESG^{☼}_t<2}$		3.924**		3.607*		0.701		0.398
		(1.99)		(1.77)		(1.03)		(0.59)
$ESG^{☼}_t \times \mathbb{1}_{ESG^{☼}_t<2}$		1.552*		1.425*		0.263		0.099
		(1.90)		(1.67)		(1.18)		(0.45)
$ESG^{\$}_t$	-0.117**	-0.082	-0.070	-0.021	-0.178***	-0.166***	-0.153***	-0.125***
	(-2.28)	(-1.36)	(-1.32)	(-0.33)	(-4.80)	(-3.98)	(-4.12)	(-2.97)
$\mathbb{1}_{ESG^{\$}_t\leq-40}$		-1.182**		-1.120**		-0.897		-0.816
		(-2.34)		(-2.19)		(-1.50)		(-1.36)
$ESG^{\$}_t \times \mathbb{1}_{ESG^{\$}_t\leq-40}$		-0.613***		-0.617***		-0.300*		-0.330**
		(-2.98)		(-2.94)		(-1.84)		(-2.06)
R^{ex}_t	-0.161***	-0.161***	-0.162***	-0.162***	-0.099***	-0.099***	-0.100***	-0.100***
	(-23.17)	(-23.17)	(-23.34)	(-23.34)	(-17.23)	(-17.23)	(-17.33)	(-17.33)
β^{mkt}_t	0.409***	0.415***	0.298***	0.304***	0.140*	0.141*	0.106	0.106
	(4.23)	(4.30)	(2.81)	(2.87)	(1.81)	(1.81)	(1.27)	(1.26)
$Log(Size_t)$	-0.179***	-0.187***	-0.080	-0.087	-0.472***	-0.470***	-0.643***	-0.644***
	(-3.12)	(-3.28)	(-1.23)	(-1.35)	(-6.84)	(-6.79)	(-9.28)	(-9.23)
$Log(BTM_t)$	-0.014	-0.014	-0.036	-0.039	0.064	0.064	-0.000	-0.003
	(-0.29)	(-0.28)	(-0.67)	(-0.74)	(1.34)	(1.35)	(-0.01)	(-0.05)
MOM_t	0.262***	0.261***	0.268***	0.267***	0.554***	0.553***	0.565***	0.565***
	(5.61)	(5.56)	(5.71)	(5.68)	(9.49)	(9.48)	(9.48)	(9.48)
$Log(Turn_t)$			0.224***	0.223***			0.242***	0.249***
			(3.63)	(3.67)			(4.05)	(4.13)
$Log(LEV_t)$			0.123*	0.134**			0.288***	0.296***
			(1.91)	(2.05)			(4.22)	(4.29)
EPS_t			0.202***	0.199***			0.399***	0.399***
			(4.00)	(3.94)			(10.76)	(10.76)
Inv_t			-0.147***	-0.148***			-0.189***	-0.189***
			(-3.19)	(-3.21)			(-3.50)	(-3.51)
Constant	0.904***	0.885***	1.008***	0.984***	1.590***	1.587***	1.451***	1.443***
	(8.65)	(8.34)	(8.60)	(8.27)	(14.45)	(14.37)	(12.85)	(12.74)
N	47089	47089	47067	47067	122718	122718	122641	122641
Industry FE	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock
Adj. R^2	0.145	0.145	0.146	0.146	0.124	0.124	0.125	0.125

Note: The first and last 4 columns report return-predictability regression coefficients and standard errors clustered at a stock level, using realized excess returns as dependant variables for S&P 500 stocks and for all CRSP stocks, respectively. All regressions include SIC 2-digit industry (robust to using NAICS 3 or 4-digit codes) and quarter fixed effects. The sample period is from 2007/1 to 2021/12. Details of $ESG^{☼}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All regressors are standardized each month to have zero mean and unit variance, except for β^{mkt}_t. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.11: ESG Implied Cost of Capital

	$\mathbb{E}_t[R^{GLS}_{t+1}]$							
	S&P 500 Stocks				All Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ESG_t^{☼}$	-0.022***	-0.019***	-0.024***	-0.021***	-0.005	-0.003	-0.013***	-0.014***
	(-5.66)	(-5.19)	(-6.18)	(-5.63)	(-1.34)	(-0.86)	(-3.72)	(-4.01)
$\mathbb{1}_{ESG_t^{☼}<2}$		-0.003		0.007		0.067		-0.134
		(-0.01)		(0.03)		(0.52)		(-1.39)
$ESG_t^{☼} \times \mathbb{1}_{ESG_t^{☼}<2}$		-0.009		-0.009		0.020		-0.007
		(-0.08)		(-0.07)		(0.45)		(-0.21)
$ESG_t^{\$}$	-0.032***	-0.034***	-0.025***	-0.025***	-0.046***	-0.047***	-0.041***	-0.043***
	(-6.67)	(-6.69)	(-6.11)	(-6.02)	(-12.20)	(-11.38)	(-13.72)	(-14.46)
$\mathbb{1}_{ESG_t^{\$}\leq -40}$		0.005		-0.017		-0.027		-0.053
		(0.10)		(-0.33)		(-0.48)		(-0.94)
$ESG_t^{\$} \times \mathbb{1}_{ESG_t^{\$}\leq -40}$		0.016		0.003		-0.005		-0.007
		(0.95)		(0.19)		(-0.39)		(-0.45)
β_t^{mkt}	0.105***	0.105***	0.099***	0.099***	0.039***	0.040***	0.128***	0.129***
	(9.35)	(9.36)	(9.46)	(9.51)	(4.22)	(4.26)	(9.85)	(9.84)
$Log(Size_t)$	-0.018***	-0.017***	-0.006	-0.006	-0.118***	-0.119***	-0.112***	-0.112***
	(-2.76)	(-2.66)	(-0.81)	(-0.83)	(-16.68)	(-16.73)	(-16.46)	(-16.32)
$Log(BTM_t)$	0.272***	0.272***	0.265***	0.265***	0.534***	0.535***	0.459***	0.459***
	(28.97)	(28.79)	(28.58)	(28.29)	(33.41)	(33.69)	(34.38)	(34.64)
MOM_t	-0.031***	-0.031***	-0.029***	-0.030***	0.005	0.006	-0.014*	-0.015*
	(-5.90)	(-5.98)	(-5.12)	(-5.17)	(0.83)	(0.85)	(-1.80)	(-1.82)
$Log(Turn_t)$			0.012*	0.011*			-0.192***	-0.193***
			(1.83)	(1.74)			(-14.93)	(-15.00)
$Log(LEV_t)$			0.017***	0.017***			0.073***	0.073***
			(3.31)	(3.23)			(6.89)	(6.81)
Inv_t			0.001	0.001			0.030***	0.030***
			(0.27)	(0.31)			(6.26)	(6.34)
Constant	0.540***	0.540***	0.546***	0.544***	0.976***	0.976***	0.908***	0.908***
	(32.88)	(32.94)	(28.64)	(28.27)	(32.38)	(32.31)	(30.34)	(30.31)
N	47671	47671	47661	47661	129644	129644	129610	129610
Adj. R^2	0.519	0.519	0.530	0.531	0.573	0.572	0.620	0.619

Note: The first and last 4 columns report Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using the implied cost of capital following Gebhardt et al. (2001) based on the regression-based approach of Hou et al. (2012) as dependant variables for S&P 500 and all CRSP stocks, respectively. Details of $ESG^{☼}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. EPS_t is omitted from regressors to prevent it from explaining too much variation of ICC that is estimated from past and current earnings. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.12: Counts of Mutual Funds Sensitive to $ESG^{\sun}$ or $ESG^{\$}$ Updates

Panel A	p	All MFs			Traditional MFs			4 & 5 Globe		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$b_i^{\sun} > 0$ (< 0)	0.05	419	417	422	358	353	357	61*	64*	65*
		(223)	(223)	(230)	(192)	(192)	(200)	(31)	(31)	(30)
	0.025	295	297	304*	248	251	255	47**	46**	49**
		(137)	(137)	(138)	(118)	(118)	(120)	(19)	(19)	(18)
	0.005	135*	127*	129*	110*	101	104*	25***	26***	25***
		(58)	(62)	(62)	(51)	(55)	(54)	(7)	(7)	(8)
$b_i^{\$} > 0$ (< 0)	0.05	802***	811***	820***	663***	676***	681***	139***	135***	139***
		(202)	(210)	(202)	(184)	(192)	(188)	(18)	(18)	(14)
	0.025	640***	638***	651***	531***	529***	537***	109***	109***	114***
		(131)	(137)	(133)	(117)	(123)	(119)	(14)	(14)	(14)
	0.005	375***	381***	385***	306***	313***	311***	69***	68***	74***
		(66)	(66)	(61)	(61)	(61)	(56)	(5)	(5)	(5)
Screened n		3026	3026	3017	2620	2620	2611	406	406	406

Panel B	p	All MFs			Traditional MFs			4 & 5 Globe		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$b_i^{\sun} > 0$ (< 0)	0.05	419	417	422*	358	353	357	61**	64**	65**
		(223)	(223)	(230)	(192)	(192)	(200)	(31)	(31)	(30)
	0.025	295*	297*	304*	248	251*	255*	47***	46***	49***
		(137)	(137)	(138)	(118)	(118)	(120)	(19)	(19)	(18)
	0.005	135**	127**	129*	110*	101*	104*	25***	26***	25***
		(58)	(62)	(62)	(51)	(55)	(54)	(7)	(7)	(8)
$b_i^{\$} > 0$ (< 0)	0.05	802***	811***	820***	663***	676***	681***	139***	135***	139***
		(202)	(210)	(202)	(184)	(192)	(188)	(18)	(18)	(14)
	0.025	640***	638***	651***	531***	529***	537**	109***	109***	114***
		(131)	(137)	(133)	(117)	(123)	(119)	(14)	(14)	(14)
	0.005	375***	381***	385***	306***	313***	311***	69***	68***	74***
		(66)	(66)	(61)	(61)	(61)	(56)	(5)	(5)	(5)
Screened n		3026	3026	3017	2620	2620	2611	406	406	406

Note: Both Panels A and B show counts out of all, traditional, and ESG (i.e., Morningstar's Sustainability Globe ratings of 4 & 5) mutual funds that are sensitive to changes to $ESG^{\sun}$ or $ESG^{\$}$, after controlling for their turnover sensitivities to portfolio stocks' 36-month market β (column (1)), Carhart 4-factor β's (column (2)), or firm-characteristic variables used in (5) in Table 1.5 (column (3)) in the first stage. Globe ratings are as of 2021 November. The counts of mutual funds allocating significantly higher weights on stocks experiencing $ESG^{\sun}$ or $ESG^{\$}$ increases at the corresponding p-values are tabulated without parentheses while those allocating significantly lower weights on such stocks are tabulated with parentheses. For inference on counts, Panel A uses normal approximation of correlated binomial assuming a constant pair-wise correlation across mutual funds' turnovers. Panel B infers an empirical distribution of counts by jumbling up all stock-level ($ESG^{\sun}_{i,t}$,$ESG^{\$}_{i,t}$) pair and randomly assigning them back to stocks without replacement at any given month t. Resulting distributions of counts are under the null hypothesis that presumes mutual funds are not sensitive to changes in ESG proxies. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.13: Risk-neutral Volatilities

	$\sigma^{BKM,*}_{t+1\|t}$ (in %)							
	S&P 500 Stocks				All Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ESG^{\text{☼}}_t$	-0.110**	-0.101*	-0.096**	-0.083*	-0.034	-0.036	-0.055	-0.045
	(-2.06)	(-1.85)	(-2.14)	(-1.86)	(-0.58)	(-0.58)	(-0.94)	(-0.73)
$\mathbb{1}_{ESG^{\text{☼}}_t<2}$		-0.318		-1.815		-1.726**		-1.570*
		(-0.21)		(-0.81)		(-2.34)		(-1.85)
$ESG^{\text{☼}}_t \times \mathbb{1}_{ESG^{\text{☼}}_t<2}$		-0.264		-0.889		-0.579*		-0.665*
		(-0.38)		(-0.86)		(-1.89)		(-1.88)
$ESG^{\$}_t$	-0.377***	-0.315***	-0.144***	-0.048	-0.654***	-0.518***	-0.562***	-0.383***
	(-5.54)	(-4.40)	(-2.69)	(-0.74)	(-10.24)	(-8.59)	(-8.95)	(-6.63)
$\mathbb{1}_{ESG^{\$}_t\leq-40}$		0.389		0.145		0.255		-0.529
		(0.76)		(0.34)		(0.30)		(-0.68)
$ESG^{\$}_t \times \mathbb{1}_{ESG^{\$}_t\leq-40}$		0.005		-0.181		-0.331		-0.669**
		(0.02)		(-0.80)		(-1.18)		(-2.57)
$Log(Vol(R_{t-11:t}))$	1.710***	1.711***	1.121***	1.121***	3.620***	3.618***	2.974***	2.950***
	(22.76)	(22.79)	(16.52)	(16.56)	(29.34)	(29.56)	(28.64)	(28.80)
β^{mkt}_t	0.576***	0.577***	0.509***	0.509***	0.238**	0.245**	0.173*	0.178*
	(7.58)	(7.62)	(7.64)	(7.67)	(2.46)	(2.54)	(1.88)	(1.95)
$Log(Size_t)$	-0.497***	-0.506***	0.298***	0.288***	-2.941***	-2.966***	-2.380***	-2.401***
	(-6.06)	(-6.16)	(3.74)	(3.63)	(-19.50)	(-19.78)	(-15.50)	(-15.72)
$Log(BTM_t)$	0.185***	0.186***	0.052	0.048	0.175**	0.165*	0.044	0.024
	(2.67)	(2.67)	(0.81)	(0.75)	(2.06)	(1.96)	(0.55)	(0.29)
MOM_t	-0.165***	-0.165***	-0.154***	-0.153***	-0.136***	-0.139***	-0.028	-0.029
	(-4.06)	(-4.06)	(-4.21)	(-4.18)	(-2.66)	(-2.73)	(-0.59)	(-0.61)
$Log(Turn_t)$			1.302***	1.307***			1.435***	1.503***
			(14.64)	(14.61)			(9.40)	(9.90)
$Log(LEV_t)$			0.312***	0.328***			0.300**	0.334**
			(3.47)	(3.61)			(2.11)	(2.38)
EPS_t			-0.528***	-0.525***			-0.701***	-0.696***
			(-11.67)	(-11.72)			(-14.80)	(-15.06)
Inv_t			-0.039	-0.039			0.034	0.030
			(-1.41)	(-1.40)			(0.90)	(0.80)
Constant	10.932***	10.901***	10.860***	10.816***	18.212***	18.236***	17.154***	17.123***
	(163.35)	(167.83)	(214.12)	(220.71)	(98.30)	(98.84)	(83.13)	(83.42)
N	46059	46059	46039	46039	93608	93608	93567	93567
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock
Adj. R^2	0.519	0.519	0.549	0.549	0.571	0.572	0.586	0.587

