Decoding Demand: a Demand System Approach to uncover Green Preferences of U.S. Institutional Investors

A Master's Thesis

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Abstract

We specify and estimate a characteristics-based demand system to study the heterogeneity of U.S. institutional investors' green demand. We find that pension funds, insurance companies, banks, and investment advisors are important drivers of the taste for green assets, but only explain little of the demand variation. For a subsample of large investors, we regress the demand coefficients on a number of investor-specific characteristics, and observe that institutional investors with concentrated portfolios and long-term, passive, and value-like investing strategies are associated with higher demand for green assets. We also explore the impact of being a member of the Principles of Responsible Investment (PRI) on green demand, where we find that signatories have a higher green demand, which trickles down in the signatories' organization, but not upwards. Among PRI investors, we observe that the higher demand for green assets is mainly driven by early, short-term-oriented signatories with a high portfolio concentration and a preference for large stocks. Using a difference-in-difference approach, we do, however, not find convincing evidence of a PRI signing effect on green demand. Our results propose a range of signals to facilitate the identification of green investors, which are relevant to market participants, policymakers, and promoters of sustainable investing.

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1 Introduction

As the global community grapples with the urgent challenges of climate change and resource depletion, it is imperative that all market participants – including governments, consumers, companies, and investors – recognize the critical role they play in promoting environmental sustainability and take collective action to succeed in the transition towards a sustainable society. While investors usually do not act as direct issuers of emissions, they have the ability to impact companies' cost of capital and decision-making through their (collective) allocation of funds and active ownership strategies. By directing their funds and efforts towards more sustainable companies, they can contribute to the green transition (Kölbel, Heeb, Paetzold, & Busch, 2020).

The surge of sustainable investing (SI) practices shows that investors are becoming increasingly aware of their role. SI describes the practice of investors directing capital to companies that pursue sustainable operations. While SI typically concerns three sustainability dimensions known as environment, social, and governance (ESG), the *environment* aspect has, in recent years, received the most attention from investors and their customers alike (Pastor, Stambaugh, & Taylor, 2022; Matos, 2020). Overall, the field has seen substantial inflows of capital in the past decade, particularly in equity markets (Coqueret, 2021). Having increased almost three-fold from 2014 to 2018, the value of global ESG assets is forecasted to hit USD 53 trillion by 2025, accounting for about a third of global assets under management (AUM) (Bloomberg Intelligence, 2021). Albeit being more widespread in Europe, SI increasingly attracts investors in the U.S. (Matos, 2020).

The main promise of SI is that investors who collectively allocate capital to firms with superior environmental performance trigger a reduction in those firms' cost of capital – thereby allowing them to push their environmentally beneficial activities (van der Beck, 2021). However, the effectiveness of SI is often seen to be threatened by non-sustainable investors, who pick up under-priced brown assets on the hunt for return opportunities (Noh & Oh, 2023). We are not yet at a point where *all* investors agree on the importance of sustainability. To design policies and direct funds to the *right* (that is, environmentally conscious) money managers, it is pivotal for market participants to understand the heterogeneity of investors' green demand and the drivers thereof.

To facilitate the understanding of this heterogeneity, the market needs strong signals. While some investor-level characteristics, like investment horizon or activeness, have previously been linked to green preferences, the field is still lacking a holistic picture.

Investors' membership in SI initiatives, such as the Principles of Responsible Investment (PRI), could serve as such a signal. Being initiated by the United Nations in 2006, the PRI is a set of principles that should commit investors to, and guide them in, responsible investment practices (PRI, n.d.-a). After years of rapid growth, PRI has become one of the world's largest investor networks, comprising over 3,750 signatories and USD 120 trillion AUM (PRI, n.d.-a). Albeit its prevalence, the effectiveness of PRI for the implementation of SI is a topic of debate, with critics arguing it being a *greenwash*. Studies of its impact on investors' greenness reveal mixed evidence (Brandon, Glossner, Krueger, Matos, & Steffen, 2022; Noh & Oh, 2023; Dyck, Lins, Roth, & Wagner, 2019). Because of the widespread adoption, it is important to investigate whether PRI membership works as a signal for green investors.

When speaking about investors, we are referring to *institutional* investors, which describe professional money managers that manage funds on behalf of their ultimate beneficiaries or clients (Matos, 2020). In recent years, equity markets have seen a vast emergence of institutional ownership as the main form of ownership in publicly listed companies. In 2017, the OECD reported an average institutional ownership of 40% in public companies globally, with the highest share (72%) being observed in the U.S. (Matos, 2020). With institutional investors being the largest owners, they are also the ones being best positioned to impact firms' valuations (van der Beck, 2021) and policies (Dyck et al., 2019), and the ones carrying the largest responsibility to act in favor of the green transition. As such, it is the institutional investors' green asset demand which warrants close scrutiny.

1.1 Research Question and Design

Based on the facts outlined above, we see the urgency to study the following research question:

How can we describe green asset demand of U.S. institutional investors and explain the heterogeneity thereof?

To approach this question, we first need to get an understanding of institutional investors' green asset demand. Instead of directly observing the greenness of institutions' portfolios, we leverage a methodology proposed by Koijen and Yogo (2019) and estimate an asset demand system based on an alternative specification of investor's characteristics-based demand (Koijen, Richmond, & Yogo, 2022). Using this approach allows us to control for a variety of asset characteristics that are relevant for an investor and thereby measure their dedicated *green* demand more precisely. For the estimation of the asset demand system, we employ quarterly portfolio holdings of institutional investors based on their Form 13(f) filings. We summarize this first step as:

Subquestion 1: *How can we describe the asset demand of institutional investors in the U.S. using asset characteristics?*

Following the estimation of investors' (green) demand, we aim to show and confirm its inherent heterogeneity. An intuitive source of heterogeneity is different types of investors, such as banks, pension funds, insurance companies, or mutual funds. Large parts of investor heterogeneity in the literature are studied along those types (see, for instance Bolton and Kacperczyk (2021)). We therefore aim to quantify which extent of heterogeneity can be explained by type and what remains for further investigation. We summarize this step as:

Subquestion 2: *What level of demand heterogeneity among U.S. institutions do we observe and to which extent can this be explained by investor type?*

After having confirmed (green) demand heterogeneity, we proceed to explain the part of it that is not merely driven by different investor types. While we test multiple variables that have previously been shown to be indicative of institutions' green preferences, we explicitly focus on the effect of investors' membership in the PRI on green demand. We summarize the last part of our analysis as:

Subquestion 3: *Which factors drive U.S. institutions' green demand heterogeneity and what role plays membership in the PRI?*

The answers to these questions have important implications for both academia and practice. In the academic dimension, the application of the increasingly popular asset demand system with updated data tests the robustness of previous results, and the study of drivers of demand heterogeneity adds insights to a field that still lacks completeness. In the practical dimension, the confirmation and discovery of strong signals for investors' greenness enhance the assessment of money managers for market participants and regulatory bodies, allowing for more informed fund allocation decisions and more effective policy designs. Moreover, granular insights on the effectiveness of PRI enable its initiators to assess the suitability of their governing principles and admission criteria.

1.2 Delimitations

Before commencing, it deems necessary to draw some delimitations and thus narrow the scope of our thesis. First, as emphasized by our research question, we will exclusively focus on *U.S.* investors. This inherent country-specific focus is driven by both data limitations and the fact that the U.S. accounts for the greatest share of historical carbon emissions (Popovich & Plumer, 2021). Second, the research question specifically considers *institutional* investors, which is motivated by the rise of institutional investment (Matos, 2020) and its importance for the impact of SI. This implies that the asset demand of retail investors is out of scope. Third, we are naturally restricted to *large* institutional investors, since only investment managers with more than USD 100 million in AUM are pursuant to Form 13(f) filings, which provide public disclosure of institutions' holdings of publicly listed equities (SEC, 2023a). Fourth, by explicitly focusing on the *green* demand of institutions, we only consider the demand for the E dimension of the ESG framework, which is motivated by the aforementioned dominance of *environmental* aspects in SI. Finally, although we do acknowledge the importance of studying investors' demand for other financial asset classes, such as bonds and real assets, we will only consider publicly listed equities in this thesis. This is largely driven by the limited availability of holdings data for other asset classes than equities (Koijen & Yogo, 2019). Hence, going forward, we will refer to assets as publicly traded securities.

1.3 Structure

The remainder of this paper is organized as follows. Chapter 2 reviews literature related to our study, and Chapter 3 describes the variety of datasets used for our analysis. Chapter 4 introduces the methodology we apply to approach the subquestions outlined above, before Chapter 5 outlines the results of our analysis and thereby attempts to answer these questions. Chapter 6 discusses our results in light of their limitations and proposes potential mitigation strategies. Chapter 7 concludes.

2 Literature Review

The intersection between investor heterogeneity and SI is a topic that has received an increasing amount of attention in the finance literature (Koijen et al., 2022; Noh & Oh, 2023; Brandon et al., 2022). To arrive at a model which will allow us to understand the heterogeneity of investor preferences for green assets, the first part of this literature review will take its departure from the early contributions to modern portfolio theory to get a holistic idea of investor preferences and equilibrium dynamics in the financial markets. Subsequently, the contributions and shortcomings of traditional and neoclassical asset pricing models in financial economics will be discussed. This will be done to highlight the inherent empirical limitations of these models and thus motivate the increased use of demand-system asset pricing models. Subsequently, emerging literature on demand-system asset pricing models will be presented to, lastly, examine the most relevant explanations and empirical findings of why institutional investors differ in their preferences for environmentally sustainable assets.

2.1 Traditional Asset Pricing Models

One of the long-standing contributions to modern portfolio theory is the mean-variance optimization framework invented by Markowitz (1952, 1959) as it is used extensively in empirical asset pricing models to understand investor preferences and behavior. In his model, Markowitz (1952, 1959) assumes asset demand to be homogeneous and examines the optimal portfolio weights for investors with rational expectations, who aim to minimize the variance of portfolio returns for a given set of assets. That is, all investors exhibit mean-variance preferences. Given the expected return and variance for a set of risky assets and the mean-variance preferences of investors, Markowitz (1952, 1959) argues that the only mean-variance efficient portfolio is the combination between assets which provides the lowest variance of all possible portfolio combinations with an equal expected return.

Building on Markowitz's mean-variance portfolio theory and the simplifying assumption of investors being rational optimizers with mean-variance preferences and homogenous beliefs, the capital asset pricing model (CAPM) was introduced as a model of equilibrium prices of financial assets by Treynor (1961), Sharpe (1964), Lintner (1965), Mossin (1966), and Black (1972). The CAPM states that the risk premium of an asset, denoted i, is given by:

$$E[R_i] - R_f = \beta_i(E[R_m] - R_f) \tag{2.1}$$

where $E[R_i]$, R_f, and $E[R_m]$ are the expected return of asset i, a risk-free rate, and expected return of the market portfolio, respectively. As illustrated in Equation (2.1), the CAPM values the risk premium of an asset relative to its risk exposure to the market risk premium, which is the market portfolio of all risky assets less the return of the risk-free asset. Accordingly, the model assumes that investors agree on (a) a risk-free asset and (b) an efficient frontier of risky assets. In Equation (2.1), it is pivotal to understand that, since the CAPM is an equilibrium model of asset prices, the average investor will, under the assumption that she has mean-variance optimal preferences, hold the market portfolio, as the market would otherwise not be in equilibrium (Munk, 2021). Accordingly, the risk premium of any risky asset will be equal to the product of its market beta, β, and market risk premium, which implies that risky assets are priced relative to their covariance with the market (Munk, 2021).

Following the emergence of the CAPM, scholars started to find empirical contradictions between the model and other explanations of the cross-section of expected returns. Most prominently, Banz (1981) finds a strong negative relationship between firm size, as measured by its market equity, and average returns, which implies that firms with a low market equity have historically earned higher returns. Similarly, Bhandari (1988) discovers a positive relationship between the debt-to-equity ratio of firms and their expected returns while Basu (1983) argues that the earnings' yield holds explanatory power in the cross-section of expected returns. At last, Stattman (1980) and Rosenberg, Reid, and Lanstein (1985) find that a firm's ratio of book value of common equity to its market value has proven to be positively related to average returns. Thus, the immediate response to the emergence of the CAPM proved that other market phenomena do not support the simple linear relationship between expected average returns and market risk exposure.

As a response to the empirical contradictions of the CAPM, Fama and French (1992) propose a three-factor asset pricing model by imposing a linear multi-factor structure on expected returns consistent with Merton (1973) and Ross (1976). To study the cross-section of expected returns, Fama and French (1992) assume investors to be rational individuals with heterogeneous risk aversion whose primary concerns are long-term average returns. Accordingly, Fama and French (1992) develop a three-factor model to estimate the risk-premium of an asset by its exposure to three tradable factors – market, size, and value. The market factor is included due to its ability to capture strong times-series variation in returns. The model is extended by the size and value factors as these are capable of measuring the riskiness and thus the risk-premium of an asset, which is consistent with Banz (1981), Basu (1983), Bhandari (1988), Stattman

(1980), and Rosenberg et al. (1985).

Following the canonical three-factor model, other empirical asset pricing models with traded factors have attempted to identify additional factors to more accurately explain the cross-section of returns. For example, Carhart (1997) adds a momentum factor to the three-factor model to account for the anomaly of short-term momentum in returns. Moreover, Fama and French (2015) extend their three-factor model to include factors capturing profitability and investment patterns in stock returns, which they find outperforms their former factor model empirically. The five-factor model thus depicts excess returns as following a factor structure contingent on five factors: the market risk premium, small minus big, high minus low, robust minus weak, and conservative minus aggressive, where the latter four are returns of long-short portfolios in the top and bottom deciles when sorting stocks for the respective characteristics:

$$E[R_{i,t}] - R_{f,t} = \alpha_i + \beta_{1,i}(E[R_{m,t}] - R_{f,t}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}RMW_t + \beta_{5,i}CMA_t + \epsilon_{i,t} \quad (2.2)$$

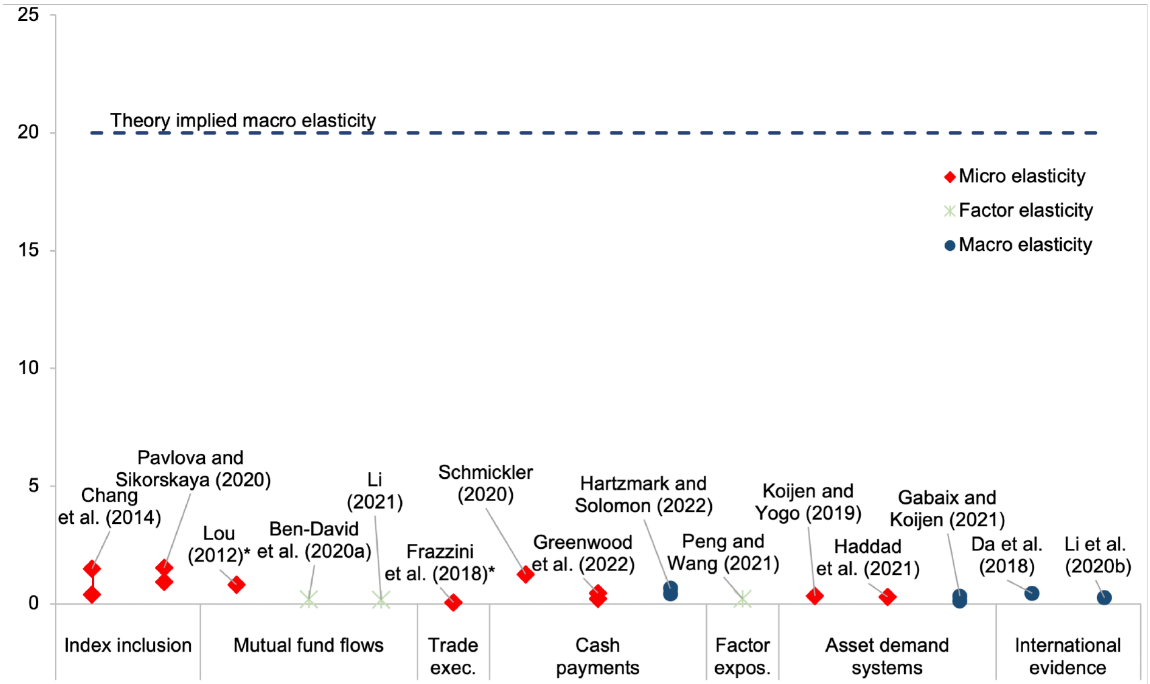
The models portrayed above are examples of empirical asset pricing models where expected returns follow a factor structure and the loading of the *tradable* factors depends on the characteristics of the individual stocks (Fama & French, 1992, 1993, 2015; Carhart, 1997). Other empirical asset pricing models attempt to study the cross-section of expected returns using *non-tradable* factors, i.e. factors that are not directly observable or easily quantifiable in financial markets. For example, N. Chen, Roll, and Ross (1986) consider a five-factor model including macroeconomic quantities such as industrial production, expected inflation changes as measured through the nominal interest rate, and changes in the term premium as factors.

Until this point of the literature review, all the models discussed have in common that they fall under the broader category of neoclassical asset pricing models. That is, models in which markets are assumed to be efficient and investors have rational expectations. In his article "Efficient Capital Markets: A Review of Theory and Empirical Work", Fama (1970) suggests that markets are only efficient if asset prices incorporate and reflect all available information, making it effectively impossible to consistently achieve abnormal returns. The ideas behind the rational expectation formation can largely be credited to Muth (1961), who argues that all economic agents will essentially have the same expectations about future asset prices as these will be formed using all available information, including information about the behavior of other agents. In the end, these assumptions imply that all investors will incorporate the same information into their expectations, leading to a convergence of beliefs and prices in the market.

Within the intersection between macroeconomics and financial economics, i.e. macro-finance, emerging literature attempts to document the inability of neoclassical asset pricing models to explain the price volatility of financial markets (Brunnermeier et al., 2021; Haddad, Huebner, & Loualiche, 2021). For example, Petajisto (2009) finds that neoclassical asset pricing models assume a virtually flat demand curve, which follows from the intuition that if the demand of one group of investors shifts, then other investors will step in quickly to ensure that markets clear. Inevitably, this means that equity prices should not move a lot following changes in demand as markets will be perfectly elastic. This, however, has been proven not to be the case by Petajisto (2011), who finds clear evidence of steep and downward-sloping demand curves. Specifically, he finds that unexpected supply shocks, proxied by index changes to the S&P 500, have significant price effects as index changes trigger purchases and sales by index funds, which collectively move prices. This contradicts the intuition of neoclassical asset pricing models in that additions and deletions to the S&P 500 do not change the idiosyncratic risk of assets meaning that prices should, in theory, remain unaffected (Petajisto, 2009, 2011). Similarly, Da, Larrain, Sialm, and Tessada (2018) provide evidence for downward-sloping demand curves at the aggregate market level by studying significant price pressures in the Chilean equity markets arising from coordinated advice from private financial advisors, which trigger capital reallocations of pension funds.

In line with the rationale of inelastic demand, Koijen and Gabaix (2021) propose a framework to study fluctuations of the aggregate stock market wherein capital is intermediated by financial institutions. They show that the price elasticity of demand in the stock market is small meaning that flows in and out of the markets have large impacts on prices. Based on this finding, Koijen and Gabaix (2021) formulate an *Inelastic Markets Hypothesis* whereby they study how the aggregate equities market in the U.S. responds to financial flows (e.g. selling bonds to buy stocks and vice-versa). They find that a one-dollar inflow into the equities market increases the aggregate market value by $3-8, implying that markets are reactive to financial flows. Conversely, if the price of the equity market portfolio increases by $3-8, demand will only fall by one dollar, suggesting that the price elasticity is approximately 0.11-0.33 – that is, equities markets are inelastic.

Figure 1: Empirical and neoclassical estimates of demand elasticities



Note: This figure depicts empirical estimates of macro elasticity relative to the theory implied elasticity of a neoclassical asset pricing model assuming constant absolute risk aversion (Koijen & Gabaix, 2021).

In Figure 1, the implied macro-elasticity of neoclassical asset pricing models is plotted relative to recent empirical estimates (Koijen & Gabaix, 2021). Macro-elasticity is a measure used by Koijen and Gabaix (2021) to study how the valuation of the aggregate equities market changes if an investor sells bonds to buy equities and vice-versa. As depicted in Figure 1, the price elasticities of demand implied by neoclassical asset pricing models are much higher than empirical estimates, suggesting that these models are highly incapable of capturing the complex dynamics of real-world financial markets and asset demand. For a range of important, quantity-related questions, such as the demand impact of certain types of investors, this presents a problem (Koijen & Yogo, 2019).

2.2 Asset Demand & Demand-System Asset Pricing Models

One of the main strengths of demand-system asset pricing models is their sufficient flexibility for inelastic demand curves across investors, contrary to traditional asset pricing models while allowing for rich heterogeneity in demand. With the increased availability of portfolio holdings data and econometric instruments, asset demand systems have recently made it possible to study quantity-related questions at the conjunction of asset demand, investor characteristics and prices (Gabaix, Koijen, Mainardi, Oh, & Yogo, 2022; Koijen & Yogo, 2019; van der Beck, 2022, 2021; Haddad et al., 2021). There has, however, been a significant time-gap between the first contributions to demand system asset pricing and the models we see today.

The early contributions of Brainard and Tobin (1968), Tobin (1969), and Friedman (1977) on asset-demand systems have, to a large extent, shaped modern research and models of asset demand. In the article called "Pitfalls in Financial Model Building", Brainard and Tobin (1968) study dynamic demand systems of simultaneous nonlinear first-order difference equations in 20 and 23 variables for the financial sector alone and for two variants of an extended model.[1] They show how demand systems are displaced from equilibria by simulating (1) a once-for-all increase in a single endogenous variable and (2) a sinusoidal fluctuation in an exogenous variable over 24 units of time (Brainard & Tobin, 1968). In the same vein, Tobin (1969) attempts to specify a so-called menu of assets and debts that appear in portfolios, the factors that determine asset demand, as well as supply, and how asset prices and interest rates clear the markets. He finds that financial events and policies affect the aggregate demand and flow of funds as they change the valuations of physical assets relative to their replacement costs (Tobin, 1969). Another early contribution to asset-demand systems is Friedman (1977), who attempts to reconcile conflicting views on the importance of financial flow variables in determining long-term interest rates. Accordingly, he uses a set of structural equations representing supplies of and demands for long-term bonds to focus on the types of investor behavior that lead to the short-run importance of financial flow variables (Friedman, 1977).

Fast forward 40 years with little progress in the literature on demand-system asset pricing, Koijen and Yogo (2019) (hereafter KY19) leverage newly available data on institutional holdings and instrumental variables to construct an equilibrium model that matches asset demand with supply by imposing market clearing. Specifically, they develop a characteristics-based asset demand system from the optimal portfolio choice of investors that have heterogeneous beliefs and face short-sale constraints. Based on the assumptions of an investor's optimization problem as in Lucas (1978), and a factor structure of returns, where factor loadings are explained by asset characteristics, KY19 show that investors' demand for an asset boils down to characteristics-based demand. In this instance, asset demand depends on a number of observable charac-

[1]The first extension considers a demand-system in which the response to changes in income is only weakly related to investment changes, while the second extensions hold that agents respond strongly to changes in income as measured by their portfolio holdings (Brainard & Tobin, 1968).

teristics, such as dividends and systematic risk, and latent demand, which is unobservable to the econometrician. Moreover, KY19 propose an instrumental variable for the market equity characteristic to address endogeneity issues between asset demand and prices, which allows them to identify the demand for market equity. They estimate characteristics-based demand using a generalized method of moments (GMM) estimator and publicly available equity holdings data of institutional investors in the U.S.

