International ESG Equity Investing and Heterogeneous Asset Demand

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Abstract

I study how sustainable investing impacts cross-sectional equity prices and valuation with institutional investors' heterogeneous demand and tastes internationally. To obtain a sustainability measure for companies around the world and to capture the ESG tilt in portfolios of institutional investors, I construct a reveal-preference sustainability measure for each firm instead of using a third-party ESG score. With Factset international institutional holding data from 2010 to 2021, I apply an equilibrium asset pricing framework to empirically estimate heterogeneous preference, allowing for investment portfolio choices within and across countries. I find that separately estimated investor demands are sensitive to the sustainability of firms. The demand of investors on average increases by 26% following a one standard deviation increase in the perceived greenness, but there exists huge investor heterogeneity across countries; for example, investors from mainland China would decrease their demand by 21%. With the estimated coefficients, I conduct counterfactual analyses that consider the implications when the ESG coefficient increases following realized climate risk and when a subset of ESG investors switch to holding a market-weighted portfolio to understand the significance of different groups of institutional investors.

1 Introduction

Over the past decade, the sustainable investment sector has experienced tremendous growth. This surge in interest towards sustainable investments has catalyzed the launch of new funds integrating Environmental, Social, and Governance (ESG) criteria into their investment strategies. There are currently over 40 ESG-related standards, codes, and associations including the UN Principles for Responsible Investment signed by over 7,000 institutional investors in 135 countries.

Institutional investors play a significant role in allocating capital around the world. A report by OECD in 2019 shows that institutional managers control more than 40% of the public equity market capitalization by the end of 2017. The Global Sustainable Investment Alliance reported in 2021 that over 17 trillion dollars in investment fund assets in the United States were managed using ESG criteria in 2020, and ESG investing is more pervasive in Europe. In addition, Larry Fink, chairman and CEO of BlackRock, wrote in the letter to CEOs in 2020, that "our investment conviction is that sustainability- and climate-integrated portfolios can provide better risk-adjusted returns to investors" and in 2022 wrote that they have seen a tectonic shift of capital and "this is just the beginning – the tectonic shift towards sustainable investing is still accelerating".

Although the ESG investment sector has seen rapid expansion, there is ongoing debate about the price impact and the potential returns of sustainable investments. The dominant theoretical perspective proposes that if investors favor sustainability, they might experience enhanced utility that compensates for potentially lower expected returns from holding more sustainable stocks. Conversely, empirical studies often indicate that portfolios with an ESG focus have yielded strong returns in recent years. The effect of sustainable investing on equity prices also remains a topic of contention. While sustainable investors might opt to divest from industries such as petroleum firms, this essentially shifts ownership to funds not governed by ESG principles. As a result, the real impact of sustainable investing hinges on the extent to which market prices need to adjust to attract other investors to acquire these divested shares.

With the rise of globalization and the reduction of barriers to cross-border investments, investors can invest internationally more conveniently at a lower cost. Thus, it is crucial to examine the differences in institutional investors across countries and the substitutability of cross-country investment. With FactSet international ownership data, I employ a structural model to estimate the heterogeneous investor demand following the asset pricing demand system approach. This framework allows me to quantitatively delineate the relationship between valuations, expected returns, and characteristics, tracing them back to institutional investors from different countries.

Thus, this paper is motivated to empirically test the implications of recent theoretical ESG investing papers and provide new empirical evidence to explain the equity price impact of ESG investing with heterogeneous beliefs and tastes. I focus on the cross-section of equities for better identification and empirical implementation. The research question is how sustainable investing affects valuation and which countries of institutional investors are more sensitive to changes in firms' sustainability at each time period. In addition, I aim to answer where differences in cross-sectional returns and their variance come from. As the social norm and concept of ESG investing grows, how much of the returns and their variation can be explained by it?

Because third-party ESG scores have limited coverage for stocks in emerging countries (Matos, 2020) and other concerns such as inconsistent ratings (Berg et al., 2020), to measure the ESG preference for all stocks around the world, I start by identifying a set of ESG funds using a list of sustainability keywords. I pool the holdings of the identified ESG funds and construct an aggregate ESG portfolio using portfolio holdings data. For each stock, I calculate the deviation between its portfolio weight in this aggregate ESG portfolio and its weight in the aggregate mutual fund portfolio. This deviation is a revealed preference indicator, reflecting the perceived sustainability of each stock. The more positive the deviation is, the more sustainable it is perceived by investors. The purpose of this constructed ESG measure is to capture the perceived greenness of a representative ESG fund regardless of whether the belief/preference of ESG investors is true or whether the list of identified ESG funds is comprehensive.

Using the perceived company-level ESG measure, I start with simple reduced-form regressions to motivate that sustainability is an important characteristic and should be considered as a factor explaining investor demand. The cross-sectional valuation regressions from 2010 to 2021 suggest that the perceived sustainability measure and MCSI ESG score have been both consistently valued by investors over the period. In addition, the return regressions suggest that ESG measures are significantly correlated with the cross-sectional returns.

To comprehensively assess the quantitative impact of sustainable characteristics considering the huge heterogeneity across investors, I use a structural model to estimate various demands for equities among investors. This approach is designed to capture the nuances of investor stock demand through the implementation of a logit function, building upon the theoretical foundation laid by Koijen and Yogo (2019). This model includes factors such as the sales-to-book ratio, international sales, the Lerner index, and book equity. Given the existence of explicit and implicit barriers to investing abroad, I use a nested logit model to estimate investment decision choices within-country and cross-country each year, allowing for heterogeneity among different investors and different time periods.

Since latent demand is correlated with asset prices, I use an instrumental variable approach to address the concern of the endogeneity of prices in demand estimation. The original instrument in Koijen and Yogo (2019) is built upon the investors' investment mandate which is set exogenously. Given the imperfect identification of the investment universe, I use the dividend payout-induced flows as an instrument following Schmickler and Tremacoldi-Rossi (2022). The intuition of the instrument is that funds tend to reinvest the dividend payout proportionally in their existing portfolio. To ensure that the dividend payout of a firm does not contain value information, the dividend flow of a company is constructed as the sum of all dividend payouts of all other firms excluding itself.

The results of the demand estimations reveal that, on average, institutional investors exhibit a positive response to firms' perceived commitment to ESG criteria. This demand for firm sustainability appears to be independent of potential correlations with other characteristics of the firms, highlighting a distinct preference for ESG adherence among these investors. Despite there exists large variation in demands, by averaging the estimates based on investors' wealth and country of origin, I find that the demand of investors in Spain positively react the most to changes in the perceived sustainability of stocks while Chinese investors react negatively. On aggregate, I find that a 1% change in the standard deviation of the perceived greenness of the stock leads to a 26% increase in demand. In terms of the demand for cross-country investment, I find that the substitutability is still limited, suggesting that investors on aggregate still prefer to invest domestically due to various rational and behavioral reasons.

Then, using the derived demand curves, I decompose the variance in stock returns across different stocks into components resulting from variations in stock characteristics and investor groups. This allows me to quantitatively assess the proportion of stock return variance attributable to the shift towards ESG investing. Then, I conduct counterfactual analyses to understand the implications of the investors' heterogeneous green demand on equity prices: if the coefficient on ESG measure increases following realized climate risk, and if a subset of ESG investors, e.g. active investors and investors from Europe, switch to hold a market-weighted portfolio to understand the contribution of this group of investors on prices. In addition, I re-estimate the valuation regressions using the counterfactual prices and compare how the coefficients change. Overall, my paper adds to the ongoing discussion on the effectiveness and impact of ESG equity investing and provides new insights into heterogenous institutional investor demand across different countries with asset pricing implications.

Relevant literature and contribution

This paper mainly contributes to the literature that studies sustainable investing with asset pricing implications, which have been explored and reviewed by studies such as Giglio, Kelly, and Stroebel (2021) and Coqueret (2022). Empirical findings regarding the price impact and realized returns from sustainable investing are mixed. Many papers suggest that sustainable firms have lower returns in equilibrium as they are hedging against climate risks. For instance, Hong and Kacperczyk (2009) found that sin stocks, such as those in the alcohol and tobacco industries, outperformed others. Bolton and Kacperczyk (2021b) and Bolton and Kacperczyk (2021a) observed the existence of a carbon premium. Hsu et al. (2022) also noted superior stock market performance in firms with high chemical emissions. In contrast, there is substantial evidence showing the superior performance of sustainable stocks compared to their counterparts. This has led to theories suggesting market under-reaction as a plausible explanation. Görgen et al. (2020) observed that firms with high carbon emissions yielded lower average returns between 2010 and 2017. Moreover, Hong, Li, and Xu (2019) identified a negative correlation between drought risk and stock returns.

Theoretical studies have also explored how climate risks and ESG considerations are priced in financial assets. Pástor, Stambaugh, and Taylor (2021) analyzed equilibrium sustainable investing and concluded that green assets have lower expected returns and outperform when positive shocks hit ESG factors, which captures the shift in customers' taste for green products and investor taste for green holding. Pedersen, Fitzgibbons, and Pomorski (2021) found that ESG investor is willing to take a smaller Sharpe ratio to invest in companies with higher ESG scores. They suggest that ESG factors might predict future returns if they encompass pertinent information about a firm's fundamentals or the inclinations of sustainable investors. The theoretical studies such as Pástor et al. (2021) and Pedersen et al. (2021) suggest that green stocks compared with brown stocks have lower expected returns, due to the sustainable preferences and beliefs of investors. Nevertheless, with an unexpected increase in sustainable preferences due to reasons such as climate risk, there may exist more hedging benefits of holding green stocks, which increases the prices and results in higher returns than holding brown stocks. In their subsequent study, Pástor, Stambaugh, and Taylor (2022) found that the correlation between ESG demand and returns exists only when it reflects collective changes in preferences towards sustainable investments. It suggests that prices would remain constant if the capital flow is driven by past return performance instead of climate-related concerns. This paper shares the same objective to measure how the green demand of institutional investors affects prices and returns. The simultaneous endogeneity of holdings and equity prices poses a huge challenge in establishing a causal relationship. Hence, this paper contributes to this literature by applying the asset pricing demand system approach to quantitatively estimate causal demand curves and how ESG preferences are priced in the cross-section of stock valuation and hence impact returns.

This paper adds to the literature that examines institutional investor demand for ESG-governed equities. Some studies, such as those by Gormsen et al. (2023) and Krueger et al. (2020) employed survey methods. The majority of research in this area directly investigates the portfolio choices of these investors. For instance, Gibson et al. (2020) developed a sustainability variable at the portfolio level for U.S. investors, discovering that institutions with higher sustainability scores tend to achieve better returns. Van der Beck (2022) analyzed flows into ESG funds and discovered that the price effects associated with sustainable investing inflows primarily explain their high returns. Papers also focused on examining different types of institutional investors. For instance, Starks, Venkat, and Zhu (2017) observed that institutions with a longer investment horizon are more likely to invest in firms with higher ESG scores, exhibiting greater patience due to the potential long-term financial benefits of ESG practices. Similarly, Gibson, Krueger, and Schmidt (2021) found that investors with longer horizons not only have portfolios with higher ESG scores but also experience higher risk-adjusted returns. The location of the investor also plays a significant role; Dyck, Lins, Roth, and Wagner (2019) showed that international institutional investors from countries with strong social norms encourage firms to adopt ESG practices, and they noted that long-horizon U.S. institutions invest more in firms with higher ESG scores. My paper contributes to this subset of literature by providing quantitative estimates on heterogeneous preferences in ESG investing of institutional investors across countries. These estimates provide a deeper understanding of how sustainable investment demand varies across different investors and also trace the temporal evolution of this demand in relation to sustainable and fundamental characteristics.