Note: The first and last 4 columns report return-predictability regression coefficients and standard errors clustered at a stock level, Bakshi et al. (2003)'s options-based risk-neutral return volatilities as dependant variables for S&P 500 stocks and for all CRSP stocks, respectively. All regressions include SIC 2-digit industry (robust to using NAICS 3 or 4-digit codes) and year fixed effects. The sample period is from 2007/1 to 2021/12 and restricted to observations whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of $ESG^{\text{☼}}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All regressors are standardized each month to have zero mean and unit variance. On average, standard deviations of $ESG^{\text{☼}}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.14: Higher Risk-neutral Moments

	$SKEW^*_{t+1\|t}$				$KURT^*_{t+1\|t}$			
	S&P 500 Stocks		All Stocks		S&P 500 Stocks		All Stocks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ESG^{☼}_t$	0.012	0.010	0.001	0.004	-0.087	-0.011	0.030	0.022
	(0.70)	(0.56)	(0.06)	(0.30)	(-0.41)	(-0.05)	(0.19)	(0.15)
$\mathbb{1}_{ESG^{☼}_t<2}$		-0.561		-0.098		-1.321		0.456
		(-0.94)		(-0.58)		(-0.21)		(0.23)
$ESG^{☼}_t \times \mathbb{1}_{ESG^{☼}_t<2}$		-0.245		-0.104		-0.585		0.727
		(-0.99)		(-1.55)		(-0.22)		(0.89)
$ESG^{\$}_t$	0.065***	0.009	0.088***	0.027***	-1.408***	-0.258	-1.601***	-0.553***
	(3.33)	(0.53)	(5.73)	(2.69)	(-4.83)	(-1.19)	(-6.58)	(-4.85)
$\mathbb{1}_{ESG^{\$}_t\leq-40}$		0.045		-0.094		-6.293		-4.243
		(0.17)		(-0.30)		(-1.52)		(-0.78)
$ESG^{\$}_t \times \mathbb{1}_{ESG^{\$}_t\leq-40}$		0.161		0.151		-5.667**		-4.234**
		(1.17)		(1.39)		(-2.47)		(-2.17)
Constant	-1.550***	-1.528***	-0.396***	-0.388***	14.562***	14.115***	1.837***	1.676***
	(-94.29)	(-92.99)	(-12.71)	(-12.76)	(69.99)	(72.76)	(4.49)	(4.22)
N	46039	46039	93567	93567	46039	46039	93567	93567
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock
Adj. R^2	0.188	0.189	0.167	0.170	0.237	0.241	0.207	0.217

Note: The first and last 4 columns report return-predictability regression coefficients and standard errors clustered at a stock level, Bakshi et al. (2003)'s options-based risk-neutral return skewness and kurtosis as dependant variables, respectively. For each higher moment, first and last two columns include only S&P 500 stocks and all CRSP stocks, respectively. All columns include the most rich set of control variables (i.e., control variables in (3), (4), (7), or (8) in Table 1.13). All regressions include SIC 2-digit industry (robust to using NAICS 3 or 4-digit codes) and quarter fixed effects. The sample period is from 2007/1 to 2021/12 and restricted to observations whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of $ESG^{☼}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All regressors are standardized each month to have zero mean and unit variance. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.15: Industry Controls (S&P 500 Stocks)

	$t \geq 2007$				$t \geq 2015$			
	$\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$		$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$		$\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$		$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$	
$ESG_t^{☼}$	-0.008	-0.005	-0.017	-0.010	-0.022**	-0.021*	-0.044**	-0.042*
	(-1.10)	(-0.63)	(-1.10)	(-0.63)	(-2.00)	(-1.93)	(-2.01)	(-1.94)
$\mathbb{1}_{ESG_t^{☼}<2}$		-0.343		-0.728		0.046		0.018
		(-0.67)		(-0.71)		(0.08)		(0.02)
$ESG_t^{☼} \times \mathbb{1}_{ESG_t^{☼}<2}$		-0.194		-0.407		0.007		-0.016
		(-0.86)		(-0.90)		(0.03)		(-0.03)
$ESG_t^{\$}$	-0.020**	-0.007	-0.039**	-0.015	-0.026**	-0.014	-0.052**	-0.028
	(-2.19)	(-0.64)	(-2.18)	(-0.64)	(-1.99)	(-0.87)	(-1.98)	(-0.87)
$\mathbb{1}_{ESG_t^{\$}\leq -40}$		0.007		-0.000		-0.077		-0.168
		(0.11)		(-0.00)		(-0.71)		(-0.78)
$ESG_t^{\$} \times \mathbb{1}_{ESG_t^{\$}\leq -40}$		-0.028		-0.062		-0.062		-0.129
		(-0.85)		(-0.92)		(-1.09)		(-1.14)
Constant	0.285***	0.279***	0.690***	0.679***	0.261***	0.255***	0.688***	0.677***
	(11.44)	(11.18)	(13.86)	(13.60)	(8.75)	(8.66)	(11.54)	(11.48)
N	46039	46039	46039	46039	23998	23998	23998	23998
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49
Clustered SE	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock
Adj. R^2	0.452	0.452	0.450	0.450	0.359	0.359	0.354	0.354

Note: The first (last) 4 columns report return-predictability regression coefficients and standard errors clustered at a stock level, using Martin and Wagner (2019) (Kadan and Tang (2020)) expected excess returns as dependant variables for the sample of S&P 500 stocks when SIC 2- or NAICS 3-digit fixed effects are included. The sample period is from 2007/1 to 2021/12 and I further restrict to stocks whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of $ESG^{☼}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All columns include the most rich set of control variables (i.e., control variables in (5), (6), (11), or (12) in Table 1.5. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.16: Top 20 Industries with Strongest Intensities of Two Preferences

FF-49 Ranks	**Non-pecuniary** ($ESG^{☼}$)	**Pecuniary** ($ESG^{\$}$)
1	Non-Metallic & Industrial Metal Mining***	Automobiles & Trucks**
2	Tobacco Products**	Restaurants, Hotels, & Motels*
3	Restaurants, Hotels, & Motels*	Precious Metals**
4	Transportation**	Tobacco Products**
5	Petroleum & Natural Gas***	Defense***
6	Measuring & Control Equipment***	Electrical Equipment**
7	Electrical Equipment***	Retail***
8	Electronic Equipment***	Machinery**
9	Consumer Goods***	Computer Software**
10	Healthcare***	Healthcare***
11	Computers***	Communication***
12	Aircraft***	Recreation***
13	Food Products***	Apparel***
14	Medical Equipment***	Consumer Goods***
15	Retail***	Entertainment***
16	Construction***	Rubber and Plastic Products***
17	Wholesale***	Beer & Liquor***
18	Business Services***	Transportation***
19	Defense***	Non-Metallic & Industrial Metal Mining***
20	Machinery***	Computers***

Note: Based on the regression result adding three extra regressors $\mathbb{1}_{\text{industry}}$, $ESG^{☼}_{i,t} \times \mathbb{1}_{\text{industry}}$ and $ESG^{\$}_{i,t} \times \mathbb{1}_{\text{industry}}$ to (5) of Table 1.5 for one industry at a time, absolute value of (i) coefficient on $ESG^{☼}_{i,t}$ ($ESG^{\$}_{i,t}$), if coefficient on $ESG^{☼}_{i,t} \times \mathbb{1}_{\text{industry}}$ ($ESG^{\$}_{i,t} \times \mathbb{1}_{\text{industry}}$) is not significant at 10% level, or (ii) the sum of coefficients on $ESG^{☼}_{i,t}$ and $ESG^{☼}_{i,t} \times \mathbb{1}_{\text{industry}}$ ($ESG^{\$}_{i,t}$ and $ESG^{\$}_{i,t} \times \mathbb{1}_{\text{industry}}$), if both coefficients are, or the sum is, significant at 10% level, are ranked. All coefficients have the correct signs (i.e., negative $ESG^{☼}$ and $ESG^{\$}$ coefficients) and *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively, of the coefficients. The sample is restricted to S&P 500 stocks. The sample period is from 2007/1 to 2021/12 and restricted to observations whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. To ensure any given industry consists of at least 2 unique stocks, industries with less than $15 \times 12 = 180$ (yr×mo) observations are dropped. To exclude financial sector stocks, stocks with Fama-French 49 industry codes of 45 to 48 are dropped.

Table 1.17: Institutional Ownership

	S&P 500 Stocks				All Stocks			
	MW		KT		$\gamma = 4$		$\gamma = 7$	
$ESG_t^{\text{☼}}$	-0.012**	-0.010**	-0.023**	-0.020**	-0.027***	-0.013*	-0.031***	-0.008
	(-2.40)	(-2.09)	(-2.40)	(-2.09)	(-4.07)	(-1.97)	(-3.36)	(-0.73)
$ESG_t^{\text{☼}} \times \mathbb{1}_{IO_t \leq 0.6}$		-0.027*		-0.054*		-0.122***		-0.184***
		(-1.73)		(-1.73)		(-2.86)		(-2.66)
$ESG_t^{\$}$	-0.006*	-0.010**	-0.012*	-0.020**	-0.054***	-0.058***	-0.068***	-0.078***
	(-1.69)	(-2.51)	(-1.69)	(-2.51)	(-4.17)	(-4.37)	(-4.59)	(-5.27)
$ESG_t^{\$} \times \mathbb{1}_{IO_t \leq 0.6}$		0.041***		0.082***		0.024		0.054
		(3.27)		(3.27)		(0.61)		(1.31)
$\mathbb{1}_{IO_t \leq 0.6}$		0.081***		0.162***		0.221***		0.338***
		(4.74)		(4.74)		(2.76)		(4.39)
IO_t	-0.048***	-0.035***	-0.097***	-0.069***	-0.265***	-0.151***	-0.442***	-0.282***
	(-6.95)	(-4.81)	(-6.95)	(-4.81)	(-5.31)	(-3.00)	(-6.60)	(-4.44)
Constant	0.310***	0.305***	0.745***	0.736***	1.138***	1.027***	1.489***	1.338***
	(9.56)	(9.42)	(12.43)	(12.16)	(7.93)	(7.21)	(8.64)	(7.44)
N	46705	46705	46705	46705	49458	49458	68427	68427
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.491	0.494	0.491	0.494	0.399	0.409	0.417	0.425

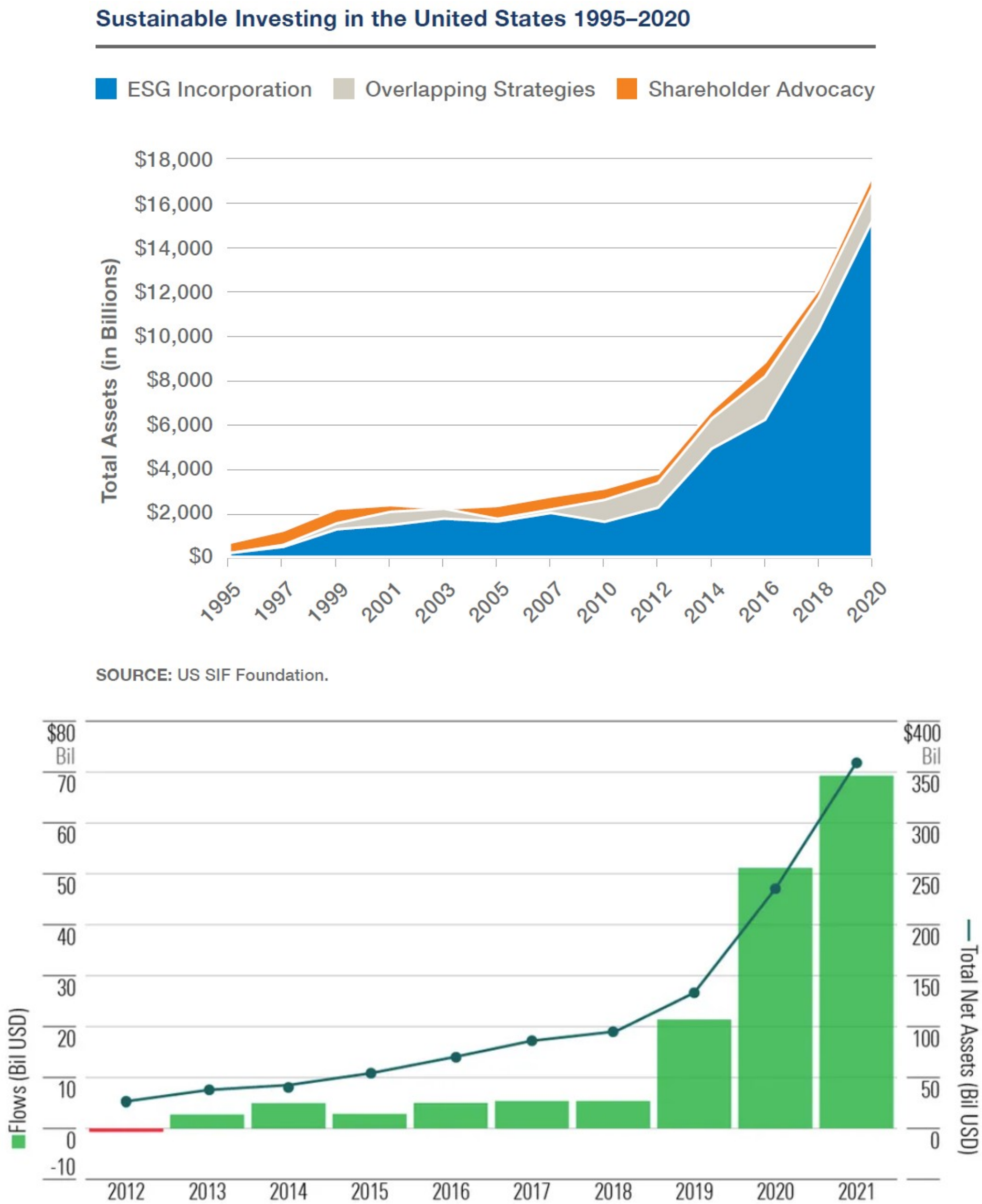
Note: The first 4 and last 4 columns report Fama and MacBeth (1973) regression coefficients of (1.6) and Newey and West (1987) standard errors with 3 lags using Martin and Wagner (2019) or Kadan and Tang (2020) expected excess returns as dependant variables for the sample of only S&P 500 stocks and all CRSP stocks, respectively. For all CRSP stocks, I consider those that satisfy the following two sufficient conditions for Kadan and Tang (2020) measure to be a valid lower-bound estimate of expected returns: (i) $Cov(R_{i,t}, R_{m,t}) \leq 0$ and (ii) $\frac{Var(R_{i,t})}{Cov(R_{i,t}, R_{m,t})} \leq \gamma$ for the previous 12 months. The sample period is from 2007/1 to 2021/12 and I further restrict to stocks whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of $ESG^{\text{☼}}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All columns include the most rich set of control variables (i.e., control variables in (5), (6), (11), or (12) in Table 1.5. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. $\mathbb{1}_{IO_{i,t} \leq 0.6}$ denotes a dummy variable that equals 1 if stock i's institutional ownership share is less than or equal to 60%. On average, standard deviations of $ESG^{\text{☼}}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 1.18: Domestic vs. Multinational Companies