Upon estimation of the characteristics-based demand system, KY19 demonstrate the empirical relevance of their model through four asset pricing applications. First, they estimate the price impact of latent demand shocks arising from imperfectly elastic aggregate demand. Second, they show that 81% of the cross-sectional variance of stock returns can be explained by latent demand shocks, meaning that stock returns are mostly explained by excess volatility rather than changes to observable characteristics. Third, they decompose variance to understand if larger institutions, given their size, can be accredited more responsibility for the volatility around the Great Financial Crisis. In contrast to their hypothesis, they find smaller institutions and households explain 41% and 47% of the market volatility around 2008, respectively. They conjecture this to be driven by the largest institutions typically being diversified buy-and-hold investors, who invest in more liquid stocks that have a smaller price impact. Finally, KY19 attempt to predict cross-sectional variance in stock returns using demand-system asset pricing. They find that their estimate of long-run expected returns, which is based on the assumption that latent demand reverts to its mean over time, uncovers a new source of predictability.

Building on their earlier contribution to demand-system asset pricing literature, Koijen et al. (2022) (hereafter KRY22) extend their model to measure the impact of changes in the demand of various investors as quantified by fluctuations in wealth and asset prices. In contrast to the KY19 model, they make three main adjustments. First, they model richer heterogeneity across investors by augmenting the previous GMM estimator with a ridge penalty, which allows them to estimate demand curves even for small investors with limited portfolio holdings. Second, instead of using the six conventional investor types in KY19, they group investors based on their type and investment strategy (e.g. time-horizon, passive/active share, and size) to study if the variation in demand coefficients can be explained by the aforementioned characteristics. Third, they extend the selection of characteristics in their specification of characteristics-based demand by an environmental and governance characteristic, as they find those to be explanatory of the variation in stock's valuation ratios. Based on these adjustments, they estimate an asset demand system for the period of 2010 to 2019.

KRY22 use the demand system and corresponding coefficients to study (1) the impact of the transition from active to passive investment management, (2) the impact of climate-related shifts in asset demand on price and welfare, and (3) to measure the impact of investors on asset prices. First, they find that the reallocation of capital from active to passive managers has had an insignificant impact on firm-level valuations, while the impact on price-informativeness is small yet not systematically related to changes in institutional flows to passive managers. Second, they observe that investors stand to benefit from a change in the demand for green assets if they tilt their portfolio towards firms with higher environment scores before the demand shift and that long-term investors are likely to benefit the most. Third, they show that, using counterfactual experiments reallocating capital from one group of investors to the others, small active investment advisors and hedge funds exert the largest impact on prices, while the impact of long-term investors is only modest.

The number of recent contributions to the literature on demand-system asset pricing is quite limited albeit growing given that the interests in the area was only recently reignited by KY19. In his paper on flow-driven ESG returns, van der Beck (2021) extends KY19's asset demand system to study stock-specific and cross-elasticities of substitution. By doing so, he attempts to understand which assets the markets favor to accommodate the growing flow of funds toward the ESG investment industry. van der Beck (2021) uncovers substantial heterogeneity in the price impact of different mutual funds and finds that high ESG-taste stocks would have strongly underperformed had it not been for flow-driven price pressures.

Another recent contribution to the demand-system asset pricing literature is Gabaix et al. (2022), who add insight into the asset demand of U.S. households by studying the portfolio holdings, flows, and returns of households on a security-level. They find that demand elasticities are much smaller than suggested by standard theories and vary significantly across households depending on wealth. For some household groups, Gabaix et al. (2022) even find that asset demand elasticities are negative, which points towards a positive feedback strategy whereby households buy stocks in a rising market and sell stocks in a falling market. In a similar vein, Huebner (2023) uses a demand-system approach to quantify which features of investors' trading strategies lead to momentum in equilibrium. Jansen (2021) shows that, using an exogenous shock in the government bonds market, the banking sector is the most price-elastic and tends to be more responsible for absorbing demand shocks. Lastly, van der Beck and Jaunin (2021) attempt to quantify the impact of so-called Robinhood investors in the U.S. equity market by estimating demand curves for retail and institutional investors to, subsequently, derive aggregate pricing implications via market clearing. Accordingly, they find that the demand inelasticity of U.S. institutional investors allows Robinhood traders to have a substantial impact on the asset prices in the market for equities.

2.3 Sustainable Investing & Investor Heterogeneity

Due to our emphasis on the demand for green assets, this paper relates to the large body of literature on sustainable investing. In recent years, SI has received increasing attention due to external contingencies, such as climate disasters, imposing risks on portfolio holdings, constraining and affecting investors' returns. Much of this attention has been drawn towards the valuation of green assets, which is a topic of debate. In a meta-analysis assessing 2000 empirical studies on ESG assets, Friede, Busch, and Bassen (2015) find that 90% report a positive impact of ESG portfolio tilt on performance. On the contrary, a variety of studies argue that green assets are more likely to be overpriced (Krüger, 2015; Bauer & Smeets, 2015; Zerbib, 2019; Bénabou & Tirole, 2010; Baker, Bergstresser, Serafeim, & Wurgler, 2018). For example, Baker et al. (2018) establish that green bonds earn lower yields than traditional bonds. Similarly, Barber, Morse, and Yasuda (2019) find that venture capital funds with a focus on impact investing earn lower returns than their peers. Moreover, Bolton and Kacperczyk (2021) argue that carbon emissions do indeed affect the cross-section of expected return, but that it is the firms with higher emissions who earn the highest returns in the short-term.

Given that this paper analyses heterogeneous preferences between investors, it builds upon SI-related research that studies investors' drivers to hold green assets. Andersson, Bolton, and Samama (2016) find that green assets work as a natural hedge against climate risks (Andersson et al., 2016). Zerbib (2019) studies how some investors are likely to acquire assets with higher ESG ratings as they earn non-pecuniary utility from doing so. To understand the market dynamics and investor preferences for green assets, Pástor, Stambaugh, and Taylor (2021) study an equilibrium model, which allows for heterogeneity among investors' preferences, where these distinct preferences can move portfolio holdings and asset prices. They suggest a three-fund separation model, where investors can hold the market portfolio, a risk-free asset, and an ESG portfolio. Moreover, the authors propose a utility function in which agents earn utility not only from their holdings but also from the aggregate social impact of their investments.

Based on these assumptions, they find that investors with ESG preferences have a green tilt away from the market portfolio. In equilibrium, green assets provide lower returns than brown assets, but they outperform if the ESG factor is subject to a positive shock - i.e., they are a natural climate hedge (Pástor et al., 2021). Similarly, Starks, Venkat, and Zhu (2017) study ESG beliefs and preferences among institutional investors and investigate how investment time horizons are related to portfolio holdings. They find that investors with longer time horizons tilt their portfolios more toward firms with a high ESG-performance whilst being less likely to re-balance their position if subject to earnings surprises or poor returns.

Thus far, much research has been done on mutual funds and how their flows react to ESG salient information. Hartzmark and Sussman (2019) use sustainability ratings of mutual funds as provided by Morningstar to study how investors react to the greenness of the holdings of mutual funds. They find a positive relationship between the capital allocated to mutual funds by investors and the sustainability rating of the mutual fund. Hence, mutual fund investors tend to allocate most money to funds with a high sustainability rating and the least to funds with a low rating. As a result, Hartzmark and Sussman (2019) argue that, for mutual funds, ESG signals are equally important as value signals in attracting funds.

Similar to Hartzmark and Sussman (2019), Bialkowski and Starks (2016) find that environmentally conscious and socially responsible mutual funds generally show comparatively larger growth and a lower performance sensitivity to financial inflows. This, they find, arises from these investors' non-financial considerations. Moreover, Cao, Titman, Zhan, and Zhang (2022) study the difference between socially responsible and conventional institutional investors and how the former type tends to focus more on the ESG performance of firms and less on traditional and quantitative measures of value. To study the heterogeneity in investment strategies, i.e. pursuing an ESG vis-a-vis a quantitative performance assessment strategy, they group institutional investors by the value-weighted ESG scores of their portfolio holdings using the MSCI KLD database. Here, they find that socially responsible investors differ in their trading strategies from their counterparts in that they generally exhibit lower turnover in their portfolio and are less sensitive to quantitative value signals (Cao et al., 2022).

In their study of *sin* stocks, i.e. stocks with high expected returns yet a negative social or environmental impact, Hong and Kacperczyk (2009) find that norm-constrained institutional investors are less likely to hold these types of stocks. This, they argue, arises from the fact that norm-constrained investors are more likely to face greater litigation risks affecting their reputation and expected returns if investing in sin stocks. Additionally, Hong and Kacperczyk (2009) suggest that pension funds and insurance companies are especially constrained by social norms as their holdings are subject to more public scrutiny – consequently, they are less likely to hold sin stocks. On the other end of the spectrum, mutual and hedge funds are likely more willing to invest in sin stocks as they are deemed to act as natural arbitrageurs in the market. In line with that finding, others argue that hedge funds and mutual funds with a large active portfolio share tend to exhibit more *greenwashing* behavior (Liang, Sun, & Teo, 2021; S. Kim & Yoon, 2023).

The role of pension funds in financing green growth initiatives has been studied by Croce, Kaminker, and Stewart (2011), who categorize them as long-term, risk-averse investors with a preference for projects that provide a steady, inflation-adjusted income stream. Yet, their asset allocation towards green investments has, historically, remained low. The authors suggest that this is largely due to scale issues, low market liquidity, lack of expertise, and regulatory disincentives. Similarly, Bolton and Kacperczyk (2021) study how corporate carbon emissions are linked to the portfolio holdings of institutional investors as well as if investors emphasize firm- or industry-specific emissions in their investment screening. Here, they claim that mutual funds, pension funds, and insurance companies do, in particular, underweight firms with a high production carbon emission, which is likely due to their exclusionary screening techniques based on scope one carbon emission intensity. Interestingly, however, Bolton and Kacperczyk (2021) also find, by excluding the oil and gas, utilities, and motor industries, that there is no significant divestment of firms with high carbon emissions. This implies that institutional investors tend to exclusively screen companies for carbon emission intensities based on the industries they operate in.

With an explicit focus on the influence of PRI membership on green demand, this paper builds upon a body of research that has studied the initiative and its members in more detail. Majoch, Hoepner, and Hebb (2017) investigate reasons to join the PRI from a stakeholder-theory perspective. Analyzing unique survey data, they find that the PRI's normative (reputational consequences) and utilitarian (clientele demands) power elements are major drivers of an investor's decision to sign and have grown in importance over the years of PRI's existence. Moreover, they observe that the alignment between the investors' and PRI's values is an important driver for members to join, especially in the early years. This driver, they hypothesize, will likely be associated with a higher degree of implementation of PRI's principles. In a more recent study, Hoepner, Majoch, and Zhou (2021) find normative and cultural-cognitive factors, along with the presence of mandatory ESG regulation, to be crucial elements in determining the signature likelihood of an investor. Specifically, they report that investors who operate under less mandatory ESG regulation join PRI more often. Apart from the motivation of signatories, there is an ongoing debate about the effectiveness of the PRI. While some studies argue that PRI allows for greenwashing (N. Eccles, 2010; Liang et al., 2021), Sievänen, Sumelius, Islam, and Sell (2013) find that the initiative is an important tool for the widespread adoption of responsible investment practices in the investment industry. Moreover, Dyck et al. (2019) show that PRI investors drive E&S performance of their portfolio companies more extensively, and Dimson, Karakaş, and Li (2018) report the success of PRI's *coordinated engagement* strategies.

Most closely related to our study are two papers which focus explicitly on the greenness of investors' portfolio holdings and the drivers thereof. While Brandon et al. (2022) zoom in on the effects of PRI membership, Noh and Oh (2023) take a more broad view on drivers of greenness. Brandon et al. (2022) scrutinize the portfolio holdings and *ESG footprints* of institutional investors in conjunction with membership in the PRI. To study whether signing the PRI increases the sustainability of an investor's portfolio, they leverage global equity holdings and PRI survey data and calculate ESG scores for the investors' portfolios. Subsequently, they compare the scores across PRI and non-PRI members by regressing ESG scores on a PRI-dummy variable and a number of investor-specific characteristics (country of origin, portfolio turnover, size, portfolio activeness, average stock size, etc.). Here, they find that the PRI signatories exhibit portfolios with overall higher ESG scores. For the environment score in specific, they document higher scores for non-U.S., but not U.S. PRI investors. They hypothesize that this is largely due to the fact that most U.S. PRI signatories are late joiners, who are more likely to perceive the PRI label as a commercial benefit rather than a means to invest more responsibly.

To understand whether the act of signing the PRI changes the portfolio holdings of the investors, Brandon et al. (2022) match each PRI signatory with a non-PRI signatory and run a difference-in-difference regression. They find that the signatories' ESG scores increase substantially upon signing. This signing effect is, however, largely driven by higher *social* and *governance* portfolio scores while the *environment* score is not associated with a change upon signing. In terms of investor characteristics, Brandon et al. (2022) report a negative and statistically significant relationship between portfolio greenness and the number of holdings, industry concentration, portfolio turnover, portfolio activeness, and average stock size. Conversely, they observe that large institutional investors, as measured by their AUM, tend to exhibit more green portfolios.

In an arms-length extension of the asset-demand system put forward by Koijen and Yogo (2019) and the green portfolio tilt (or lack thereof) of PRI signatories studied by Brandon et al. (2022), Noh and Oh (2023) attempt to unveil the heterogeneity of financial intermediaries in their demand for environmentally sustainable assets. On top of the environment score, they specify an asset demand system using two additional sustainability characteristics: (1) carbon emission intensity and (2) the number of green patents. Based on the estimated demand coefficients, they observe strong heterogeneity, especially for the environment score. To examine the relationship between green demand and investor characteristics, Noh and Oh (2023) use cross-sectional regressions. Specifically, they regress the environment score demand coefficients on four types, four continuous, one location, and two style indicators.[2] In an additional analysis, they investigate whether PRI signatories in their dataset exhibit different demand towards the three environmental characteristics than their non-PRI counterparts. The two regressions allow the authors to systematically study investor heterogeneity in the demand for green assets.

From the first regression, Noh and Oh (2023) find that hedge funds have, compared to investment advisors, stronger preferences for assets with both high environment scores and high carbon emissions, which implies that hedge funds are more likely to hold a brown portfolio while advertising themselves as green investors by boosting their portfolio environment score. Moreover, the findings from the first regression also suggest that investors who are more elastic, active or have a lower portfolio turnover are associated with a higher demand for green assets. Interestingly, Noh and Oh (2023) argue that value-like investors do not have a higher demand for green assets relative to a generalist investor, while the opposite goes for growth investors. Along the same line as Brandon et al. (2022), they also find that U.S. investors generally do not have as high preferences for green assets compared as their non-U.S. counterparts. Finally, Noh and Oh (2023) show from their second cross-sectional regression that signatory status is not associated with higher sustainable demand and that PRI signatories have generally not increased their sustainable portfolio holdings post-signing.

[2]The continuous indicators are given by price inelasticity, log AUM, active share, and quarterly portfolio turnover. Moreover, Noh and Oh (2023) include four type indicators for hedge funds, private banking, long-term, and broker-dealer, one indicator for U.S. investors, and two indicators for value and growth investment styles.

2.4 Contribution

Despite the growing body of literature focusing on sustainable investing, uncertainty remains regarding what drives and explains investors' heterogeneous green demand. Using the three-step approach outlined in Section 1, our paper will contribute to different areas of research. First, we will add insights to the literature on demand-system asset pricing models by replicating the model of KY19 with the extended set of characteristics proposed by KRY22 and different data. This replication serves as a robustness test of previous results, including the ones concerning demand (in)elasticities (Petajisto, 2011; Jansen, 2021; Koijen & Gabaix, 2021; Gabaix et al., 2022).

Second, based on the asset demand system, we will be able to contribute to the literature on green preferences of investors, and confirm if and how green demand differs across institutional investors. This will allow us to test and validate the findings of Hong and Kacperczyk (2009), Bialkowski and Starks (2016), Starks et al. (2017), Hartzmark and Sussman (2019), Cao et al. (2022), and, most closely, Noh and Oh (2023). Moreover, we potentially find new demand patterns among different types of institutional investors, which will enhance the understanding of green demand dispersion.

Third, with the explicit focus on the impact of a PRI membership on investor greenness, our paper contributes to research on the initiative. Most directly, we will be able to validate and enhance the findings of Brandon et al. (2022), and thereby provide further insights into the effectiveness of PRIs principles in influencing members' investment behavior. Along with previous studies in that direction, our analysis thereby fills a gap pointed towards by Majoch et al. (2017), and provides helpful evidence on the *greenwash* debate surrounding PRI (Hoepner et al., 2021; N. Eccles, 2010; Sievänen et al., 2013).

We conclude the literature review with a brief summary of what we have covered. Starting from the early contributions to portfolio optimization theory, we have motivated the urgency for studying demand-system asset pricing models by portraying widely discussed empirical and theoretical shortcomings of neoclassical asset pricing models. Within asset demand systems, we documented the early beginnings, and the recent revival of the field, which has largely been inspired by the pioneering work of KY19. Switching gears from asset pricing to sustainable investing, we outlined recent and relevant work on the valuation of green assets, investors' green preferences, and the PRI initiative. Lastly, we illustrated how our study contributes to different strains of academic literature.

3 Data Collection

In the following section, we will pivot the attention toward the data necessary to answer and discuss the research questions at hand in a comprehensive way. Firstly, we will explain how we observe the portfolio holdings of institutional investors by leveraging their Form 13(f) filings. Secondly, we outline the plethora of data sources we use to gain insights into both stock fundamentals and other characteristics, such as environment and corporate governance scores. Lastly, we will provide general information on the PRI along with a description of the PRI dataset we use.

3.1 Institutional Holdings Data

In the US, it is mandatory for institutional investment managers with an aggregate market value of over USD 100 million in AUM to make a quarterly report disclosing equity holdings under Form 13(f) as provisioned by the Securities and Exchange Commission (SEC) (SEC, 2023a). Managers are obliged to report detailed information on their portfolio holdings per quarter-end, including the number of shares held in publicly listed companies, but excluding their cash, bond, or short positions (SEC, 2023a).

The publicly available 13(f) filings run back to the late 1970s and have been consolidated in a structured way by Thomson Reuters in their Institutional Holdings (s34) database. This database includes data on the portfolio composition of U.S. institutional investors at the end of each quarter as well as their distinct type (WRDS, 2023a). As the completeness of the database is highly contingent on the accuracy of the reports and the extent to which Thomson Reuters includes all reporting details, the data must be processed thoroughly to account for errors. One well-documented error in the Thomson Reuters database is that it exhibits a significant increase in the number of stale holdings starting in 2013 due to under-reporting issues (Ben-David, Franzoni, Moussawi, & Sedunov, 2021). Supposedly, Thomson Reuters fixed this issue in 2018, but the update omitted a number of securities by mistake (WRDS Research, 2017). To deal with the issues of stale holdings and omitted securities, we adopt a similar approach as KY19, who use an archived version of the holdings data for all observations prior to June 2013 and otherwise the data currently available on Wharton Research Data Services (WRDS). To clean and treat the data, we use a mix of our own code and a STATA script provided by Kojien (n.d.), which contains the programs used by KY19 to estimate their asset demand system.

In the s34 database, asset managers are grouped into types to differentiate between their distinct characteristics such as investment strategies and regulatory status. Specifically, each investor is assigned a type code from one to five, where (1) identifies banks, (2) insurance companies, (3) investment companies, (4) investment advisors, and (5) other 13(f) institutions.[3] Unfortunately, these type codes contain substantial errors from 1998 and onwards (WRDS Research, 2008), which we attempt to solve by adopting a similar approach as KY19: First, we replace the type code of all managers after 1998 if they have previously been assigned a type code. Second, we consistently use the most recent type code if a manager's type code changes over time. Last, we collect and consolidate all available SEC form ADV filings for registered investment advisors from 2006 to today.[4] Using the consolidated ADV filings, we use a bigram algorithm to match manager names with investment advisors and reassign them from the fifth to the fourth type code if a valid match exists.

Once the s34 typecodes are fixed, we create, consistent with KY19, new type codes for both mutual and pension funds by reassigning managers to the former if they are included in the Mutual Fund Holdings Database (WRDS, n.d.-f) and the latter if they are part of TowerWatson's global top 300 pension funds list (Tower Watson, 2022). Subsequently, to ensure that managers are assigned the correct type code, we reassign managers' type codes if they are included in the Thomson Reuters Ownership Database (WRDS, n.d.-e). Here, we use the Central Index Key (CIK) of each asset manager and reassign type codes as follows: Managers with a CIK of 101 and 302 are reassigned to banks, 108 to insurance companies, CIK of 106, 107, 113, and 402 to investment advisors, CIK of 401 to mutual funds, and CIK of 110 and 114 to pension funds. After processing the type codes, we end up with the following categorization of institutional investors: (1) banks, (2) insurance companies, (3) investment advisors, (4) mutual funds, (5) pension funds, and (6) other 13(f) institutions.[5]

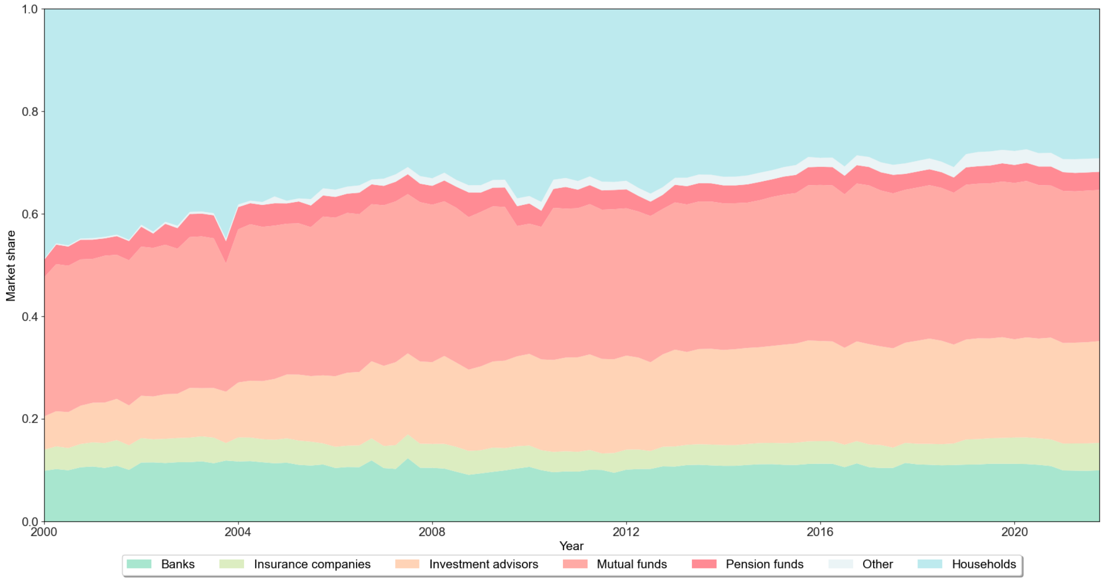
To estimate the dollar value of the portfolio holdings of each manager, we merge the holdings data, containing the number of holdings per stock, with asset-specific data on prices and shares outstanding. Accordingly, we collect data from the Center for Research in Asset Prices (CRSP) Monthly Stock Database. For a detailed description of how we process the CRSP data, we refer to Section 3.2.1. To merge the CRSP and holdings data, we merge on both date and a unique security-level identifier. For the date, we use the *fdata* from the holdings data and the *datadate* from the CRSP data.