Furthermore, I contribute to the international asset pricing literature by providing additional empirical evidence on market segmentation and cross-border investment decisions. Past literature identifies explicit and implicit variables that impact pricing and the degree of market integration. For instance, Carrieri, Chaieb, and Errunza (2013) estimated the evolution of integration and showed that barriers such as institutional environment explain the extent of financial globalization. Bailey, Chung, and Kang (1999) used an international asset pricing approach to study what drives demand for cross-border investments. The literature has also studied cross-border portfolio investment. Leuz, Lins, and Warnock (2009) discovered that U.S. investors tend to hold fewer foreign assets in countries where there is a higher incidence of firm-level earnings manipulation, particularly in countries characterized by poor disclosure norms, lax securities regulations, and inadequate protection for outside shareholders. Additionally, Bailey, Kumar, and Ng (2008) provided a detailed analysis of the motivations and consequences of foreign equity investment for US institutional investors. My paper thus not only provides suggestive empirical evidence on the existence of explicit and implicit barriers but also shows the aggregate heterogeneous preference in cross-country investment.

Finally, this paper contributes to the burgeoning research on the asset pricing demand system by Koijen and Yogo (2019). They introduce a structural model for estimating U.S. investors' demand curves, connecting these estimated coefficients to asset prices in equilibrium. Building upon this, Koijen, Richmond, and Yogo

(2022) further quantified the impact of market trends on asset prices and price informativeness and showed that the transition to passive investment management and climate-induced shifts have potentially large impacts on equity prices and wealth distribution in the US. A lot of new studies have applied demand estimation to specific asset pricing questions. For example, Gabaix, Koijen, Mainardi, Oh, and Yogo (2022) studied the asset demand on US households, Jansen (2021) studied the demand on government bonds, and Huebner (2023) studied the equity momentum. Similarly, Noh, Oh, and Song (2023) included ESG scores, emission, and green patents in the demand system and showed that investor demands on sustainability weakly predict firms' future improvements in sustainability. My paper contributes to this growing field by offering a structural examination of ESG investing, both within and across countries through an emphasis on individual investors' asset demand.

The organization of this paper is as follows: Section 2 introduces the data on institutional portfolio holdings and the construction of ESG preferences. Section 3 briefly outlines the structural model for within-country and cross-country choices and its estimation with instrumental variables. Section 4 reports the key results and Section 5 presents variance decomposition and counterfactuals. Section 6 concludes.

2 Data

2.1 Institutional Holdings and Firm Fundamentals

The data on portfolio holdings and firm characteristics are from FactSet and I mainly follow data-cleaning steps in Ferreira and Matos (2008) and Bartram et al. (2015). While FactSet does not explicitly detail its data sources, it primarily gathers information from public filings across various countries, complemented by data from companies' annual reports. Factset contains two main databases on holdings: the aggregate institutional filings and the mutual fund database. To ensure comprehensive data coverage, I primarily use the institutional database. However, I also incorporate holdings data from the mutual fund database in cases where the parent management institution is not available in the institutional ownership data. I limit the holdings to common equities and ADRs[1].

Since the reporting period is inconsistent across institutions and funds, and fundamental data for international stocks are reported on an annual basis, I use the filling in the last quarter if there are multiple fillings each year. In addition, since a company can have multiple securities, I select the unique security for each company by identifying whether the security is the primary security. Specifically, I select the security that firstly matches the following criteria: only one security in a company, whether it is uniquely defined as the primary security in the Factset ownership data, and whether its ID is listed as the primary security ID in the Factset Symbology database. Therefore, I construct panel data of equity holding on the institutional level by year by aggregating the security level to the company level and aggregating the fund level to the institutional level.

Table 1 reports the time series median and 90th percentile for assets under management which is calculated as the total market-value holdings of each institution, number of stocks, and number of institutions across all countries from 2010 to 2021. There are over 4700 institutional investors recorded in Factset in 2021 with the median institution managing over 0.2 billion USD. Most institutions hold relatively concentrated portfolios since

[1]The security types are in either SHARE, SHARE, ADR, DR, GDR (Global Depository Receipt), or NVDR (Non-Voting Depository Receipt)

the median institution held less than 100 stocks and the more active institution at the 90% percentile held over 1000 stocks.

[Table 1 about here].

As discussed previously, with the rise of globalization and the decrease in barriers to cross-border investment, there has been a significant increase in ownership by foreign institutional investors. I use the international holding data to show the fraction of market capitalization held by foreign institutions around the world in 2021 in Figure 1. US and Brazil have more domestic investors than foreign investors and countries including the UK, Sweden, Canada, Austria, and Japan also have some proportion of domestic ownership relative to foreign ownership. However, other than these countries, the ownership of domestic institutions reported in Factset is rather low relative to foreign investors. For one's interest, I also include US institutional investors' holdings in Figure A1 in the appendix.

[Figure 1 about here.]

Institutions have concentrated portfolios and the distribution of ownership becomes more concentrated over time following the popularity of passive investing especially in the US and Europe (Azar et al., 2018; Ben-David et al., 2021). Consistently, in my data sample, the number of stocks held by the median US institutional investor decreased from 148 to 95 while the number of institutions and AUM steadily increased from 2010 to 2011. To further provide some insight, I also list the largest 15 investors around the world in 2021 in Table A1.

The firm characteristics data are from the Factset fundamentals database. Market equity is calculated as price multiplied by the total shares outstanding. When a firm possesses multiple share classes, the aggregate count of outstanding shares at the company level is recalibrated to account for the respective par values of each share class. Additionally, stock prices are converted into U.S. dollars using point-in-time exchange rates. To maintain accuracy, both the prices and the number of shares outstanding are adjusted to accommodate any stock splits.

For characteristics that help account for most of the cross-sectional variation in valuations, I have chosen the following factors motivated by previous literature (Koijen and Yogo, 2019; Koijen et al., 2022; Noh et al., 2023). I use log book equity to capture the size and market beta as a measure of equity market risk. For the measures of productivity and markups, I use sales-to-book equity, dividend-to-book equity, and net purchases from Factset Fundamentals. The sales-to-book ratio is total sales divided by equity plus deferred taxes and investment tax credits minus preferred stock. Inspired by models in Melitz (2003) which suggests that the most productive firms engage in exporting to other countries, I employ the measure of foreign sale shares, which is calculated as international sales divided by total sales. I also use the Lerner index to capture industry concentration and the rise of superstar firms following literature such as Gutiérrez and Philippon (2017) and is calculated as the operating income before depreciation minus depreciation and amortization if available or operated income divided by sales. I winsorize the sales-to-book ratio and dividend-to-book ratio at 97.5% by country and by year, and I standardize all the characteristics cross-sectionally by country and by year as well.

2.2 ESG measures

There is a rapid growth of availability in ESG data with measures and ratings from well-established companies such as Bloomberg, MSCI, and Refinitiv and more specialized providers such as Sustainalytics and Vigeo EIRIS. Thus, a natural candidate to measure the ESG tilt of sustainable portfolios is the ratings provided by various agencies. However, there are many concerns regarding data quality. A firm's sustainability is challenging to rate and it is not uncommon for rating agencies to disagree in their conclusions. Berg et al. (2022), Abhayawansa and Tyagi (2021) and Widyawati (2020) report the divergence in scores and suggest potential explanations including discrepancies in data collection procedures, the scope of categories considered, and the measurement methods used. There are also potential concerns such as backfilling in ratings provided by Refinitiv ESG (Berg et al., 2020) and recent papers find that third-party ESG scores are inflated and distorted by greenwashing (Yang, 2021; Bams and van der Kroft, 2022). More importantly, for ESG ratings and scores, the coverage on international stocks especially those in emerging markets is limited (Matos, 2020) and hence is inadequate for the purpose of this paper.

Still, as MSCI ESG ratings cover more firms than the other agencies and exhibit the least noise (Berg et al., 2022), I use MSCI ESG ratings for robustness checks. MSCI ESG ratings measure exposure to and management of long-term, industry-material, and financially material ESG risks and opportunities for more than 8,700 companies globally with approximately 14,000 issuers including subsidiaries. The dataset includes company-level ratings and scores from 1999-2022.

Another possible and potentially more interesting measure is to create a revealed preference measure of investors' ESG taste. The idea of using investor taste and view on ESG-friendly stocks is motivated by Van der Beck (2022) who showed that flows towards ESG funds create buying pressure and increase the price of green stocks using the U.S. 13F holding and mutual fund data.

From the Factset database, I identify ESG mutual funds using the funds' proper names. A fund is defined as an ESG/sustainable/green fund if its name includes one of the following words in the following list: *ESG, SRI, CSR, environmental, social, governance, green, sustainable, climate, clean, carbon, gender, solar, renewable, ethical*. The largest identified ESG fund is the iShares ESG Aware MSCI USA ETF with a total asset under management of over 27 billion USD at the end of 2021. The investment objective of this fund is to track the investment performance of an index that includes U.S. companies with positive ESG characteristics as identified by the index provider. It also seeks to maintain risk and return profiles similar to those of the MSCI USA Index. For one's interest, Table A3 reports the top thirty ESG funds by AUM with their country, entity type, and style as of December 2021.

Table 2 reports the summary statistics of identified ESG funds across the sample. From 2010 to 2021, the number of ESG funds increased from 671 to over 2500 with an average of $0.49 billion USD assets under management and over 180 stocks held in their portfolio.

[Table 2 about here.]

Based on the sample of ESG funds, I construct the aggregate ESG portfolio where portfolio weights are based on the ratio of each ESG fund's holdings to the total AUM.

$$w_{t,n}^{ESG} = \frac{P_{t,n}Q_{t,n}^{ESG}}{\sum_{n=1}^{N} P_{t,n}Q_{t,n}^{ESG}}$$

The last two columns in Table 2 report the summary statistics of the ESG portfolio. As we can see, the total assets under management grew from 213 billion USD in 2010 to over 1.2 trillion USD in 2021. The aggregate ESG portfolio should remain consistent regardless of the number of identified ESG funds, provided that the sampled ESG funds accurately represent the average fund within the ESG investment industry.

One question that may arise is how different is the ESG portfolio to the market portfolio. By construction, as ESG investing grows and more capital flows to ESG funds, this aggregate ESG portfolio should converge to the market portfolio in the limit. Following this intuition, I also compute the "active share" (Cremers and Petajisto, 2009) which represents the divergence of the ESG portfolio from the overall market portfolio. Formally, I calculate the active share as $\frac{1}{2}\sum_n |w_{t,n}^{ESG} - w_{t,n}^{MF}|$ where $w_{t,n}^{MF}$ is the weight of the aggregate market portfolio for all mutual funds calculated similarly to the ESG portfolio weight $w_{t,n}^{ESG}$. In 2010, this identified ESG portfolio tilted about 50% of assets compared to the mutual fund portfolio and the active share declined to 37.5% in 2021. Therefore, despite the heterogeneity in ESG funds' portfolios and that different selections of keywords may identify different ESG funds, the ESG portfolio should be representative of the average ESG fund's portfolio.