	S&P 500 Stocks				All Stocks			
	MW		KT		$\gamma = 4$		$\gamma = 7$	
$ESG_t^{☼}$	-0.012***	-0.025***	-0.024***	-0.050***	-0.044***	-0.059***	-0.062***	-0.060***
	(-2.66)	(-4.28)	(-2.66)	(-4.28)	(-5.08)	(-5.69)	(-5.25)	(-4.57)
$ESG_t^{☼} \times \mathbb{1}_{Mult_t}$		0.025***		0.051***		0.044***		0.011
		(2.69)		(2.69)		(3.48)		(0.56)
$ESG_t^{\$}$	-0.012***	0.004	-0.023***	0.007	-0.070***	-0.016*	-0.093***	-0.029***
	(-3.05)	(0.68)	(-3.05)	(0.68)	(-4.52)	(-1.93)	(-5.02)	(-2.74)
$ESG_t^{\$} \times \mathbb{1}_{Mult_t}$		-0.028***		-0.056***		-0.116***		-0.147***
		(-3.63)		(-3.63)		(-4.72)		(-5.25)
$\mathbb{1}_{Mult_t}$	0.048***	0.049***	0.096***	0.099***	0.140***	0.069**	0.220***	0.146***
	(5.84)	(5.91)	(5.84)	(5.91)	(3.78)	(2.50)	(4.64)	(3.86)
Constant	0.293***	0.290***	0.712***	0.705***	0.981***	1.016***	1.209***	1.241***
	(9.19)	(9.26)	(12.15)	(12.41)	(7.98)	(8.06)	(8.09)	(8.16)
N	46705	46705	46705	46705	49458	49458	68427	68427
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.480	0.481	0.480	0.481	0.388	0.390	0.398	0.400

Note: The first 4 and last 4 columns report Fama and MacBeth (1973) regression coefficients of (1.7) and Newey and West (1987) standard errors with 3 lags using Martin and Wagner (2019) or Kadan and Tang (2020) expected excess returns as dependant variables for the sample of only S&P 500 stocks and all CRSP stocks, respectively. For all CRSP stocks, I consider those that satisfy the following two sufficient conditions for Kadan and Tang (2020) measure to be a valid lower-bound estimate of expected returns: (i) $Cov(R_{i,t}, R_{m,t}) \leq 0$ and (ii) $\frac{Var(R_{i,t})}{Cov(R_{i,t}, R_{m,t})} \leq \gamma$ for the previous 12 months. The sample period is from 2007/1 to 2021/12 and I further restrict to stocks whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of $ESG^{☼}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All columns include the most rich set of control variables (i.e., control variables in (5), (6), (11), or (12) in Table 1.5. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. $\mathbb{1}_{Mult_{i,t}}$ denotes a dummy variable that equals 1 if stock i's issuer company is multinational (i.e., firm fundamental (Compustat) data come from both domestic and international sources). On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 1.1: Persistent Growth of ESG Integration in the US



**Source: Morningstar Direct as of Dec. 31, 2021. Includes Sustainable Funds as defined in Sustainable Funds U.S. Landscape Report, January 2022. Includes funds that have liquidated, but excludes funds of funds.

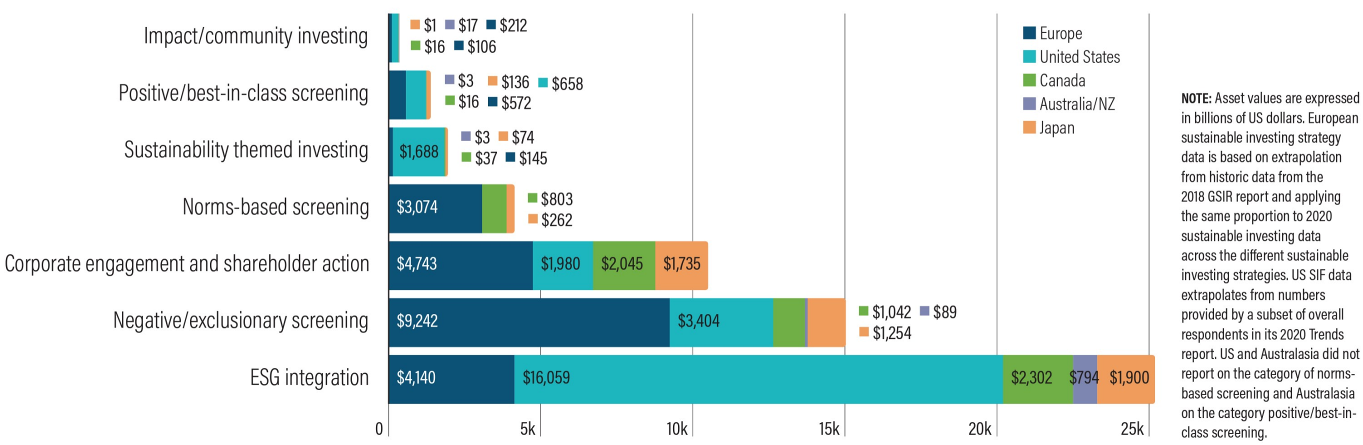
Figure 1.2: MSCI IVA Rating: Key ESG Issues

3 Pillars	10 Themes	35 ESG Key Issues	
Environment	**Climate Change**	Carbon Emissions Product Carbon Footprint	Financing Environmental Impact Climate Change Vulnerability
	Natural Capital	Water Stress Biodiversity & Land Use	Raw Material Sourcing
	Pollution & Waste	Toxic Emissions & Waste Packaging Material & Waste	Electronic Waste
	Environmental Opportunities	Opportunities in Clean Tech Opportunities in Green Building	Opportunities in Renewable Energy
Social	**Human Capital**	Labor Management Health & Safety	Human Capital Development Supply Chain Labor Standards
	Product Liability	Product Safety & Quality Chemical Safety Financial Product Safety	Privacy & Data Security Responsible Investment Health & Demographic Risk
	Stakeholder Opposition	Controversial Sourcing Community Relations	
	Social Opportunities	Access to Communications Access to Finance	Access to Health Care Opportunities in Nutrition & Health
Governance*	**Corporate Governance**	Ownership & Control Board	Pay Accounting
	Corporate Behavior	Business Ethics Tax Transparency	

** The Governance Pillar carries weight in the ESG Rating model for all companies.*

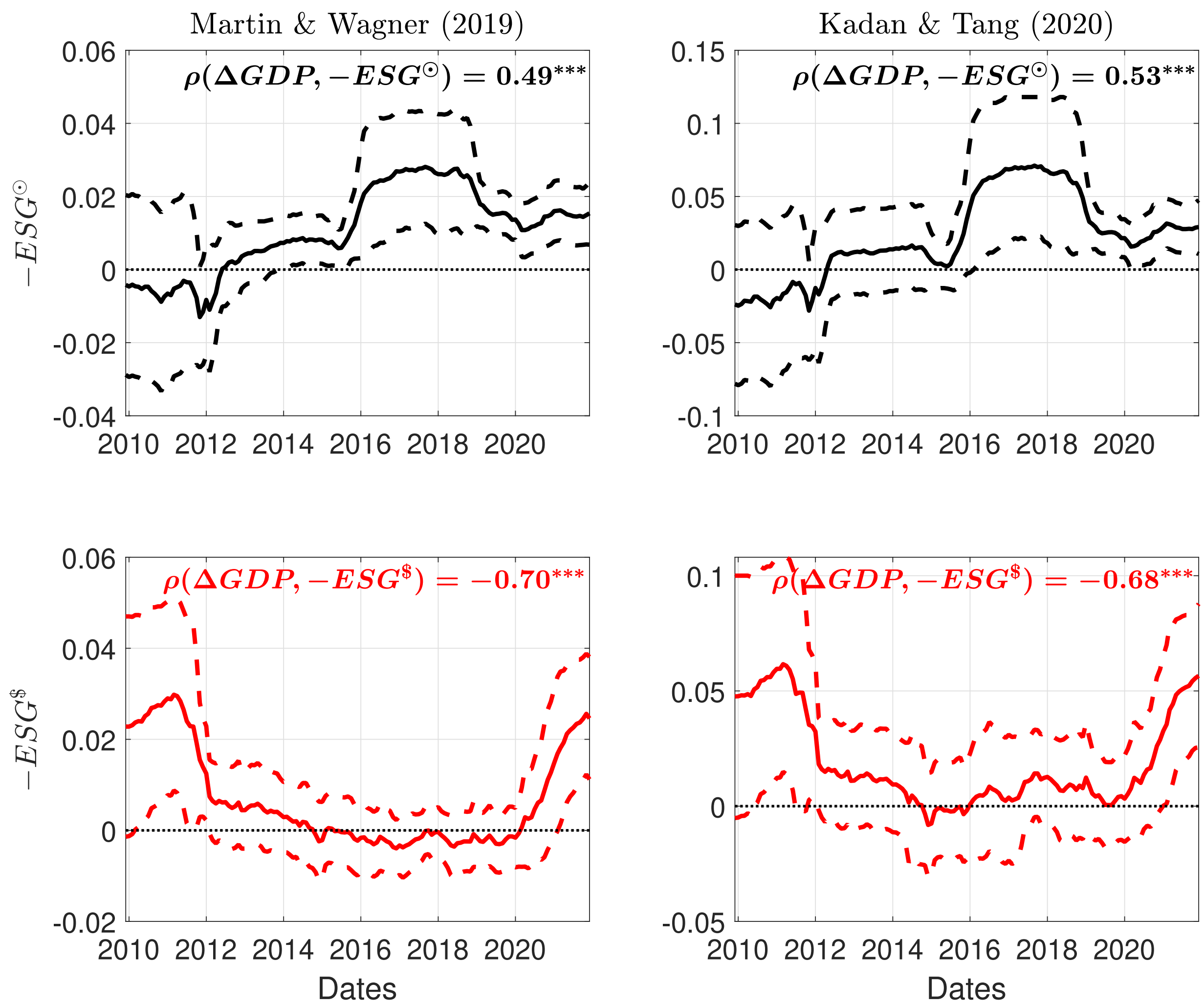
Figure 1.3: RepRisk RRI Rating: Key ESG Issues

Figure 1.4: Global Sustainable Investment Alliance (GSIA) Report 2020



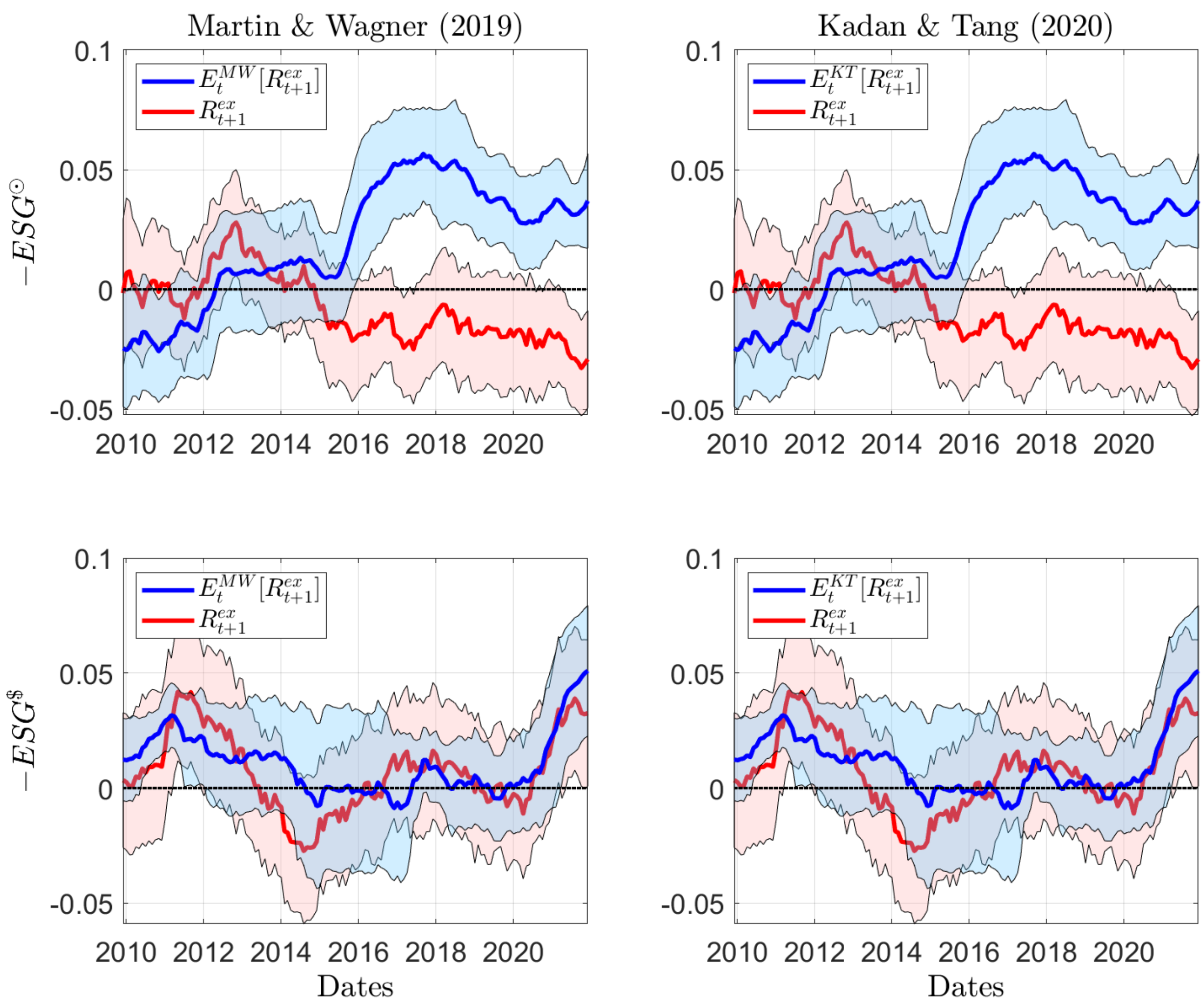
**Note: The report is largely based on a survey sent out to 682 money managers and 1,146 institutional investors. US SIF identified a universe of 397 money managers and 553 institutional investors with $43.8 and $10.3 trillion in assets under management, respectively. Of them, 384 money managers and 530 institutions were confirmed as incorporating ESG criteria, affecting $16.6 and $6.2 trillion in assets, respectively. In addition, 1,204 community investing institutions with $266 billion in assets under management were analyzed. US numbers are extrapolated based on a subset of respondents who gave information about their sustainable investing strategies. For more information about the report, see US SIF Report on US Sustainable and Impact Investing Trends 2020 and Global Sustainable Investment Review 2020.