[3]The 'Other' category in the s34 database includes pension funds, university endowments, endowments, and other 13(f) institutions (WRDS Research, 2008).

[4]Form ADV contains information about all SEC-registered investment advisors (SEC, 2023b).

[5]For a more detailed description of the different investor types, please consult Appendix A.1.

Figure 2: Market share per investor type



Note: The figure plots the market share of each institutional investor in the U.S. Holdings data is sourced from Thomson Reuters and stock data from CRSP. The household sector is the residual investor.

As a stock-level identifier, we use *CUSIP*.[6]

Once merged, we define a manager's AUM as the dollar value of her total holdings, which is measured by the sum of the product of all her shares and their corresponding prices. Subsequently, we construct a household sector from all the residual shares outstanding, which will be described in more detail in Section 4.1.3. We assign this sector a type code of 0. In line with KY19, we define an investor's investment universe, which includes all the investable stock of that specific investor (i.e. the stocks an investor is allowed to hold). For a more detailed description of why and how we define the investment universe, we refer to Section 4.1. Finally, after having processed the holdings data, we end up with 67,522,910 holdings observations from 2000 to 2021. Even though we will restrict our sample period later, we deem it relevant to include summary statistics for the holdings data for a broader time horizon to understand the evolution of the different types of investors. Within the sample period (2010-2019), we report 34,600,229 observations.

In Table 1, we list summary statistics of Form 13(f) holdings data merged with the

[6]The *CUSIP* number consists of nine characters, with the first six characters identifying the issuer of the security and the last two identifying the specific security.

CRSP data from 2000 until the end of 2021.[7] One ought to notice that the number of institutions in the sample increases significantly and so does their aggregate market share, which implies that the capital intermediated by institutional investors increases while the market share of the household sector decreases. Looking at Figure 2, which plots the evolution of each investor type's market share over time, this trend is confirmed. Here, we also observe that the market share of investment advisors has increased substantially, while the market share of banks, insurance companies, mutual funds, and pension funds has been fairly constant. Mutual funds seem to consistently carry the highest market share of all institutional investors. As expected, the category including other 13(f) institutional investors has the lowest aggregated market share, while pension funds are tracing right behind. Interestingly, we see a reallocation of capital from mutual funds to households and back around both 2004 and 2010, which is likely due to improper or missing Form 13(f) filings.

Inspecting the three rightmost columns in Table 1, we note that the median value of AUM has decreased along with both the median number of stocks held and the median number of stocks in the investment universe. The same trends can be observed for investors in the respective 90^{th} percentiles. Combined with the fact that more institutional investors have entered the U.S. market, this observation suggests that the market share dispersion has increased over time and that investors hold a more concentrated portfolio. Moreover, the decrease in the number of stocks in the investment universe indicates that investors have more narrow mandates over time.

[7] For more granular summary statistics for each type of investor, we refer to Appendix B.1.

Table 1: Summary statistics of Form 13(f) holdings data

Period	Number of Institutions	% of market held	Assets under management (mUSD)		Number of stocks in portfolio		Number of stocks in investment universe	
			Median	90th percentile	Median	90th percentile	Median	90th percentile
2000-04	1,808	57	370	6,061	86	509	144	862
2005-09	2,454	65	332	5,395	72	453	143	905
2010-14	2,894	66	316	5,448	67	442	121	790
2015-19	3,925	70	295	5,139	65	444	108	739
2020-21	5,046	71	264	4,622	62	396	105	705

Note: The table reports the mean value for each summary statistic for each period based on the holdings data from the SEC Form 13(f), which is sourced from the Thomson-Reuters s34 database. For each period, we use equal-weighted averages for the summary statistics

3.2 Asset Characteristics

3.2.1 Fundamentals & Market Data

In specifying the asset demand system, we compute asset characteristics from stock fundamentals and market data. In this subsection, we will first explain how we employ various measures of stock fundamentals using the quarterly and annual fundamentals data from the CRSP-Compustat Merged Database (WRDS, n.d.-b). Second, we report how market data on stock prices and shares outstanding is sourced from the CRSP Monthly Stock database (WRDS, n.d.-c). Third, we will present summary statistics of the stock characteristics computed using stock fundamentals and market data. For a detailed description of how we define the characteristics, we refer to Section 4.1.3.

A. Quarterly and annual stock fundamentals

To get stock fundamental data, we pull accounting information (capital structure, balances, expenses, revenues, etc.) for all publicly held companies during our sample period. To clean and process the fundamental data, we rely on the STATA script provided by Kojien (n.d.). For both the quarterly and annual data, we replace duplicates stemming from changes in the fiscal year-end by their median values and missing values for assets, stockholders' equity, and liabilities by using the accounting equation. For the quarterly data specifically, we aggregate financial flow variables annually using their lagged values to reduce noise from seasonal trends, account for differences in accounting periods, and increase the cross-firm comparability.[8] Moreover, we redefine split-adjusted shares outstanding as the product of common shares outstanding by a company-specific adjustment factor to account for any stock splits that occur subsequent to the end of the quarter. Once cleaned, we construct a number of variables similar to KY19 for the fundamentals quarterly and annual data, which we specify in more detail in Appendix A.2. Finally, we merge the quarterly and annual fundamentals data using the CRSP *ldate* and *PERMNO*.[9] We primarily rely on the Compustat quarterly data, but in cases where a quarterly observation is missing, we leverage the latest available annual observation instead. This substitution is performed while ensuring that the observation aligns with the corresponding financial year.

[8]The flow variables include COGS, revenue, deferred taxes and investment tax credit, interest and related expenses, and selling, general and administrative expenses.

[9]*PERMNO* is a permanent and unique identifier assigned to each individual security traded on a U.S. stock exchange.

B. Stock market data

To get market data, we use the CRSP Monthly Stock database (WRDS, n.d.-c), where we pull monthly observations on periodic returns, periodic returns without dividends, shares outstanding, Standard Industrial Classification (SIC) codes, prices, delisting returns, delisting returns without dividends, date, *PERMNO*, *CUSIP*, *datadate*, and share code (WRDS, n.d.-c). After pulling, we filter observations to only include securities with a share code of 10, 11, 12, or 18 in accordance with KY19.[10] Subsequently, we fill in missing SIC codes if the stock has previously been assigned one and re-specify missing prices to be equal to zero. To merge the fundamentals and CRSP data, we use the *link date* from the fundamentals data and merge the datasets on *PERMNO*. Accordingly, we merge the data from CRSP with the most recent fundamental observations from at least six months and no more than 18 months prior to the CRSP date to ensure that the fundamentals were publicly available on the trading date. Next, we use the Fama-French 12 industry classification to assign an industry to each of the securities based on their SIC codes (Fama & French, 2023). At last, we only include observations from each quarter-end to make the observations compatible with the holdings data. Once processed, cleaned, and merged, we end up with 174,824 quarterly security-level observations from 2010 to 2019. The number of individual securities being traded in the financial markets is fairly constant during our sample period, as can be seen in Appendix B.2, with a median value of 4,723.

C. Summary statistics of characteristics from fundamentals and market data

In Table 2, we present the summary statistics for all the asset characteristics used for our specification of characteristics-based demand in the sample period running from 2010 through 2019. We will focus on the asset fundamentals for now and discuss the statistics on the entrenchment index, environment score, foreign sales share (FSS), and market beta later this section. For the fundamentals, we see that the data in our sample is complete. That is, all the institutional investors' holdings are tied to fundamental data. For book equity, as measured in million USD, we report a few outliers where the value of book equity is equal to zero. This is, however, entirely realistic, albeit unlikely, as it implies that the liabilities of a company match the book value of its assets. For the dividend-to-book equity characteristic, we observe a minimum value of zero, which implies that a firm did not issue any dividends for a quarter. The maximum value of 0.25 implies that a company has issued dividends worth a quarter of its book

[10] We remove all other 13(f) securities to only include ordinary common shares traded on the New York Stock Exchange, the American Stock Exchange, and Nasdaq (CRSP, 2023).

Table 2: Summary statistics of asset characteristics

Variable	Obs. (mil.)	Mean	SD	Min	Max	Q10	Q50	Q90	% miss
Book equity	34.6	13,173	34,851	0.00	422,338	185	2,028	31,513	0%
Dividend	34.6	0.03	0.05	0.00	0.25	0.00	0.02	0.10	0%
Sales/book	34.6	2.15	2.52	0.00	15.20	0.40	1.28	4.78	0%
Market equity	34.6	29,443	74,892	0.62	1,287,643	378	5,063	74,474	0%
Lerner index	34.6	0.13	0.22	-1.00	0.52	0.00	0.13	0.37	0%
Market beta	34.6	1.19	0.58	-0.39	3.19	0.49	1.13	1.93	0%
Entrenchment	23.9	4.00	0.82	1.00	6.00	3.00	4.00	5.00	31%
Environment	22.5	55.50	28.75	21.00	100.00	38.00	54.00	75.57	35%
FSS	34.6	0.30	0.28	0.00	2.01	0.00	0.25	0.69	0%

Note: This table reports the summary statistics of our asset characteristics within our sample period (2010-2019) as dictated by the restricted amount of environment scores. Book and market equity are measured in million USD.

value of equity. In terms of market equity, we observe a significant spread between the minimum and maximum value of USD 0.62 and 1,287,643 million, respectively. This is, however, entirely realistic and implies that the share price and/or shares outstanding are low for the former and high for the latter. For the Lerner index, we observe that the mean firm in our sample captures positive margins of 13%, implying that the mean firm has some degree of market power. The highest margin observed lies at 52%, and corresponds to a firm with substantial market power.

3.2.2 Fama-French Factors

To estimate the market beta of each security, we rely on the online database provided by Kenneth R. French (n.d.). Here, we extract monthly observations on the return of a risk-free asset, a size factor, value factor, and the market risk premium. Subsequently, we merge each *PERMNO/date* combination from the CRSP-Compustat dataset (including delisting adjusted returns) with the Fama-French factor returns and estimate the market betas. For a description of the market beta estimation, please consult Section 4.1.3. Once estimated, we take the quarter-end observations of the market beta for each security and append them to the CRSP-Compustat quarterly data. As seen in Table 2, the average market beta is 1.19, which implies that the expected returns of the securities in our sample are, on average, slightly more volatile than the market. We see that some assets have negative market betas with a minimum value of -0.39, which implies that the expected return of this asset negatively covaries with the market risk-premium. The maximum market beta of 3.19 suggests that the expected return of some of the securities in our sample contain a lot of systematic risk.

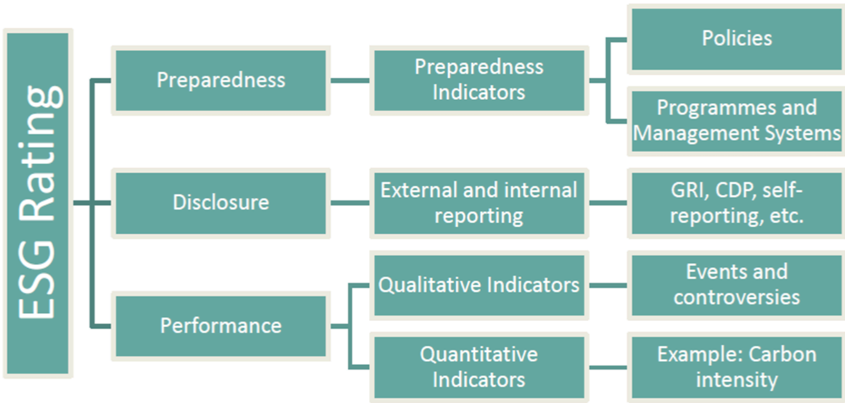
3.2.3 Sustainalytics

To score the environmental performance of the firms in our sample, we use historical industry-weighted environment scores provided by Sustainalytics in their legacy database (WRDS, 2023b). Sustainalytics is a highly acknowledged rating agency among academics and investment professionals as their ESG scores are being used extensively by Morningstar, an investment research and financial services provider (Hartzmark & Sussman, 2019). Given the nature of our research question, we will only focus on the environment aspect of ESG and thus rely on environment scores. Since environment scores are only available from 2010 through 2019, our sample period is naturally limited to this time frame.

The firms in the Sustainalytics database are allocated a score depending on their performance on and preparedness for a number of different ESG-related issues as depicted in Figure 3 (Sustainalytics, 2017). Considering the subcategories, which all attribute to the final environment score, the firm preparedness assesses the extent to which a company is ready to face material environmental risks. In terms of the disclosure dimension, the reflects if a firm is transparent in how they face climate issues and conform to international best practices. The performance dimension of the assessment is split into a quantitative and a qualitative leg. The former assesses measurable metrics and statistics including the intensity of carbon emissions, while the latter is based on an analysis looking into firm-related events and controversies impacting the environment (Sustainalytics, 2017). The importance of the different issues is then weighted for each industry to account for only the most material issues to a firm. Subsequently, each firm in the Sustainalytics database will be scored from 0-100, where 100 is the best and 0 is the worst environment score (Sustainalytics, 2017).

The Sustainalytics global legacy data runs from 2010 through 2019 where scores are observed on a monthly basis with a total of 491,548 observations (WRDS, 2023b). Each firm in the database can be identified using one or multiple firm- or stock-specific identifiers as the database includes either a Capital IQ ID (*CIQ*), an International Securities Identification Numbering (*ISIN*) identifier, a Company ID provided by Sustainalytics, or a ticker. Using all the identifiers above is essential to maximizing the matches, i.e. the number of securities in the holdings data with an environment score. We follow the methodology of WRDS (2023b) and append the environment scores to

Figure 3: Sustainalytics' ESG rating dimensions



Note: Sustainalytics' methodology to assign ESG ratings to a company considers a preparedness, disclosure, and performance dimension (Sustainalytics, 2017).

the other stock characteristics using the four consecutive linking approaches below:[11]

Linking approaches:

1. *ISIN/CIQ* to *GVKEY*
2. *CIQ* to *CUSIP* to *PERMNO*
3. *ISIN/CIQ* to *GVKEY* to *PERMNO*
4. *Ticker* to *PERMNO*

Using the first linking approach, we find a Global Company Key (*GVKEY*) for each *CIQ* using the 'G_NAMES' database from Compustat. Similarly, we find a corresponding *GVKEY* for each *ISIN* using Sustainalytics' reference table. Subsequently, we relate the *GVKEYs* to a *GVKEY/PERMNO* pair from the fundamentals data while ensuring that the link is valid using the link-end date. Using this approach, we manage to relate 152,254 individual *PERMNOs* to an environment score. For the second linking approach, we match each *CIQ* identifier with a corresponding *CUSIP* from the *CIQ* Identifiers database on WRDS and pair each *CUSIP* with a *PERMNO* from the CRSP Stock Header Information database. Here, we append 41,284 additional *PERMNOs* to the Sustainalytics data. Subsequently, we replicate the first approach but rather than using the monthly stock data, we use the CRSP/Compustat merged database, which

[11]Since the environment score is firm-specific, it cannot vary across different securities issued by the same company meaning that we can use multiple ways to get match scores to the holdings data.

provides a link between *GVKEY* and *PERMNO*. Using this approach, we get 2,172 additional matches. Finally, for the fourth approach, we find the *PERMNO* associated with each ticker using the CRSP stock-header database giving us 102,282 new matches. In sum, out of 491,548 observations, we manage to match 297,992 environment scores to a *PERMNO*.

After the linking exercise, we start processing and cleaning the data to check for any *PERMNO*/date duplicates and if we observe different scores for the same firm on the same date. We find that stocks traded on the Bombay Stock Exchange are all assigned the same *PERMNO* through the fourth linking approach and, consequently, remove these observations. Moreover, we find a few duplicates due to name changes and mergers, which we fix manually. For the last few observations where we observe different environment scores for the same firm on the same date, we take the mean score and remove the other observations. Once cleaned, 272,172 observations remain, which we merge onto the holdings data. Following the methodology of KRY22, we append the most recent environment score up to 18 months before the end of the quarter. Finally, as seen in Table 2, we end up with 22,529,337 observations where an environment score is recovered for an asset. This implies that we are missing environment scores for 31% of the observations in the holdings data. In those instances, we set the environment score equal to zero.

The mean environment score of 55.50 indicates that the firms in our sample receive, on average, a medium score in terms of their climate performance and risk preparedness. We do see, however, that two firms receive a score of 100 indicating that they perform outstandingly and are not associated with any future climate risks.

3.2.4 Institutional Shareholder Services (ISS)

Similar to KRY22, we use the Entrenchment Index as suggested by Bebchuk, Cohen, and Ferrell (2008) to study how public firms' governance structures are important drivers of asset demand. We create the entrenchment index using the Governance Data from the Institutional Shareholder Services (ISS) Database on WRDS (WRDS, n.d.-d), where we, within our sample period, acquire annual firm-level observations on the presence of corporate governance provisions. To create the entrenchment index, we follow the methodology of Bebchuk et al. (2008) and pull data on six provisions known as staggered boards, limits to shareholder amendments of the bylaws, supermajority requirements for mergers, supermajority requirements for charter amendments, poison pills, and golden parachute arrangements. The first four provisions measure the extent to which shareholders can overrule the will and power of management while the last two provisions are known as important measures taken in preparation for a hostile offer. For each observation, we score the firms in the database from zero to six depending on the number of provisions the firm has had for each period (Bebchuk et al., 2008). For example, if a firm has experienced provisions for staggered boards and poison pills, then it will get a score of two.

To merge the entrenchment index scores with the CRSP-Compustat data, we use the same approach as in Section 3.2.3. Specifically, we use the CRSP Stocknames database to pair each *CUSIP* with a *PERMNO* ensuring that the date of the observation is between the start- and end-date of the *CUSIP-PERMNO* match. Subsequently, we merge the entrenchment index with the CRSP-Compustat data using the most recent score within the last 18 quarters and assign all other observations a score of 0. In the end, we end up with 23,945,509 securities where we observe an entrenchment index score in the holdings data, corresponding to 31% missing observations. From Table 2, one ought to notice that the mean value of 4.00 implies that the average firm has four corporate governance provisions in place, while the maximum value of 6.00 suggests that we do observe firms with all six corporate governance provisions.

3.2.5 Compustat Segments Data

To estimate the foreign sales share, we use the Compustat Segments database and retrieve firm-level data on net sales, export sales, geographic segment type, date of observations, and various firm-level identifiers (WRDS, n.d.-a). We account for two types of export sales: domestically and internationally distributed sales. To distinguish between the two types, we use the geographic segment type indicator and group the sales. Once grouped, we aggregate the foreign, export, and net sales for each company on every given date. To merge the data onto the CRSP-Compustat data, we use a similar approach to the previous mapping exercises, whereby we bridge from GVKEY to PERMNO while ensuring that the link is still valid at the date of the match.

As seen in Table 2, the average foreign sales share is 0.30, which implies that the average ratio of foreign sales is less than half of total net sales. Intuitively, the minimum value of 0 implies that some companies do not export their goods to international buyers. The maximum value of the foreign sales share shows that there is a substantial outlier in our data, as the maximum value of 2.01 would imply that a firm sells twice as much to foreign buyers than its total sales. We describe how to account for outliers in the characteristics in Section 4.1.3.

3.3 Principles for Responsible Investments

PRI is, as its name suggests, a set of six principles guiding investors in environmentally conscious investing with the aim to manage climate risks and enhance returns. PRI was initiated in 2006 by a group of the world's largest institutional investors in close collaboration with the United Nations. By signing the principles, which warrants an annual membership fee, investors pledge to adopt the principles in their operational frameworks and commit to publicly disclosing an annual report on their investment considerations (PRI, n.d.-a). The six principles, which investors pledge to follow, are:

1. Incorporating ESG issues into the investment analysis and decision-making processes.
2. Engage as active owners and incorporate ESG issues into ownership policies and practices.
3. Seeking appropriate disclosure on ESG issues by the entities in which the signatories invest.
4. Promoting acceptance and implementation of the Principles within the investment industry.
5. Working together with other signatories to enhance the effectiveness of implementing the Principles.
6. Reporting on the activities and progress towards implementing the Principles.

The size of the PRI has been increasing steadily, and hitting roughly 4,900 signatories with USD 121 trillion in AUM in 2022, making it the largest investor initiative in the world (PRI, 2023). Even though the PRI has seen an increase in smaller investors as signatories, it primarily attracts larger investors, causing them to be over-represented in the initiative compared to the overall market. Brandon et al. (2022) report that the amount of signatories with more than USD 100,000 million in AUM has increased steadily throughout the years to 5% in 2017, while roughly 20% of the signatories had USD 10,000-100,000 million in AUM, and 45% of the signatories USD 1,000-10,000 million in AUM. PRI reports the average AUM in 2022 to be USD 24,500 million (PRI, 2023).

From the PRI, we import information on all the signatories from the beginning of 2006 to the last quarter of 2022. For each signatory, we get the name of the investor as well as the country-specific location of their headquarters and the date of the signatory. Given that the PRI is a global initiative, the list of country-specific headquarters locations is rather exhaustive and includes 95 different countries. However, the U.S. remains the country with the most signatories, totaling 1,036 headquarters, while the remainder is largely concentrated in Western Europe.

To conclude the data section, we have provided an extensive explanation of which data we use to study the research question outlined in the introduction (Section 1). First, to gain insights into the portfolio holdings of U.S. institutional investors, we leverage the form 13(f) filings as systematized by Thomson Reuters in their s34 database. Second, to assign characteristics to the asset held by investors, we use CRSP for stock-specific data, Compustat for stock fundamentals and segments data, the Fama-French database for factor returns, Sustainalytics for environment scores, and the Institutional Shareholder Service Database for governance data. Third, we use signatory data from the PRI to study the commitments of investors. For each dataset, we have provided detailed explanations of how we process and consolidate the data.

4 Methodology

In this chapter, we will outline the steps we conduct to answer the research question and the related subquestions raised in the opening paragraphs. We begin by introducing the asset demand system as specified by KY19, providing both the theoretical background and the practical estimation steps. Next, we outline approaches to demonstrate demand heterogeneity. Finally, we describe how we attempt to explain green demand heterogeneity, which involves specifying a range of regression models that utilize the outputs from the asset demand system. In the order outlined here, the sections will provide the framework to approach subquestions 1, 2, and 3, respectively.