Based on this aggregate ESG portfolio, I can obtain a measure of the sustainable tastes of investors for security n

$$\tau_{t,n} = w_{t,n}^{ESG} - w_{t,n}^{all} \tag{1}$$

where $w_{t,n}^{all}$ represents the aggregate portfolio formed by aggregating the holdings of all funds, not just ESG funds. Consequently, firms exhibiting a higher value of $\tau_{t,n}$ are considered to be 'greener', as they hold a greater weight in the ESG portfolio compared to the market portfolio. This measure, based on revealed preferences, is applicable to all stocks included in the dataset, and hence is another advantage of using this measure instead of using the MSCI ESG scores because its coverage on companies outside the U.S. is relatively limited.

A key characteristic of this measure is that it estimates the cross-sectional price deviations due to ESG investments and it does not aim to be a true measure of sustainability which is not part of the goal of this paper. Despite efforts to categorize funds as 'green' or 'ESG', there remains skepticism about whether these funds genuinely invest in sustainable companies and if the aggregate ESG fund portfolio focuses more on green stocks. Particularly, the social and governance aspects of ESG investing often see wide variations in interpretations. For instance, the question of whether the least polluting company in the energy sector should be included in ESG fund investments and considered sustainable is contentious. While this paper does not aim to definitively classify sustainable ratings or identify an exact set of sustainable companies, it does explore whether $\tau_{t,n}$ the deviation of the ESG portfolio from the market portfolio correlates to objective sustainability variables.

Specifically, I test with a panel OLS regression of $\tau_{t,n}$ and a probit regression of the ESG dummy $I(\tau_{t,n}^{ESG} > 0)$

with time fixed effects and results are presented in Table A4. The coefficients on sustainable characteristics are statistically significant and this suggests that the holdings of ESG funds are correlated with stocks with higher third-party ESG scores or better sustainability performance. This finding seems to be contradictory to the empirical evidence that investors who signed the UNPRI do not have higher ESG ratings (Liang et al., 2021; Kim and Yoon, 2023). This contradictory evidence underlines this concern about true versus perceived sustainability.

Overall, this perceived ESG measure is still highly correlated to the commonly used ESG ratings because the greenness tilt reflects people's perception of how ESG-friendly a firm is. It captures the ESG taste of the institutional investors, regardless of whether the belief is correct or not.

2.3 Stylized Facts

With the set of stock characteristics and the ESG preference measure, I run valuation and return regressions with the following specification.

$$y_t(n) = \alpha_{t,c} + \mathbf{x_t}(n)\gamma + \epsilon_t(n) \tag{2}$$

where $y_t(n)$ is the outcome variable including the company n's log market-to-book ratio and return, $\alpha_{t,c}$ are country-by-year fixed effects, and $\mathbf{x_t}(n)$ is the set of stock characteristics including ESG preference, the MSCI ESG score and other factors to capture firms' fundamentals. Observations are on the stock-by-year level and the characteristics are all cross-sectionally standardized in each country and each year during the period from 2010 to 2021.

Table 3 presents the coefficients from the regressions with year and year-by-country fixed effects. The coefficients for ESG preference are similar across the columns. When controlling for year and country fixed effects, as in Column (2), a one standard deviation increase in the perceived ESG measure is associated with a 23.9% higher market-to-book ratio. For returns, one standard deviation increase in the perceived ESG measure is associated with a 3.28% increase in the cross-sectional returns as shown in Column (6).

[Table 3 about here.]

Similarly, I estimate the above equation cross-sectionally for each year and find that the ESG coefficients are significantly positive throughout the years and there seems to be a small upward trend as shown in Figure A2. I also run the valuation and return regressions for selected countries including the US, UK, China, Japan, and Switzerland in Table A5 and find the estimated coefficients of the perceived ESG measure are all positive.

In summary, my findings indicate that sustainability characteristics positively affect stock prices across different cross-sections and time periods. This suggests that these factors might play a significant role as the other fundamental factors in the demand curves discussed in Section 3.

3 Model & Estimation

To investigate investor heterogeneity and the quantitative significance of ESG characteristics, I use a structural model to estimate the demand functions of investors for stocks. Specifically, following Koijen and Yogo

(2019), I model asset demand functions with ESG measures as new characteristics in the demand system, and further consider cross-country substitutions with a nested logit model.

Consider N financial assets where each asset is denoted as n from 0 to N. There are a total of I investors where each investor is i with the index starting from 1, and a total number of C countries indexed by $c = 1, \ldots, C$. The asset indexed at 0 is an outside asset which is the remaining wealth outside these N financial assets for each investor. The assets are differentiated along K characteristics and ESG measures are one of the K characteristics. Let $x_{k,t}(n)$ be characteristic k of asset n so $\mathbf{x}_t$ is the $N \times K$ matrix whose (n, k)th element is $x_{k,t}(n)$. For equities, the characteristics could include different fundamental measures including dividends, book equity, profitability, and investment which have been introduced in Section 2.1.

Let $A_{i,t}$ be wealth that investor i can choose to invest across the equities in its investment universe $\mathcal{N}_{i,t} \in \{0, ..., N\}$, which consists of a predefined set of equities, as dictated by an investment mandate. For instance, for ESG mutual funds, their institutional investors may only hold stocks with high ESG scores. In the case of an index fund, its investment universe consists of the equities that form the index. The total count of these equities is represented by $|\mathcal{N}_{i,t}|$. Any wealth that lies beyond these N assets is considered as the outside asset.

Let $\mathbf{w}_{i,t}$ represent the vector of portfolio weights with $|\mathcal{N}_{i,t}|$ dimensions for each investor. Due to heterogeneous beliefs, investors may have different expectations of returns based on the same observed characteristics. It is also possible that investors observed some characteristics that are not observed by economists, denoted as $\log(\epsilon_{i,t}(n))$.

Assuming that investors' demand for stocks follows a one-factor structure, it is shown in Appendix A of Koijen and Yogo (2019) that The optimal portfolio weights $\mathbf{w}_{i,t}$ of an investor are determined by logit functions that include the characteristics of stocks and latent demand. The basis for the demand functions can be established through a discrete choice model featuring independently and identically distributed Logit errors and Koijen and Yogo (2019) detailedly discussed the micro foundation.

Because of the implicit and explicit barriers for cross-border investments, I use a nested logit specification such that investors may imperfectly substitute to invest in assets across borders. The portfolio weight of asset n can be expressed as follows without loss of generality,

$$w_{i,t}(n, c) = w_{i,t}(n|c) w_{i,t}(c) \tag{3}$$

where $w_{i,t}(n|c)$ is the conditional portfolio weight for investor i within country c and $w_{i,t}(c)$ is investor i's aggregate portfolio weight in country c. Thus, the inner nest $w_{i,t}(n|c)$ in Equation (3) describes the substitution across stocks within a country, and the outer nest $w_{i,t}(c)$ describes the substitution across countries.

3.1 Market Clearing

Before specifying portfolio weights, for completeness, let $ME_t(n, c)$ be the market equity of firm n in the country c which is calculated as the product of $P_t(n)$ stock price and $S_t(n)$ be common shares outstanding. The market clearing condition is that

$$ME_t(n,c) = \sum_{i=1}^{I} w_{i,t}(n,c)A_{i,t} = P_t(n)S_t(n) \tag{4}$$

such that the market value of shares outstanding should equal total investor demand for this stock. Within each country c, the portfolio weights should sum up to one, that is $\sum_{n\in\mathcal{N}_{i,t}} w_{i,t}(n|c) = 1$. Across countries, the aggregate portfolio weights should also sum up to one, that is $\sum_c w_{i,t}(c) = 1$.

Since the portfolio weight on outside assets for investor i is $w_{i,t}(0,c)$, the total investment in the outside assets across countries can be calculated as $\sum_c A_{i,t}w_{i,t}(0,c)$. Thus, by the constraints on the within and across-country weights, the previous equation can be rewritten as

$$ME_t(n,c) = \sum_{i=1}^{I} \frac{w_{i,t}(n,c)\sum_c A_{i,t}w_{i,t}(0,c)}{1-\sum_c\sum_{n=1}^{N} w_{i,t}(n,c)}$$

where the stock's total value equals the sum of portfolio weights of all investors, weighted by the asset values. It is assumed that shares outstanding, the characteristics and holdings of outside assets are exogenous to solve for equilibrium asset prices.

3.2 Within-country Demand System

The portfolio weight within a country for each stock n is

$$w_{i,t}(n|c) = \frac{\delta_{i,t}(n|c)}{1+\sum_{m\in\mathcal{N}_{i,t}}\delta_{i,t}(m|c)} \tag{5}$$

where

$$\log\left(\frac{\omega_{i,t}(n|c)}{\omega_{i,t}(0|c)}\right) = \log\big(\delta_{i,t}(n|c)\big) = \beta'_{\mathbf{i,t,c}}\mathbf{x_{t,c}}(n) + \alpha_{0,i,t,c} + \epsilon_{i,t,c}(n) \tag{6}$$

where $\epsilon_{i,t,c}(n)$ is latent demand, $\alpha_{0,i,c,t}$ are investor by country by year fixed effects, and $w_{i,t}(0|c)$ is the portfolio weight on the outside asset in each country. By the budget constraint, the weight of the portfolio in the outside asset within a country at time t is as follows:

$$w_{i,t}(0|c) = \frac{1}{1+\sum_{m\in\mathcal{N}_{i,t}}\delta_{i,t}(m|c)}$$

Equation 6 represents a characteristics-based demand model, where the weights of portfolio are determined by observable factors such as log market equity and ESG measures, and unobserved characteristics $\epsilon_{i,t,c}(n)$. $\epsilon_{i,t,c}(n) = 0$ means that the investor i does not hold n stock in that time period. Thus, an investor with a higher portfolio holding of sustainable firms would have a high coefficient on ESG measures and a low coefficient on stocks' value characteristics such as log book equity. For each investor i in the country c in year t, I can estimate his/her demand function using an instrument described later in Section 3.3.

Given that many institutional portfolios are concentrated, as discussed in the data section, the cross-section in an investor's holdings might be too limited to accurately estimate Equation (6). Following the literature, I calculate the coefficients for each institution only if there are over 1,000 holdings present at each time point. Institutions with less than 1,000 holdings are grouped together based on similar characteristics. Specifically, I separate institutions by country, by quantiles of assets under management conditional on the country, by entity types and their sub-types of the institutions, and by the manager style. In the end, on average, a group has over 2000 holdings with at least 1000 holdings in each group.

The financial markets are also highly concentrated. In 2021, 1,174 firms out of a total of 8,146 represented the top 90% of U.S. market capitalization, and the largest 96 firms represented over 50% of the total US market capitalization. The patterns are similar in other countries and Table A2 presents the firm size distribution in each country. Therefore, in order to ensure that the demand estimates are not driven by small and micro-capitalization firms, the universe of assets of each country in my study consists of the top 90% stocks. The outside asset is thus defined as the companies with market capitalization at the bottom 10% in a country. In the robustness check, I also plan to define an outside asset in each country as those equities that have any missing data on key firm characteristics.

3.3 Instrumental Variable

The identifying assumption of Equation 6 is the moment condition that

$$\mathbb{E}[\epsilon_{i,t}(n)|ME(n), x(n)] = 1$$

which suggests that shares outstanding, prices, and other characteristics are considered to be exogenous. However, this assumption is unlikely to hold for institutions and households because latent demand is likely not independent of asset prices.[2] For example, some bad news may occur to a firm that is not captured by the firm characteristics but by the latent demand. Investors may choose to reduce the portfolio holdings of that firm and its stock price will drop simultaneously. Hence, I would get biased estimates if I run a simple OLS regression.