Figure 1.5: Time-Varying ESG Equity Premia (S&P 500 Stocks)



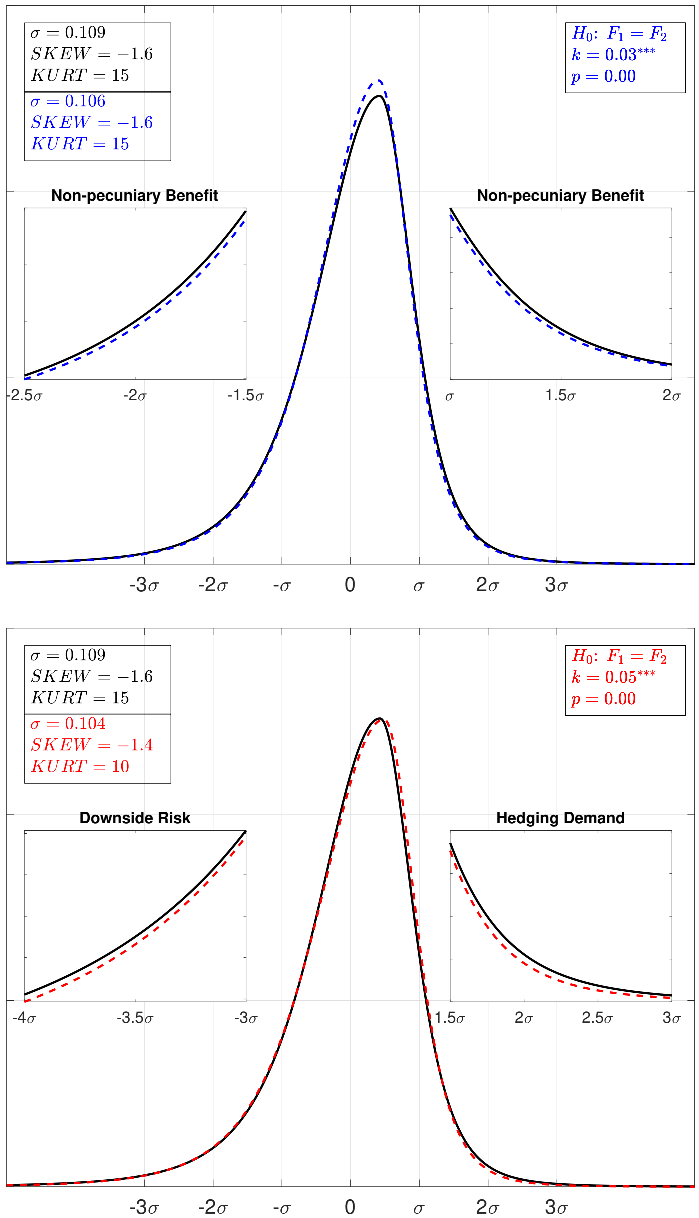
Note: Top (bottom) panels plot the inverse of Martin and Wagner (2019) and Kadan and Tang (2020) estimated $ESG^{☼}$ ($ESG^{\$}$) λ's (solid lines) and their 95% confidence intervals (dashed lines) of the first Fama and MacBeth (1973) regression in (1.2) over the window of past 3 years for S%P 500 stocks. For example, λ's on date 2010/1 are estimates over the period from 2007/2 to 2010/1. Confidence intervals are based on Newey and West (1987) standard errors with 3 lags. The formal test of cyclicality is provided by computing correlation between 36-month average of lagged real GDP growth (details in 1.1) and 36-month rolling window λ's. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. The trends are robust to using windows of past 4 or 5 years. Y-axis represents the change in one-month-ahead expected returns (in %) associated with 1 standard deviation increase in $ESG^{☼}$ and $ESG^{\$}$ ratings. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively.

Figure 1.6: *Ex-ante* vs. *Ex-post* ESG Equity Premia (S&P 500 Stocks)



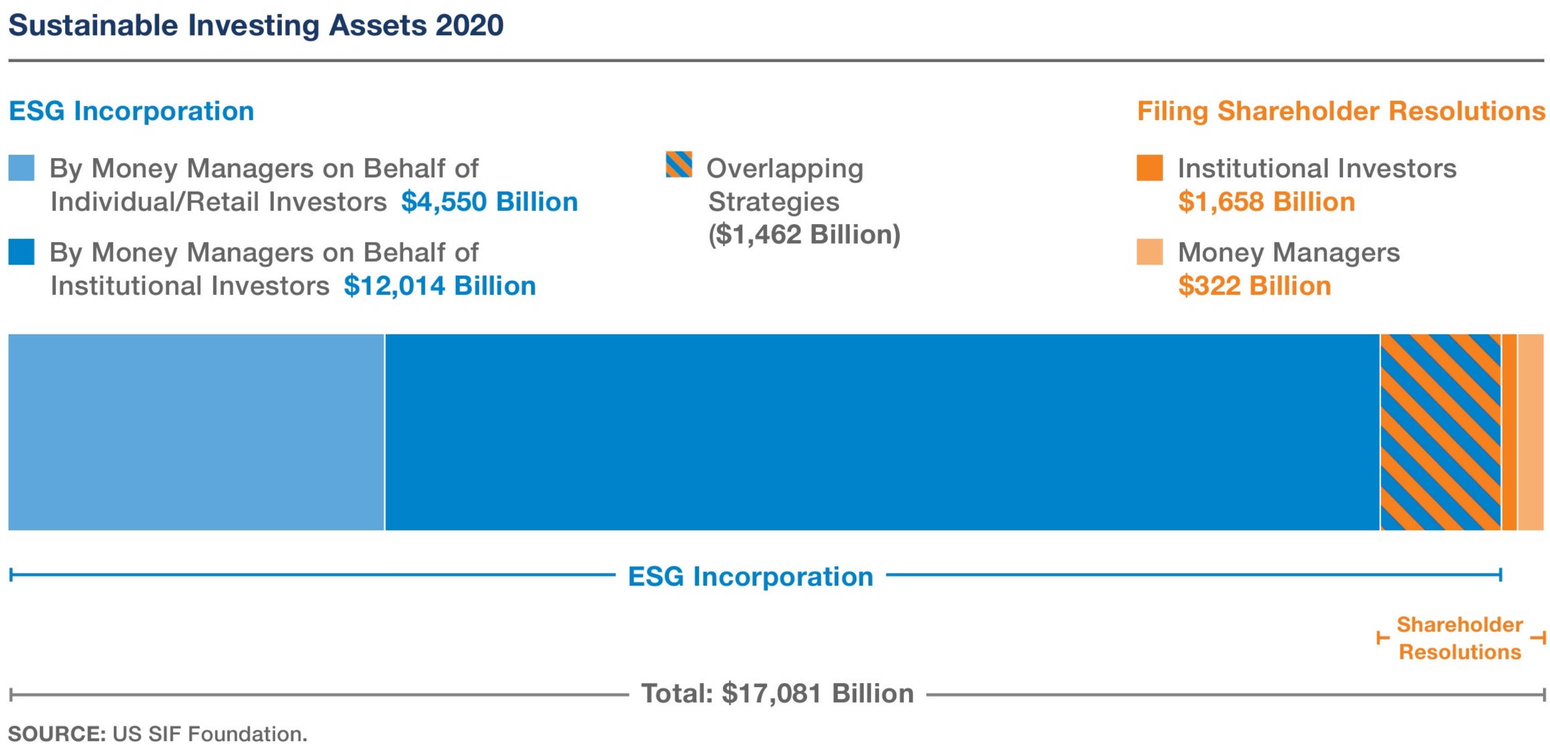
**Note: The blue lines at the top (bottom) panels plot the inverse of Martin and Wagner (2019) and Kadan and Tang (2020) estimated $ESG^{☼}$ ($ESG^{\$}$) λ's (solid lines) and their 95% confidence intervals (blue shaded regions) of the first Fama and MacBeth (1973) regression in (1.2) over the window of past 3 years for S%P 500 stocks. The red lines and red shaded regions denote λ's and their 95% confidence intervals, respectively, estimated through (1.3) using realized returns. For example, λ's on date 2010/1 are estimates over the period from 2007/2 to 2010/1. Confidence intervals are based on Newey and West (1987) standard errors with 3 lags. For comparability, all regression estimates here are based on standardized variables (both independent and dependent variables), so Y-axis represents the standard-deviation change in one-month-ahead expected or realized returns associated with 1 standard deviation increase in $ESG^{☼}$ and $ESG^{\$}$ ratings. The trends are robust to using windows of past 4 or 5 years. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively.

Figure 1.7: Graphical Illustration of $ESG^{\text{☼}}$ & $ESG^{\$}$ Effects on Risk-neutral Distributions



**Note: Top (bottom) panel plots reshaping of risk-neutral probability distribution when a stock moves from the lowest to highest $ESG^{\text{☼}}$ quintile ($ESG^{\$}$ quintile), ceteris paribus. Black-solid line represents the base, while blue-dashed and red-dashed lines denote distributions after the movements, using the skew-t distribution of Theodossiou (1998) and results from Tables 1.13 and 1.14 on S&P 500 stocks. More specifically, I use regression results without non-linearity variables if none of their coefficients (i.e., μ's and $\tilde{\lambda}$'s) is significant at 5% level. Only when any of them are significant at 5% level do I use regression results with non-linearity variables. Kolmogorov-Smirnov test statistic k and the corresponding p-values are presented.

Figure 1.8: U.S. ESG Capital: Institution vs. Retail



**Note: The report is largely based on a survey sent out to 682 money managers and 1,146 institutional investors. US SIF identified a universe of 397 money managers and 553 institutional investors with $43.8 and $10.3 trillion in assets under management, respectively. Of them, 384 money managers and 530 institutions were confirmed as incorporating ESG criteria, affecting $16.6 and $6.2 trillion in assets, respectively. In addition, 1,204 community investing institutions with $266 billion in assets under management were analyzed. US numbers are extrapolated based on a subset of respondents who gave information about their sustainable investing strategies. For more information about the report, see US SIF Report on US Sustainable and Impact Investing Trends 2020 and Global Sustainable Investment Review 2020.

APPENDIX A: APPENDIX TO CHAPTER 1

A.1 Equilibrium Non-pecuniary Preferences

Recent papers by Pastor et al. (2021) and Pedersen et al. (2021) offered simple and tractable equilibrium models that feature investors with non-pecuniary preferences. When deciding to allocate wealth over the cross-section of firms, investors attend to firms' pre-determined ESG credentials as they derive utility from holding ESG-friendlier firms. The following framework generalizes the two models by picking up their key ingredients and illustrates how the non-pecuniary preferences affect asset prices.

Consider a infinitesimally sized representative agent in a one-period set-up with her initial wealth at time t normalized to 1. There exists a risk-free asset whose gross return equals $R_{f,T}$ in all future states at the terminal period T and $N-1$ assets whose returns are uncertain at time t and will be realized at T. Denote risky assets' returns as $R_{i,T}$ for $i = \{1, ..., N-1\}$ and the market return as $R_{m,T}$. Each asset has time-t observable ESG credential g_i where the risk-free asset carries $g_f = 0$. Taking prices and thus the return distributions of assets as given, the agent maximizes her terminal expected utility that integrates her wealth and non-pecuniary outcomes by choosing portfolio weights $\{\omega_i\}$,

$$\max_{\{\omega_i\}} \mathbb{E}_t u\left(\sum_i \omega_i \left(R_{i,T} + \delta g_i\right)\right), \qquad s.t. \ \sum_i \omega_i = 1$$

where the utility function $u(\cdot)$ is assumed twice differentiable with $u' > 0$ and $u'' < 0$ and $\delta > 0$ denotes her desire for non-pecuniary benefits relative to that for pecuniary proceeds. The first-order condition yields an Euler equation

$$\mathbb{E}_t\left[\frac{u'(R_{m,T} + \delta g_m)}{\lambda}(R_{i,T} + \delta g_i)\right] = \mathbb{E}_t\left[M_{t,T}(R_{i,T} + \delta g_i)\right] = 1, \ \ \forall i,$$

where λ is a positive Lagrange multiplier, $g_m = \sum_i \omega_i g_i$ an overall market ESG credential, and $M_{t,T}$ a stochastic discount factor (SDF).[1] Notice, non-pecuniary preferences affect not only the SDF unless $g_m = 0$ but also the equilibrium return of any risky asset i with g_i. All else equal, the

[1]Dynamic settings will alter the forms of SDF $M_{t,T}$, but the Euler equation maintains the same form and must hold across all settings.

Euler equation implies assets with higher ESG credentials command lower expected returns, echoing the main results of the aforementioned papers. Intuitively, agents are willing to sacrifice pecuniary returns for satiating their non-pecuniary preferences, thereby lowering the expected returns of firms with higher g.