4.1 Asset Demand System

As Section 2 indicated, the novel asset demand system proposed by KY19 allows to estimate investor- and time-specific demand curves based on empirical portfolio holdings data. While the asset demand system can be used to answer a variety of "quantity"-related questions, it also helps to uncover rich heterogeneity across investors (Koijen et al., 2022). As such, the first part of our methodology aims to replicate an asset demand system in the fashion of KY19. To establish a background, this section will begin giving a brief introduction to the theoretical foundation of the asset demand system, and continue describing the estimation process. While doing this, we point out instances where we depart from KY19 and adjust the model to our needs.

4.1.1 Theoretical Foundations

We start by providing a broad intuition of the derivation of the asset demand system. KY19 begin by micro-founding the investor's optimal portfolio, based on which they explain the risk-return trade-off rational investors will face to decide about the portfolio weights they should put on the assets in their opportunity set. Under the assumption of a factor structure of returns, where factor loadings are fully determined by the asset's underlying characteristics, these optimal weights can then be reduced to *characteristics-based demand*. In this situation, the entire variation in portfolio weights is explained by observable and unobservable characteristics of the underlying assets. Based on this complete explanation of the demand side, KY19 back-out an asset's price by imposing "market clearing" – that is, setting demand equal to supply, where the latter is determined exogenously through an asset's shares outstanding. For the purpose of this paper, we will focus on the first part of the model, which defines the demand system based on characteristics-based demand. To allow for simplicity and comparability, we will adapt KY19's notation wherever applicable. As such, lowercase variables denote the logarithm of their uppercase counterpart, variables in boldface indicate N-dimensional vectors, $\mathbf{1}$ is a vector of ones, $\mathbf{0}$ a vector of zeros, and $\boldsymbol{I}$ the identity matrix.

A. Portfolio choice problem

To construct the asset demand system, we assume that investors I, indexed by $i = 1, ..., I$, face short-sale constraints and have heterogeneous beliefs, based on which they invest their wealth A_i in a universe of $\mathcal{N}_{i,t}$ assets, called the investment universe, which is a subset of the total universe of N assets: $\mathcal{N}_{i,t} \subseteq 1, ..., N$. As indicated by the index, the investment universe is individual for each investor i and across time t, reflecting the various investment mandates institutions typically oblige (see, for example, Celik and Isaksson (2014)). In line with KY19, we refer to the assets within an investor's universe as the *inside asset*, while the remaining assets comprise the *outside asset.* Within the asset allocation process, the investor aims at maximizing her expected log utility in period T by choosing a vector of portfolio weights $\boldsymbol{w}_{i,t}$, which dimensions equal the number of assets in the investor's universe, $|\mathcal{N}_{i,t}|$. As such, the investor's portfolio choice problem can be described as:

$$\max_{\boldsymbol{w}_{i,t}} \mathbb{E}_{i,t}[log(A_{i,T})]. \tag{4.1}$$

If, in line with KY19, $P_t(n)$ and $D_t(n)$ denote as an asset n's price and dividend per share at date t, respectively, the corresponding gross return can be written as $R_t(n) = (P_t(n) + D_t(n))/P_{t-1}(n)$. The intertemporal budget constraint of investor i is then given as:

$$A_{i,t+1} = A_{i,t}(R_{t+1}(0) + \boldsymbol{w'}_{i,t}(\boldsymbol{R}_{t+1} - R_{t+1}(0)\mathbf{1})), \tag{4.2}$$

where $R_{t+1}(0)$ is the gross return on the outside asset at date $t + 1$. Intuitively, this budget constraint relates an investor i's wealth at date $t+1$, $A_{i,t+1}$, to her wealth in the previous period, $A_{i,t}$, by applying the returns the investor gained throughout period t, both in the inside and outside assets. On top of the budget constraint, the investor faces short sale constraints:

$$\boldsymbol{w_{i,t}} \geq \mathbf{0}, \tag{4.3}$$

$$\mathbf{1'}\boldsymbol{w_{i,t}} < 1. \tag{4.4}$$

Constraint (4.3) indicates that none of the investor's portfolio weights are allowed to be smaller than zero, while constraint (4.4) requires the sum of an investor's portfolio weights to be smaller than 1. Given these constraints, the Lagrangian of the portfolio choice problem becomes:

$$L_{i,t} = \mathbb{E}_{i,t}\left[log(A_{i,T}) + \Sigma_{s=t}^{T-1}(\Lambda'_{i,s}\boldsymbol{w_{i,s}} + \lambda(1 - \mathbf{1'}\boldsymbol{w_{i,s}}))\right], \tag{4.5}$$

where $\Lambda_{i,t}$ and $\lambda_{i,t}$ correspond to the Lagrange multipliers on the short-sale constraints. This Lagrangian can be solved by applying the typical algorithm. While we refer to KY19's appendix for the detailed steps, we provide the resulting Euler equation that follows from the first-order condition:

$$\mathbb{E}_{i,t}\left[\left(\frac{A_{i,t+1}}{A_{i,t}}\right)^{-1}\boldsymbol{R}_{t+1}\right] = \mathbf{1} - (\boldsymbol{I} - \mathbf{1}\boldsymbol{w}'_{i,t})(\Lambda_{i,t} - \lambda_{i,t}\mathbf{1}). \tag{4.6}$$

Since we are dealing with a log utility function here, the goal function (1) contains log returns of the investor's portfolio. To be able to write the investor's portfolio returns as a linear combination of the returns on the inside and outside asset, KY19 leverage an approximation put forth by Campbell and Viceira (2002). Based on this approximation, they arrive at an equation for the optimal portfolio:

$$\boldsymbol{w}_{i,t} = \Sigma_{i,t}^{-1}(\mu_{i,t} - \Lambda_{i,t} - \lambda_{i,t}\mathbf{1}), \tag{4.7}$$

where $\mu_{i,t}$ and $\Sigma_{i,t}$ are the conditional mean and covariance of log excess returns, respectively. The key insight from this optimal portfolio weight is that it reflects the risk-return trade-off the investor is facing, with risk being defined as the covariance of an asset's return. Going forward, we will use the version of equation (4.7) for which the short-sale constraint is not binding, i.e., $\Lambda_{i,t} = 0$. KY19 use a partition of the covariance matrix to derive this solution, but in the interest of simplicity and relevance, we will refrain from including the corresponding derivation steps here and refer to their paper's appendix for a more detailed description of this step.

B. Characteristics-based demand

In the following, we will explain KY19's key assumptions under which the optimal portfolio weight reduces to characteristics-based demand. In line with a large body of literature in asset pricing, to which we also refer in Section 2, KY19 assume a factor structure in returns. As Munk (2021) describes, a factor model explains an asset's risk premium through its exposure to priced factors, which are common across all assets. In their factor structure assumption, KY19 leverage the five-factor model put forth by Fama and French (2015), and consider stock characteristics on size (log book equity), profitability, investment, and systemic risk (market beta) to be the drivers of expected returns.

The characteristics are combined into a vector, $\boldsymbol{x}_t(n)$, which contains an asset n's observable characteristics at time t. If all investors would base their investment decision solely on the observable characteristics $\boldsymbol{x}_t(n)$ and are assumed to be rational, every investor would essentially hold the same portfolio, which would resemble a similar case as classical asset pricing models based on homogeneous beliefs (e.g, CAPM) predict. In this model, however, we assume heterogeneous beliefs: Investors can form different expectations about the returns of an asset, which are influenced by varying tastes for the observable, but also unobservable characteristics. As such, the information set of an investor i is, next to the observable characteristics $\boldsymbol{x}_t(n)$, extended by an unobservable component, called latent demand, and denoted as $log(\varepsilon_{i,t}(n))$. Combined with the market equity of asset n at time t, which serves as an indicator for the asset's price, the total information set of investor i at date t therefore becomes:

$$\hat{\boldsymbol{x}}_{i,t}(n) = \begin{bmatrix} me_t(n) \\ \boldsymbol{x}_t(n) \\ log(\varepsilon_{i,t}(n)) \end{bmatrix} \tag{4.8}$$

On top of the factor structure in expected returns, KY19 assume that expected returns and factor loadings, the elements of this factor structure, are entirely explained by an asset's characteristics, i.e. $\hat{\boldsymbol{x}}_{i,t}(n)$. If expected returns are explained by a factor structure, the covariance matrix of expected returns, $\Sigma_{i,t}$, is so as well. This assumption allows us to sufficiently explain an asset's expected return and risk (given by the covariance matrix) through its characteristics. As shown in the portfolio choice problem, the investor ultimately cares about a trade-off between risk and return when forming his portfolio allocation decision. With risk being equivalent to the covariance matrix of returns, and both expected returns and covariance matrix being explained entirely by characteristics, the investor ultimately cares about an asset's characteristics in choosing portfolio weights. With this insight, we can specify an expression for characteristics-based demand as given in Corollary 1 to Proposition 1 in KY19:

$$w_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)}, \tag{4.9}$$

which is the portfolio weight of investor i at time t on asset n, with

$$\delta_{i,t}(n) = exp\left[\beta_{0,i,t} me_t(n) + \sum_{k=1}^{K-1} \beta_{k,i,t} x_{k,t}(n) + \beta_{K,i,t}\right] \varepsilon_{i,t}(n), \tag{4.10}$$

where the βs are the coefficients related to the characteristics indexed by k. Accordingly, the portfolio weight on the outside asset is:

$$w_{i,t}(0) = 1 - w_{i,t}(n) = \frac{1}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)}, \tag{4.11}$$

To arrive at the expressions of characteristics-based demand seen above, we generally focus on the intuition. For a detailed derivation of Equation (4.10), we refer to KY19.

Intuitively, Equation (4.9) expresses investor i's share of characteristics-based demand towards asset n to investor i's total characteristics-based demand for all assets in his investment universe, at time t. In Equation (4.10), the K's characteristic is assumed to be a constant ($x_{K,t}(n) = 1$) such that the corresponding coefficient, $\beta_{K,i,t}$, gives the intercept. The mean of latent demand $\varepsilon_{i,t}$ is normalized at 1 to ensure a non-zero demand for inside assets (given by the intercept), even in cases where all characteristics are zero. Since the data in our empirical application of the asset demand system does not include short positions (see Section 3.1), latent demand is restricted to positive values, i.e. $\epsilon_{i,t}(n) \geq 0$.

The interpretation of the remaining β values goes as follows: $\beta_{0,i,t}$, the coefficient in front of $me_t(n)$, states the investor's price inelasticity of demand, as it magnifies to which extent the investor will change her demand if prices change (and with shares outstanding being exogenous, market equity changes). Accordingly, the demand elasticity is given as $1 - \beta_{0,i,t}$, and a higher (lower) $\beta_{0,i,t}$ corresponds to more inelastic (elastic) demand. KY19 show that, for both individual and aggregate demand curves to be downward sloping, it is sufficient to assume that $\beta_{0,i,t} < 1$. As outlined in Section 2.2, a key element of the asset demand system is to allow individual or aggregate demand to impact prices, which requires downward-sloping demand curves. The $\beta_{k,i,t}$ coefficients indicate the investor's demand for the corresponding characteristics. A higher (lower) coefficient indicates a larger (smaller) demand of a given investor to a specific characteristic, sensitive towards time.

C. Selection of characteristics

Since our analysis focuses explicitly on investors' sustainability preferences, we alter KY19's selection of stock characteristics to the one applied by KRY22. In their demand system specification, they leverage a set of eight characteristics, which we will explain and motivate in the following:

- **Log book equity**: Has been proven to have explanatory power of cross-sectional stock returns (Fama & French, 1993) and captures size effects.
- **Sales-to-book equity**: Is included as a measure of firm-level productivity. Output, proxied by sales, is a common and intuitive metric in economics to estimate productivity (Katayama, Lu, & Tybout, 2009). Sales-to-book equity scales this metric by book equity as an attempt to measure the output per unit of capital deployed in the firm.
- **Foreign sales share**: Has been found to be a predictor of a firm's productivity,

as only the most productive firms export products abroad (Melitz, 2003). The foreign sales share is calculated by dividing a firm's export sales by its total (domestic and export) sales.

- **Lerner index**: Reflects the margins a firm is able to capture in the market and is commonly used as a measure of market power (see, e.g., Elzinga and Mills (2011)). Recent literature has related higher market power to lower productivity and higher profitability. For instance, De Loecker, Eeckhout, and Unger (2020) study the increase of market power in the U.S. over the past 50 years and find concurrent in-(de-)creases in profitability (productivity), where the latter relationship stems from under-investment in capital, distorted rent distributions, and lower levels of business dynamics and innovation.

- **Dividend-to-book equity**: Dividends are a commonly known measure for company fundamentals. Primed by the *information content of dividends hypothesis* (Miller & Modigliani, 1961), which states that dividend payouts convey information about future profitability, dividends have been frequently used in the finance literature to investigate firms' profitability (see, for instance, Nissim and Ziv (2001)). While Miller and Modigliani (1961) argue that dividend payouts should be irrelevant for investors under perfect market conditions, more recent studies find evidence for investor's dividend appetite (e.g., Harris, Hartzmark, and Solomon (2015), Baker and Wurgler (2004)).

- **Market beta**: Derived from the CAPM, beta is widely acknowledged as a measure of a stock's systemic risk level, and is frequently included in contemporary asset pricing models, for instance in Fama and French (1992).

- **Environment score**: Obtained from Sustainalytics, a third-party ESG rating service provided by Morningstar, the environment score (*env*) measures firm-level environmental sustainability performance. Sustainalytics ratings have been found to predict fund flows (Hartzmark & Sussman, 2019) and are therefore an important driver in asset demand. In a similar vein, Hong and Kacperczyk (2009) find that *sin* stocks yield higher returns, induced by investors demanding a higher premium due to social norms.

- **Governance score**: We use the *entrenchment index* by Bebchuk et al. (2008) as an indicator for firm-level governance. Counting the presence of six governance provisions – namely staggered board, golden parachute, bylaw amendment limitations, charter amendment limitations, poison pills, and supermajority requirements for mergers – the index reflects poor governance and has been found to be a predictor of firm value and stock returns. The relevance of governance structures for firm value has moreover been found, for instance, in Gompers, Ishii, and Metrick (2003), who report positive returns for a long-short strategy in good-poor governance firms.

We refrain from including additional characteristics tested by KRY22 (namely investment, earnings surprise, and net stock issuance), as they are shown to provide little additional information to explain variations in stock valuations (more detail in Section 4.1.4). It is important to mention that, based on the asset holdings data we use to estimate characteristics-based demand, we are not able to distinguish between investors' motivations for demanding a certain characteristic. Among possible reasons can be expectations about future returns or risks, hedging beliefs, or non-monetary benefits such as reputation (KRY22).

4.1.2 Estimation Assumptions

Equation (4.10) can be interpreted as a non-linear regression model. However, before we proceed with the estimation process, we need to specify key assumptions around the exogeneity of characteristics and an instrument for market equity. Again, since the estimation of our asset demand system closely resembles the one built by KY19, we will follow most of their methodology for this part.

A. Exogenous characteristics

A first key assumption to estimate Equation (4.10) is the exogeneity of characteristics – that is, the explanatory variables specified in Equation (4.10) are uncorrelated with the error terms. We can formulate this assumption as a moment condition. Moment conditions are the common phrase used for equations in the context of the Generalized Method of Moments (GMM) estimation (Stock & Watson, 2019), which we will use for the estimation and therefore introduce in more detail later.

$$\mathbb{E}[\epsilon_i | me(n), \boldsymbol{x}(n)] = 1. \tag{4.12}$$

The assumption stated here is common for many asset pricing models.[12] While KY19 maintain it for the eight firm-level characteristics ($\boldsymbol{x}(n)$) and shares outstanding, they relax it for the price. The assumption of asset prices being exogenous is typically justified by arguing that individual investors are small *price takers* which lack the

[12]In most applications, the right-hand side would give a zero, indicating the error term to be uncorrelated with the characteristics. The 1 here stems from the normalization of latent demand at 1.

necessary demand quantities to effectively move prices. In this model, however, we aim to resemble a more realistic situation in which both large investors such as institutions as well as households through coordinated actions can have an impact on prices. To achieve this, KY19 develop an instrument for market equity, which we introduce in the following.

B. Market equity instrument

The market equity instrument proposed by KY19 builds upon investors' investment mandates. According to FCLT Global, a non-profit organization focusing on the support of long-term investors, investment mandates are "investment management contracts between asset owners and asset managers" (Leatherman et al., 2022, p. 4), and specifies critical elements of the investment strategy such as benchmark, term, and capacities. As such, the investment mandate is the key determinant of the investor's investment universe, i.e., the investable assets. For instance, Vanguard, a large U.S.-based investment advisor with over \$8 trillion assets under management, states in the *Investment approach* of their *ESG International Stock ETF*, that they are attempting to track the performance of a benchmark index (FTSE Global All Cap ex US Choice) by screening for ESG criteria, excluding certain industries or activities, and employing a passive, index-sampling strategy (Vanguard, n.d.). KY19 define an indicator function to specify whether an asset n is part of the investor's investment universe $\mathcal{N}_{i,t}$:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \begin{cases} \mathbb{I}_{i,t}(n)\delta_{i,t}(n) & \text{if } n \in \mathcal{N}_{i,t} \\ \mathbb{I}_{i,t}(n) = 0 & \text{if } n \notin \mathcal{N}_{i,t}, \end{cases} \tag{4.13}$$

which explains investor i's portfolio weight in asset n as the characteristics-based demand from Equation (4.10) in case n is part of the investment universe, and as zero otherwise. Therefore, the portfolio weight of an asset can be zero both due to the investor actively choosing not to invest in it, or due to the asset not being part of the investment universe. Assuming that investment mandates are defined exogenously, cross-sectional differences of investment mandates induce exogenous variation in demand, which we can utilize to identify investors' demand for prices.

Thinking about the mechanism of how instrumental variables work lends some intuition to this identification. If an explanatory variable X is endogenous, its variation can be split in two parts: the one that is correlated with the error term, and the one that is not. The idea of instrumental variable regression is to find information that isolates the second part (Stock & Watson, 2019). In our case, the first part is variation in prices that is induced by changes in (characteristics-based) demand, which we call the endogenous component of demand. The second part, however, resembles price changes that are induced by its underlying asset being part of the investment universes of more or larger investors. Since these investment universes are determined exogenously, the second part is the exogenous component of demand. For instance, assets that are part of the S&P 500, a leading stock index in the U.S., are part of the investment universes of numerous and large investors. This creates a high (exogenous) demand for those assets, which, given downward-sloping demand curves, drives up their prices. The market equity instrument based on investment universes is an attempt to capture this exogenous component of demand and utilize it to identify investors' appetite for prices.

Another important assumption required for the market equity instrument is that the wealth distribution of investors ($A_{i,t}$) is exogenous. With those two exogenous components, we can specify the instrument for market equity as follows:

$$m\hat{e}_{i,t}(n) = \log\left(\sum_{j\neq i} A_{j,t} \frac{\mathbb{I}_t(n)}{1 + \sum_{m=1} \mathbb{I}_t(m)}\right) \tag{4.14}$$

Essentially, the instrument calculates the market equity for asset n as the sum of the hypothetical value all investors – for which the asset is part of their investment universe – would hold if they were to hold equal-weighted portfolios of all assets in their investment universe. In more detail, the latter fraction calculates the share under equal weights: if an investor's universe were to contain 10 assets, the share of asset n, being part of his investment universe, would equal 0.1. Multiplying this share by the investor's wealth gives the hypothetical position the investor would hold in her portfolio. Taking the sum of those positions across all investors gives the total *hypothetical* market equity for asset n. The more investment universes the asset is included in, the higher the instrument is going to be - mirroring the presumably *higher* prices for frequently demanded assets.

The implementation of the instrument comes with three main challenges. First, the measurement of the investment universe, given that investors rarely disclose their mandates publicly. To circumvent this, KY19 propose a way to measure the investment universe based on the available holdings data, which we adapt in our methodology. In this approach, the investment universe of an investor i is approximated by the set of all assets she is currently holding or has held in the previous 11 quarters. To support the assumption of the investment universe being exogenous and lend credibility to the instrument, this set ideally does not change much over time. KY19 test this by calculating the proportion of shares in an investor's current portfolio that have been part of his portfolio in the previous quarter(s). We run the same test with our dataset and

Table 3: Percentage of assets held in the previous quarter(s)

	Previous quarter										
AUM percentile	1	2	3	4	5	6	7	8	9	10	11
1	82	85	87	89	90	91	92	93	93	94	95
2	85	88	89	91	92	93	94	94	95	95	96
3	85	88	90	91	92	93	93	94	94	95	95
4	85	88	89	91	92	92	93	94	94	94	95
5	85	87	89	90	91	92	93	93	94	94	95
6	84	87	89	90	91	92	92	93	94	94	94
7	83	86	88	89	90	91	92	93	93	94	94
8	83	87	89	90	91	92	92	93	93	94	94
9	86	89	91	92	93	93	94	94	95	95	95
10	92	94	95	95	96	96	97	97	97	97	98

Note: The table reports the share of assets held in the previous quarter(s), clustered by AUM percentiles. The data is sourced from Thomson Reuters (holdings data) and CRSP (stock data). The program to compile the table is from Kojien (n.d.).

obtain the results reported in Table 3.

As we can see, investors tend to hold fairly similar assets across time. This holds especially true for large investors in the top AUM percentile, where 98 percent of the assets currently held have been part of the investor's portfolio in the previous 11 quarters. This hints towards the presence of investment mandates. In line with this insight and the approach of KY19, we restrict the institutions used to construct the instrument to ”sticky” ones, where at least 95% of assets have been held in the previous 11 quarters, and exclude households. The cutoff at 11 quarters is chosen since additional persistence gains from going further back in time are found to be small.

With the proposed instrument, identification of the true coefficient relies on variation of the investment universe across investors. Therefore, a second challenge to the instrument would be a constant investment universe. In such a case, $m\hat{e}_{i,t}(n)$ would be constant across all assets, offering no variation exploitable for identification. As we report in Table 1, the median institution's investment universe was comprised by 121, 108, and 105 assets in the time periods between 2009-2012, 2013-2017, and 2018-2021, respectively. With a total of approximately 4,000 assets in our dataset, we can argue that investors hold fairly concentrated portfolios, neglecting the possibility of a constant investment universe. These empirical findings align well with what KY19 report.

The instrument's third challenge concerns relevance. In the general instrumental variable model, viable instruments need to fulfill two conditions: relevance and exogeneity (Stock & Watson, 2019). We have argued for the exogeneity extensively, but still need to confirm the relevance. For an instrument to be relevant, it should not be multicollinear with the endogenous variable it aims to replace and it should have a nonzero coefficient in the population regression of the endogenous variable on the instrument, potentially including control variables. To test these conditions, we follow the methodology outlined by KY19, and regress log market equity on the instrumental variable and the other characteristics. We run the regression for each investor and each quarter in the form

$$me_t(n) = \gamma_0(n) + \gamma_1 m\hat{e}_{i,t}(n) + \boldsymbol{\gamma}'_{me}\boldsymbol{x}_t(n) + \omega_t(n), \tag{4.15}$$

where γ_0 is the constant and $\omega_t(n)$ the error term. In line with KY19, we pool investors with less than 1000 holdings per quarter into bins, which we will explain in more detail later. Based on the regression results, we calculate the t-statistics for γ_1 by dividing the coefficient by its standard deviation. Taking the minimum t-statistic across all investors per quarter, we check whether it surpasses a critical value of 4.05, which serves as a threshold for rejecting the hypothesis of an instrument being irrelevant (Stock & Yogo, 2005). The results are reported in Figure 4. As the graph shows, the minimum t-statistic lies well above the critical value for all quarters between 2010 and 2019. Therefore, we can reject the hypothesis of the market equity instrument to be irrelevant.