In Koijen and Yogo (2019), they originally used investment mandates of investors such that there would be differences in demand that are exogenous. The intuition is that the pool of securities available for institutional investors to hold is predetermined and unchanging; for example, green funds may only choose to hold environmental-friendly firms and may never choose to hold petroleum companies. Thus, the boundaries of the investment mandates $\mathcal{N}_i = \cup_{t=1}^{T} \mathcal{N}_{i,t}$ should be exogenous. Consequently, the instrument for the market equity of stock n can be constructed as follows:

$$\hat{ME}_{i,t}(n) = \log\left(\sum_{j \neq i} A_{j,t} \frac{\mathbf{I}_j(n)}{1 + |\mathcal{N}_j|}\right)$$

where the indicator function $\mathbf{I}_j(n)$ equals 1 when stock n falls within the investment universe of the investor. This instrument relies on the AUM distribution among other investors as well as the investment universe, and thus is considered exogenous given the identifying assumptions. Therefore, the identification is derived from

[2]Another baseline assumption is that characteristics other than market-to-book ratio are exogenous. Appendix D.3. in Koijen et al. (2022) provides a discussion on further relaxing this baseline assumption and they find that the identification strategy is sufficiently general to apply to a model with more endogenous characteristics.

the cross-sectional differences within the investment universe, rather than from the time-series changes caused by firms entering or leaving the investment universe.

Since most international institutions do not disclose their investment mandates, I estimate the investment universe in each year as the collection of assets that were held at any point during the past 10 years. To understand the validity of the estimates, I calculated the persistence of the set of stocks that have been held previously and I found institutions with the top decile AUM hold about 87% of the same set of stocks in the previous 10 years. Table A6 on the persistence of the set of stocks by AUM and by year is included for reference.

Given that the investment universe cannot be perfectly measured, I use another instrument variable following the fund flow-induced trading literature to address the potential challenge to the identification. Lou (2012) showed that funds sell proportionally to their past holdings, although the proportion is slightly lower for inflows. The intuition is that mutual funds are forced to partially liquidate their existing holdings when their clients request redemptions. However, fund flow data for international funds are limited and the assumption that flows are independent of firms' fundamentals might be too strong. I follow the construction of dividend payout-induced fund trades from Schmickler and Tremacoldi-Rossi (2022) as the funds typically reinvest the total payouts proportionally back into their current portfolios.

For each fund, I calculate dividend flow $df_{i,t}$ which is the aggregate dividend payout divided by its AUM

$$df_{i,t}(n) = \sum_{m \neq n} D_{t,m} Q_{i,t-1,m} / A_{i,t-1}$$

where $D_{t,m}$ is the dividend of stock m in period t and m does not equal stock n itself in order to ensure that the dividend does not reveal information about the stock's own fundamentals. The instrument is then constructed as the sum of the dividend flows of all other institutions.

$$DIT_{i,t}(n) = \sum_{j \neq i} df_{j,t}(n) Q_{j,t-1}(n)$$

Using the instrument, I would obtain a weaker assumption of the condition where

$$\mathbb{E}[\epsilon_{i,t}(n) | \hat{ME}(n), x(n)] = 1$$

Thus, I use both a nonlinear GMM with the above moment condition and a linear IV with the condition of $\mathbb{E}[\log(\epsilon_{i,t}(n)) | \hat{me}(n), x(n)] = 0$ to estimate demand curves.

3.4 Across-country Demand System

To model the portfolio weight across countries, I define the denominator $1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m|c)$ in Equation 5 as $\zeta_{i,t}(c)$. Since $w_{i,t}(0|c) = 1/\left(1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m|c)\right)$, $\zeta_{i,t}(c)$ represents the reciprocal of the proportion invested in the external asset. Therefore, when it is small, outside assets are relatively more attractive to investors than inside assets in the country c. This is because investors may consider the prices of the inside assets to be high relative to the observed characteristics and latent demand and hence they may consider relocating their wealth from country c to another country.

Given this intuition, at time t in country c, the portfolio weight can be modeled as

$$w_{i,t}(c) = \frac{\zeta_{i,t}(c)^{\lambda_{i,c}}\delta_{i,t}(c)}{\sum_{l=1}^{C}\left(\zeta_{i,t}(l)^{\lambda_l}\delta_{i,t}(l)\right)} \tag{7}$$

where $\delta_{i,t}(c) = \exp(\alpha_{i,t,c} + \xi_{i,t}(c))$ and $\lambda_{i,c}$ represents the strength of substitution across countries for investor i. When $\lambda_{i,c} = 1$, the model becomes a standard logit model:

$$w_{i,t}(n,c) = \frac{\delta_{i,t}(c)\delta_{i,t}(n|c)}{C + \sum_{l=1}^{C}\sum_{m\in\mathcal{N}_{i,t}}\delta_{i,t}(m|l)\delta_{i,t}(l)}$$

It suggests that the across-country and within-country elasticity of substitution is the same and the equity markets between countries are fully integrated. In the other special case where $\lambda_{i,c} = 0$,

$$w_{i,t}(n,c) = \frac{\delta_{i,t}(n|c)}{1 + \sum_{m\in\mathcal{N}_{i,t}}\delta_{i,t}(m|c)}\frac{\delta_{i,t}(c)}{\sum_{l=1}^{C}\delta_{i,t}(l)}$$

This represents that the equity markets between markets are segmented and investors do not change their allocation in response to prices and other characteristics in another country. These two special cases illustrate that the $\lambda_{i,c}$ is an important measure for cross-country substitution. The higher the estimate, the stronger substitution across countries, suggesting that a demand shock would have more salient effects on prices in other countries.

By dividing Equation (7) for country c by this equation for the U.S., I obtain

$$\begin{aligned}\ln\left(\frac{w_{i,t}(c)}{w_{i,t}(US)}\right) &= \lambda_{i,c}\ln\left(1 + \sum_{m\in\mathcal{N}_{i,t}}\delta_{i,t}(m|c)\right) - \lambda_{i,US}\ln\left(1 + \sum_{m\in\mathcal{N}_{i,t}}\delta_{i,t}(m|US)\right) + \alpha_i + \epsilon_{i,t} \\ &= -\lambda_{i,c}\ln\left(\frac{w_{i,t}(0|c)}{w_{i,t}(0|US)}\right) + \alpha_i + \epsilon_{i,t} \end{aligned} \tag{8}$$

where $-\lambda_c$ is the elasticity of the total share between country c and US with respect to the proportion in the external assets. Thus, it quantifies the extent to which an investor would relocate assets from country c to the US if the investor within country c changes to hold the outside asset. I then estimate Equation 8 by country with a pooled regression with investor fixed effects to allow for variations in the proportion of external assets among various investors.

4 Estimation Results

There are many different ways to report demand estimates as the data has over 10,000 investors by year after pooling. I standardize all the characteristics cross-sectionally such that I can interpret them as the percentage change in demand per one standard deviation change in the stock characteristics.

For each country in each year, I compute the AUM-weighted average of the βs across all investors in Equation (5), and then I calculate the equal-weighted average across years for each country. As shown in the top row of Table 4, on average, there is a positive demand for perceived sustainability, as indicated by a wealth-weighted coefficient of 0.26. This implies that, on average, an investor increases their demand by 26% for each standard deviation increase in a stock's perceived greenness. On average, it shows that investors have a positive preference towards sustainable investments.

I report the summary statistics of the estimation results by country in the remaining Table 4. The coefficient on the log book equity reflects the elasticity of demand with respect to price while the coefficient on the ESG measure β_{ESG} represents how demand reacts to the perceived greenness. The higher the coefficient, the more sensitive demand curves are to the characteristics. Across all the countries, investors in Spain on average are most positively sensitive to greenness while investors in China and Hong Kong on average have negative coefficients on the perceived greenness. Overall, the coefficients of perceived ESG are smaller than characteristics such as market-to-book, foreign sales, and log book equity.

[Table 4 about here.]

Figure 2 reports the distribution of estimated coefficients for investors with a blue dashed line representing the mean and a red line representing the wealth-weighted average of US investors. We can see that the distribution of coefficients on the perceived ESG measure is similar to a normal distribution with a slightly positive mean. Figure 2 also suggests that there exists significant heterogeneity in the demand coefficients across investors and this finding underscores the significance of considering investor heterogeneity to fully understand the demand dynamics for greenness and ESG investing.

[Figure 2 about here.]

In Table 5, I report the estimates of λ_c based on Equation (8). Recall that λ_c represents the strength of substitution across countries and $\lambda_c = 1$ suggests that cross-country and within-country substitution is the same while $\lambda_c = 0$ suggests that changes in firm characteristics and ESG measure do not change cross-country demand. Overall, Spain has the lowest λ with a coefficient of 0.045 and Denmark has the highest coefficient of 0.225. The estimates are relatively close to zero and this suggests that the substitutability across countries is limited and there may still exist significant explicit and implicit barriers for cross-border investments.

[Table 5 about here.]

In addition, I present the time-series summary statistics of the AUM-weighted estimates from 2010 to 2022 in Table A7, and the demand coefficients are relatively consistent across years.

There are a total of 7 characteristics in the baseline specification of the model. I further test if the results are robust to the selection of stock characteristics and include additional two variables: investment and the ratio of net repurchases to book equity. The estimates are quantitatively similar, suggesting that the baseline specification is not sensitive to the choice of characteristics.

5 Decomposition & Counterfactuals

The literature has been studying the extent to which various factors account for the cross-sectional variance in equity returns following Fama and MacBeth (1973). With the estimates on heterogenous demand functions, I can quantify the significance of characteristics by decomposing the contribution to cross-sectional stock return variances. In conducting the counterfactuals, I closely follow the method in Koijen and Yogo (2019).

Based on the asset demand system in Section 3, I define the log price as an implicit function of factors as follows

$$\mathbf{p}_t = \mathbf{g}(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t)$$

where $\mathbf{s}_t$ is a n-dimensional vector of shares outstanding, $\mathbf{A}_t$ is a I-dimensional vector of investors' assets under management, $\mathbf{x}_t$ are stocks' characteristics, β_t is a $K \times I$ matrix of coefficients on characteristics and ϵ_t is the latent demand and is a $N \times I$ matrix such that $\epsilon_{i,t}(n)$ is the (n, i)th element.