Consequently, the effect of non-pecuniary preferences percolates to risk-neutral moments and distribution. In an arbitrage-free complete market, $M_{t,T}$ exists and is unique. Suppressing subscripts temporarily, notice that

$$\begin{aligned}\mathbb{E}[MR] &= \int\int MRp(M,R)dMdR = \int\int MRp(M|R)p(R)dMdR \\ &= \int R\left(\int Mp(M|R)dM\right)p(R)dR,\end{aligned}$$

where $p()$ denotes a density under physical measure. Therefore, we have

$$R_f\mathbb{E}[MR] = \int R\underbrace{R_f\left(\int Mp(M|R)dM\right)p(R)}_{\equiv q(R)}dR,$$

where $\int q(R)dR = 1$ so that $q()$ is a new probability measure on the same probability space as the physical measure.[2] Because M is unique, $q()$ is unique. Now, define q as a risk-neutral density and denote $\mathbb{E}^*$ as the expectation operator under the risk-neutral measure. Then, for any integer a greater than 1,

$$R_f\mathbb{E}[MR^a] = \int R^a R_f\left(\int Mp(M|R)dM\right)p(R)dR = \mathbb{E}^*[R^a].$$

By the Euler equation,

$$\mathbb{E}_t^*[R_{i,T}] = R_{f,T}\mathbb{E}_t[M_{t,T}R_{i,T}] = R_{f,T} - \delta g_i, \tag{A.1}$$

and using these identities, a centralized risk-neutral variance of any risky asset i's return can be expressed as

[2]To ensure $\int q(R)dR = R_f\int M\left(\int p(M|R)p(R)dR\right)dM = R_f\mathbb{E}[M] = 1$ in the presence of non-pecuniary utility, $g_f = 0$ is necessary to ensure $\mathbb{E}[M] = 1/R_f$. Arguably, a risk-free asset is ESG-neutral and any measure of non-pecuniary benefit can be linearly transformed such that $g = 0$ represents ESG-neutrality.

$$
\begin{aligned}
Var_t^*(R_{i,T}) &= \mathbb{E}_t^*[R_{i,T}^2] - (\mathbb{E}_t^*[R_{i,T}])^2 = R_{f,T}\mathbb{E}_t[M_{t,T}R_{i,T}^2] - (R_{f,T} - \delta g_i)^2 \\
&= R_{f,T}Cov_t(M_{t,T}R_{i,T}, R_{i,T}) + (R_{f,T} - \delta g_i)\left(\mathbb{E}_t[R_{i,T}] - (R_{f,T} - \delta g_i)\right),
\end{aligned}
$$

and therefore,

$$
\frac{Var_t^*(R_{i,T})}{R_{f,T}} = \underbrace{Cov_t(M_{t,T}R_{i,T}, R_{i,T})}_{\perp g_i} + (R_{f,T} - \delta g_i)\underbrace{\left(\mathbb{E}_t[R_{i,T}] - (R_{f,T} - \delta g_i)\right)}_{\perp g_i}. \tag{A.2}
$$

Observe that the bracketed terms in (A.2) are g-invariant. For assets i and i' whose return distributions are identical and perfectly correlated, when $g_{i'}$ diverges from g_i, it causes a mean shift only so that the first bracketed term stays the same. By rearranging the Euler equation, we have $\mathbb{E}_t[R_{i,T}] + \delta g_i = R_{f,T}\left(1 - Cov_t(M_{t,T}, R_{i,T})\right)$. Again, the covariance is g-invariant, so g-invariant RHS necessitates LHS to be g-invariant as well. Therefore, the second bracketed term is g-invariant and equals $-R_{f,T}Cov_t(M_{t,T}, R_{i,T})$ which must be positive. This shows the risk-neutral variance decreases with g. Assuming the regressions are well specified, the IVA coefficient corresponds to $\delta\left(\mathbb{E}_t[R_{i,T}] - (R_{f,T} - \delta g_i)\right)$ with the term in parenthesis approximates 1. Given the unconditional average monthly expected stock return is around 1, the IVA coefficient should close in on δ, unless δ is too high. Therefore, IVA coefficients can be interpreted as non-pecuniary equity premia.

This relation reflects that risk-averse investors, who internalize non-pecuniary benefits, regard ESG-friendlier stocks effectively less risky. Because ESG credentials are pre-determined, investing in asset i increases expected utility by $u(\delta g_i)$ unconditionally. The immediate jump of certainty equivalent is tantamount to $R_{i,T}$ being less systematically volatile. Recall, both MW and KT measures of expected returns are based on risk-neutral variances of stocks. Hence, in the presence of non-pecuniary preferences, they must reveal the effects of it, which I show is the case in section 1.3.

By the same token, the non-pecuniary preferences should be identified through option-implied risk-neutral means of stock returns if properly decomposed. Bakshi et al. (2003) compute the risk-neutral mean $\mu_{T|t}^{*,BKM}$ assuming $\delta = 0$, which must diverge from the mean directly recovered from the risk-neutral distribution $\mu_{T|t}^*$, if $\delta \neq 0$. Namely, borrowing the notations defined in section 1.2.2,

$$\mu_{i,T|t}^{*,BKM} = \mathbb{E}_t^{*,BKM}[r_{i,T}] = R_{f,T}\left(1 - \frac{V_i(t,T)}{2} - \frac{W_i(t,T)}{6} - \frac{X_i(t,T)}{24}\right) - 1,$$

for any stock i. The expression relies on the Euler equation with $\delta = 0$, and hence omits non-pecuniary preference component within the risk-neutral means if $\delta \neq 0$ according to (A.1). Indeed, estimating the following Fama and MacBeth (1973) regression in which I back out the non-pecuniary component, if any, on the left hand side,

$$\mu_{i,t+1|t}^{*,BKM} - \mu_{i,t+1|t}^{*} = c + \mu\mathbb{1}(IVA_{i,t} < 2) + \delta IVA_{i,t} + \tilde{\delta} IVA_{i,t} \times \mathbb{1}(IVA_{i,t} < 2) + e_{i,t+1}, \tag{A.3}$$

yields statistically significant and positive δ for both S&P 500 and non S&P 500 stocks, regardless of restricting the sample to just include stocks with information on firm fundamentals available or not, as shown in Table A.2.

Table A.1: ESG Implied Cost of Capital (Hou et al. (2012) Methods)

	S&P 500 Stocks				All Stocks ($\geq$ 2012)			
	CT	OJ	E	HVZ	CT	OJ	E	HVZ
$ESG_t^{☼}$	-0.018**	-0.017*	0.033	-0.016**	-0.015**	-0.015*	0.051*	-0.022***
	(-2.48)	(-1.91)	(1.46)	(-2.05)	(-2.13)	(-1.90)	(1.86)	(-3.68)
$ESG_t^{\$}$	-0.043***	-0.030***	-0.067***	-0.042***	-0.193***	-0.225***	-0.691***	-0.182***
	(-4.30)	(-3.67)	(-2.68)	(-3.00)	(-13.91)	(-12.41)	(-15.19)	(-14.94)
β_t^{mkt}	-0.014	-0.042	0.081	0.025	0.109***	0.088***	0.277***	0.112***
	(-0.46)	(-1.35)	(0.83)	(0.85)	(3.15)	(2.63)	(4.03)	(4.20)
$Log(Size_t)$	-0.220***	-0.271***	-0.365***	-0.196***	-0.526***	-1.070***	-2.973***	-0.629***
	(-11.84)	(-17.24)	(-7.03)	(-9.56)	(-17.75)	(-18.19)	(-18.23)	(-32.56)
$Log(BTM_t)$	0.202***	0.089***	0.161***	0.153***	0.686***	0.301***	0.287***	0.411***
	(6.68)	(6.85)	(3.93)	(10.40)	(14.24)	(15.37)	(6.15)	(17.57)
MOM_t	-0.016	-0.038***	-0.104***	-0.033**	0.064*	0.014	-0.438***	-0.018
	(-1.15)	(-3.12)	(-3.99)	(-2.39)	(1.73)	(0.44)	(-6.08)	(-0.51)
$Log(Turn_t)$	-0.039*	0.001	0.165***	-0.001	-0.798***	-0.594***	-0.195**	-0.573***
	(-1.91)	(0.03)	(3.28)	(-0.02)	(-18.23)	(-17.87)	(-2.55)	(-13.91)
$Log(LEV_t)$	0.493***	0.632***	1.071***	0.585***	1.042***	0.993***	1.443***	1.176***
	(25.58)	(21.81)	(21.65)	(30.09)	(17.21)	(17.22)	(13.62)	(20.05)
Inv_t	0.015	-0.023**	-0.270***	-0.039***	0.141***	0.069***	-0.588***	-0.018
	(1.29)	(-2.02)	(-3.25)	(-3.14)	(5.25)	(2.91)	(-6.85)	(-0.85)
Constant	1.239***	2.780***	2.741***	1.657***	1.601***	3.736***	6.005***	2.211***
	(10.15)	(22.90)	(28.61)	(21.91)	(16.51)	(40.15)	(26.28)	(33.05)
N	46640	44124	34073	31447	103708	89103	82003	64975
Adj. R^2	0.478	0.509	0.496	0.601	0.510	0.511	0.479	0.603

Note: The first and last 4 columns report Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using ICC measures of CT (Claus and Thomas (2001)), OJ (Ohlson and Juettner-Nauroth (2005)), E (Easton (2004)), and HVZ (a "composite" ICC measure that is an equal-weighted average of the five, non-missing, individual ICC estimates that HVZ use) based on the regression-based approach of Hou et al. (2012) as dependant variables of equation (1.2) for S&P 500 (whole sample) and all CRSP stocks (from 2012 to 2021), respectively. Details of $ESG^{☼}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. EPS_t is omitted from regressors to prevent it from explaining too much variation of ICC that is estimated from past and current earnings. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.2: Non-pecuniary Utility

	$\mu^{*,BKM}_{t+1\|t} - \mu^{*}_{t+1\|t}$ (in %)							
	S&P 500 Stocks				All Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ESG^{\text{☼}}_t$	0.0011**	0.0012**	0.0009*	0.0009*	0.0029***	0.0031***	0.0008*	0.0009*
	(2.06)	(2.05)	(1.90)	(1.89)	(7.12)	(7.24)	(1.89)	(1.88)
$\mathbb{1}_{ESG^{\text{☼}}_t<2}$		0.0047		0.0056		0.0013		0.0056
		(0.91)		(0.80)		(0.16)		(1.04)
$ESG^{\text{☼}}_t \times \mathbb{1}_{ESG^{\text{☼}}_t<2}$		0.0011		0.0016		-0.0023		0.0016
		(0.54)		(0.50)		(-0.61)		(0.80)
Constant	-0.0078***	-0.0078***	-0.0076***	-0.0076***	-0.0142***	-0.0142***	-0.0078***	-0.0079***
	(-14.88)	(-14.76)	(-15.07)	(-14.94)	(-29.70)	(-29.52)	(-14.15)	(-13.91)
N	60281	60281	57243	57243	152495	152495	57243	57243
N/A Fundamentals	Yes	Yes	No	No	Yes	Yes	No	No
Adj. R^2	0.033	0.033	0.032	0.032	0.040	0.041	0.032	0.032

Note: The first and last 4 columns report Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using Bakshi et al. (2003)'s options-based risk-neutral return mean *minus* the risk-neutral return mean directly recovered the estimated risk-neutral probability distribution as dependant variables for S&P 500 stocks and for all CRSP stocks, respectively. The sample period is from 2007/1 to 2021/12 and restricted to observations whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of $ESG^{\text{☼}}$ and $ESG^{\$}$ are presented in section 1.2.1. Columns (1), (2), (5), and (6) allow stocks with missing firm fundamentals in the sample, while other columns do not. All regressors are standardized each month to have zero mean and unit variance. On average, standard deviations of $ESG^{\text{☼}}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.3: $ESG^{\text{☼}}$-industry adjusted ESG *Ex-ante* Equity Premia (S&P 500 Stocks)

	$\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$				$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ESG_t^{\text{☼}}$	-0.009	-0.014*	-0.005	-0.003	-0.019	-0.027*	-0.010	-0.006
	(-1.58)	(-1.66)	(-1.27)	(-0.49)	(-1.58)	(-1.66)	(-1.27)	(-0.49)
$\mathbb{1}_{ESG_t^{\text{☼}}<2}$		0.184**		0.035		0.368**		0.070
		(2.43)		(0.61)		(2.43)		(0.61)
$ESG_t^{\text{☼}} \times \mathbb{1}_{ESG_t^{\text{☼}}<2}$		0.108**		0.010		0.216**		0.021
		(2.59)		(0.31)		(2.59)		(0.31)
$ESG_t^{\$}$	-0.057***	-0.055***	-0.014***	-0.008	-0.114***	-0.111***	-0.028***	-0.015
	(-6.35)	(-5.66)	(-3.53)	(-1.56)	(-6.35)	(-5.66)	(-3.54)	(-1.56)
$\mathbb{1}_{ESG_t^{\$}\leq -40}$		-0.149**		-0.161**		-0.299**		-0.322**
		(-2.50)		(-2.27)		(-2.50)		(-2.27)
$ESG_t^{\$} \times \mathbb{1}_{ESG_t^{\$}\leq -40}$		-0.063**		-0.075**		-0.126**		-0.150**
		(-2.49)		(-2.44)		(-2.49)		(-2.44)
β_t^{mkt}	0.415***	0.415***	0.239***	0.238***	0.829***	0.829***	0.479***	0.477***
	(8.04)	(8.05)	(6.17)	(6.19)	(8.04)	(8.05)	(6.17)	(6.19)
$Log(Size_t)$	-0.107***	-0.108***	0.029***	0.028***	-0.214***	-0.216***	0.057***	0.057***
	(-8.77)	(-8.75)	(4.43)	(4.41)	(-8.77)	(-8.75)	(4.43)	(4.41)
$Log(BTM_t)$	0.027***	0.026***	0.010**	0.009**	0.053***	0.052***	0.019**	0.018**
	(3.11)	(3.08)	(2.26)	(2.11)	(3.11)	(3.08)	(2.26)	(2.11)
MOM_t	-0.081***	-0.081***	-0.074***	-0.075***	-0.163***	-0.163***	-0.148***	-0.149***
	(-4.02)	(-4.06)	(-4.16)	(-4.15)	(-4.02)	(-4.06)	(-4.16)	(-4.15)
$Log(Turn_t)$			0.205***	0.206***			0.410***	0.412***
			(13.82)	(13.91)			(13.82)	(13.91)
$Log(LEV_t)$			0.036**	0.037**			0.073**	0.074**
			(2.36)	(2.35)			(2.36)	(2.35)
EPS_t			-0.088***	-0.088***			-0.176***	-0.175***
			(-7.91)	(-7.91)			(-7.91)	(-7.91)
Inv_t			-0.004	-0.003			-0.008	-0.006
			(-0.92)	(-0.70)			(-0.92)	(-0.70)
Constant	0.134***	0.137***	0.313***	0.312***	0.393***	0.399***	0.752***	0.750***
	(5.04)	(5.08)	(9.93)	(9.99)	(9.02)	(9.44)	(12.88)	(13.26)
N	46725	46725	46705	46705	46725	46725	46705	46705
Adj. R^2	0.321	0.322	0.477	0.479	0.321	0.322	0.477	0.479

Note: The first and last 6 columns report Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using Martin and Wagner (2019) and Kadan and Tang (2020) expected excess returns as dependant variables, respectively. The sample consists of S&P 500 index constituents during 2007/1 $\sim$ 2021/12 whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. Details of industry-adjusted $ESG^{\text{☼}}$, $ESG^{\$}$, and control variables are presented in section 1.2.1 and Table 1.1. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. On average, standard deviations of $ESG^{\text{☼}}$ and $ESG^{\$}$ are approximately 2.3 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.4: Orthogonalized ESG *Ex-ante* Equity Premia (S&P 500 Stocks)