Based on KY19's approach, we showed how we can construct an instrument for market equity that tackles the endogeneity concerns of prices in our nonlinear regression model. The instrument successfully checks the requirements of being exogenous and relevant. As such, we can adjust the initial moment condition in Equation 4.12 and incorporate the instrument:

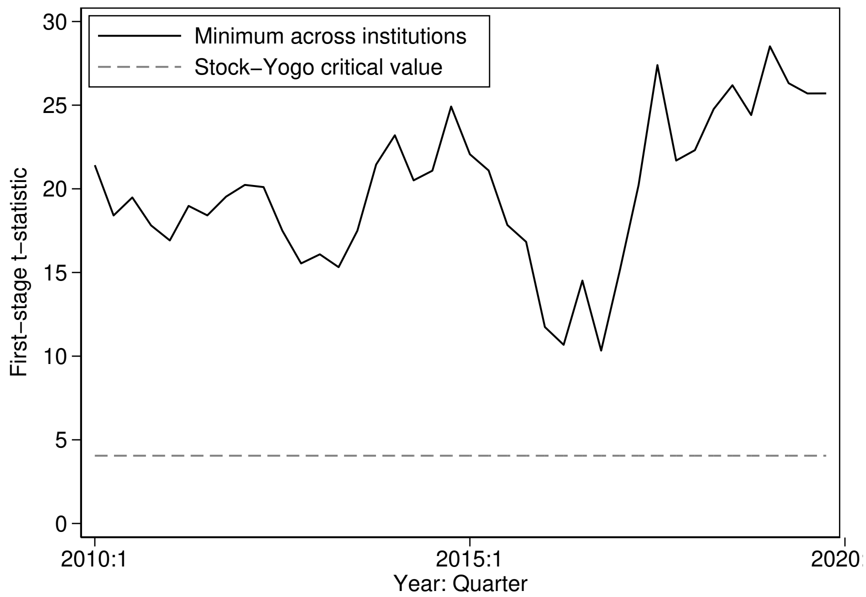
$$\mathbb{E}[\epsilon_i | \hat{me}(n), \boldsymbol{x}(n)] = 1. \tag{4.16}$$

This moment condition is central to our GMM estimation, which we will describe in more detail in the following section.

4.1.3 Estimation Process

Based on the assumptions and empirical evidence given in the previous paragraphs, we can now proceed to estimate the asset demand system. In this section, we will briefly

Figure 4: Minimum t-statistic of market equity instrument regressions



Note: Minimum first-stage t-statistic for the coefficient on $\hat{me}_t(n)$ (γ_1) in a regression of $me_t(n)$ on $\hat{me}_t(n)$ and control variables. The data is from CRSP and Compustat. The program to compile the graph is from Kojien (n.d.).

describe how we treat the input data, before we introduce our estimator. We note that large parts of the program we have written to estimate the asset demand system are adapted from the code underlying the KY19 paper, as the authors have generously provided extensive STATA programs to replicate their results (Kojien, n.d.).

A. Data preparation

The asset demand system uses three main data sources as inputs: institutional holdings data, stock information, and firm-level fundamentals. As described in Section 3, the data is mainly sourced from Form 13(f) filings compiled in the Thomson Reuters s34 database, CRSP and Compustat, respectively.

For the institutional holdings data, we conduct some cleaning steps to deal with well-known data quality issues of the s34 database. Most notably, we use archived s34 data for periods before June 2013, and adjust investor types leveraging s34 and external data. Once cleaned, we merge the quarterly holdings data with CRSP stock data to calculate the nominal value of the holdings, construct the household sector, and create the investment universe including zero holdings. These steps are covered in detail in Section 3. As an important next step, we calculate the share each investor holds in the outside asset. To do so, we first define inside assets according to the following conditions:

1. Asset has no missing value in either of the characteristics: book equity, dividend-to-book equity, foreign sales share, Lerner index, sales-to-book equity, market-to-book equity, or beta.

2. Asset has the share code 10 or 11.

The first condition requires data on the characteristics to be available. We adjust this condition from KY19 to reflect our selection of characteristics, but exclude the environmental and governance characteristic. Due to the limited amount of available data for these two, imposing a data completeness requirement would drastically reduce our sample size. We instead follow KRY22 and create dummy variables indicating missing observations for the environment and governance scores, which we subsequently include in the estimation. Studying the prevalence of methods to handle missing data in four leading economics journals, Abrevaya and Donald (2017) find that roughly 20% of papers leverage the dummy variable method. We thus deem this approach to be appropriate and adapt it from KRY22.

The second condition refers to the share codes used by CRSP. The codes 10 and 11 refer to ordinary shares traded on the New York Stock Exchange (NYSE), the American Stock Exchange, or Nasdaq, not foreign, and not real-estate investment trusts. Filtering for these codes aligns with the subsample of stocks used in Fama and French (1992) and Fama and French (2015).

After defining the inside assets, we construct the household sector. The s34 holdings data only contains the portfolio holdings of institutional investors. To represent the ownership structure of the entire stock market, we follow KY19, and proxy the household sector using the residual market capitalization after accounting for all institutional holdings.[13] To do so, we take all unsuccessfully matched observations when merging stocks on holdings and attribute them to the household sector.

As a next step, we deal with small institutions in the holdings dataset. This treatment is motivated by a higher likelihood of erroneous holdings among the smallest institutions and the properties of our GMM estimator. Given that we attempt to estimate demand functions per investor and quarter, the number of observations for each estimation can be limited, especially considering the fairly concentrated portfolios we found before. A

[13] We report the market capitalization in Appendix B.3

low number of observations threats both the validity and feasibility of our estimator (Hall, 2005). As such, we apply two treatments to small institutions. First, we group the smallest institutions in the institutional holdings dataset and merge them into the household sector. In line with KRY22, we classify institutions as *smallest* based on three characteristics:

- Less than 10m USD AUM in a given quarter.
- Less than 10 holdings in a given quarter.
- Less than 1m USD holdings in the outside asset in a given quarter.

This classification affects approximately 500,000 investor-quarter observations, which accounts for roughly 10% of the initial holdings dataset. Second, we apply *pooled estimation* (KY19). We define a minimum threshold of quarterly holdings per investor of 1,000, and group all investors below that threshold into bins conditional on type and AUM percentiles. We then estimate the demand functions in two steps: First, on institution level, for every institution with more than 1,000 holdings in a given quarter, and second, on a bin level, for all other institutions. Binning based on type and AUM ensures that we are pooling holdings for presumably similar investors, attempting to lose as little heterogeneity as possible. The threshold of 1,000 holdings is chosen arbitrarily, based on convergence issues arising with smaller thresholds (KY19). Since our study explicitly focuses on investor heterogeneity, we acknowledge the pooled estimation as a limitation to our approach. We will discuss its implications and possible mitigation strategies in Section 6.

After elaborating on our treatment of the institutional holdings data, we turn to the stock and fundamental data to derive the eight characteristics that define our specification of characteristics-based demand. For a detailed description of how we obtain and clean stock and fundamental data, we refer to Section 3.2.1 and 3.2.2. We describe how to construct each of our characteristics in the following:

- **Log book equity**: We calculate log book equity at time t as the natural logarithm of the *be* variable from Compustat's fundamental dataset: $LNbe_t(n) = \log(be_t(n))$.
- **Sales-to-book equity**: We calculate sales-to-book equity by taking Compustat's *sale* variable and divide it by book equity: $sale\_be_t(n) = \frac{sale_t(n)}{be_t(n)}$. To account for outliers, we winsorize the values at the 97.5 percentile each quarter.

- **Foreign sales share**: We leverage data from Compustat's segment database to identify export sales as the sum of *sale* in the segment *geotp3* (foreign segments) and *salexg* in the segment *geotp2* (domestic segments), and total sales as the sum of *sale* and *salexg*. Thus, we define: $fss_t(n) = \frac{sale_{t,geotp3}(n)+salexg_{t,geotp2}(n)}{sale_t(n)+salexg_t(n)}$.

- **Lerner index**: Using Compustat's fundamentals data, we caculate the Lerner index as operating income before depreciation (*oibdp*) plus depreciation (*dp*) divided by sales (*sale*): $lerner_t(n) = \frac{oibdp_t(n)+dp_t(n)}{sale_t(n)}$. To account for outliers, we winsorize values at the 2.5 and 97.5 percentile and truncate the left tail of the distribution at -1 each quarter.

- **Dividend-to-book equity**: Using Compustat's fundamentals data, we compute the ratio as an asset's dividend per split-adjusted share times shares outstanding (*shrout*) divided by book equity: $divA\_be_t(n) = \frac{divA_t(n)}{be_t(n)}$. To account for outliers, we winsorize values at the 97.5 percentile each quarter.

- **Market beta**: In line with KY19, we calculate beta ($beta_t(n)$) by regressing monthly excess stock returns over the 1-month Treasury bill rate on market excess returns in a 60-month moving window, requiring a minimum availability of 24 months with non-missing data: $r_t(n) - r_t(f) = \alpha_t + \beta_t(n) * [r_t(m) - r_t(f)]$. For Treasury bill rates and market excess returns, we rely on data from Kenneth R. French's online database (French, n.d.). To account for outliers, beta values are winsorized at the 2.5 and 97.5 percentile each quarter.

- **Environment score**: From Sustainalytics, we use historical, industry-weighted scores solely focused on the *environment* dimension of ESG. Due to the limited availability of scores, we forward-fill missing values for up to 18 months. The remaining missing values are indicated by a dummy variable (KRY22).

- **Governance score**: Leveraging data from the *Institutional Shareholder Services (ISS)*, a provider of environmental, social, and governance data, we compute the entrenchment index (*ei*) as the sum of the six provisions[14], where each provision takes the value of 1 in case it is present within the firm. Intuitively, larger entrenchment indices indicate weaker governance structures. Again, due to many missing values, we forward-fill missing values for up to 18 months and indicate the remaining missing values with a dummy variable (KRY22).

[14] As stated above, the provisions used in Bebchuk et al. (2008) include: staggered board, golden parachute, bylaw amendment limitations, charter amendment limitations, poison pills, and supermajority requirements for mergers

In line with KRY22, we standardize all characteristics cross-sectionally and per quarter by subtracting the mean and dividing by the standard deviation:

$$x_{k,t}^{std.} = \frac{x_{k,t} - \overline{x}_{k,t}}{\sigma_{x,k,t}}. \tag{4.17}$$

The standardization brings variables on an equal scale and makes their interpretation consistent: The regression coefficient of a standardized variable is interpreted as the change in the dependent variable for a one-standard-deviation change in the explanatory variable.

B. GMM Estimator

Having described the assumptions underlying the non-linear regression model as well as the necessary data inputs, we will begin introducing the estimator. In line with most parts in the construction of the asset demand system, our selection of the estimator is largely adapted from KY19, both theoretically and practically. As the title implies, we use a Generalized Method of Moments (GMM) estimator to estimate investor-specific and quarterly demand functions based on the model specified in Equation (4.10). GMM as an econometric method has first been introduced by Hansen (1982), and since then gained large popularity in a variety of applications, especially within (empirical) finance and economics research, where it often replaces the Maximum Likelihood estimator (MLE). GMM's main benefits in comparison to MLE are two-fold: First, GMM avoids specifying a probability distribution of the underlying data. In a large number of applications within finance, such distribution is unknown therefore needs to be chosen arbitrarily when applying the MLE estimator. Second, GMM estimation is computationally more convenient (Hall, 2005). While information about probability distributions might be unavailable, many models within empirical finance offer *moment conditions*, which are the main ingredient for GMM estimation. Moment conditions are equations that contain information about underlying relationships of the data. As we have seen previously, in our case, the moment conditions express the exogeneity of characteristics (see Equation (4.16)). GMM thereby allows us to estimate characteristics-based demand solely based on information implied by the underlying model, without having to make additional assumptions about the distribution of our data.

It is a unique property of the general GMM estimator that it can estimate models even in cases where the number of moment conditions exceeds the number of unknown coefficients, that is, the model is *over-identified*. Over-identification typically arises if there are multiple instruments specifying one endogenous variable. In such cases, the estimator leverages a multi-step estimation approach and specifies a weight-matrix that selects certain moment conditions to optimize the estimator for efficiency – that is, it has the smallest variance of all possible estimators (Hall, 2005). Our application, however, resembles a different case of GMM estimation, in which the number of moment conditions equals the number of unknown coefficients. The model is said to be *just-identified*. To see this, we can think about the underlying assumption of the moment condition in Equation (4.16), which states that the characteristics are exogenous. As we assume this for every characteristic, we have a moment condition of the kind $\mathbb{E}[\varepsilon_{i,t} x_{k,t}(n)] = 1$ for all K characteristics, including the market equity instrument $\hat{me}_{i,t}(n)$, totaling nine moment conditions. At the same time, given the non-linear regression model in the form of Equation (4.10), we have an unknown coefficient in front of every characteristic, including market equity, totaling nine unknown parameters. Our model is therefore *just-identified*.

Before we proceed to specify the GMM estimator, we clarify some notation. For simplicity, we drop time and investor subscripts, and specify the asset n in subscript rather than in parentheses. We also abstract from the normalization of latent demand at 1 and instead assume it to be zero. The notation used here is adapted from Zivot (2013) and Hall (2005), and is intentionally kept simple.[15] Let $\boldsymbol{z}_n$ be a vector containing all instruments used for estimation. In our case, this includes all the characteristics $\boldsymbol{x}_n$ and the market equity instrument $\hat{me}_n$. Furthermore, let $\boldsymbol{\beta}$ be a vector of all regression coefficients. Like before, δ_n is the characteristics-based demand, and ε_n is latent demand (or, the error term). Given Equation (4.10), we can write $\varepsilon_n(\boldsymbol{\beta}) = \delta_n - \boldsymbol{z}_n\boldsymbol{\beta}$. The population moment condition is given as $\mathbb{E}[\boldsymbol{z}_n \varepsilon_n] = 0$. Following this notation, the goal function of the GMM estimator is:

$$Q(\boldsymbol{\beta}) = \left\{ \sum_n \boldsymbol{z}_n \varepsilon_n(\boldsymbol{\beta}) \right\}' \left\{ \sum_n \boldsymbol{z}_n \varepsilon_n(\boldsymbol{\beta}) \right\}. \tag{4.18}$$

The GMM estimator finds the values for $\boldsymbol{\beta}$ for which the goal function is minimized:

$$\hat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} Q(\boldsymbol{\beta}), \tag{4.19}$$

where $\hat{\boldsymbol{\beta}}$ is the estimated equivalent of $\boldsymbol{\beta}$. This estimator is sometimes referred to as the *simple instrumental-variables estimator*.

[15]For a more detailed coverage of the nonlinear GMM estimator, we refer to the aforementioned sources. Zivot (2013) provides a specific coverage of the nonlinear GMM estimator, while Hall (2005) is a general text for GMM estimation in time-series applications.

We estimate Equation (4.19) leveraging a program written by KY19. This program uses the STATA command *gmm* to estimate quarterly demand functions in two steps: First, for individual institutions if the number of holdings in a given quarter exceeds 1,000, and second, for a pool of institutions, in all other cases. The coefficient on log market equity ($\beta_{0,i,t}$) is capped at 1 to ensure downward-sloping demand curves (see Section 4.1.1). The quarterly estimates, including their standard errors, are merged and stored in two different datasets, one for institution-level demand functions, and one for pooled demand functions.

C. Alternative specification of characteristics-based demand

In the derivation of the asset demand system, we have so far used market equity ($me_t(n)$) as a characteristic capturing investors' demand for prices. In an alternative specification, KY19 use market-to-book equity instead. While this simply resembles a linear transformation of the previous characteristic and therefore does not change any of the derivations or assumptions we have explained, it has the advantage to make market equity more stationary in the cross-section.[16] It is therefore reasonable to replace the log market equity characteristic, $me_t(n)$, with log market-to-book equity, $mb_t(n) = log\left(\frac{ME_t(n)}{BE_t(n)}\right)$. This alternative specification, however, does not alter the estimation results much. Applying the properties of the logarithm to the non-linear regression model (4.10) with $mb_t(n)$ instead of $me_t(n)$ shows that both models are directly transferable:

$$
\begin{aligned}
\delta_{i,t}(n) &= exp\left[\beta_{0,i,t}mb_t(n) + \beta_{1,i,t}be_t(n) + \sum_{k=2}^{K-1}\beta_{k,i,t}x_{k,t}^{w.o.be}(n) + \beta_{K,i,t}\right]\varepsilon_{i,t}(n) \\
&= exp\left[\beta_{0,i,t}log\left(\frac{ME_t(n)}{BE_t(n)}\right) + \beta_{1,i,t}be_t(n) + \sum_{k=2}^{K-1}\beta_{k,i,t}x_{k,t}^{w.o.be}(n) + \beta_{K,i,t}\right]\varepsilon_{i,t}(n) \\
&= exp\left[\beta_{0,i,t}me_t(n) - \beta_{0,i,t}be_t(n) + \beta_{1,i,t}be_t(n) + \sum_{k=2}^{K-1}\beta_{k,i,t}x_{k,t}^{w.o.be}(n) + \beta_{K,i,t}\right]\varepsilon_{i,t}(n) \\
&= exp\left[\beta_{0,i,t}me_t(n) + (\beta_{1,i,t} - \beta_{0,i,t})be_t(n) + \sum_{k=2}^{K-1}\beta_{k,i,t}x_{k,t}^{w.o.be}(n) + \beta_{K,i,t}\right]\varepsilon_{i,t}(n),
\end{aligned}
\tag{4.20}
$$

where $x_{k,t}^{w.o.be}(n)$ indicates the stack of characteristics excluding log book equity. The last line of Equation (4.20) is of the same structure as Equation (4.10). As such, in the

[16] To illustrate this, we provide an example. A cinema chain with 1,000 theatres will have a much (presumably 10 times) higher market equity and book equity than a comparable cinema chain with only 100 theatres. Apart from size, which we already capture in the book equity characteristic, the investor will ultimately care about the price per cinema (Asness, Frazzini, & Pedersen, 2019)

alternative specification, the coefficient on log market-to-book equity is equal to the coefficient on log market equity, and the coefficient on log book equity is equal to the sum of the coefficients on log market-to-book equity and log book equity. To allow for simpler comparability of our results with KY19 and KRY22, we will use the alternative specification in the reports of our results of the asset demand system in Section 5.

4.1.4 Tests of the Asset Demand System

To test the validity of our specification of characteristics-based demand and our estimator, we employ two tests, which we will introduce in the following.

A. Characteristics-based demand

In Section 4.1.1, we motivated the selection of characteristics in the specification of characteristics-based demand based on insights from previous literature. In addition to this theoretical foundation, we aim to test the selection for robustness in an empirical application. To do so, we analyze the characteristic's explanatory power of stock valuations. We adapt an approach outlined by KRY22, and regress year-end stock valuations on the characteristics using our stock dataset:

$$mb_t(n) = \alpha_t(n) + \boldsymbol{\lambda'_{mb} x_t(n)} + u_t(n), \tag{4.21}$$

where $mb_t(n)$ indicates the market-to-book ratio of asset n at time t, $\boldsymbol{\lambda}$ is the set of regression coefficients related to the characteristics stacked in vector $\boldsymbol{x}_t(n)$, and $u_t(n)$ is the idiosyncratic shock. In line with KRY22, we hypothesize that the characteristics are important determinants of stock valuations and can explain its variation fairly well, which would be indicated by significant regression coefficients and a high adjusted R^2, respectively. This approach follows a body of literature that attempts to explain the cross-section of asset *prices* through characteristics. Asness et al. (2019) show how a selection of *quality* characteristics can explain a substantial part of price variation. Based on the present-value identity put forth by R. B. Cohen, Polk, and Vuolteenaho (2003), we can relate asset prices (or, equivalently, market-to-book ratios), to expected returns. In their paper, they derive an identity equation in which market-to-book ratios are decomposed into three components: future profitability, persistence, and expected returns. An empirical test for U.S. equity markets reveals that about 20-25% of the cross-sectional variation in market-to-book ratios can be explained by variations in expected returns. Thus, if asset prices (market-to-book ratios) are explained by characteristics, and we can relate those to expected returns using the present-value identity of R. B. Cohen et al. (2003), then characteristics are explanatory for expected returns. Ultimately, this test confirms the key assumption made in Section 4.1.1.

B. GMM Estimator

To test the validity of our GMM estimator, we follow an approach proposed by KY19, in which they estimate the demand coefficients for a hypothetical index fund and check those for consistency. More specifically, they look at one specific manager, The Vanguard Group, which is the fourth largest investor in their dataset and is supposed to hold a fully diversified portfolio covering the entire market. They replace Vanguard's holdings with actual market weights to mimic a hypothetical investor that replicates the market portfolio. Based on these weights, they estimate characteristics-based demand (Equation (4.10)) for the hypothetical fund under the moment condition of Equation (4.16) using the non-linear GMM estimator described in Section 4.1.3. In theory, if the estimator is valid, this estimation should recover a coefficient of exactly one on log market equity ($\beta_{0,i,t}$), and exactly zero on all the other coefficients, since the only characteristic that would determine this investor's demand should be the market equity level of an asset. Practically, KY19 replace the weights Vanguard holds in each asset, relative to the outside asset, according to the following formula:

$$\frac{w(n)}{w(0)} = exp\left\{me_t(n) + \beta_{K,i,t}\right\} \tag{4.22}$$

Adding and subtracting $be_t(n)$ easily converts this into the case where market equity is scaled by book equity:

$$\begin{aligned} \frac{w(n)}{w(0)} &= exp\left\{me_t(n) + be_t(n) - be_t(n) + \beta_{K,i,t}\right\} \\ &= exp\left\{(me_t(n) - be_t(n)) + be_t(n) + \beta_{K,i,t}\right\} \\ &= exp\left\{log(\frac{ME_t(n)}{BE_t(n)}) + be_t(n) + \beta_{K,i,t}\right\} \end{aligned} \tag{4.23}$$

Intuitively, Equation (4.22) and (4.23) adjust portfolio weights such that they match the characteristics-based demand for a coefficient of 1 on log market equity and zero on the other characteristics, or a coefficient of 1 on log market-to-book equity and book equity and zero on the other coefficients, respectively. To see how this resembles the case for which the investor holds each asset in proportion to its market weights, we refer to Appendix C.1, where we derive Equation (4.22) from the definition of portfolio weights given in Equation (4.9) and (4.11).

We apply the same methodology and run the test for Vanguard, which in our dataset resembles the largest investor based on average AUM in the time period 2010 to 2019, with an average of USD 1,7 trillion in AUM and an average number of holdings per period of approximately 3,800. The high number of holdings, which accounts for about

80% of the total stock universe in our dataset, justifies declaring Vanguard an index fund with a fully diversified portfolio that covers the entire market. We report the estimation results as plots of the estimated coefficients over time, which we will introduce in Section 5.