The log returns are defined as the changes in log prices and hence I can decompose the log returns as

$$\mathbf{r}_{t+1} = \mathbf{p}_{t+1} - \mathbf{p}_t = \Delta\mathbf{p}_{t+1}(\mathbf{s}) + \Delta\mathbf{p}_{t+1}(\mathbf{x}) + \Delta\mathbf{p}_{t+1}(\mathbf{A}) + \Delta\mathbf{p}_{t+1}(\beta) + \Delta\mathbf{p}_{t+1}(\epsilon) \tag{9}$$

where

$$\begin{aligned}
\Delta\mathbf{p}_{t+1}(\mathbf{s}) &= \mathbf{g}(\mathbf{s}_{t+1}, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t) - \mathbf{g}(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t) \\
\Delta\mathbf{p}_{t+1}(\mathbf{x}) &= \mathbf{g}(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_t, \beta_t, \epsilon_t) - \mathbf{g}(\mathbf{s}_{t+1}, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t) \\
\Delta\mathbf{p}_{t+1}(\mathbf{A}) &= \mathbf{g}(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_t, \epsilon_t) - \mathbf{g}(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_t, \beta_t, \epsilon_t) \\
\Delta\mathbf{p}_{t+1}(\beta) &= \mathbf{g}(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_t) - \mathbf{g}(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_t, \epsilon_t) \\
\Delta\mathbf{p}_{t+1}(\epsilon) &= \mathbf{g}(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_{t+1}) - \mathbf{g}(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_t)
\end{aligned}$$

I alter each element individually and calculate the corresponding counterfactual price vectors. Note that $\mathbf{A}_t, \beta_t, \epsilon_t$ are the investor-specific factors and hence I update each i at a time. Specifically, $\Delta\mathbf{p}_t(\mathbf{A}) = \sum_{i=1}^{I} \Delta\mathbf{p}_t(\mathbf{A}_i)$ so $\Delta\mathbf{p}_t(\mathbf{A}_i)$ represents the log returns after I have updated the wealth of the investor to $t+1$ time and $\sum_{i=1}^{I} \Delta\mathbf{p}_t(\mathbf{A}_i)$ represents the log returns after all investors' wealth are updated.

By the market clearing condition in Equation (4), I take log on both sides and obtain

$$\mathbf{p}_t = \log \sum_{i=1}^{I} A_{i,t}\mathbf{w}_{i,t}(\mathbf{p}_t) - \mathbf{s}_t \tag{10}$$

Thus, I use Newton's method to calculate the counterfactual log price vector $\mathbf{p}_t$. The Jacobian matrix for $f(\mathbf{p})$ used in the iteration is

$$\frac{\delta f(\mathbf{p};n)}{\delta p(m)} = \begin{cases} \frac{\sum_i \beta_i A_i w_i(\mathbf{p};n)(1-w_i(\mathbf{p};n))}{\sum_i A_i \mathbf{w}_i(\mathbf{p};n)}, & \text{if } m = n \\ \frac{\sum_i -\beta_i A_i \mathbf{w}_i(\mathbf{p};n) w_i(\mathbf{p};m)}{\sum_i A_i w_i(\mathbf{p};n)}, & \text{otherwise} \end{cases}$$

where $f(\mathbf{p};n)$ is the n-th element of $f(\mathbf{p})$ and $p(m)$ is the m-th element of $\mathbf{p}$.

Therefore, I decompose the cross-sectional variance of log returns as

$$\begin{aligned}\mathrm{Var}(r_{t+1}) =& \mathrm{Cov}(\Delta\mathbf{p}_{t+1}(\mathbf{s}), r_{t+1}) + \mathrm{Cov}(\Delta\mathbf{p}_{t+1}(\mathbf{x}, r_{t+1}) + \mathrm{Cov}(\Delta\mathbf{p}_{t+1}(\mathbf{A}), r_{t+1}) \\ &+ \mathrm{Cov}(\Delta\mathbf{p}_{t+1}(\beta), r_{t+1}) + \mathrm{Cov}(\Delta\mathbf{p}_{t+1}(\epsilon), r_{t+1})\end{aligned}$$

I examine the asset pricing implications of ESG investing through 2 counterfactual analyses. These analyses focus on shifts in people's preferences over time and the rising coefficients of perceived ESG metrics. In the first counterfactual analysis, I examine the contribution of each subset of ESG investors, such as active investors and investors in the household sector, on prices and valuation of characteristics when this subset of investors has no demand for sustainable characteristics.

In the second counterfactual, I model realized climate risk as an increase in the coefficient on the ESG measure for all institutions by 0.25, which is approximately the average change in portfolio weight following one standard deviation change in the ESG measure cross-sectionally as reported in Table 4.[3] As the ESG measure is weakly correlated with other firms' characteristics, I assume that the coefficients on the other characteristics remain the same. Therefore, with the steps to compute counterfactual prices described above, I iterate to get the fixed point of $\mathbf{p}_t^c$ and examine the impact on the prices and then I can run valuation regressions similar to Table 3 with the dependent variable as the difference between counterfactual and realized log market-to-book equity.

6 Conclusion

This paper studies sustainable equity investing and investigates the heterogeneity in international institutional investor demand with implications on asset prices. With Factset international institutional holding data, I apply the asset pricing demand system approach to estimate the ESG equity investing demand of institutional investors and quantify their impact on asset prices. Given the concerns about what is an unbiased ESG rating and the limited data availability for companies in the emerging market, I construct a revealed preference ESG measure to capture investors' beliefs regardless of whether their beliefs and preferences are correct or not. I find that on average across years, an increase in perceived ESG leads to an increase in investors' demand, but I also document huge heterogeneity in institutional investors' demand for firms' sustainability across countries. For instance, investors from Spain on average respond positively to increases in perceived greenness while investors from China will decrease their portfolio holdings correspondingly.

[3] I could choose a different value from 0.25 to tailor the counterfactual to a particular policy proposal.

References

Abhayawansa, S., and Tyagi, S. (2021). "Sustainable investing: The black box of environmental, social, and governance (esg) ratings." *The Journal of Wealth Management*, *24*(1), 49–54.

Azar, J., Schmalz, M. C., and Tecu, I. (2018). "Anticompetitive effects of common ownership." *The Journal of Finance*, *73*(4), 1513–1565.

Bai, J., Philippon, T., and Savov, A. (2016). "Have financial markets become more informative?" *Journal of Financial Economics*, *122*(3), 625–654.

Bailey, W., Chung, Y. P., and Kang, J.-K. (1999). "Foreign ownership restrictions and equity price premiums: what drives the demand for cross-border investments?" *Journal of financial and quantitative analysis*, *34*(4), 489–511.

Bailey, W., Kumar, A., and Ng, D. (2008). "Foreign investments of us individual investors: Causes and consequences." *Management science*, *54*(3), 443–459.

Bams, D., and van der Kroft, B. (2022). "Divestment, information asymmetries, and inflated esg ratings." *Information Asymmetries, and Inflated ESG Ratings (June 3, 2022)*.

Bartram, S. M., Griffin, J. M., Lim, T.-H., and Ng, D. T. (2015). "How important are foreign ownership linkages for international stock returns?" *The Review of Financial Studies*, *28*(11), 3036–3072.

Ben-David, I., Franzoni, F., Moussawi, R., and Sedunov, J. (2021). "The granular nature of large institutional investors." *Management Science*, *67*(11), 6629–6659.

Berg, F., Fabisik, K., and Sautner, Z. (2020). "Is history repeating itself? the (un) predictable past of esg ratings." *The (Un) Predictable Past of ESG Ratings (August 24, 2021). European Corporate Governance Institute–Finance Working Paper*, *708*.

Berg, F., Koelbel, J. F., and Rigobon, R. (2022). "Aggregate confusion: The divergence of esg ratings." *Review of Finance*, *26*(6), 1315–1344.

Bolton, P., and Kacperczyk, M. (2021a). "Do investors care about carbon risk?" *Journal of financial economics*, *142*(2), 517–549.

Bolton, P., and Kacperczyk, M. (2021b). "Global pricing of carbon-transition risk." Tech. rep., National Bureau of Economic Research.

Carrieri, F., Chaieb, I., and Errunza, V. (2013). "Do implicit barriers matter for globalization?" *The Review of Financial Studies*, *26*(7), 1694–1739.

Coqueret, G. (2022). *Perspectives in Sustainable Equity Investing*. CRC Press.

Cremers, K. M., and Petajisto, A. (2009). "How active is your fund manager? a new measure that predicts performance." *The Review of Financial Studies*, *22*(9), 3329–3365.

Dyck, A., Lins, K. V., Roth, L., and Wagner, H. F. (2019). "Do institutional investors drive corporate social responsibility? international evidence." *Journal of Financial Economics*, *131*(3), 693–714.

Easley, D., and O'hara, M. (2004). "Information and the cost of capital." *The Journal of Finance*, *59*(4), 1553–1583.

Fama, E. F., and MacBeth, J. D. (1973). "Risk, return, and equilibrium: Empirical tests." *Journal of Political Economy*, *81*(3), 607–636.

Ferreira, M. A., and Matos, P. (2008). "The colors of investors' money: The role of institutional investors around the world." *Journal of Financial Economics*, *88*(3), 499–533.

Gabaix, X., Koijen, R. S., Mainardi, F., Oh, S., and Yogo, M. (2022). "Asset demand of us households." *Working Paper*.

Gibson, R., Glossner, S., Krueger, P., Matos, P., Steffen, T., et al. (2020). "Responsible institutional investing around the world." Tech. rep., Swiss Finance Institute.

Gibson, R., Krueger, P., and Schmidt, P. S. (2021). "Esg rating disagreement and stock returns." *Financial Analysts Journal*, *77*(4), 104–127.

Giglio, S., Kelly, B., and Stroebel, J. (2021). "Climate finance." *Annual Review of Financial Economics*, *13*, 15–36.

Goldstein, I., Kopytov, A., Shen, L., and Xiang, H. (2022). "On esg investing: Heterogeneous preferences, information, and asset prices." Tech. rep., National Bureau of Economic Research.

Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., and Wilkens, M. (2020). "Carbon risk." *Working Paper*.

Gormsen, N. J., Huber, K., and Oh, S. (2023). "Climate capitalists." *Working Paper*.

Gutiérrez, G., and Philippon, T. (2017). "Declining competition and investment in the us." Tech. rep., National

Bureau of Economic Research.
Hong, H., and Kacperczyk, M. (2009). "The price of sin: The effects of social norms on markets." *Journal of financial economics*, *93*(1), 15–36.
Hong, H., Li, F. W., and Xu, J. (2019). "Climate risks and market efficiency." *Journal of econometrics*, *208*(1), 265–281.
Hsu, P.-H., Li, K., and Tsou, C.-Y. (2022). "The pollution premium." *The Journal of Finance*.
Huebner, P. (2023). "The making of momentum: A demand-system perspective." *Working Paper*.
Jansen, K. A. (2021). "Long-term investors, demand shifts and yields." *Working Paper*.
Kim, S., and Yoon, A. (2023). "Analyzing active fund managers' commitment to esg: Evidence from the united nations principles for responsible investment." *Management Science*, *69*(2), 741–758.
Koijen, R. S., Richmond, R. J., and Yogo, M. (2022). "Which investors matter for equity valuations and expected returns?" Tech. rep., National Bureau of Economic Research.
Koijen, R. S., and Yogo, M. (2019). "A demand system approach to asset pricing." *Journal of Political Economy*, *127*(4), 1475–1515.
Koijen, R. S., and Yogo, M. (2020). "Exchange rates and asset prices in a global demand system." Tech. rep., National Bureau of Economic Research.
Krueger, P., Sautner, Z., and Starks, L. T. (2020). "The importance of climate risks for institutional investors." *The Review of Financial Studies*, *33*(3), 1067–1111.
Leuz, C., Lins, K. V., and Warnock, F. E. (2009). "Do foreigners invest less in poorly governed firms?" *The Review of Financial Studies*, *22*(8), 3245–3285.
Liang, H., Sun, L., and Teo, M. (2021). "Greenwashing: Evidence from hedge funds." *Working Paper*.
Lou, D. (2012). "A flow-based explanation for return predictability." *The Review of Financial Studies*, *25*(12), 3457–3489.
Matos, P. (2020). *ESG and responsible institutional investing around the world: A critical review*. CFA Institute Research Foundation.
Melitz, M. J. (2003). "The impact of trade on intra-industry reallocations and aggregate industry productivity." *econometrica*, *71*(6), 1695–1725.
Noh, D., Oh, S. S., and Song, J. (2023). "Unpacking the demand for sustainable equity investing." *Working Paper*.
Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2021). "Sustainable investing in equilibrium." *Journal of Financial Economics*, *142*(2), 550–571.
Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2022). "Dissecting green returns." *Journal of Financial Economics*, *146*(2), 403–424.
Pedersen, L. H., Fitzgibbons, S., and Pomorski, L. (2021). "Responsible investing: The esg-efficient frontier." *Journal of Financial Economics*, *142*(2), 572–597.
Schmickler, S., and Tremacoldi-Rossi, P. (2022). "Spillover effects of payouts on asset prices and real investment." *Available at SSRN*.
Starks, L. T., Venkat, P., and Zhu, Q. (2017). "Corporate esg profiles and investor horizons." *Working Paper*.
Van der Beck, P. (2022). "Flow-driven esg returns." *Working Paper*.
Widyawati, L. (2020). "A systematic literature review of socially responsible investment and environmental social governance metrics." *Business Strategy and the Environment*, *29*(2), 619–637.
Yang, R. (2021). "What do we learn from ratings about corporate social responsibility (csr)?" *Columbia Business School Research Paper*.