	$\mathbb{E}_t^{MW}[R_{t+1}^{ex}]$						$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$E\hat{S}G_t^{☼}$	-0.026***	-0.023***	-0.014***	-0.011**	-0.014***	-0.011**	-0.051***	-0.045***	-0.028***	-0.021**	-0.028***	-0.022**
	(-4.20)	(-3.41)	(-2.96)	(-2.03)	(-2.90)	(-2.02)	(-4.19)	(-3.41)	(-2.96)	(-2.03)	(-2.90)	(-2.02)
$\mathbb{1}_{E\hat{S}G_t^{☼}<2}$		0.237		0.238		0.296		0.474		0.476		0.592
		(1.44)		(0.90)		(1.08)		(1.44)		(0.90)		(1.08)
$E\hat{S}G_t^{☼} \times \mathbb{1}_{E\hat{S}G_t^{☼}<2}$		0.058		0.062		0.083		0.116		0.124		0.167
		(0.81)		(0.59)		(0.76)		(0.81)		(0.59)		(0.76)
$E\hat{S}G_t^{\$}$	-0.055***	-0.053***	-0.015***	-0.010*	-0.014***	-0.009*	-0.110***	-0.107***	-0.030***	-0.020*	-0.028***	-0.019*
	(-6.05)	(-5.05)	(-3.46)	(-1.89)	(-3.41)	(-1.82)	(-6.05)	(-5.06)	(-3.46)	(-1.89)	(-3.41)	(-1.82)
$\mathbb{1}_{E\hat{S}G_t^{\$}\leq-40}$		-0.048		-0.123**		-0.113**		-0.096		-0.246**		-0.226**
		(-0.96)		(-2.41)		(-2.26)		(-0.96)		(-2.41)		(-2.26)
$E\hat{S}G_t^{\$} \times \mathbb{1}_{E\hat{S}G_t^{\$}\leq-40}$		-0.028		-0.064***		-0.060**		-0.056		-0.127***		-0.119**
		(-1.24)		(-2.71)		(-2.57)		(-1.24)		(-2.71)		(-2.57)
β_t^{mkt}	0.415***	0.414***	0.239***	0.235***	0.240***	0.236***	0.830***	0.827***	0.477***	0.469***	0.480***	0.472***
	(8.06)	(8.03)	(6.16)	(6.08)	(6.17)	(6.10)	(8.06)	(8.03)	(6.16)	(6.08)	(6.17)	(6.10)
$Log(Size_t)$	-0.102***	-0.105***	0.030***	0.028***	0.030***	0.028***	-0.204***	-0.209***	0.059***	0.056***	0.060***	0.057***
	(-8.78)	(-8.84)	(4.72)	(4.30)	(4.74)	(4.32)	(-8.78)	(-8.84)	(4.72)	(4.30)	(4.74)	(4.32)
$Log(BTM_t)$	0.026***	0.028***	0.009**	0.011**	0.008*	0.010**	0.052***	0.055***	0.017**	0.021**	0.017*	0.021**
	(3.12)	(3.24)	(2.04)	(2.31)	(1.97)	(2.25)	(3.12)	(3.24)	(2.03)	(2.31)	(1.96)	(2.25)
MOM_t	-0.081***	-0.079***	-0.074***	-0.072***	-0.074***	-0.072***	-0.161***	-0.158***	-0.147***	-0.144***	-0.147***	-0.144***
	(-4.03)	(-4.04)	(-4.10)	(-4.09)	(-4.13)	(-4.12)	(-4.03)	(-4.04)	(-4.10)	(-4.09)	(-4.13)	(-4.12)
$Log(Turn_t)$			0.205***	0.207***	0.204***	0.206***			0.409***	0.414***	0.407***	0.412***
			(14.20)	(14.18)	(14.00)	(14.02)			(14.20)	(14.19)	(14.00)	(14.02)
$Log(LEV_t)$			0.038**	0.038**	0.039**	0.039**			0.077**	0.077**	0.077**	0.078**
			(2.50)	(2.51)	(2.51)	(2.53)			(2.50)	(2.51)	(2.51)	(2.53)
EPS_t			-0.089***	-0.088***	-0.088***	-0.087***			-0.178***	-0.176***	-0.176***	-0.174***
			(-7.52)	(-7.52)	(-7.74)	(-7.75)			(-7.52)	(-7.52)	(-7.73)	(-7.75)
Inv_t					-0.004	-0.004					-0.009	-0.009
					(-1.00)	(-1.04)					(-1.00)	(-1.04)
Constant	0.134***	0.134***	0.314***	0.316***	0.313***	0.315***	0.394***	0.394***	0.755***	0.758***	0.751***	0.755***
	(5.09)	(5.03)	(9.93)	(9.80)	(9.94)	(9.80)	(9.01)	(8.88)	(12.87)	(12.71)	(12.86)	(12.71)
N	46571	46571	46561	46561	46551	46551	46571	46571	46561	46561	46551	46551
Adj. R^2	0.323	0.321	0.477	0.477	0.478	0.479	0.323	0.321	0.477	0.477	0.478	0.479

Note: The first and last 4 columns report Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using Martin and Wagner (2019) and Kadan and Tang (2020) expected excess returns as dependant variables, respectively. The sample consists of S&P 500 index constituents during 2007/1 $\sim$ 2021/12 whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. $E\hat{S}G_t^{☼}$ and $E\hat{S}G_t^{\$}$ are orthogonalized $ESG_t^{☼}$ and $ESG_t^{\$}$ from estimating the residuals of the following respective regressions for each stock: $ESG_t^{☼} = a_t + b_t ESG_t^{\$} + e_t$ and $ESG_t^{\$} = a_t + b_t ESG_t^{☼} + e_t$, respectively, with at least 25 observations. Control variables are presented in Table 1.1. All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. On average, standard deviations of $E\hat{S}G_t^{☼}$ and $E\hat{S}G_t^{\$}$ are approximately 1.1 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.5: Orthogonalized ESG *Ex-ante* Equity Premia (All Stocks)

	$\mathbb{E}_t^{KT}[R_{t+1}^{ex}]$							
	$\gamma = 4$		$\gamma = 5$		$\gamma = 6$		$\gamma = 7$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$E\hat{S}G_t^{☼}$	-0.045***	-0.039***	-0.050***	-0.043***	-0.057***	-0.049***	-0.059***	-0.051***
	(-4.41)	(-4.82)	(-4.37)	(-4.34)	(-4.54)	(-4.68)	(-4.47)	(-4.50)
$\mathbb{1}_{E\hat{S}G_t^{☼}<2}$		-72.010		-66.786		-68.660		-67.900
		(-1.02)		(-1.01)		(-1.01)		(-1.01)
$E\hat{S}G_t^{☼} \times \mathbb{1}_{E\hat{S}G_t^{☼}<2}$		-23.906		-22.144		-22.768		-22.539
		(-1.03)		(-1.02)		(-1.02)		(-1.03)
$E\hat{S}G_t^{\$}$	-0.080***	-0.058***	-0.090***	-0.062***	-0.099***	-0.070***	-0.106***	-0.075***
	(-4.59)	(-3.53)	(-4.77)	(-3.62)	(-4.79)	(-3.66)	(-5.02)	(-3.83)
$\mathbb{1}_{E\hat{S}G_t^{\$}\leq -40}$		-0.356***		-0.496***		-0.522***		-0.557***
		(-2.72)		(-3.67)		(-3.65)		(-3.69)
$E\hat{S}G_t^{\$} \times \mathbb{1}_{E\hat{S}G_t^{\$}\leq -40}$		-0.195***		-0.252***		-0.269***		-0.291***
		(-3.81)		(-4.91)		(-4.88)		(-4.97)
Constant	0.976***	0.994***	1.080***	1.095***	1.133***	1.147***	1.196***	1.210***
	(7.90)	(8.02)	(8.00)	(8.10)	(7.99)	(8.12)	(7.96)	(8.10)
N	48993	48993	57630	57630	63473	63473	67699	67699
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.386	0.381	0.391	0.389	0.388	0.387	0.395	0.395

Note: Each pair of columns reports Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using Kadan and Tang (2020) expected excess returns as dependant variables for the sample of CRSP stocks that satisfy the following two conditions: (i) $Cov(R_{i,t}, R_{m,t}) \leq 0$ and (ii) $\frac{Var(R_{i,t})}{Cov(R_{i,t},R_{m,t})} \leq \gamma$ for the previous 12 months. Meeting both (i) and (ii) is a sufficient condition for Kadan and Tang (2020) expected returns to be legitimate lower bounds of actual expected returns, given the acceptable range of relative risk aversion parameter value is lower than γ. The sample period is from 2007/1 to 2021/12 and I further restrict to stocks whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. $E\hat{S}G_t^{☼}$ and $E\hat{S}G_t^{\$}$ are orthogonalized $ESG_t^{☼}$ and $ESG_t^{\$}$ from estimating the residuals of the following respective regressions for each stock: $ESG_t^{☼} = a_t + b_t ESG_t^{\$} + e_t$ and $ESG_t^{\$} = a_t + b_t ESG_t^{☼} + e_t$, respectively, with at least 25 observations. Control variables are presented in Table 1.1. All columns include the most rich set of control variables (i.e., control variables in (5), (6), (11), or (12) in Table 1.5). All regressors are standardized each month to have zero mean and unit variance, except for β_t^{mkt}. On average, standard deviations of $E\hat{S}G_t^{☼}$ and $E\hat{S}G_t^{\$}$ are approximately 1.1 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.6: Orthogonalized ESG *Ex-post* Equity Premia

	R^{ex}_{t+1}							
	S&P 500 Stocks				All Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{ESG}^{☼}_t$	0.042	0.024	0.063	0.045	0.054	0.041	0.060	0.050
	(0.81)	(0.46)	(1.32)	(0.91)	(1.07)	(0.80)	(1.27)	(1.03)
$\mathbb{1}_{\hat{ESG}^{☼}_t<2}$		-2.224		-2.067		67.955		65.733
		(-0.25)		(-0.25)		(0.96)		(0.96)
$\hat{ESG}^{☼}_t \times \mathbb{1}_{\hat{ESG}^{☼}_t<2}$		-0.970		-0.821		21.164		20.519
		(-0.29)		(-0.26)		(0.99)		(0.99)
$\hat{ESG}^{\$}_t$	-0.053	0.011	-0.045	0.011	-0.147**	-0.080	-0.138**	-0.069
	(-0.96)	(0.17)	(-0.94)	(0.21)	(-2.36)	(-1.37)	(-2.32)	(-1.35)
$\mathbb{1}_{\hat{ESG}^{\$}_t\leq-40}$		-0.465		-0.427		0.940		1.068
		(-0.50)		(-0.49)		(0.47)		(0.52)
$\hat{ESG}^{\$}_t \times \mathbb{1}_{\hat{ESG}^{\$}_t\leq-40}$		-0.292		-0.241		0.141		0.188
		(-0.92)		(-0.81)		(0.23)		(0.30)
R^{ex}_t	-0.015	-0.015	-0.014	-0.014	-0.018**	-0.018**	-0.019**	-0.019**
	(-1.51)	(-1.49)	(-1.46)	(-1.45)	(-2.11)	(-2.16)	(-2.34)	(-2.39)
β^{mkt}_t	0.404	0.397	0.239	0.236	0.209	0.217	0.239	0.243
	(1.10)	(1.08)	(0.73)	(0.72)	(0.64)	(0.67)	(0.84)	(0.85)
$Log(Size_t)$	-0.022	-0.028	0.011	0.011	-0.306*	-0.296*	-0.459***	-0.449***
	(-0.24)	(-0.30)	(0.13)	(0.13)	(-1.75)	(-1.70)	(-2.89)	(-2.87)
$Log(BTM_t)$	-0.077	-0.073	-0.012	-0.014	0.044	0.048	0.032	0.032
	(-1.14)	(-1.07)	(-0.25)	(-0.29)	(0.55)	(0.60)	(0.43)	(0.42)
MOM_t	-0.082	-0.078	-0.091	-0.084	0.149	0.151	0.126	0.128
	(-0.87)	(-0.82)	(-0.99)	(-0.92)	(0.94)	(0.95)	(0.87)	(0.89)
$Log(Turn_t)$			0.194**	0.197**			0.069	0.077
			(2.29)	(2.33)			(0.58)	(0.64)
$Log(LEV_t)$			-0.095	-0.084			0.041	0.058
			(-1.03)	(-0.92)			(0.35)	(0.49)
EPS_t			0.225***	0.229***			0.378***	0.385***
			(4.26)	(4.35)			(6.57)	(6.69)
Inv_t			-0.059	-0.058			-0.051	-0.040
			(-1.27)	(-1.27)			(-0.76)	(-0.59)
Constant	0.544*	0.525*	0.711**	0.693**	0.988**	0.965**	0.884**	0.854**
	(1.80)	(1.74)	(2.46)	(2.39)	(2.42)	(2.34)	(2.17)	(2.09)
N	47601	47601	47579	47579	128420	128420	128338	128338
Adj. R^2	0.136	0.133	0.164	0.162	0.102	0.101	0.122	0.121

Note: The first and last 4 columns report Fama and MacBeth (1973) regression coefficients and Newey and West (1987) standard errors with 3 lags using realized excess returns as dependant variables for S&P 500 stocks and for all CRSP stocks, respectively. The sample period is from 2007/1 to 2021/12. $\hat{ESG}^{☼}_t$ and $\hat{ESG}^{\$}_t$ are orthogonalized $ESG^{☼}_t$ and $ESG^{\$}_t$ from estimating the residuals of the following respective regressions for each stock: $ESG^{☼}_t = a_t + b_t ESG^{\$}_t + e_t$ and $ESG^{\$}_t = a_t + b_t ESG^{☼}_t + e_t$, respectively, with at least 25 observations. Control variables are presented in Table 1.1. All regressors are standardized each month to have zero mean and unit variance, except for β^{mkt}_t. On average, standard deviations of $\hat{ESG}^{☼}_t$ and $\hat{ESG}^{\$}_t$ are approximately 1.1 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.7: Orthogonalized ESG *Ex-post* Return Predictability