Both tests outlined in this section aim to increase the validity of our estimation of characteristics-based demand and thereby the robustness of our results. Combined with the theoretical motivation provided in Section 4.1.1, we can make a sound case for our asset demand system. Remaining challenges and limitations, especially concerning the selection of the market equity instrument, will be addressed in the discussion (Section 6).

4.2 Investor Heterogeneity

The main focus of this study is to explain heterogeneity in the asset demand of institutional investors. Before we can attempt to explain the heterogeneity, we first need to uncover it. To achieve this, we employ two methods: regression models and distribution plots. This section introduces our approach to subquestion 2: demonstrating institutional investor heterogeneity in asset demand that goes beyond investor type.

4.2.1 Regressions on Type

A natural hypothesis based on the institutional holdings dataset could be that the types we assign to each investor (see Section 3.1) are sufficient in explaining heterogeneity in the demand for asset characteristics. In line with that hypothesis, much of the research concerning institutional investor heterogeneity is centered around distinguishing between investor types (for instance, Croce et al. (2011) on pension funds' role in green financing; Hong and Kacperczyk (2009) on norm-constrained investors; Bolton and Kacperczyk (2021) on the incorporation of emissions by certain types of investors). To test whether investor types are sufficient in explaining dispersion in demand coefficients, we follow KRY22, and regress each estimated coefficient on investor type dummies. The dummies take the value of 1 if a given investor is of that type, and 0 otherwise. To avoid the dummy trap and therefore perfect multicollinearity (Stock & Watson, 2019), we refrain from including a constant in the regression.

Since the regressions pool observations, i.e., demand curves, from different points in time, we include time-fixed effects. Fixed-effects is a method used for panel data, which allows capturing unobserved effects that vary across one dimension (e.g., time) but not another (e.g., entities). For a panel dataset that spans T periods, time-fixed effects are incorporated by adding $T-1$ time-specific dummies to the model which take the value of 1 if the observation is in the dummy's respective time period, and zero otherwise. This creates an individual intercept for each time period. For time-fixed effects to be applicable, it is important that the data actually entails effects which vary across time but are constant across other dimensions, e.g. entities (Stock & Watson, 2019). The presence of such effects in our estimated asset demand curves can be motivated by, for instance, the increasing demand for sustainable assets in recent years (see Section 1). This market-wide elevation of green demand over time clearly points towards the presence of time-fixed effects in our data. Since the estimated demand curves are quarterly observations spanning from the first quarter in 2010 to the fourth quarter in 2019 and totaling 40 distinct time periods, we include 39 time-dummies into the regression.

With the investor type dummy variables and time-fixed effects, we specify the regression as:

$$b_{i,t}(x) = \tau_1 PF_i + \tau_2 IC_i + \tau_3 BA_i + \tau_4 MF_i + \tau_5 IA_i + \tau_6 OT_i + \tau_7 HH_i + \sum_{s=1}^{S-1} \theta_s D_{s,i} + u_{i,t}, \tag{4.24}$$

where $b_{i,t}(x)$ are the estimated demand coefficients for the respective characteristics in $\boldsymbol{x}_t(n)$ and $me_t(n)$. PF, IC, BA, MF, IA, OT, and HH are the dummies for the seven distinct types of investors, Pension Funds, Insurance Companies, Banks, Mutual Funds, Investment Advisors, Other, and Households, respectively. $D_{s,i}$ are the quarter dummies for the time periods s, with θ_s being their respective regression coefficients. $u_{i,t}$ is the error term.

We estimate Equation (4.24) using the Ordinary Least Square (OLS) estimator, which is the common estimator used for linear regression models. OLS chooses the regression coefficients based on minimizing the squared distance between the estimated and observed values – that is, minimizing the (squared) residuals of the regression model (Stock & Watson, 2019). If the investor types would be sufficient in explaining the dispersion between characteristics, we should observe a high explanatory power in the models for the different demand coefficients. A common indicator for a model's explanatory power is the R^2 value, which indicates the fraction of variation in the dependent variable that is explained by the regressor(s). Multivariate regression models typically use another version of R^2, the *adjusted* R^2, instead. This measure corrects R^2 for the number of regressors used in the model, as by default, adding any regressor will increase R^2 independent from its individual explanatory power for the variation of the dependent variable (Stock & Watson, 2019). Next to the adjusted R^2, the significance of regression coefficients will indicate whether type is an important determinant of the dispersion in the demand coefficient. We report the results and the corresponding interpretation in Section 5.

4.2.2 Visualizations of Heterogeneity

For displaying data which disperses across one axis, histograms are a powerful method, as they group data into bins and plot the number of observations per bin along a horizontal axis (Nuzzo, 2019). We create two types of histograms. First, we plot histograms visualizing the variation in each demand coefficient across all investor types. For reference, we include lines indicating the AUM-weighted average of each investor type. Second, to deep-dive into the heterogeneity of the environmental demand coefficient, we create individual histograms for each investor type, attempting to visualize the large dispersion within the same category of investors. As Nuzzo (2019) shows, the selection of the bin size is an important parameter. Choosing the wrong bin size potentially implies drawing false conclusions about the distribution of the data. To avoid losing large amounts of data granularity, we opt for a large amount of bins, and set the number of bins to 100 for each histogram we plot.

4.3 Green Demand

After having demonstrated the presence of investor heterogeneity in our estimated asset demand system, we can proceed to attempt to explain it. As outlined in subquestion 3, we will focus on the demand for the environment characteristic.[17] Along with other variables, we specifically focus on PRI membership, where we employ signatory data from the PRI initiative to analyze whether a membership has a significant impact on green demand. We approach this analysis in three steps: First, we study whether *being* part of PRI significantly influences investors' demand coefficient for green assets. Herein, we test multiple other influential variables of green demand and inspect whether the *PRI effect* remains robust to those. Second, to increase robustness, we investigate if *becoming* part of PRI significantly changes investors' demand coefficients for green assets. Lastly, we compare the two subsets of investors in our dataset, PRI and non-PRI, in more detail, and inspect drivers of the *PRI effect*. This section will introduce how we utilize the PRI data described in Section 3.3, before it will explain the methodology behind each of the three analyses described above.

[17] We use alternating terminology for the demand for the environmental characteristic. "Green demand", "demand for green assets", "investor greenness", "green preferences", and "demand for environmental sustainability" are all used interchangeably and refer to the same concept.

4.3.1 Matching PRI and 13(f) Data

As indicated in Section 3.3, we obtain data on signatory names and their corresponding signature dates from the PRI website (PRI, n.d.-b). The signatories are institution-level data. Therefore, for the estimated demand curves, we are limited to the use of the results from the first-step, institution-level estimation. Since PRI does not report any common identifier with the 13(f) data, we employ a two-step process to match name strings between the PRI signatories (thereafter *PRI signatory*) and the investor names related to our estimated demand curves (thereafter *13(f) investors*): In the first step, we leverage a fuzzy match algorithm based on the Jaro-Winkler distance. The Jaro-Winkler distance measures common characters of two strings and transpositions needed to convert strings into each other, and has been proven to be a powerful algorithm in name-matching tasks (W. W. Cohen, Ravikumar, & Fienberg, 2003). We leverage the user-built Python package *jellyfish* to compute the Jaro-Winkler distance, and only consider matches above a threshold of 0.85, based on the program's reported distances on a scale from 0 (entirely dissimilar) to 1 (perfect similarity). In the second step, we browse through the matches manually and exclude erroneous ones. In addition, we manually check for non-matched entities in the 13(f) investors whether we are missing out on any potential matches from the PRI data. We consider two entities to be a match whenever there is an affiliation between them, and generally distinguish between four match cases:

1. *"Perfect" match*: Both PRI signatory and 13(f) investor are the exact same entity.
2. *PRI subsidiary match*: The PRI signatory is a subsidiary to the matched 13(f) investor.
3. *13(f) subsidiary match*: The 13(f) investor is a subsidiary to the matched PRI signatory.
4. *Subsidiary match*: The PRI signatory and matched 13(f) investor are different subsidiaries to the same parent organization.

For illustrative purposes, we provide exemplary matches for each case in Appendix A.3.

Based on the process described above, we manage to match 81 13(f) investors with a PRI signatory, representing about a third of the total number of investors in the institution-level dataset. The matches are split among match types as follows: 41 are *"perfect" matches*, 15 *PRI subsidiary matches*, 22 *13(f) subsidiary matches*, and 3 *subsidiary matches*. Based on the matches, we add two types of dummy variables:

first, we create a *PRI dummy*, which takes the value of 1 if an investor has been part of PRI in a given quarter, and 0 otherwise. Second, we include dummy variables for each matching type, which take the value of 1 if the match is of a given type, and 0 otherwise. The dummy variables are part of our regression analysis, which we will introduce in the following.

4.3.2 PRI Regressions

In this section, we outline how we analyze whether a PRI membership is explanatory for an investor's demand for green assets, and which other influences are relevant. In our approach, we closely follow Brandon et al. (2022), who regress investors' *ESG portfolio footprints*, measured by the number of green assets included in their quarterly holdings, on the PRI dummy and control variables. Instead of footprints, we use the demand coefficients, and run three regressions: First, we regress the environmental coefficient on the PRI dummy and include baseline variables as in Brandon et al. (2022). Second, we run the same regression but include a more extensive set of variables, in line with Brandon et al. (2022). Third, we re-run the second regression but include more variables which we hypothesize to be important for explaining green demand.

While we are primarily concerned with the influence of PRI membership on demand for greenness, we include additional variables for two main reasons: First, to test whether these variables are helpful to explain heterogeneity in the demand coefficients. Second, to avoid omitted variable bias (OVB). OVB causes the OLS estimator to be biased and inconsistent and arises when there are variables outside of the model which are determinants of the dependent variable and correlated with the regressor (Stock & Watson, 2019). For instance, in the case of our study, one could hypothesize that an indicator for investor size is both a determinant for green demand (larger investors could demand more green assets due to public exposure) and correlated with the regressor (large investors are more likely to be part of PRI) – therefore, not including size would cause OVB, and our estimator for the *PRI dummy* would be biased. We introduce each of the regression models indicated above in the following.

A. Regression 1: PRI dummy and baseline controls

The start of our analysis is the regression of the environmental coefficient $b(env)$ on four variables: *PRI dummy*, *LNaum*, *foreign*, and the type dummies from Section 4.2.1, where *LNaum* is the logarithm of the investor's quarterly AUM, and *foreign* is a dummy which takes the value 1 if an investor is headquartered in a country outside the U.S., and 0 otherwise. Again, since our demand coefficients span multiple periods, we include time-fixed effects. Thus, the regression is specified as follows:

$$b_{i,t}(env) = \lambda_0 + \lambda_1 PRIdummy_{i,t} + \lambda_2 LNaum_{i,t} + \lambda_3 foreign_{i,t} + \sum_{q=1}^{Q-1} \tau_q R_{q,i} + \sum_{s=1}^{S-1} \theta_s D_{s,i} + u_{i,t}, \tag{4.25}$$

where R_q are the type dummies excluding households (as households cannot sign up for PRI) and "Other" (to avoid the dummy variable trap), and τ_q their respective regression coefficients. The selection of variables is largely inspired by Brandon et al. (2022), and comprises intuitive characteristics to differentiate investors. We have already provided reasoning for the size and type variables. The motivation for *foreign* comes from findings which indicate higher environmental awareness of investors residing in countries with stronger environmental regulations and a more emphasized societal focus on environmental matters. In fact, Brandon et al. (2022) find no evidence for higher environmental footprints for American PRI investors, but they do so for European and Asian ones. Our analysis will test these results with a different approach and data, and a stronger emphasis on U.S. investors, since only 23% of investors with institution-level demand curves are classified as *foreign*.

B. Regression 2: PRI dummy and additional controls

In the second regression model, we include additional variables, for the same reasons as mentioned above: explain more heterogeneity and avoid OVB. Specifically, we follow Brandon et al. (2022), and add 5 variables to regression (4.25): portfolio turnover, portfolio activeness, number of stocks, and average stock size. We motivate the inclusion of those variables and explain their construction in the following.

Portfolio turnover measures the average portfolio churn of an investor and therefore serves as an indicator for investment horizon (Gaspar, Massa, & Matos, 2005). Higher (lower) turnovers are associated with a shorter (longer) investment horizon. As mentioned in Section 2.3, Starks et al. (2017) find a strong relationship between long-term investment horizons and portfolio tilts towards ESG, and similar results are reported in Gibson and Krueger (2017). In constructing portfolio turnover, we follow Gaspar et al. (2005) and calculate portfolio churn as:

$$CR_{i,t} = \frac{\sum_{j\in Q} |N_{j,i,t}P_{j,t} - N_{j,i,t-1}P_{j,t-1} - N_{j,i,t-1}\Delta P_{j,t}|}{\sum_{j\in Q} \frac{N_{j,i,t}P_{j,t} + N_{j,i,t-1}P_{j,t-1}}{2}}, \tag{4.26}$$

from which we take the 4-quarter rolling average to arrive at the portfolio turnover:

$$turnover_{i,t} = \frac{1}{4} \sum_{r=1}^{4} CR_{i,t-r+1}. \tag{4.27}$$

Intuitively, the portfolio churn $CR_{i,t}$ takes the total changes an investor does to his portfolio in a period t, corrects it by changes that are induced by price fluctuations, and divides it by the average portfolio holdings in that period. We aggregate churn across four quarters to make the turnover more robust to outliers and construct a meaningful measure of long-term-ism (Gaspar et al., 2005).

Portfolio activeness, expressed by the active share, describes the extent to which an investor deviates from a benchmark – that is, how much the investor over- and underweighs assets compared to the respective benchmark index (Cremers & Petajisto, 2009). Activeness has been used as a metric to distinguish institutional investors. D. Kim, Kim, Joe, and Oh (2021) find substantial differences in the activeness of investors with similar investment horizons, and KRY22 use the metric in an attempt to explain the demand heterogeneity they observe. Since active investors are taking bets to generate positive abnormal returns, they have been scrutinized to be more likely to sacrifice ESG matters for return opportunities (Noh & Oh, 2023). In a similar vein, Liang et al. (2021) find greenwashing among hedge funds, a particularly active type of investor. However, there is evidence that active investors demand sustainability (Noh & Oh, 2023), for example, cater to their clients' demands (L. Chen, Chen, Kumar, & Leung, 2020). In constructing active share, we follow Cremers and Petajisto (2009), and define the active share of investor i as:

$$AS_{i,t} = \frac{1}{2} \sum_{n} |w^{*}_{i,t}(n) - w^{m}_{i,t}(n)|, \tag{4.28}$$

with $w^{*}_{i,t}(n) = \frac{\delta_{i,t}(n)}{\sum_m \delta_{i,t}(m)}$, being the investor's weight in asset n, and $w^{m}_{i,t}(n)$ being the market portfolio weights based on the stocks held by investor i individually. We calculate $AS_{i,t}$ based on the merged holdings and stock data on a quarterly basis.

Number of stocks and *average stock size* are additional variables to measure investors' diversification and size focus, respectively. We construct the number of stocks as the logarithm of the number of non-zero holdings per investor per quarter, $LNnhold_{i,t} = \log(N^{n.z.}_{i,t})$, and the average stock size as the logarithm of the average market capitalization of the stocks in an investor's portfolio, $LNavgss_{i,t} = \log\left(\frac{1}{N^{n.z.}_{i,t}} \sum_{n=1}^{N^{n.z.}_{i,t}} M_t(n)\right)$, where $M_t(n)$ is the market capitalization of asset n at time t.

On top of the variables specified here, Brandon et al. (2022) include portfolio industry concentration in their regressions of the *ESG footprint* on *PRI dummy*. Industry concentration indicates how diversified an investor is across sectors, and is constructed as a dummy which takes the value of 1 for investor portfolios that span two or fewer segments, and 0 otherwise (Brandon et al., 2022). Based on the hypothesis that investors take concentrated bets on certain sectors due to an informational advantage, industry concentration serves as an indicator of the skill-level of investors (Kacperczyk, Sialm, & Zheng, 2005), and therefore offers a potential explanation of heterogeneity. We tested the specification of industry concentration with our dataset, where we categorized each stock into segments based on the Fama-French industry classifications (Fama & French, 2023). However, since the nature of our estimation limits us to the largest of investors with more than 1,000 quarterly holdings, we find that none of the investors in the institution-level estimation holds concentrated portfolios. In fact, all of these investors hold stocks across the entire set of industries (12 in total). We therefore exclude industry concentration from the analysis.

Including the additional variables, we specify the second regression model of the PRI analysis as follows:

$$\begin{aligned} b_{i,t}(env) =& \lambda_0 + \lambda_1 PRIdummy_{i,t} + \lambda_2 LNaum_{i,t} + \lambda_3 foreign_{i,t} + \lambda_4 turnover_{i,t} + \\ & \lambda_5 AS_{i,t} + \lambda_6 LNnhold_{i,t} + \lambda_7 LNavgss_{i,t} + \sum_{q=1}^{Q-1} \tau_q R_{q,i} + \sum_{s=1}^{S-1} \theta_s D_{s,i} + u_{i,t}. \end{aligned} \tag{4.29}$$

We note that the regression coefficients λ_k for $k = 0, ..., 7$ are different from the λ values in regression (4.25), but we drop additional superscripts for readability. The same applies to the regression coefficients on the type- and time-fixed effects. This regression model mostly aligns with the specification in Brandon et al. (2022) and contains the majority of variables used by Noh and Oh (2023), making our results comparable. We report results and draw comparisons to related studies in Section 5.

C. Regression 3: PRI dummy and extended controls

In the third regression model, we deviate from Brandon et al. (2022) and further include variables which we hypothesize can be meaningful in explaining investors' demand for green assets. Specifically, we include three additional variables: *match type* (from Section 4.3.1), the demand coefficient on governance, and the demand coefficient on log market(-to-book) equity. Again, we proceed by motivating each of these variables in the following.

Match type indicates the entity level on which the investor is committed to the initiative compared to the entity level of the holdings we observe. For the cases *PRI subsidiary match* and *Subsidiary match*, the investor is committed on a lower entity-level only, whereas for *"Perfect" match* and *13(f) subsidiary match*, the investor is committed on a higher entity-level. We hypothesize that investors who only are committed on a lower level do not exhibit group-level incorporation of the PRI principles to the extent of the higher level committed ones. As such, we would expect a weaker *PRI effect* for the lower-level signatories compared to the higher-level ones. This hypothesis relates to findings by Brandon et al. (2022), who analyze PRI investors' survey responses and find a significantly lower and even reversed impact of PRI membership on *ESG footprint* for investors that apply ESG incorporation strategies only in parts of their AUM. We conjecture that the commitment level entailed in the *match type* can be indicative for the extent of ESG incorporation. From a technical perspective, we include the dummy variables mentioned in Section 4.3.1 in the regression model, where we, again, exclude one dummy (*"perfect" match*) to avoid the dummy variable trap.

The demand coefficient for governance, $b_{i,t}(ei)$, indicates an investor's appetite for good firm governance. We recall that a lower score on the entrenchment index indicates better governance – therefore, *lower* values on *b(ei)* translate into demand for *better* governance. Instead of focusing solely on a company's environmental performance, investors typically include an entire ESG evaluation in their investment screening processes, which contains the additional dimensions **S**ocial and **G**overnance (R. G. Eccles, Kastrapeli, and Potter (2017); Mooij (2017)). In fact, an industry report surveying 400 global asset managers on ESG investing found that 82% name governance as the primary ESG factor impacting their investment decisions (Phillips, 2020). Based on these insights, we hypothesize that investors who care about good governance also exhibit a stronger preference for environmental sustainability. This would support the existence of holistic ESG investment strategies within environmentally-conscious investors.

As indicated in 4.1.3, the coefficient on log market equity ($\beta_{0,i,t}$; for consistency, we refer to it as $b_{i,t}(me)$ in this section) can have two interpretations: demand for (log) market equity (prices) or for (log) market-to-book equity. We already discussed that, in the former case, the coefficient can be seen as the price inelasticity of demand, as it magnifies how much an investor changes his demand upon changes in the price of the underlying asset. Noh and Oh (2023) include the coefficient on market equity as an indicator of price inelasticity in their regressions and find a higher green demand for price elastic investors. The latter, market-to-book case offers an alternative interpretation. Value investors use the market-to-book ratio to detect overpriced assets. A common value investing strategy is to long/short low/high market-to-book assets (Bird & Whitaker, 2003) to exploit such an apparent *mispricing*. In the presence of these strategies, value investors would exhibit low demand for the log-market-to-book characteristic. Albeit we cannot observe the short positions, a positive (zero) demand for low (high) market-to-book assets would still be manifested in a small $b_{i,t}(me)$. Interestingly, value portfolios have been associated with better ESG ratings (Kaiser, 2020). We, therefore, suspect higher demand for environmental sustainability from value investors, which would correlate with lower coefficients on log market-to-book-equity. While we cannot distinguish between the two possible interpretations of $b_{i,t}(me)$, we still want to offer both to provide the intuition and indicate possible areas of further research.

Including the added characteristics, we specify the third regression model as follows:

$$\begin{aligned} b_{i,t}(env) = &\lambda_0 + \lambda_1 PRIdummy_{i,t} + \lambda_2 LNaum_{i,t} + \lambda_3 foreign_{i,t} + \lambda_4 turnover_{i,t} + \\ &\lambda_5 AS_{i,t} + \lambda_6 LNnhold_{i,t} + \lambda_7 LNavgss_{i,t} + \lambda_7 b_{i,t}(ei) + \lambda_8 b_{i,t}(me) + \\ &\lambda_9 PRIsubs_{i,t} + \lambda_{10} \mathit{13F}subs_{i,t} + \lambda_{11} Subs_{i,t} + \sum_{q=1}^{Q-1} \tau_q R_{q,i} + \sum_{s=1}^{S-1} \theta_s D_{s,i} + u_{i,t}, \end{aligned} \tag{4.30}$$

where the first 8 terms come from the previous equation, and $PRIsubs_{i,t}$, $\mathit{13F}subs_{i,t}$ and $Subs_{i,t}$ are the dummy variables for the 3 match types *PRI subsidiary match*, *13F subsidiary match* and *Subsidiary match*, respectively. Again, we note that, albeit we are using the same symbol for the regression coefficients, λ_k for $k = 0, ..., 11$ are not identical to the λ values used in the models (4.25) and (4.29), but we simply drop additional superscripts for purposes of readability. The same applies to the regression coefficients on the type- and time-fixed effects. We report our results and the interpretation thereof in section 5.

4.3.3 Difference-in-Difference Regressions

The regressions outlined in the previous section aim to address the question whether PRI members exhibit a higher demand for environmental sustainability, and what other factors influence this demand. A natural question following up on this analysis would be: Is it in fact the PRI membership that makes investors demand more greenness? In order to answer this question, we use the method of difference-in-difference regressions, where we compare PRI investors' pre- and post-signature with their non-PRI peers and see whether the PRI investors show a greater rise in green demand (for a similar approach, see Brandon et al. (2022)). Before we specify the regressions we run, we will briefly introduce the general difference-in-difference estimator to establish a conceptual foundation for the setup and ease the interpretation. The theory is largely sourced from Stock and Watson (2019).