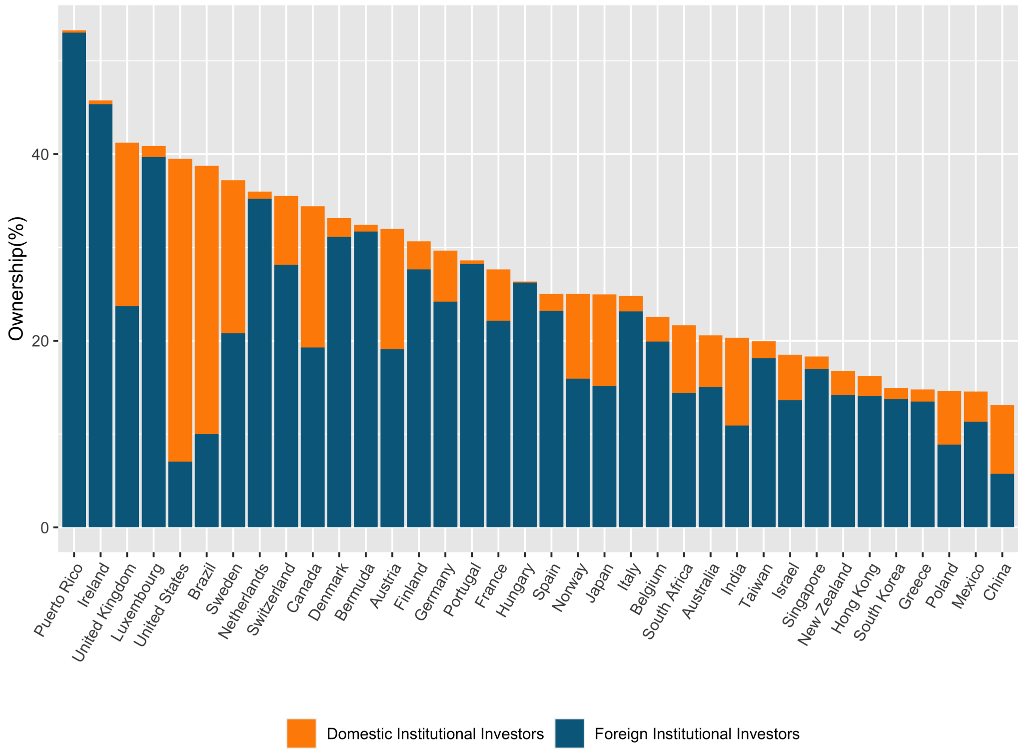

Figure 1: Percentage of Market Capitalization Owned by Institutional Investors, December 2021

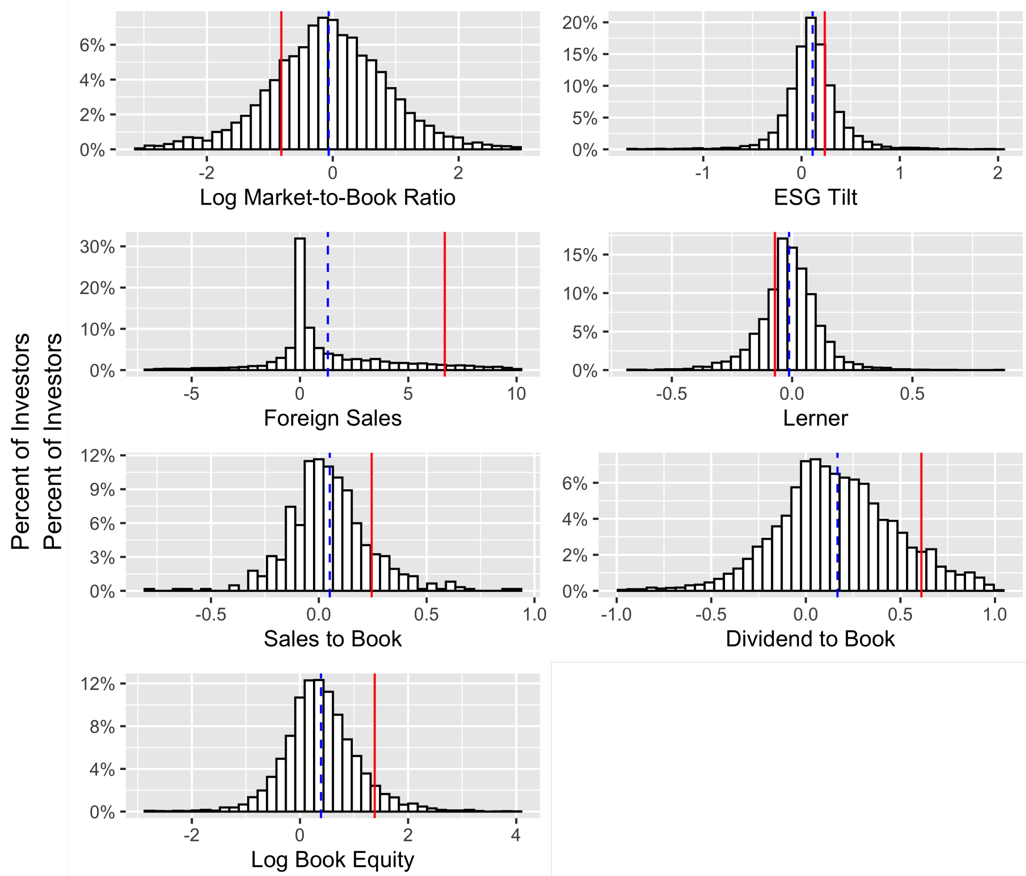

Figure 2: Asset Demand by Investors

Notes: The demand coefficients are estimated based on Equation 6. For each investor, the demand coefficients are averaged across years. The red solid vertical line is the time-series average of the wealth-weighted average of the demand coefficients for all US investors. The blue dashed line is the equal-weighted average of demand coefficients across investors.

Table 1: Summary of Factset Institutions

The table presents time series median and 90th percentile of AUM, number of stocks, and number of institutions in 2010 - 2021, based on the Factset Holding data.

	AUM ($Billions)		Number of Stocks		Number of
Year	Median	90th Percentile	Median	90th Percentile	Institutions
2010	0.1152	4.2689	95	848.2	4107
2011	0.1036	4.0224	87	826	4261
2012	0.1081	4.2333	88	814.8	4323
2013	0.1407	5.2053	94	841	4251
2014	0.1500	5.5284	98	883.3	4392
2015	0.1419	5.5566	98	919.5	4526
2016	0.1512	5.6438	100	1013.7	4414
2017	0.1830	6.9943	103	1041	4294
2018	0.1787	6.5486	105	1017.9	4252
2019	0.1780	7.0878	99	1018.2	4460
2020	0.1763	6.2769	96	1018.4	4807
2021	0.2159	7.8185	99	1062.4	4705

Table 2: Summary Statistics: ESG Funds

The table presents the time series summary statistics of ESG funds and aggregate ESG portfolio in 2010 - 2021, based on the Factset Holding data. ESG funds are identified by the list of sustainability keywords. The last two columns report the statistics for the aggregate ESG portfolio using the ESG funds where the portfolio weight $w_{t,n}^{ESG}$ on each company is the holdings of all ESG funds divided by their total assets under management. Active share is calculated as the deviation of the ESG portfolio from the aggregate market portfolio as $\frac{1}{2}\sum_n |w_{t,n}^{ESG} - w_{t,n}^{MF}|$ (Cremers and Petajisto, 2009). All AUM are reported in billion USD.

	Fund-level statistics					Aggregate ESG Portfolio	
Year	# Funds	Median AUM	90th Percentile AUM	Median # Stocks	90th Percentile # Stocks	AUM	Active Share
2010	671	0.0857	0.6954	83	302	213.3283	0.5073
2011	716	0.0592	0.5019	73	295.5	169.6924	0.5163
2012	777	0.0702	0.5785	68	307.4	196.8267	0.4858
2013	792	0.0882	0.7012	67.5	317.7	227.8705	0.4678
2014	838	0.1024	0.7573	70	355.6	253.9791	0.4616
2015	933	0.0923	0.7734	70	402.8	254.8899	0.4507
2016	1011	0.0826	0.6992	73	407	258.5237	0.4346
2017	1129	0.0834	0.7297	71	437.6	316.3585	0.4332
2018	1333	0.0679	0.6758	67	514.8	354.7598	0.4271
2019	1570	0.0721	0.7852	66	506.2	486.2172	0.4398
2020	2016	0.0848	1.0504	65	483	775.6584	0.4757
2021	2511	0.0848	1.2764	63	449	1235.2959	0.3748

Table 3: Valuation Regressions

The table presents results on the valuation and returns. ESG preference is measured as the deviation in portfolio weight from the aggregate ESG portfolio to the aggregate market portfolio. The MSCI ESG score is the weighted average of the scores received on all the key issues based on MSCI's methodology. All the stock characteristics are standardized cross-sectionally so that we can compare the magnitudes of γ across different characteristics. Columns (1) and (5) control for the time fixed effects and Columns (2)-(4) and Columns (6)-(8) further control for the year-by-country fixed effects. The data are from Factset from 2010 to 2021. The standard errors are clustered by year and country in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Dependent Variables:	Log Market-to-Book				Return			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Perceived ESG	0.2600***	0.2394***		0.2861***	0.0374**	0.0328***		0.0460**
	(0.0138)	(0.0239)		(0.0373)	(0.0144)	(0.0073)		(0.0211)
MSCI ESG Score			0.1220***	0.1102***			0.0082*	0.0065*
			(0.0089)	(0.0092)			(0.0050)	(0.0039)
Log Book Equity	-0.2924***	-0.2971***	-0.3010***	-0.3935***	-0.0320*	-0.0316***	-0.0097	-0.0240
	(0.0114)	(0.0130)	(0.0100)	(0.0161)	(0.0151)	(0.0070)	(0.0107)	(0.0167)
Foreign Sales	0.0092***	0.0114***	0.3010***	0.2330***	0.0012	0.0011	0.0031	-0.0079
	(0.0027)	(0.0025)	(0.0324)	(0.0326)	(0.0013)	(0.0008)	(0.0164)	(0.0131)
Lerner	-0.0209***	-0.0234***	-0.0254***	-0.0236***	0.0025***	0.0020**	0.0002	0.0004
	(0.0020)	(0.0024)	(0.0039)	(0.0040)	(0.0008)	(0.0008)	(0.0018)	(0.0019)
Sales to Book	0.1661***	0.1616***	0.2115***	0.1983***	0.0063	0.0052*	0.0168**	0.0146**
	(0.0079)	(0.0094)	(0.0082)	(0.0083)	(0.0052)	(0.0029)	(0.0066)	(0.0067)
Dividend to Book	0.3395***	0.3384***	0.2741***	0.2606***	-0.0233**	-0.0185***	-0.0313***	-0.0333***
	(0.0165)	(0.0114)	(0.0125)	(0.0124)	(0.0093)	(0.0052)	(0.0096)	(0.0104)
Year	Yes				Yes			
Year × Country		Yes	Yes	Yes		Yes	Yes	Yes
Observations	2,239,149	2,239,149	481,891	481,891	2,015,780	2,015,780	450,695	450,695
R^2	0.25468	0.33944	0.36605	0.40129	0.06901	0.12940	0.14121	0.14534
Within R^2	0.25444	0.26193	0.31068	0.34899	0.00518	0.00439	0.00674	0.01151

Table 4: Demand Estimation Summary by Country

The table presents the summary statistics of estimates on the investor level using the asset pricing demand system by country. I calculate the AUM-weighted average of investors within each country each year and then average the estimates across years. The holdings data are from Factset from 2010 to 2021.