	R^{ex}_{t+1}							
	S&P 500 Stocks				All Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{ESG}^{☼}_t$	0.040	0.038	0.058	0.056	0.064*	0.068**	0.074**	0.079**
	(0.97)	(0.90)	(1.40)	(1.31)	(1.95)	(1.97)	(2.14)	(2.21)
$\mathbb{1}_{\hat{ESG}^{☼}_t<2}$		2.947		3.058		-0.149		-0.277
		(1.22)		(1.27)		(-0.10)		(-0.17)
$\hat{ESG}^{☼}_t \times \mathbb{1}_{\hat{ESG}^{☼}_t<2}$		1.253		1.305		-0.090		-0.182
		(1.35)		(1.40)		(-0.13)		(-0.26)
$\hat{ESG}^{\$}_t$	-0.140***	-0.110*	-0.097*	-0.058	-0.252***	-0.247***	-0.228***	-0.207***
	(-2.71)	(-1.85)	(-1.81)	(-0.95)	(-6.30)	(-5.54)	(-5.68)	(-4.61)
$\mathbb{1}_{\hat{ESG}^{\$}_t\leq-40}$		-0.830		-0.837		-1.378*		-1.452*
		(-1.20)		(-1.19)		(-1.71)		(-1.78)
$\hat{ESG}^{\$}_t \times \mathbb{1}_{\hat{ESG}^{\$}_t\leq-40}$		-0.443		-0.461		-0.472*		-0.552**
		(-1.57)		(-1.58)		(-1.88)		(-2.18)
R^{ex}_t	-0.161***	-0.161***	-0.162***	-0.162***	-0.099***	-0.099***	-0.100***	-0.100***
	(-23.11)	(-23.12)	(-23.28)	(-23.28)	(-17.02)	(-17.02)	(-17.13)	(-17.13)
β^{mkt}_t	0.402***	0.410***	0.298***	0.305***	0.140*	0.141*	0.100	0.100
	(4.15)	(4.22)	(2.80)	(2.86)	(1.80)	(1.81)	(1.19)	(1.19)
$Log(Size_t)$	-0.195***	-0.201***	-0.104	-0.108*	-0.556***	-0.558***	-0.726***	-0.731***
	(-3.43)	(-3.54)	(-1.61)	(-1.69)	(-8.09)	(-8.11)	(-10.49)	(-10.51)
$Log(BTM_t)$	-0.021	-0.022	-0.038	-0.042	0.036	0.036	-0.027	-0.029
	(-0.41)	(-0.44)	(-0.70)	(-0.77)	(0.78)	(0.76)	(-0.49)	(-0.55)
MOM_t	0.264***	0.263***	0.269***	0.268***	0.548***	0.548***	0.560***	0.560***
	(5.62)	(5.58)	(5.72)	(5.69)	(9.35)	(9.35)	(9.34)	(9.35)
$Log(Turn_t)$			0.215***	0.216***			0.256***	0.262***
			(3.53)	(3.58)			(4.24)	(4.32)
$Log(LEV_t)$			0.115*	0.122*			0.295***	0.301***
			(1.78)	(1.88)			(4.29)	(4.34)
EPS_t			0.206***	0.205***			0.393***	0.393***
			(4.07)	(4.05)			(10.54)	(10.57)
Inv_t			-0.146***	-0.147***			-0.171***	-0.171***
			(-3.15)	(-3.16)			(-3.17)	(-3.18)
Constant	0.913***	0.896***	1.010***	0.992***	1.713***	1.713***	1.572***	1.567***
	(8.73)	(8.39)	(8.60)	(8.29)	(14.90)	(14.87)	(13.38)	(13.32)
N	46971	46971	46949	46949	120945	120945	120869	120869
Industry FE	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49	FF-49
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock
Adj. R^2	0.145	0.145	0.146	0.146	0.125	0.125	0.126	0.126

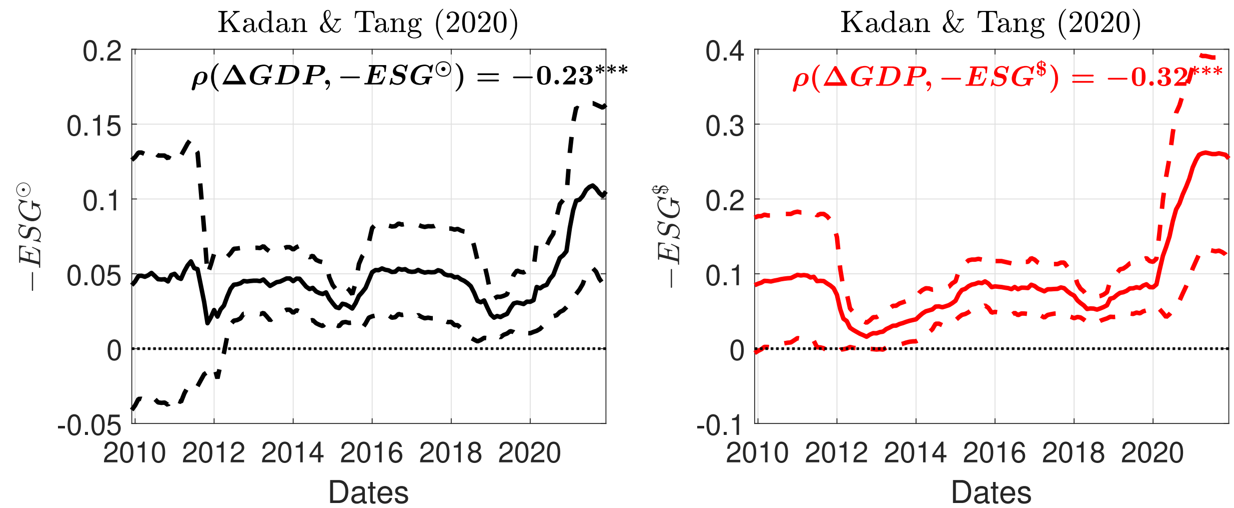
Note: The first and last 4 columns report return-predictability regression coefficients and standard errors clustered at a stock level, using realized excess returns as dependant variables for S&P 500 stocks and for all CRSP stocks, respectively. All regressions include NAICS 4-digit industry (robust to using SIC codes) and quarter fixed effects. The sample period is from 2007/1 to 2021/12. $\hat{ESG}^{☼}_t$ and $\hat{ESG}^{\$}_t$ are orthogonalized $ESG^{☼}_t$ and $ESG^{\$}_t$ from estimating the residuals of the following respective regressions for each stock: $ESG^{☼}_t = a_t + b_t ESG^{\$}_t + e_t$ and $ESG^{\$}_t = a_t + b_t ESG^{☼}_t + e_t$, respectively, with at least 25 observations. Control variables are presented in Table 1.1. All regressors are standardized each month to have zero mean and unit variance, except for β^{mkt}_t. On average, standard deviations of $\hat{ESG}^{☼}_t$ and $\hat{ESG}^{\$}_t$ are approximately 1.1 and 14, respectively. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.8: Top 20 Industries with Strongest Intensities of Two Preferences

NAICS 3-digit	Non-pecuniary ($ESG^{☼}$)	Pecuniary ($ESG^{\$}$)
1	Mining (except Oil & Gas)*	Food Services & Drinking Places**
2	Petroleum and Coal Products Manufacturing**	Rental and Leasing Services***
3	Publishing Industries (except Internet)**	Ambulatory Health Care Services***
4	Oil & Gas Extraction***	Oil & Gas Extraction*
5	General Merchandise Stores*	Publishing Industries (except Internet)***
6	Waste Management & Remediation Services*	General Merchandise Stores***
7	Accommodation*	Merchant Wholesalers, Durable Goods**
8	Computer & Electronic Product Manufacturing***	Machinery Manufacturing***
9	Hospitals***	Furniture & Related Product Manufacturing***
10	Merchant Wholesalers, Durable Goods***	Utilities**
11	Professional, Scientific, & Technical Services***	Telecommunications***
12	Leather & Allied Product Manufacturing***	Amusement, Gambling, & Recreation Industries***
13	Air Transportation***	Apparel Manufacturing***
14	Construction of Buildings***	Administrative & Support Services***
15	Food Manufacturing***	Electrical Equipment, Appliance, & Component Manufacturing***
16	Electronics & Appliance Stores***	Transportation Equipment Manufacturing***
17	Merchant Wholesalers, Nondurable Goods***	Support Activities for Mining***
18	Health & Personal Care Stores***	Plastics & Rubber Products Manufacturing***
19	Motor Vehicle & Parts Dealers***	Motor Vehicle & Parts Dealers***
20	Administrative & Support Services***	Air Transportation***

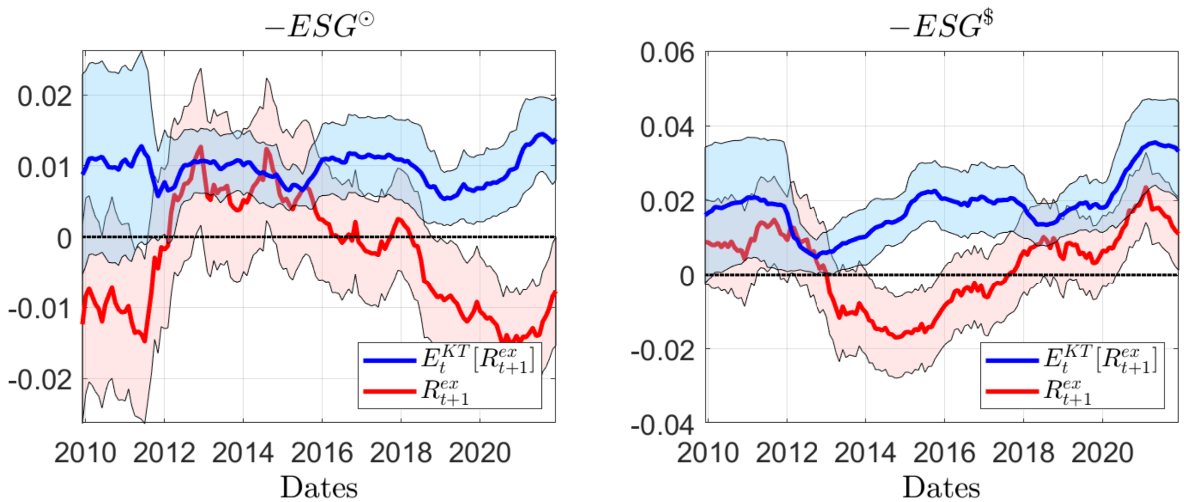
Note: Based on the regression result adding three extra regressors $\mathbb{1}_{\text{industry}}$, $ESG^{☼}_{i,t} \times \mathbb{1}_{\text{industry}}$ and $ESG^{\$}_{i,t} \times \mathbb{1}_{\text{industry}}$ to (5) of Table 1.5 for one industry at a time, absolute value of (i) coefficient on $ESG^{☼}_{i,t}$ ($ESG^{\$}_{i,t}$), if coefficient on $ESG^{☼}_{i,t} \times \mathbb{1}_{\text{industry}}$ ($ESG^{\$}_{i,t} \times \mathbb{1}_{\text{industry}}$) is not significant at 10% level, or (ii) the sum of coefficients on $ESG^{☼}_{i,t}$ and $ESG^{☼}_{i,t} \times \mathbb{1}_{\text{industry}}$ ($ESG^{\$}_{i,t}$ and $ESG^{\$}_{i,t} \times \mathbb{1}_{\text{industry}}$), if both coefficients are, or the sum is, significant at 10% level, are ranked. All coefficients have the correct signs (i.e., negative $ESG^{☼}$ and $ESG^{\$}$ coefficients) and *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively, of the coefficients. The sample is restricted to S&P 500 stocks. The sample period is from 2007/1 to 2021/12 and restricted to observations whose set of traded options with 15 to 45 days to maturity contains options with at least 15 unique moneyness (strike price / current stock price) at any given time t. To ensure any given industry consists of at least 2 unique stocks, industries with less than $15 \times 12 = 180$ (yr×mo) observations are dropped. To exclude financial sector stocks, stocks with $NAICS$ 2-digit codes of 52 and 53 are dropped.

Figure A.1: Time-Varying ESG Equity Premia (All CRSP Stocks)



Note: The figure plots the Kadan and Tang (2020) estimated $ESG^{\text{☼}}$ (left) and $ESG^{\$}$ (right) λ's in solid lines and their 95% confidence intervals in dashed lines of the first Fama and MacBeth (1973) regression in (1.2) over the window of past 3 years for all CRSP-listed stocks that satisfy the following sufficient conditions for Kadan and Tang (2020) expected returns to be legitimate lower bounds of actual expected returns: (i) $Cov(R_{i,t}, R_{m,t}) \leq 0$ and (ii) $\frac{Var(R_{i,t})}{Cov(R_{i,t}, R_{m,t})} \leq \gamma = 7$ for the previous 12 months. For example, λ's on date 2011/1 are estimates over the period from 2008/2 to 2011/1. Confidence intervals are based on Newey and West (1987) standard errors with 3 lags. The formal test of cyclicality is provided by computing correlation between 36-month average of lagged real GDP growth (details in 1.1) and 36-month rolling window λ's. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. The trends are robust to using windows of past 4 or 5 years. Y-axis represents the change in expected returns (in %) associated with 1 standard deviation increase in $ESG^{\text{☼}}$ and $ESG^{\$}$ ratings. On average, standard deviations of $ESG^{\text{☼}}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively.

Figure A.2: *Ex-ante* vs. *Ex-post* ESG Equity Premia (All Stocks)



**Note: The blue line and the blue shaded region in the left (right) plot the inverse of Kadan and Tang (2020) estimated $ESG^{☼}$ ($ESG^{\$}$) λ's and their 95% confidence intervals, respectively, of the first Fama and MacBeth (1973) regression in (1.2) over the window of past 3 years for all CRSP stocks. The red line and red shaded region denote λ's and their 95% confidence intervals, respectively, estimated through (1.3) using realized returns. For example, λ's on date 2010/1 are estimates over the period from 2007/2 to 2010/1. Confidence intervals are based on Newey and West (1987) standard errors with 3 lags. For comparability, all regression estimates here are based on standardized variables (both independent and dependent variables), so Y-axis represents the standard-deviation change in one-month-ahead expected or realized returns associated with 1 standard deviation increase in $ESG^{☼}$ and $ESG^{\$}$ ratings. The trends are robust to using windows of past 4 or 5 years. On average, standard deviations of $ESG^{☼}$ and $ESG^{\$}$ are approximately 1.2 and 14, respectively.

BIBLIOGRAPHY

Albuquerque, R., Y. Koskinen, S. Yang, and C. Zhang. 2020. Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash. *Review of Corporate Finance Studies* 9(3):593–621.

Albuquerque, R., Y. Koskinen, and C. Zhang. 2019. Corporate Social Responsibility and Firm Risk: Theory and Empirical Evidence. *Management Science* 65(10):4451–4469.

Amihud, Y. 2002. Illiquidity and Stock Returns: Cross-section and Time-series Effects. *Journal of Financial Markets* 5(1):31–56.

Aramonte, S., M. R. Jahan-Parvar, S. Rosen, and J. W. Schindler. 2021. Firm-Specific Risk-Neutral Distributions with Options and CDS. BIS Working Papers 921, Bank for International Settlements.