Differences estimation is a common practice in social sciences to create so-called *quasi-experiments* where natural experiments are complex or infeasible. The *PRI dummy* in the previously introduced regressions can be interpreted as a differences estimator, since it compares the outcome ($b_{i,t}(env)$) of a treatment group (the PRI investors) to those of a control group (the non-PRI investors). An underlying assumption of this estimation is that the treatment (signing PRI) is as-if randomly assigned - that is, the selection of investors who joined PRI is random. Since this is not a natural experiment, we cannot control the randomization, and thus there might be remaining differences between treatment and control group that we cannot control for (e.g., PRI investors are ex-ante more environmentally conscious). To allow controlling for these influences, we turn to the difference-in-difference (DID) estimator, which corrects for those potential differences between treatment and control group by comparing *changes* in the outcome variable instead of *total* values. Specifically, the DID estimator takes the difference of the differences in the outcome's sample means of the treatment and control group before and after treatment:

$$\hat{\beta}^{DID} = (\bar{Y}^{treatment,after} - \bar{Y}^{treatment,before}) - (\bar{Y}^{control,after} - \bar{Y}^{control,before}),$$

where $\bar{Y}$ are the respective means of the outcome variable. Without providing the mathematical proof here, we can estimate the DID estimator for any outcome $Y_{i,t}$ by running a regression of the form:

$$Y_{i,t} = \alpha_0 + \alpha_1 Post_{i,t} + \alpha_2 Treated_{i,t} + \beta^{DID}(Post_{i,t} * Treated_{i,t}),$$

where $Post_{i,t}$ is a dummy taking the value of 1 if the observation is after the treatment, and 0 otherwise. Accordingly, $Treated_{i,t}$ is a dummy taking the value of 1 it the observation has been treated, and zero otherwise. The DID estimator is the coefficient in front of the interaction effect.

To be able to meaningfully run the difference-in-difference regressions based on our estimated institution-level demand functions, we need to select those institutions which joined PRI *during* our sample period (between 2010 and 2019), and for which we estimated sufficient amount of demand coefficients pre- and post signature. We define *sufficient* as an interval of 4 quarters before (including the signing quarter) and 4 quarters after the signature. While we believe that, considering lengthy processes of implementing investment strategies at large institutions, choosing longer time intervals would be more appropriate to observe meaningful joining effects, we are limited to a smaller window due to limited data availability. Based on the filters described above, we are left with a sample of 15 PRI investors out of the total 81 comprising the institution-level dataset. We manually match these 15 investors with comparable non-PRI investors based on type and AUM. For each of the PRI investors and their respective peers, we collect the demand coefficients 4 quarters before (including the signing quarter) and 4 quarters after the signature. We set $Post_{i,t}$ to 1 for every observation of a PRI investor or non-PRI peer that occurred after the PRI investor has signed PRI. Similarly, we set $Treated_{i,t}$ to 1 for every observation of a PRI investor. Based on this sample, we run the following regression:

$$b_{i,t}(env) = \alpha_0 + \alpha_1 Post_{i,t} + \alpha_2 Treated_{i,t} + \beta^{DID}(Post_{i,t} * Treated_{i,t}) + u_{i,t}. \quad (4.31)$$

To rule out other influences than the *PRI dummy* in affecting the investors' change in demand for green assets, we re-run the DID regression including a set of control variables. Specifically, we choose a set of $\boldsymbol{W}_{i,t}$ control variables based on the variables that have been proven significant in the regressions of Section 4.3.2, and construct the second regression model as:

$$b_{i,t}(env) = \alpha_0 + \alpha_1 Post_{i,t} + \alpha_2 Treated_{i,t} + \beta^{DID}(Post_{i,t} * Treated_{i,t}) + \boldsymbol{\omega}'\boldsymbol{W}_{i,t} + u_{i,t}, \quad (4.32)$$

where $\boldsymbol{\omega}'$ is a vector of regression coefficients tied to the control variables stacked in $\boldsymbol{W}_{i,t}$. We will specify the control variables in Section 5, after having established significant relationships based on the regression models of Section 4.3.2. As before, we note that the α regression coefficients in both models are not identical, but we drop additional superscripts to ease readability.

The difference-in-difference regressions allow us to conjecture whether *becoming* part of PRI is driving investors elevated demand for green assets. The other possibility would be that PRI investors in our sample exhibit structural differences from the non-PRI ones, making them demand greenness irrespective of their PRI membership. We will introduce some attempts to understand potential structural differences more closely in the subsequent section.

4.3.4 PRI vs. Non-PRI

To investigate in-sample PRI vis-a-vis non-PRI investors, we begin by running regressions of the PRI dummy on investor-specific variables, providing us with an understanding of the kind of investors that join PRI. Next, we test whether PRI investors exhibit a more aligned pattern of green demand. After that, we regress the environment coefficient on a set of variables for multiple sub-groups to see how the driving factors for green demand differ and where differences in green demand are originated. Finally, we construct an additional test aiming to find out whether PRI investors behave differently following market-wide ESG shocks.

In the first regression, we follow a setup used by Brandon et al. (2022) and regress an *adjusted PRI dummy* on *foreign*, *LNaum*, *turnover*, *AS*, *avgss*, *LNnhold*, the investor types, and an additional indicator variable reflecting the Paris 2015 agreement (PA). The *adjusted PRI dummy* restricts *PRI dummy* to the matches of type *"perfect" match* or *13(f) subsidiary match*. The PA variable is motivated by the hypothesis that the influential bilateral agreement on climate change signed by 196 countries at the 2015 UN Climate Change Conference (COP21) in Paris had an impact on institutional investors' likelihood to join PRI. Next to the commonly known emission reduction goals for signing countries, the PA mobilized large financial investments in climate mitigation (Ellis & Moarif, 2017). Alessi, Battiston, and Kvedaras (2021) find a significant reduction of holdings and engagement within carbon-intense companies by European institutional investors following the agreement in 2015. Interestingly, their study also reports a reversal of this trend after the U.S. announced the cancellation of their signature in the beginning of 2017. We, therefore, test two different implementations of *PostParis*: one with a cut-off date in December 2015, and one with cut-off in January 2017. In both implementations, we set *PostParis* to 1 for every observation being past the cut-off date. Including the other variables, the regression is specified as:

$$\begin{aligned} PRIdummy^{adj}_{i,t} =& \pi_0 + \pi_1 foreign_{i,t} + \pi_2 LNaum_{i,t} + \pi_3 turnover_{i,t} + \pi_4 AS_{i,t} + \\ & \pi_5 avgss_{i,t} + \pi_6 LNnhold_{i,t} + \pi_7 PostParis_{i,t} + \\ & \sum_{q=1}^{Q-1} \tau_q R_{q,i} + \sum_{s=1}^{S-1} \theta_s D_{s,i} + u_{i,t}, \end{aligned} \tag{4.33}$$

After inspecting PRI investors, we proceed by drawing comparisons to their non-PRI peers. As a first step, we aim to test the hypothesis whether PRI investors are less heterogeneous in green demand. This is motivated by the idea that in a homogeneous group of environmentally-conscious investors, we would expect a larger consensus in valuing sustainability. To test this, we employ a Levene-test, which describes a statistical test to compare variances of two sub-groups in a sample (Brown & Forsythe, 1974). We opt for the Levene-test since it is less sensitive to the assumption of normality than comparable tests.

Following the comparison of variances, we re-run regression (4.30) for the two subgroups of PRI and non-PRI investors. The groups are made such that the first one contains all the observations for which the *adjusted PRI dummy* equals 1, and the second one contains the remainder. In specifying the models, we exclude the PRI-specific variables *adjusted PRI dummy*, *PRIsubs*, *13Fsubs*, and *Subs*, and include *PostParis*. For the PRI-subgroup, we furthermore add the variable *Signature Year*, which indicates the year in which the signatory joined the initiative. *Signature Year* is motivated by insights from Majoch et al. (2017), who find different signature drivers for PRI members across the years, which relate to varying levels of principle implementation. The regression model is therefore given by:

$$b_{i,t}^{SG} = \eta_0 + \boldsymbol{\eta}'\boldsymbol{H}_{i,t} + \sum_{q=1}^{Q-1} \tau_q R_{q,i} + \sum_{s=1}^{S-1} \theta_s D_{s,i} + u_{i,t}, \tag{4.34}$$

where $\boldsymbol{H}_{i,t}$ is the set of variables used in regression (4.30), excluding the PRI-specific variables and including *PostParis* and *Signature Year*, and $\boldsymbol{\eta}$ is a vector of corresponding regression coefficients. The *SG* superscript on $b_{i,t}(env)$ indicates the respective sub-group of PRI and non-PRI investors.

While the regressions above inspect drivers of green demand for the two groups PRI and non-PRI investors separately, we are also interested in the drivers of the *differences* between both sub-groups. To detect those, we group PRI investors into cohorts based on deciles of demand-defining variables (variables from regression (4.29), excluding *foreign*) and cut-offs for *Signature Year*. Specifically, we construct multiple indicators for investors that are part of the bottom five deciles in these variables, or for investors which signed the initiative before a certain cut-off year. We then run regressions of $b_{i,t}(env)$ on the indicator, *adjusted PRI dummy*, investor controls (variables from regression (4.30) excluding *match type* indicators), and type- and time-fixed effects:

$$b_{i,t}(env) = \kappa_0 + \kappa_1 I_{k,i,t} + \kappa_3 PRIdummy_{i,t}^{adj} + \boldsymbol{\kappa}'\boldsymbol{G}_{i,t} + \sum_{q=1}^{Q-1} \tau_q R_{q,i} + \sum_{s=1}^{S-1} \theta_s D_{s,i} + u_{i,t}, \tag{4.35}$$

where $I_{k,i,t}$ are the indicator variables for the respective k variables we construct cohorts on, and $\boldsymbol{G}_{i,t}$ are the investor control variables. Based on this specification, the coefficient on the indicator (κ_1) magnifies the extent to which the underlying variable k drives differences between PRI and non-PRI investors.

Lastly, we construct a test comparable to the difference-in-difference method described in Section 4.3.3, to see whether PRI investors react differently to market-wide ESG shocks like the PA or the U.S. PA pull-out announcement. Intuitively, we would expect a stronger positive adjustment of green demand following PA, and a weaker negative adjustment following the U.S. pull-out announcement. To construct the model, we use the date of (1) the 2015 Paris Agreement and (2) the U.S. PA pull-out as cut-offs to assign pre- and post-indicators to the treatment (PRI investors) and control (non-PRI investors) groups. Moreover, in both models, we restrict the data to a time period of three years around the respective event, use only PRI investors where the *adjusted PRI dummy* equals one, and include a set of control variables containing all variables used in the model of the sub-group regression introduced earlier. We, therefore, specify the regression as:

$$\begin{aligned} b_{i,t}(env) =& \rho_0 + \rho_1 adjPRIdummy_{i,t} + \rho_2 Post_{i,t}^{Paris;US} + \\ & \rho^{DID}(PRIdummy_{i,t} * Post_{i,t}^{Paris;US}) + \boldsymbol{\rho}'\boldsymbol{G}_{i,t} + \sum_{q=1}^{Q-1} \tau_q R_{q,i} + \sum_{s=1}^{S-1} \theta_s D_{s,i} + u_{i,t}. \end{aligned} \tag{4.36}$$

If the above intuition is correct, we should recover a positive (negative) coefficient for the interaction of *PostParis* (*PostUSA*) and *PRI dummy*.

We conclude the methodology section with a brief summary of what we have outlined. Starting from the theoretical foundations of KY19's asset demand system, we have shown how we can construct and test an asset demand system which includes an extended set of characteristics, including one characteristic on the environment, where the coefficient indicates investors' demand for green assets. We then briefly outlined how we demonstrate the presence of demand heterogeneity in our estimation results. In the last section, we showed how we can investigate whether additional variables, primarily a membership in the PRI initiative, are explanatory of the differences in the heterogeneity for green demand. Building on this methodology, the upcoming section will present and interpret the results of our analysis.

5 Analysis

In line with the structure of the methodology, this chapter will be organized in three main sections, which attempt to provide answers to the three subquestions outlined in the introductory paragraphs. We will begin by providing the results to the estimation of the asset demand system, and describe how the asset demand of institutional investors in the U.S. can be characterized. Next, we quantify investor demand heterogeneity beyond type. Finally, we report the results of our regression analyses, which will give insights into the drivers of institutional investors' demand for green assets. Again, in the order presented here, the sections will provide the insights relevant to answer subquestions 1, 2, and 3, respectively.

5.1 Asset Demand System

5.1.1 Demand Coefficients

From estimating the demand system as specified in Section 4.1, we end up with 3,912 demand curves for 202 individual investors and 7,602 demand curves from pooling investors with fewer than 1,000 holdings by type and AUM. To gain a systematic overview of the magnitude and meaning of the coefficients, we present summary statistics of both AUM- and equal-weighted demand coefficients in Table 4. At first glance, one ought to notice that the demand coefficients are consistent with those estimated by Noh and Oh (2023) in terms of both magnitude and interpretation. For the demand coefficient on the log market-to-book characteristic, for example, the AUM- and equal-weighted averages of our estimates are 0.778 and 0.326 respectively, which are close to the AUM- and equal-weighted averages estimated by Noh and Oh (2023) of 0.699 and 0.349. Moreover, the fact that the equal-weighted average coefficient is significantly smaller than the AUM-weighted average implies that larger institutions have, on average, more inelastic demand. A similar intuition goes for most demand coefficients, as we observe significant differences between the AUM- and equal-weighted averages, with the AUM-weighted averages generally ranging closer to zero than the equal-weighted ones. This implies that the demand coefficients of larger investors tend to differ from the average investor. Moreover, it reflects the tendency of large investors taking less extreme positions, which is consistent with them holding more diversified portfolios.

To understand the intuition behind the average demand coefficient reported in Table 4, the AUM-weighted average demand coefficient for the environment score of 0.014 implies, ceteris paribus, that a one-standard-deviation change of the environment score is associated with a 1.4% increase in demand. As measured by the equal-weighted de-

Table 4: Summary statistics of demand coefficients

	AUM-weighted		Equal-weighted				
	Mean	SD	Mean	SD	Q10	Q50	Q90
Log market-to-book	0.778	0.232	0.379	0.326	-0.011	0.372	0.831
Log book equity	1.062	0.198	0.525	0.308	0.175	0.496	0.923
Foreign sales share	0.034	0.044	0.016	0.140	-0.146	0.013	0.179
Lerner index	0.039	0.087	0.141	0.216	-0.112	0.135	0.399
Dividend-to-book	0.026	0.077	0.050	0.126	-0.097	0.042	0.210
Market beta	-0.011	0.045	-0.101	0.155	-0.292	-0.095	0.081
Sales-to-book equity	0.063	0.073	0.016	0.129	-0.134	0.011	0.169
Environment score	0.014	0.086	0.021	0.121	-0.121	0.024	0.164
Entrenchment index	-0.010	0.059	-0.057	0.116	-0.193	-0.055	0.070

Note: This table reports the summary statistics of the AUM- and equal-weighted demand coefficients from the estimation of pooled- and institution-level demand curves.

mand coefficient, the associated change to the demand for an asset per one standard deviation of its environment score is slightly higher and equal to 2.1%. As such, investors demand firms with higher environment scores. For the entrenchment index, we observe the opposite for both the AUM- and equal-weighted averages, with coefficients of -0.010 and -0.057, respectively. The negative coefficients indicate that the average investor dislikes firms with a higher entrenchment index, which reflects poor governance. Intuitively, we also find a negative average coefficient for the AUM- and equal-weighted market beta coefficient, meaning that investors demand less of an asset on average if its systematic risk increases.

In Appendix C.2, we plot the times series evolutions of aggregated AUM- and equal-weighted average coefficients. One ought to notice that the demand inelasticity, as measured by the AUM-weighted average of the $b_{i,t}(me)$ demand coefficient, takes a significant dip around 2015. This implies the average investor's demand was more elastic during this period. When looking at Appendix C.3, which plots the AUM-weighted average of the demand coefficients by institution type over time, this decrease in inelasticity can likely be attributed to the household sector, whose log market-to-book coefficient takes a significant drop in this period. Interestingly, households even exhibit a negative coefficient during this period, which suggests that they demand more of an asset as its price increases. The negative coefficient could be explained by positive feedback trading among households (Gabaix et al., 2022), but might also be related to influences we cannot explain based on our selection of characteristics. Looking at

Appendix C.4, which portrays the latent demand recovered through Equation (4.10), we observe that households' latent demand peaks during this period. This indicates a large portion of unexplained demand variation for this investor type in 2015, which is a pattern consistent with KY19.

The evolution of the demand coefficients of the characteristics, as displayed in Appendix C.2, shows that we mostly do not observe noteworthy time trends, contrary to KY19. This is likely due to the short time period we observe. As one exception from this general observation, it seems that the equal-weighted average coefficient measuring the inelasticity of investors ($b_{i,t}(me)$) does exhibit an upwards trend, which suggests that investors' demand has, on average, become more inelastic between 2010 and 2019. Similarly, the equal-weighted average demand coefficients for the two productivity measures, $b_{i,t}(fss)$ and $b_{i,t}(sale_be)$, seem to be subject to a small downward trend, which implies that the average investor's demand for productivity is slightly decreasing over time. We attribute remaining, smaller time variations to data or estimation errors. The aforementioned coefficients are, however, not the main focus of this study. Accordingly, we will turn to investigate time trends in the demand coefficient for environment more closely.

We plot the evolution of both the AUM- and equal-weighted average environment coefficients in Figure 5. Here, one should notice that both averages take a drastic decrease at the beginning of 2015, yet increase substantially thereafter. The AUM-weighted average seems to peak at the beginning of 2016, while the equal-weighted average coefficient keeps increasing until mid-2016, where it takes a dip only to increase again until mid-2017. Both of the increases indicate that investors intensified their demand for green assets around 2016, making it all the more interesting to study the post-implementation effects of the PA. Inspecting the development of coefficients per investor type in Appendix C.3, we observe that the decrease is primarily driven by banks and investment advisors, while the increase stems from mutual funds, insurance companies, investment advisors, and households. This suggests that both phenomena are somewhat independent from each other since they are mostly driven by different agents in the market.

5.1.2 Validity of the Asset Demand System

Before proceeding with the analysis, it deems necessary to test the validity of the specification of the characteristics-based demand system and the GMM estimator using the two tests put forward in Section 4.1.4. First, we use stock-specific data to test if

Figure 5: Evolution of the average environment score coefficients

Note: This graph depicts the times-series evolution of the AUM- and equal-weighted environment score demand coefficient from pooled and institution-level estimation.

our set of asset characteristics are statistically significant determinants of and can explain the cross-sectional variation in valuation ratios. Second, we test the validity of the GMM estimator by estimating demand coefficients for a hypothetical index fund holding the market portfolio.

A. Valuation Regression

We adopt an approach suggested by KRY22 to test whether our asset characteristics can explain the cross-sectional variation in valuation ratios as measured by an asset's log market-to-book equity ratio. The regression results are presented in Appendix D.1, where we use Equation (4.21) to run regressions for two sample periods and two sets of asset characteristics. For the former (column (1)), year-end stock valuations are regressed on log book equity, market beta, dividend-to-book equity, FSS, Lerner index, and sales-to-book equity, where the sample period stretches over a period of 20 years given that more observations are available. For the latter (column (2)), we include the entrenchment index and environment score as regressors, limiting the sample period to 10 years due to the unavailability of these characteristics outside of 2010-2019.

From the regressions, we find that all the stock characteristics have coefficients statistically different from zero on all significance levels. Along with an F-statistic of 593.33 (column (2)), we can reject the null of joint statistical insignificance for the characteristics in explaining valuation ratios.[18] More so, we find that adding the two additional

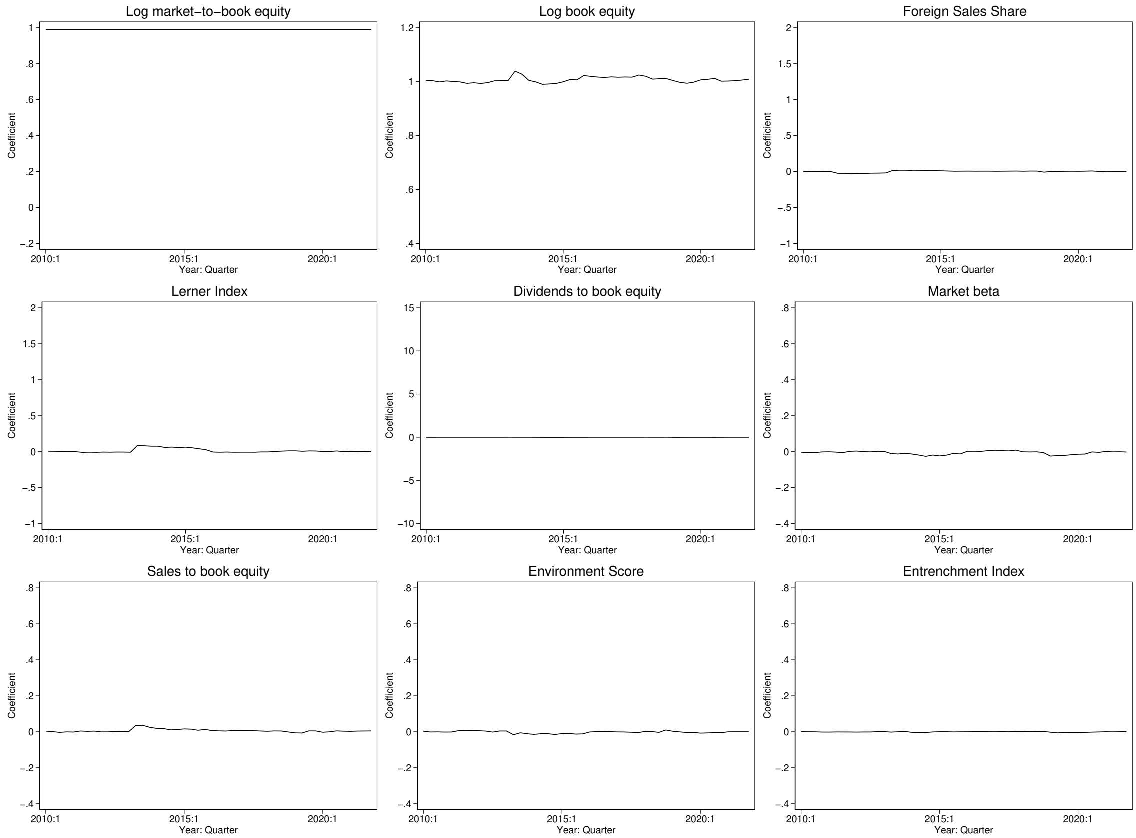
[18] The degrees of freedom for the F-statistic in regression in column (2) are 19 and 24048 for numerator and denominator, respectively. As such, the critical value for 1% significance is 1.88.

stock characteristics increases the adjusted R^2 of the regression from 0.211 to 0.319. Accordingly, environment score and entrenchment index increase the model's explanatory power substantially, making them valuable characteristics for the asset demand system. While the adjusted R^2 reported in Appendix D.1 is significantly lower than the one reported by KRY22, it ranges well within the benchmark of Noh and Oh (2023). We suspect the gap to KRY22 to arise from large discrepancies in sample sizes, as their study solely focuses on the largest 90% of stocks and we cover the overall stock market. We, therefore, conclude that the set of characteristics we use possesses significant explanatory power of the variation in valuation ratios, making it appropriate for our specification of characteristics-based demand.