Country	MB	Perceived ESG	Foreign Sales	Lerner	Sales to Book	Dividend to Book	Book Equity
Overall	-0.709	0.260	5.136	-0.070	0.188	0.547	1.178
Austria	-0.403	0.201	0.565	0.021	-0.080	0.429	0.364
Canada	-0.580	0.378	4.110	-0.028	0.137	0.469	0.817
China	1.810	-0.210	0.474	0.059	-0.129	-0.004	1.609
Denmark	-1.064	0.415	3.913	-0.031	0.116	0.599	0.279
France	0.219	0.197	0.498	-0.008	-0.063	0.345	1.021
Germany	-0.358	0.641	1.494	-0.035	-0.060	0.474	0.552
Hong Kong	0.642	-0.196	1.529	0.060	-0.069	0.133	0.917
Italy	-0.062	0.266	1.026	-0.027	0.014	0.215	0.681
Japan	-0.921	0.174	0.758	-0.058	0.225	-0.043	0.058
Luxembourg	-0.644	0.356	2.369	-0.007	-0.085	0.414	-0.269
Singapore	-0.748	0.171	0.199	-0.057	0.072	0.297	0.041
South Africa	0.033	0.116	-0.783	0.022	-0.009	0.201	0.924
Spain	-7.833	1.345	0.458	-0.135	1.364	3.461	-0.821
Sweden	-0.942	0.382	2.412	-0.069	0.124	0.530	0.463
Switzerland	0.089	0.275	1.627	-0.033	-0.026	0.303	1.162
Taiwan	-0.869	0.271	0.308	0.001	0.001	0.289	-0.684
United Kingdom	-0.385	0.296	1.980	-0.125	0.058	0.407	0.885
United States	-0.817	0.236	6.683	-0.072	0.245	0.611	1.382

Table 5: Demand Estimation - Cross-Country Substitution

The table presents the estimates on λ_c using the asset pricing demand system in Equation (8). The holdings data are from Factset from 2010 to 2021.

Country	λ
Spain	0.045
Japan	0.047
Singapore	0.059
Switzerland	0.06
Italy	0.072
South Africa	0.09
Hong Kong	0.093
China	0.096
Canada	0.098
Taiwan	0.102
Luxembourg	0.123
Sweden	0.158
United Kingdom	0.166
Austria	0.198
France	0.221
Germany	0.221
Denmark	0.225

Appendix

Table A1: Top 30 Institutions

The table presents the top 30 institutions by their assets under management with the country of origin at the end of 2021. AUM are reported in billion USD.

Country	AUM ($ Billion)	Name
ES	15872.3543	Sabadell Asset Management SA SGIIC SU (Sabadell AM)
US	6280.3167	The Vanguard Group, Inc. (VGI)
FR	2481.7365	Allianz Global Investors GmbH (France) (AllianzGI-FR)
US	2251.5927	BlackRock Fund Advisors (BFA)
ES	2107.7004	Urquijo Gestión SA SGIIC Sociedad Unipersonal (Urquijo Gestión)
US	1782.0907	Fidelity Management & Research Co. (FMR)
TH	1342.8052	Krungsri Asset Management Co., Ltd. (KSAM)
US	1141.7640	Capital Research & Management Co., doing business as Capital World Investors (CWI)
US	1072.6668	SSgA Funds Management, Inc. (SSgA FM)
US	1064.1157	T. Rowe Price Associates, Inc. (Price Associates)
NO	1015.7352	Norges Bank Investment Management (NBIM)
US	950.3597	Geode Capital Management LLC (GCM)
US	865.4195	Capital Research & Management Co. (Global Investors)
US	544.8594	JPMorgan Investment Management, Inc. (JPMIM)
US	522.2878	Dimensional Fund Advisors LP (Dimensional)
GB	497.0340	BlackRock Advisors (UK) Ltd. (BlackRock UK)
US	491.2241	Wellington Management Co. LLP (WMC)
DE	432.0411	Allianz Global Investors GmbH (AGI)
US	426.8665	Invesco Capital Management LLC (ICM)
US	420.9139	Massachusetts Financial Services Co.
US	403.3884	Charles Schwab Investment Management, Inc. (CSIM)
GB	377.8104	BlackRock Investment Management (UK) Ltd. (BIM-UK)
FR	343.4376	Amundi Asset Management SA (Investment Management) (Amundi-IM)
GB	343.2196	Goldman Sachs Asset Management International (GSAMI)
US	342.8577	Invesco Advisers, Inc.
US	268.1657	Capital Research & Management Co. (CR&M)
GB	261.3802	Baillie Gifford & Co.
JP	261.0046	Nomura Asset Management Co., Ltd. (NAM)
US	259.5223	TIAA-CREF Investment Management LLC (TCIM)
US	256.2703	Franklin Advisers, Inc.

Table A2: Firm Size Distribution by Country

The table presents firm size distribution as measured by market capitalization in selected countries in 2010 and 2016.

Country	2010			2021		
	50th Percentile Mkt Cap	90th Percentile Mkt Cap	# Firms	50th Percentile Mkt Cap	90th Percentile Mkt Cap	# Firms
United States	119	1248	6683	96	1174	8146
Japan	79	681	3001	66	668	3273
China	126	1037	2142	95	1799	5148
Canada	30	293	2116	25	273	1947
United Kingdom	17	197	1679	29	302	1677
India	28	251	979	35	310	1273
Taiwan	30	355	952	21	347	1234
Australia	14	177	934	20	200	951
Hong Kong	18	208	867	21	164	787
South Korea	23	170	782	22	461	1772
Germany	11	77	746	17	114	886
France	14	81	664	10	71	872
Israel	7	108	542	25	172	585
Malaysia	15	123	435	19	138	445
Singapore	12	98	369	7	82	303
Poland	7	64	341	9	61	228
Pakistan	7	62	326	20	104	298
Sweden	8	57	319	21	138	681
Switzerland	6	54	302	8	61	538
Brazil	10	90	288	8	98	419
South Africa	12	79	287	10	62	300
Italy	6	59	266	11	71	434
Thailand	11	75	215	20	132	368
Norway	3	42	201	7	66	319
Spain	4	34	197	7	37	607
Viet Nam	9	62	190	13	70	214
Turkey	9	61	178	17	98	204
Indonesia	13	62	174	12	97	276
Luxembourg	1	10	171	9	77	1134
Belgium	3	30	149	4	36	144
Netherlands	9	40	144	5	29	165
Denmark	3	22	136	3	29	215
Ireland	6	23	134	5	55	746
Finland	4	30	111	5	35	261

Table A3: Top 30 ESG Funds

The table presents the top 30 ESG funds and their assets under management with the country of origin and entity type and style by the end of 2021. The ESG institutions are identified by the list of sustainability keywords. AUM are reported in billion USD.

Fund	AUM	Country	Style
iShares Tr. - ESG Aware MSCI USA ETF	27.5129	US	Index
Nordea 1 - Global Climate & Environment Fund	14.5544	DK	GARP
iShares IV Plc - MSCI USA SRI UCITS ETF	11.8276	GB	Index
NT UCITS Common Contractual Fd. - World Cus. ESG Eq. Ind. Fd.	11.3494	GB	Growth
Pictet - Global Environment Opportunities	10.7690	CH	GARP
AM One Global ESG High Quality Growth Equity Mother Fund	10.0405	US	Growth
Vontobel Fund - MTX Sustainable Emerging Markets Leaders	8.4830	CH	Growth
BlackRock Global Funds - Sustainable Energy Fund	8.4182	GB	GARP
iShares Tr. - ESG Aware MSCI EAFE ETF	8.2463	US	Index
iShares IV Plc - MSCI World SRI UCITS ETF	7.5811	GB	Index
Northern Trust UCITS FGR Fd. - World Custom ESG Eq. Index	7.4548	GB	Growth
Brown Advisory Sustainable Growth Fund	7.4453	US	Growth
BlackRock ACS I - World ESG Equity Tracker Fund	7.4451	GB	GARP
BNPPF Private SICAV - Sustainable Balanced	7.3987	BE	Growth
Nordea 2 - Global Responsible Enhanced Equity Fund	7.3483	SE	Growth
iShares Tr. - ESG Aware MSCI EM ETF	7.2716	US	Index
State Street World ESG Screened Index Equity Fund	7.2629	GB	Index
Putnam Sustainable Leaders Fund	7.2445	US	GARP
iShares Global Clean Energy ETF	6.7820	US	Index
Amundi Index Solutions - MSCI USA SRI PAB	6.6786	FR	Growth
Amundi Index MSCI Europe ESG Broad CTB	6.6264	FR	Growth
iShares II Plc - Global Clean Energy UCITS ETF	6.6143	GB	Index
Vanguard ESG US Stock ETF	6.4208	US	Index
iShares II Plc - MSCI Europe SRI UCITS ETF	6.2810	GB	Index
Mirova Funds - Global Sustainable Equity Fund	6.0119	US	GARP
BlackRock UCITS Funds - CCF Dev. World (ESG Screened) Index	5.6524	GB	Index
Northern Trust UCITS FGR Fd. - EM Custom ESG Equity Index	5.5218	GB	Growth
iShares IV Plc - MSCI USA ESG Enhanced UCITS ETF	5.4664	GB	Index
Pictet - Clean Energy Fund	5.3933	CH	GARP
Calvert US Large Cap Core Responsible Index Fund	5.3503	US	GARP