Baker, S. D., B. Hollifield, and E. Osambela. 2020. Asset Prices and Portfolios with Externalities. SSRN Working Paper 3344940, Social Science Research Network.

Bakshi, G., N. Kapadia, and D. Madan. 2003. Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options. *Review of Financial Studies* 16(1):101–143.

Bansal, R., and A. Yaron. 2004. Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles. *Journal of Finance* 59(4):1481–1509.

Barber, B. M., A. Morse, and A. Yasuda. 2021. Impact Investing. *Journal of Financial Economics* 139(1):162–185.

Barko, T., M. Cremers, and L. Renneboog. 2022. Shareholder Engagement on Environmental, Social, and Governance Performance. *Journal of Business Ethics* pp. 777–812.

Berg, F., K. Fabisik, and Z. Sautner. 2021a. Is History Repeating Itself? The (Un)predictable Past of ESG Ratings. ECGI Working Paper 708/2020, European Corporate Governance Institute.

Berg, F., F. Heeb, and J. F. Kölbel. 2022a. The Economic Impact of ESG Ratings. SSRN Working Paper 4088545, Social Science Research Network.

Berg, F., J. F. Kölbel, A. Pavlova, and R. Rigobon. 2021b. ESG Confusion and Stock Returns: Tackling the Problem of Noise. SSRN Working Paper 3941514, Social Science Research Network.

Berg, F., J. F. Kölbel, and R. Rigobon. 2022b. Aggregate Confusion: The Divergence of ESG Ratings. *Review of Finance* 26(6):1315–1344.

Bialkowski, J., and L. T. Starks. 2016. SRI Funds: Investor Demand, Exogenous Shocks and ESG Profiles. Working paper, University of Canterbury.

Bollen, N. P. B. 2007. Mutual Fund Attributes and Investor Behavior. *Journal of Financial and Quantitative Analysis* 42(3):683–708.

Bolton, P., and M. Kacperczyk. 2021. Do Investors Care about Carbon Risk? *Journal of Financial Economics* 142(2):517–549.

Bonnefon, J.-F., A. Landier, P. Sastry, and D. Thesmar. 2022. Do Investors Care About Corporate Externalities? Experimental Evidence. SSRN Working Paper 3458447, Social Science Research Network.

Breeden, D. T., and R. H. Litzenberger. 1978. Price of State-contingent Claims Implicit in Option Prices. *Journal of Business* 51(4):621–651.

Campbell, J. Y., and J. H. Cochrane. 1999. By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. *Journal of Political Economy* 107(2):205–251.

Cao, J., A. Goyal, X. Zhan, and W. E. Zhang. 2021. Unlocking ESG Premium from Options. SFI Research Paper Series 21-39, Swiss Finance Institute.

Carhart, M. M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52(1):57–82.

Carr, P., and L. Wu. 2009. Variance Risk Premiums. *Review of Financial Studies* 22(3):1311–1341.

Chabi-Yo, F., C. Dim, and G. Vilkov. 2022. Generalized Bounds on the Conditional Expected Excess Return on Individual Stocks. *Management Science* forthcoming.

Chava, S. 2014. Environmental Externalities and Cost of Capital. *Management Science* 60(9):2223–2247.

Chen, J., H. Hong, M. Huang, and J. D. Kubik. 2004. Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. *American Economic Review* 94(5):1276–1302.

Chen, L., Y. Chen, A. Kumar, and W. S. Leung. 2021. Do Active Fund Managers Exploit Material ESG Information? Miami Herbert Business School Research Paper Series 3747085, University of Miami.

Choi, D., Z. Gao, and W. Jiang. 2020. Attention to Global Warming. *Review of Financial Studies* 33(3):1112–1145.

Claus, J., and J. Thomas. 2001. Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets. *Journal of Finance* 56(5):1629–1666.

Cochrane, J. H. 2011. Presidential Address: Discount Rates. *Journal of Finance* 66(4):1047–1108.

Coqueret, G. 2021. Perspectives in Sustainable Equity Investing. SSRN Working Paper 3715753, Social Science Research Network.

Cox, J. C., S. A. Ross, and M. Rubinstein. 1979. Option Pricing: A Simplified Approach. *Journal of Financial Economics* 7(3):229–263.

Dai, R., H. Liang, and L. Ng. 2021. Socially Responsible Corporate Customers. *Journal of Financial Economics* 142(2):598–626.

D'Avolio, G. 2002. The Market for Borrowing Stock. *Journal of Financial Economics* 66(2-3):271–306.

Di Giuli, A., and L. Kostovetsky. 2014. Are Red or Blue Companies More Likely to Go Green? Politics and Corporate Social Responsibility. *Journal of Financial Economics* 111(1):158–180.

Dimson, E., O. Karakaş, and X. Li. 2015. Active Ownership. *Review of Financial Studies* 28(12):3225–3268.

Diniz, C. A. R., M. H. Tutia, and J. G. Leite. 2010. Bayesian Analysis of a Correlated Binomial Model. *Brazilian Journal of Probability and Statistics* 24(1):68–77.

Easton, P. D. 2004. PE Ratios, PEG Ratios, and Estimating the Implied Expected Rate of Return on Equity Capital. *The Accounting Review* 79(1):73–95.

Eccles, R. G., L.-E. Lee, and J. C. Stroehle. 2019. The Social Origins of ESG: An Analysis of Innovest and KLD. *Organization & Environment* 33(4):575–596.

Edmans, A. 2011. Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices. *Journal of Financial Economics* 101(3):621–640.

El Ghoul, S., O. Guedhami, C. C. Y. Kwok, and D. R. Mishra. 2011. Does Corporate Social Responsibility Affect the Cost of Capital? *Journal of Banking and Finance* 35(9):2388–2406.

Elton, E. J. 1999. Presidential Address: Expected Return, Realized Return and Asset Pricing Tests. *Journal of Finance* 54(4):1199–1220.

Epstein, L. G., and S. E. Zin. 1989. Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework. *Econometrica* 57(4):937–969.

Fama, E. F., and K. R. French. 1989. Business Conditions and Expected Returns on Stocks and Bonds. *Journal of Financial Economics* 25(1):23–49.

Fama, E. F., and K. R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33(1):3–56.

Fama, E. F., and K. R. French. 2007. Disagreement, Tastes, and Asset Prices. *Journal of Financial Economics* 83(3):667–689.

Fama, E. F., and K. R. French. 2017. International Tests of a Five-Factor Asset Pricing Model. *Journal of Financial Economics* 123(3):441–463.

Fama, E. F., and J. D. MacBeth. 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81(3):607–636.

Figlewski, S. 2010. Estimating the Implied Risk-Neutral Density for the US Market Portfolio. In T. Bollerslev, J. R. Russell, and M. Watson (eds.), *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*, chap. 15, pp. 323–353. Oxford University Press.

Flammer, C. 2015. Does Corporate Social Responsibility Lead to Superior Financial Performance? A Regression Discontinuity Approach. *Management Science* 61(11):2549–2568.

Friede, G., T. Busch, and A. Bassen. 2015. ESG and Financial Performance: Aggregated Evidence from More Than 2000 Empirical Studies. *Journal of Sustainable Finance & Investment* 5(4):210–233.

Gebhardt, W. R., C. M. C. Lee, and B. Swaminathan. 2001. Toward an Implied Cost of Capital. *Journal of Accounting Research* 39(1):135–176.

Gibson, R., S. Gloßner, P. Krüger, P. Matos, and T. Steffen. 2021. Do Responsible Investors Invest Responsibly? ECGI Working Paper 712/2020, European Corporate Governance Institute.

Gilchrist, S., V. Yankov, and E. Zakrajšek. 2009. Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets. *Journal of Monetary Economics* 56(4):471–493.

Gillan, S. L., A. Koch, and L. T. Starks. 2021. Firms and Social Responsibility: A Review of ESG and CSR Research in Corporate Finance. *Journal of Corporate Finance* 66(C).

Glossner, S. 2021. Repeat Offenders: ESG Incident Recidivism and Investor Underreaction. SSRN Working Paper 3004689, Social Science Research Network.

Hartzmark, S. M., and A. B. Sussman. 2019. Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows. *Journal of Finance* 74(6):2789–2837.

Heeb, F., J. F. Kolbel, F. Paetzold, and S. Zeisberger. 2022. Do Investors Care about Impact? SSRN Working Paper 3765659, Social Science Research Network.

Heinkel, R., A. Kraus, and J. Zechner. 2001. The Effect of Green Investment on Corporate Behavior. *Journal of Financial and Quantitative Analysis* 36(4):431–449.

Hoepner, A. G. F., I. Oikonomou, Z. Sautner, L. T. Starks, and X. Zhou. 2022. ESG Shareholder Engagement and Downside Risk. SSRN Working Paper 2874252, Social Science Research Network.

Hong, H., and M. Kacperczyk. 2009. The Price of Sin: The Effects of Social Norms on Markets. *Journal of Financial Economics* 93(1):15–36.

Hou, K., M. A. van Dijk, and Y. Zhang. 2012. The Implied Cost of Capita: A New Approach. *Journal of Accounting and Economics* 53(3):504–526.

Hou, K., C. Xue, and L. Zhang. 2015. Digesting Anomalies: An Investment Approach. *Review of Financial Studies* 28(3):650–705.

Humphrey, J., S. Kogan, J. Sagi, and L. Starks. 2021. The Asymmetry in Responsible Investing Preferences. NBER Working Paper Series 29288, National Bureau of Economic Research.

Ilhan, E., Z. Sautner, and G. Vilkov. 2021. Carbon Tail Risk. *Review of Financial Studies* 34(3):1540–1571.

Jeffers, J., T. Lyu, and K. Posenau. 2021. The Risk and Return of Impact Investing Funds. SSRN Working Paper 3949530, Social Science Research Network.

Kacperczyk, M., C. Sialm, and L. Zheng. 2008. Unobserved Actions of Mutual Funds. *Review of Financial Studies* 21(6):2379–2416.

Kadan, O., and X. Tang. 2020. A Bound on Expected Stock Returns. *Review of Financial Studies* 33(4):1565–1617.

Kim, D. 1995. The Errors in the Variables Problem in the Cross-Section of Expected Stock Returns. *Journal of Finance* 50(5):1605–1634.

Korteweg, A., and S. Nagel. 2016. Risk-Adjusting the Returns to Venture Capital. *Journal of Finance* 71(3):1437–1470.

Lee, C. M. C., E. C. So, and C. C. Y. Wang. 2021. Evaluating Firm-Level Expected-Return Proxies: Implications for Estimating Treatment Effects. *Review of Financial Studies* 34(4):1907–1951.

Lettau, M., S. C. Ludvigson, and P. Manoel. 2021. Characteristics of Mutual Fund Portfolios: Where Are the Value Funds? NBER Working Paper Series 25381, National Bureau of Economic Research.

Liang, H., and L. Renneboog. 2017. On the Foundations of Corporate Social Responsibility. *Journal of Finance* 72(2):853–910.

Lins, K. V., H. Servaes, and A. Tamayo. 2017. Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis. *Journal of Finance* 72(4):1785–1824.

Ludvigson, S. C., and S. Ng. 2009. Macro Factors in Bond Risk Premia. *Review of Financial Studies* 22(12):5027–5067.

Lustig, H., N. Roussanov, and A. Verdelhan. 2014. Countercyclical Currency Risk Premia. *Journal of Financial Economics* 111(3):527–553.

Madhavan, A., A. Sobczyk, and A. Ang. 2021. Toward ESG Alpha: Analyzing ESG Exposures through a Factor Lens. *Financial Analysts Journal* 77(1):69–88.

Malz, A. M. 2014. A Simple and Reliable Way to Compute Option-Based Risk-Neutral Distributions. Staff Reports 677, Federal Reserve Bank of New York.

Martin, I. W. R. 2017. What Is the Expected Return on the Market? *Quarterly Journal of Economics* 132(1):367–433.

Martin, I. W. R., and C. Wagner. 2019. What Is the Expected Return on a Stock? *Journal of Finance* 74(4):1887–1929.

Nagel, S. 2005. Short Sales, Institutional Investors and the Cross-section of Stock Returns. *Journal of Financial Economics* 78(2):277–309.

Newey, W. K., and K. D. West. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55(3):703–708.

Novy-Marx, R. 2013. The Other Side of Value: The Gross Profitability Premium. *Journal of Financial Economics* 108(1):1–28.

Ohlson, J. A., and B. E. Juettner-Nauroth. 2005. Expected EPS and EPS Growth as Determinants of Value. *Review of Accounting Studies* 10:349–365.

Pastor, L., R. F. Stambaugh, and L. A. Taylor. 2021. Sustainable Investing in Equilibrium. *Journal of Financial Economics* 142(2):550–571.

Pastor, L., R. F. Stambaugh, and L. A. Taylor. 2022. Dissecting Green Returns. *Journal of Financial Economics* 146(2):403–424.

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

Renneboog, L., J. Ter Horst, and C. Zhang. 2011. Is Ethical Money Financially Smart? Nonfinancial Attirbutes and Money Flows of Socially Responsible Investment Funds. *Journal of Financial Intermediation* 20(4):562–588.

Riedl, A., and P. Smeets. 2017. Why Do Investors Hold Socially Responsible Mutual Funds? *Journal of Finance* 72(6):2505–2550.

Sautner, Z., L. van Lent, G. Vilkov, and R. Zhang. 2021. Pricing Climate Change Exposure. SSRN Working Paper 3792366, Social Science Research Network.

Seltzer, L., L. T. Starks, and Q. Zhu. 2021. Climate Regulatory Risks and Corporate Bonds. SSRN Working Paper 3563271, Social Science Research Network.

Tang, D. Y., J. Yan, and C. Y. Yao. 2022. The Determinants of ESG Ratings: Rater Ownership Matters. SSRN Working Paper 3889395, Social Science Research Network.

Theodossiou, P. 1998. Financial Data and the Skewed Generalized T Distribution. *Management Science* 44(12):1595–1722.

van der Beck, P. 2021. Flow-Driven ESG Returns. Swiss Finance Institute Research Paper Series 21-71, Swiss Finance Institute.

Wachter, J. A. 2013. Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility? *Journal of Finance* 68(3):987–1035.

Whelan, T., U. Atz, T. V. Holt, and C. Clark. 2021. ESG and Financial Performance: Uncovering the Relationship by Aggregating Evidence from 1,000 Plus Studies Published between 2015–2020. Center for sustainable business, NYU Stern School of Business.

Yang, R. 2021. What Do We Learn From Ratings About Corporate Social Responsibility? SSRN Working Paper 3165783, Social Science Research Network.

Zerbib, O. D. 2022. A Sustainable Capital Asset Pricing Model (S-CAPM): Evidence from Environmental Integration and Sin Stock Exclusion. *Review of Finance* forthcoming.