Table A4: ESG Portfolio Tilt and ESG Scores

The table presents the estimates for panel OLS and probit regressions. The sustainability characteristics include MSCI ESG score, climate change theme score, whether the company is in the fossil fuel industry, and carbon emission score. The control variables include log of book equity, market beta, and volatility. Climate change theme score is on a scale of 0-10 and represents the weighted average of the MSCI key issue Scores that fall under the climate change theme: carbon emissions, product carbon footprint, climate change vulnerability, and financing environmental impact. The carbon emission score is also on a scale of 0-10 and is relevant to those companies with significant carbon footprints: companies that proactively invest in low-carbon technologies and increase the carbon efficiency of their facilities or score higher on this key issue, while companies that allow legal compliance to determine product strategy, focus exclusively on activities to influence policy setting, or rely heavily on exploiting differences in regulatory frameworks score lower. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Dependent Variables:	$\tau_{t,n}^{ESG}$		$I(\tau_{t,n}^{ESG} > 0)$	
Model:	(1) OLS	(2) OLS	(3) Probit	(4) Probit
ESG Score	0.0001*	0.0001	0.0519***	0.0460***
	(6.6×10^{-5})	(8.67×10^{-5})	(0.0123)	(0.0157)
Climate Change Score	0.0002***	0.0001***	0.0485***	0.0376***
	(4.01×10^{-5})	(3.11×10^{-5})	(0.0071)	(0.0066)
I(Fossil Fuel)	0.0012**	0.0013**	0.3224***	0.3374***
	(0.0005)	(0.0005)	(0.0834)	(0.0809)
Carbon Emission Score		0.0001**		0.0216**
		(4.96×10^{-5})		(0.0084)
Controls, Year FE	Yes	Yes	Yes	Yes
Observations	266,950	230,059	266,950	230,059
Squared Correlation	0.01494	0.01872	0.08554	0.09441

Clustered (year)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A5: Valuation and Return Regressions

The table presents results on the valuation and returns. ESG preference is measured as the deviation in portfolio weight from the aggregate ESG portfolio to the aggregate market portfolio. The MSCI ESG score is the weighted average of the scores received on all the key issues based on MSCI's methodology. All the stock characteristics are standardized cross-sectionally so that we can compare the magnitudes of γ across different characteristics. Columns (1) and (5) control for the time fixed effects and Columns (2)-(4) and Columns (6)-(8) further control for the year-by-country fixed effects. The data are from Factset from 2010 to 2021. The standard errors are clustered by year and country in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Panel A	Log Market-to-Book				
Model:	US	UK	China	Japan	Switzerland
ESG Preference	0.3269***	0.2072***	0.7645***	0.7249***	0.0457***
	(0.0489)	(0.0278)	(0.0479)	(0.0841)	(0.0041)
Log Book Equity	-0.2773***	-0.2889***	-0.7820***	-0.2585***	-0.2312***
	(0.0176)	(0.0200)	(0.0363)	(0.0372)	(0.0147)
Foreign Sales	0.0433**	0.0329**	0.0029	0.0578	0.0574**
	(0.0191)	(0.0114)	(0.0094)	(0.0352)	(0.0236)
Lerner	-0.0409***	-0.0122***	0.0098	1.543***	-0.0440***
	(0.0027)	(0.0025)	(0.0095)	(0.4367)	(0.0077)
Sales to Book	0.2429***	0.2013***	0.0365**	0.0808***	0.1555***
	(0.0081)	(0.0123)	(0.0153)	(0.0100)	(0.0115)
Dividend to Book	0.2276***	0.3872***	0.2165***	0.8028***	0.4028***
	(0.0134)	(0.0236)	(0.0235)	(0.0494)	(0.0112)
Year	Yes	Yes	Yes	Yes	Yes
Observations	518,767	113,255	183,151	290,924	36,770
Within R^2	0.25751	0.44107	0.31879	0.23768	0.40063

Panel B	Return				
Model:	US	UK	China	Japan	Switzerland
ESG Preference	0.0472	0.0194	0.1119**	0.1445**	0.0027
	(0.0278)	(0.0121)	(0.0458)	(0.0467)	(0.0022)
Log Book Equity	-0.0200	-0.0329*	-0.0453	-0.0588***	-0.0264
	(0.0236)	(0.0153)	(0.0372)	(0.0175)	(0.0166)
Foreign Sales	-0.0042	0.0011	0.0107	0.0212	0.0097*
	(0.0047)	(0.0040)	(0.0084)	(0.0437)	(0.0044)
Lerner	-0.0013	0.0042**	-0.0022	0.0707	0.0049**
	(0.0019)	(0.0014)	(0.0043)	(0.0783)	(0.0019)
Sales to Book	0.0144	0.0042	0.0041	0.0020	-0.0183
	(0.0082)	(0.0106)	(0.0075)	(0.0075)	(0.0175)
Dividend to Book	-0.0358**	-0.0075	-0.0094	0.0004	0.0085
	(0.0152)	(0.0110)	(0.0147)	(0.0138)	(0.0081)
Year	Yes	Yes	Yes	Yes	Yes
Observations	466,787	101,434	168,258	264,988	33,176
R^2	0.06916	0.12430	0.13521	0.14471	0.12650

Table A6: Persistence of the set of stocks held

The table presents the persistence of the set of stocks that were held by institutions in the previous 1, 5 and 10 years respectively.

	Previous Year		
AUM Percentile	1	5	10
1	75.69	80.00	81.16
2	73.33	79.11	80.52
3	71.45	77.24	78.49
4	72.49	78.17	79.41
5	73.44	78.86	80.24
6	74.40	80.09	81.33
7	73.68	79.84	81.23
8	74.91	81.03	82.34
9	77.17	82.69	83.81
10	81.31	85.98	87.02

Table A7: Demand Estimation Summary by Year

The table presents the summary statistics of estimates on the investor level using the asset pricing demand system by country. I calculate the AUM-weighted average of investors within each country each year. Then I compute the total-AUM weighted average of these estimates across countries. The holdings data are from Factset from 2010 to 2021.

Year	Log Market-to-Book	ESG Tilt	Foreign Sales	Lerner	Sales to Book	Dividend to Book	Log Book Equity
2010	-0.502	0.310	3.350	-0.064	0.138	0.399	1.211
2011	-0.411	0.244	3.161	-0.027	0.055	0.566	1.216
2012	-0.568	0.115	0.653	-0.079	0.140	0.486	1.356
2013	-0.649	0.233	1.621	-0.084	0.165	0.529	1.215
2014	-0.283	0.175	5.191	-0.029	0.099	0.435	1.237
2015	-0.861	0.332	1.671	-0.030	0.267	0.524	1.030
2016	-0.698	0.160	1.960	-0.081	0.226	0.494	1.254
2017	-0.662	0.107	1.655	-0.181	0.226	0.487	1.253
2018	-1.601	0.526	0.900	-0.072	0.312	0.844	0.862
2019	-1.985	0.628	0.596	-0.126	0.360	1.027	0.799
2020	-0.592	0.439	2.892	-0.050	0.227	0.391	1.144
2021	-0.299	0.143	0.946	-0.012	0.035	0.385	1.566

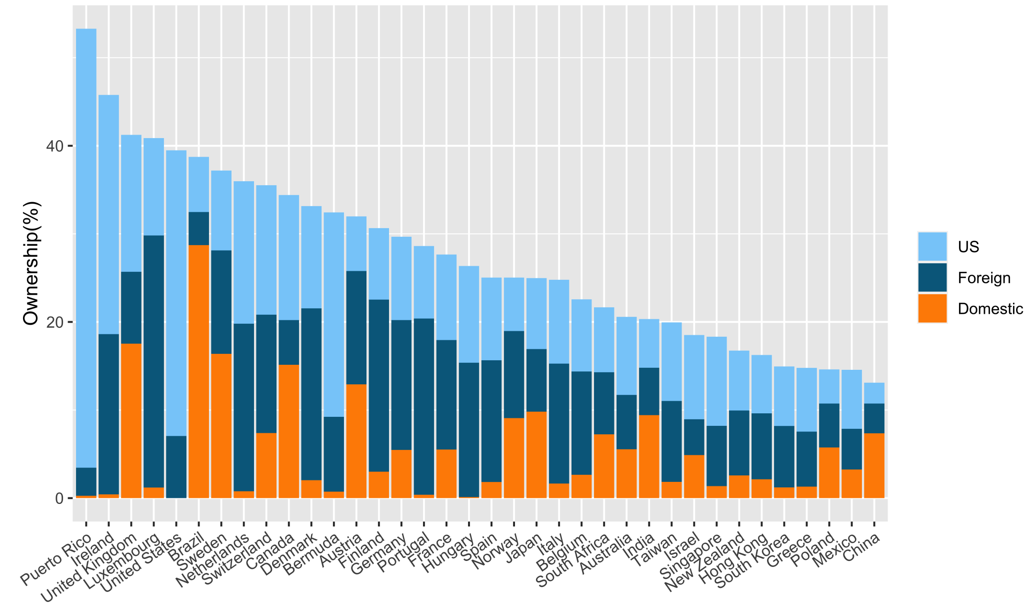

Figure A1: Percentage of Market Capitalization Owned by Institutional Investors, December 2021

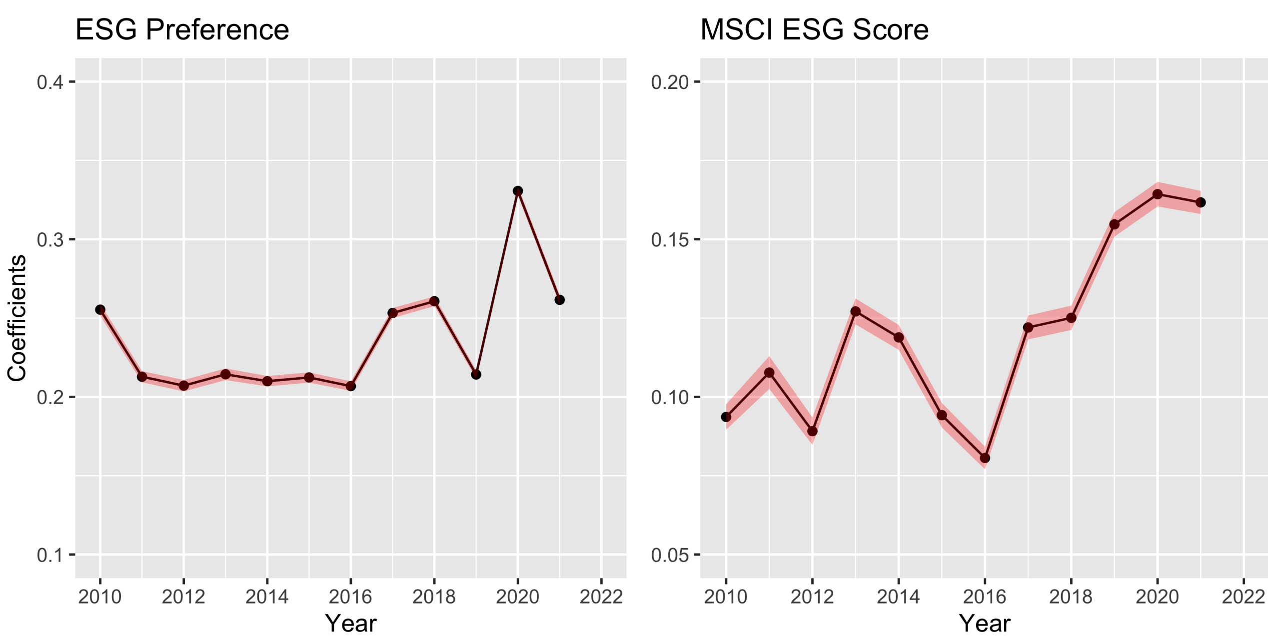

Figure A2: Valuation Regressions: Time Series of Coefficients

This figure plots the time series of coefficients by estimating the valuation regressions cross-sectionally with country fixed effects. The red shaded areas are the 95% confidence intervals based on the clustered standard errors.