B. Estimation Results on a Hypothetical Index Fund

To test the validity of the GMM estimator, we estimate the demand coefficients of a hypothetical index fund as described in section 4.1.4. Figure 6 reports the demand coefficients obtained from the estimation using alternative normalization. In line with our expectation, we recover a coefficient of one for the log-market-to-book equity characteristic and log book equity, and zero for all other coefficients, apart from small estimation errors. This implies that the demand of the hypothetical index fund, which holds the market portfolio, remains only contingent on changes in the market equity of assets throughout the sample period. This is consistent with the findings of KY19. More importantly, these results imply that the GMM estimator passes the validity test.

Figure 6: Hypothetical index fund coefficients



Note: Time-series of demand coefficients for a hypothetical index fund holding the market portfolio.

5.2 Investor Heterogeneity

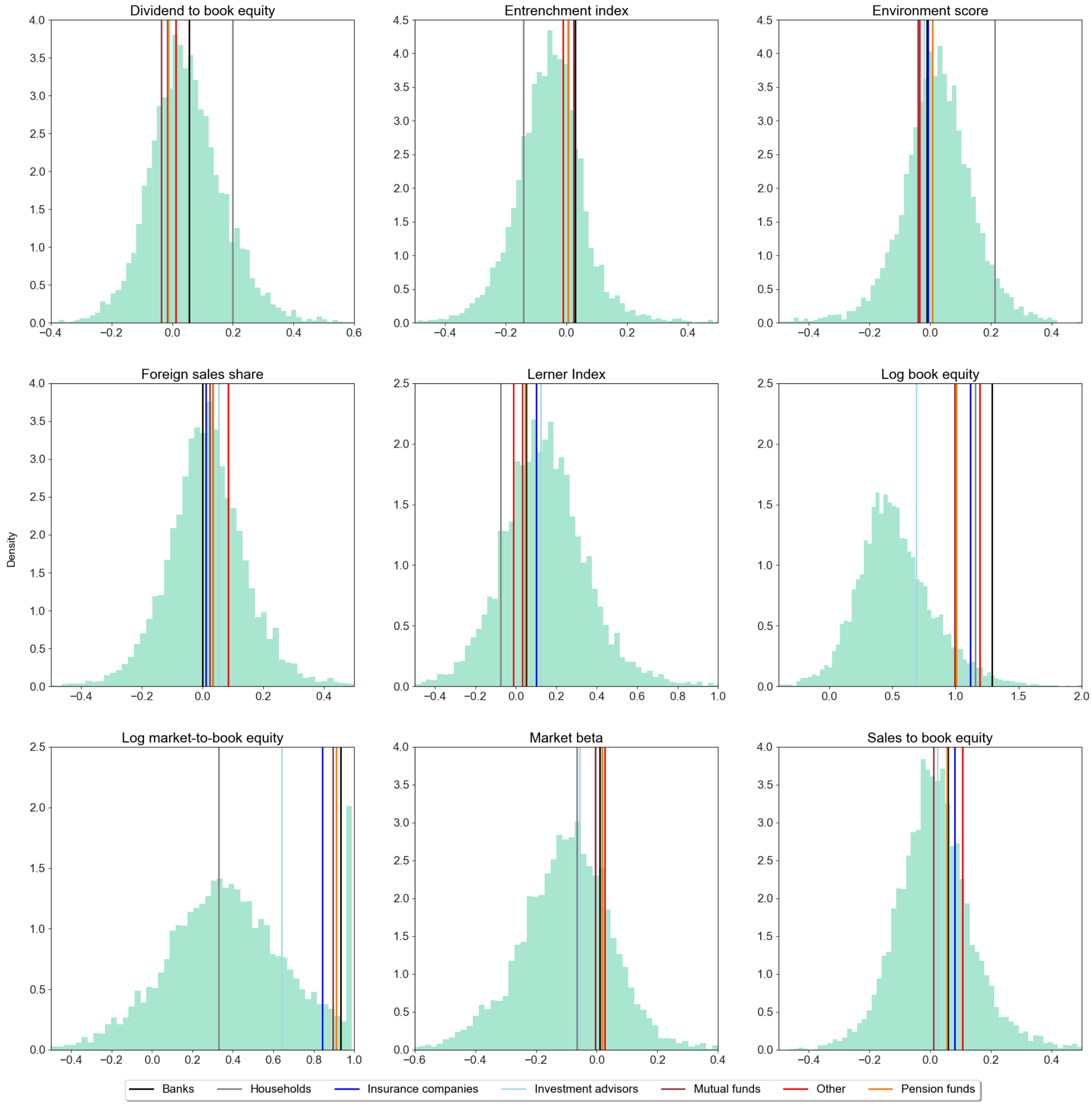
From the demand system estimated by GMM, we summarize all demand coefficients in Figure 7, where we plot coefficients for each characteristic in histograms. The vertical lines represent the AUM-weighted average of the demand coefficients per investor type and characteristic. Next to Figure 7, Table 5 shows the results from regressing the average demand curve coefficients on investor type for each characteristic. Based on the specification of the regression, the reported coefficients allow for two insights: First, their significance indicates whether investor types are important determinants in the variation of a demand coefficient. Second, they reflect the investor-group equal-weighted average demand coefficient when controlling for time-fixed effects. The distributions and regression both help to get an understanding of the heterogeneity, or the lack thereof, between investor types. In the following, we will walk through each characteristic and explain how its demand differs among investor types. Subsequently, we will discuss the explanatory power of investor types for demand variation.

For the first characteristic, namely the log market-to-book equity, Table 5 suggests that the seven different investor types are indeed statistically significant determinants of the demand elasticity of an investor. Institutional investors seem to, on average, have inelastic demand, except for investment advisors. This aligns well with KY19, KRY22, and Petajisto (2009, 2011), who argue that the demand of financial intermediaries is much more inelastic than suggested by neoclassical asset pricing models. The distribution of market-to-book equity coefficients in Figure 7 confirms this observation, as it peaks, similarly to KRY22, around a value of 1, which implies that the demand of a large amount of investors in our sample is highly inelastic. The more inelastic demand observed for investment advisors is likely due to their more concentrated portfolios and low AUM, which makes them highly exposed to price fluctuations. Apart from the institutional investors, households have, on average, the highest elasticity of demand, which is consistent with the findings of KY19 and KRY22.

Moving on to the demand coefficients on log book equity, the results portrayed in Table 5 suggest that all investor types exhibit a positive demand for firm size. As the only group, investment advisors fall somewhat short of this size demand. Interestingly, Figure 7 shows that the AUM-weighted average coefficients generally exceed the peak of the distribution substantially. This is likely caused by large institutional investors pulling coefficients up, which is also reflected in a slightly positive skew of the distribution and the discrepancy in AUM- and equal-weighted averages reported for the log book equity coefficient in Table 4. Overall, as suggested by the coefficient's significance, investor types are important determinants of variation in the demand for firm size.

For the foreign sales share, we do not observe substantial differences in demand coefficients for most investor types, except insurance companies and other 13(f) institutions. As Table 5 suggests, the average insurance company has a negative demand for firms with foreign sales. The opposite goes for other 13(f) institutions, who, on average, demand firms that diversify their sales to other geographical locations. Generally, the low amount of significant coefficients points towards the investor type not being a strong determinant of variation in the foreign sales share demand coefficient. For the Lerner index, Table 5 displays positive demand coefficients across all investor types. Most notably, when looking at the equal-weighted averages implied by the regression coefficients, it seems that banks have the highest demand for high-Lerner firms and pension funds the least. Moreover, the significance of most regression coefficients indicates that investor types are important determinants of the demand for the Lerner index.

Figure 7: Distribution of demand coefficients from non-linear GMM



Note: Histograms plotting characteristics-based demand coefficients from 2010-2019 for each distinct characteristic. Vertical lines indicate the AUM-weighted average coefficient for each type of institution averaged over time.

In terms of the dividend-to-book equity demand coefficients, pension and mutual funds exhibit, on average, negative coefficients. As such, the average pension and mutual fund move away from firms with dividend payouts. For pension funds, this confirms their long-term investment time horizon (Croce et al., 2011), which is reflected in a preference for re-investing retained earnings as opposed to issuing dividends. On the contrary, we see that banks, investment advisors, and other 13(f) institutions have, on average, positive demand coefficients for the dividend-to-book equity characteristic, which suggests that they demand dividend payouts. Again, the significance of many investor type coefficients in Table 5 indicates type to be an important determinant of the variation in the dividend-to-book equity demand coefficient.

In Table 5, one ought to notice that all investor types, except for pension funds, have, on average, negative market beta demand coefficients. This suggests that the average investor does not demand systematic risk. Inspecting the regression coefficients, banks seem to demand systematic risk the least. As mutual funds and insurance companies have coefficients closer to zero, they are, on average, more indifferent about the systematic risk of an asset. However, looking at Figure 7, we observe the AUM-weighted average coefficients for each investor type, except investment advisors and mutual funds, are positive, yet very close to zero. At the same time, the distribution of coefficients shows a slightly negative skew. Both observations imply that large investors generally demand more market beta, thereby tolerating more systematic risk. Like before, the significance of coefficients in the type regressions suggests that investor type is a relevant determinant of the variation in the market beta demand coefficient.

By regressing the demand-system sales-to-book equity coefficient on investor type, we note that most investor types exhibit a positive demand for firm productivity. Similarly to KRY22, we observe that households have the strongest taste for productive firms. Only mutual funds and investment advisors appear to be, on average, indifferent about sales-to-book equity ratios. In line with the previous interpretation, the significance of the majority of regression coefficients indicates that type is an important determinant of variation in the demand for sales-to-book equity ratios.

Turning to the environment score demand coefficients, we recover significantly positive demand for environmental sustainability for all investor types except mutual funds. The latter does not, on average, demand green assets, as their coefficient is slightly below zero. This observation is consistent with Hong and Kacperczyk (2009), who hypothesize that mutual funds tend to be natural arbitrageurs in the marketplace being more willing to buy sin stocks. For pension funds and insurance companies, we observe higher green demand, which aligns with Hong and Kacperczyk (2009) who argue that these two types of institutions are particularly constrained by social norms and scrutiny from the public. Similarly, Bolton and Kacperczyk (2021) report that pension funds and insurance companies have a greater appetite for environmentally friendly stocks and tend to underweight firms with a high production carbon emissions, and Bolton, Li, Ravina, and Rosenthal (2020) find more environmental consciousness among pension funds by studying investor ideologies. Interestingly, however, it seems that, among institutional investors, investment advisors have the highest demand for green assets, which we attribute to their smaller size and less diversified portfolios. In line with that intuition, when comparing the results from Table 5 to the environment score coefficient distribution plot in Figure 7, we see that the AUM-weighted average coefficients of the institutional investors hover closer to zero. Hence, larger institutional investors tend to have, on average, lower demand for green assets, which we relate to implications of portfolio size and diversification. Apart from institutional investors, Table 5 and Figure 7 show that the average household demands green assets by a significant margin, which is consistent with KRY22, and could be related to households' non-pecuniary benefits of holding these assets (Pástor et al., 2021). At last, the significance of coefficients in the type regression confirms that investor types are relevant in explaining dispersion in the demand for green assets.

For the last demand coefficient, namely the entrenchment index, we observe negative coefficients across all investor types, suggesting that investors tend to tilt their portfolios towards firms with a low entrenchment score. We recall that a lower entrenchment score corresponds to *better* governance. For mutual funds, we record the smallest demand coefficient, in absolute terms. Again, this aligns well with the findings from Hong and Kacperczyk (2009), as this type of investor is assumed to be less restricted by social norms and rather acts as a natural arbitrageur. Similarly to KRY22, we find that the average household exhibits the strongest demand for firms with good governance. As for the previous demand coefficients, we find that the investor type is helpful in explaining heterogeneity in demand for governance.

Table 5: Demand curve heterogeneity

	Dependent variable:								
	b_LNme	b_LNbe	b_fss	b_lerner	b_divA_be	b_beta	b_sale_be	b_env	b_ei
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pension funds	0.970***	0.963***	0.003	0.047***	-0.028***	-0.004	0.017**	0.019**	-0.012*
	(0.020)	(0.022)	(0.008)	(0.013)	(0.008)	(0.009)	(0.008)	(0.008)	(0.006)
Insurance companies	0.811***	0.914***	-0.021***	0.103***	-0.002	-0.038***	0.029***	0.018**	-0.021***
	(0.020)	(0.022)	(0.008)	(0.013)	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)
Banks	0.780***	1.112***	-0.006	0.208***	0.109***	-0.104***	0.037***	0.018**	-0.033***
	(0.019)	(0.021)	(0.008)	(0.013)	(0.007)	(0.009)	(0.008)	(0.007)	(0.006)
Mutual funds	0.842***	0.808***	0.005	0.074***	-0.041***	-0.037***	-0.008	-0.009	-0.003
	(0.019)	(0.020)	(0.007)	(0.012)	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)
Investment advisors	0.579***	0.602***	-0.006	0.108***	0.025***	-0.103***	0.004	0.024***	-0.047***
	(0.017)	(0.018)	(0.007)	(0.011)	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)
Other	0.723***	0.881***	0.032***	0.043***	0.049***	-0.076***	0.037***	0.020**	-0.053***
	(0.022)	(0.024)	(0.009)	(0.015)	(0.009)	(0.010)	(0.009)	(0.009)	(0.007)
Households	0.489***	1.115***	-0.024	0.005	0.177***	-0.079***	0.064***	0.180***	-0.151***
	(0.053)	(0.057)	(0.021)	(0.035)	(0.020)	(0.023)	(0.021)	(0.020)	(0.017)
Observations	11,512	11,512	11,512	11,512	11,512	11,512	11,512	11,512	11,512
R^2	0.161	0.210	0.033	0.041	0.101	0.077	0.029	0.023	0.038
Adjusted R^2	0.158	0.207	0.029	0.037	0.097	0.073	0.026	0.019	0.034
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Regressions of demand-system coefficients on type, including time-fixed effects. Statistical significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Although it might seem from the paragraphs above that we can uncover substantial heterogeneity by regressing the different demand coefficients on type, we also find that the adjusted R^2 for each individual regression is low. Similar to KRY22, we obtain the largest adjusted R^2 for the log market-to-book regression (column (1)), with a value of 0.158. In all other regressions, the adjusted R^2 lies below 0.1, and for the majority even below 0.05. This suggests that differences in type only explain little variation in demand coefficients among the investors in our sample. Hence, there remains plenty of heterogeneity to be uncovered beyond type, refuting the hypothesis raised in Section 4.2.1 that type could suffice as a determinant of demand heterogeneity. Among all the different demand coefficient regressions, we report the lowest adjusted R^2 for the environment score, which is also reflected in a large spread between the coefficient's 10th and 90th percentile (see Table 4). This shows that, for this characteristic in particular, there is still a lot of heterogeneity that can be uncovered - making it all the more relevant to understand the variation in the demand for green assets among institutional investors.

5.3 Green Demand

As we have seen in the previous section, we report substantial heterogeneity in investors' demand for asset characteristics, which remains unexplained by type and is especially pronounced within the environmental characteristic. Similar to KY19 and KRY22, we can raise the question which factors drive this heterogeneity. The objective of the present section is to address this question. By focusing on the environmental characteristic, we want to describe which investors demand more sustainability and why. The main variable in this investigation will be membership in the Principles of Responsible Investment (PRI) initiative. Since this variable is, along with other variables we will include in the analysis, measured on an institutional level, we are restricted to the use of the institution-level estimation results. These account for about a third of all estimated demand functions (3,912) and comprise 202 investors. Given the estimation threshold of 1,000 quarterly holdings, this institution-level sub-sample naturally focuses on the largest institutions in the holdings dataset. We furthermore exclude households from the observations since they are outside the scope of this analysis. Table 6 summarizes the composition of the sub-sample in a similar fashion to Table 1.

Table 6: Summary statistics of institution-level sub-sample

Period	Number of Institutions	Assets under management (mUSD)		Number of stocks in portfolio	
		Median	90th percentile	Median	90th percentile
2010-11	136	10,719	100,445	1,111	2,228
2012-13	147	12,217	101,674	1,147	2,086
2014-15	168	12,720	124,433	1,109	1,942
2016-17	173	12,561	127,504	1,177	1,963
2018-19	177	13,894	149,260	1,171	1,899

Note: This table shows the summary statistics of the institutions for which we estimated institution-level demand functions.

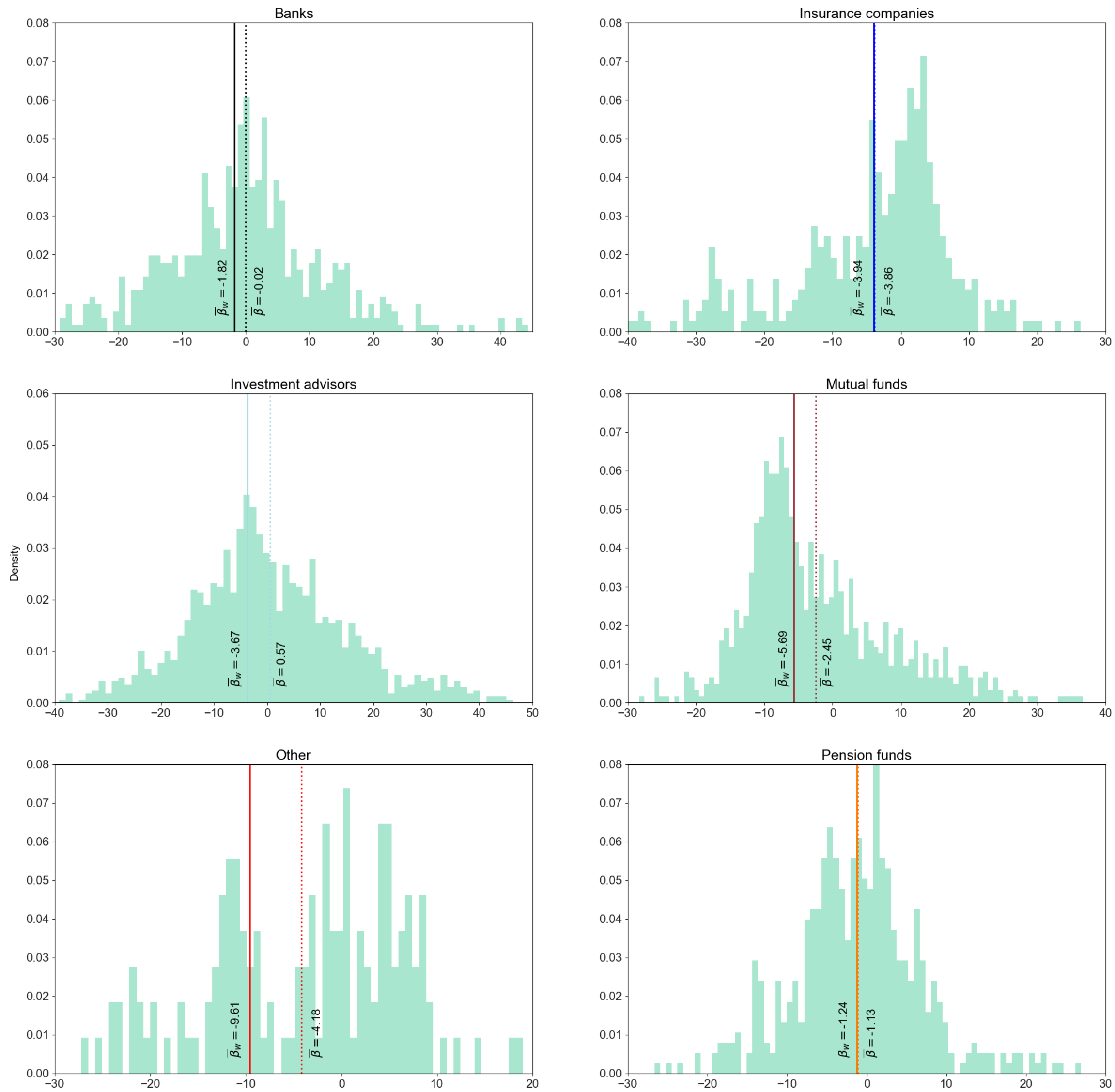
While the restriction to the sub-sample presents a limitation to our study, we still deem our approach to be appropriate for three main reasons: First, as we have seen in Section 3.3, the majority of US PRI investors are large financial intermediaries. We conjecture that we will obtain the most matches between 13(f) and PRI investors in the upper-end AUM percentiles. Second, we prioritize estimation precision over breadth. As with most estimators, the GMM estimator abides by the law of large numbers, allowing for more reliable estimation results with a higher number of observations (i.e., holdings). Third, as seen in Appendix B.4, the sub-sample is still well spread across all investor types. We discuss the limitation implied by our sub-sample and potential mitigation strategies in more detail in Section 6.

In the following, we will start by confirming green demand heterogeneity in the large-investors-only sub-sample, and proceed introducing the results from the regression analysis described in Section 4.3.2.

5.3.1 Sustainability demand among large investors

Limiting the institution-level estimation to large investors with quarterly holdings exceeding 1,000 can be seen as filtering our overall selection of investors for size. Since size is a factor to categorize investors (see, for instance, KRY22, Brandon et al. (2022), Noh and Oh (2023)), one could suspect that this already removes substantial parts of demand heterogeneity. We re-assure the continuous presence of dispersed demand for green assets by plotting the demand coefficients in histograms per type. Figure 8 confirms the insights derived from the full sample. Across all types, we see dispersed distributions. The most bell-shaped plot can be seen for investment advisors, in line

Figure 8: Distribution of environment score demand coefficients from institution-level estimation



Note: Distribution of the environment score demand coefficients for the in-sample managers. Vertical lines show the average environment demand coefficient weighted by AUM, $\overline{\beta}_w$*, for each investor type. The dashed vertical lines show the equal-weighted average coefficient,* $\overline{\beta}$*. The coefficients have been scaled by* $x100$ *for readability.*

with them contributing the largest number of observations to the sample. Consistent with the entire set of estimated demand functions, insurance companies and pension funds exhibit larger sustainability demand coefficients than mutual funds. For most types, the equal-weighted average coefficient exceeds the AUM-weighted average coefficient, indicating that larger institutions tend to have lower demand coefficients. The high dispersion within other 13(f) institutions can be due to the low sample size (6 investors between 2018-19) or the fact that this category pools investors with largely different investment strategies (e.g., hedge funds and endowments).

We also re-run the regressions of the environment coefficient on type for the institution-level sub-sample, and confirm previous findings (see Appendix D.2). With a low adjusted R^2 of 2.1%, type is still unable to explain the majority of variation in the environment coefficients.

5.3.2 PRI Regressions

As outlined in the Methodology, the main variable we aim to investigate regarding its influence on investors' green demand is the membership in the PRI initiative. Based on what we discussed about PRI in Section 3.3, we expect higher green demand among PRI investors, and thereby attempt to propose a variable that can contribute to the explanation of investor's green demand dispersion. We run three different regression analyses and report the results in the following.

A. Regression 1: PRI dummy and baseline variables

We recall from Equation (4.25) that the first regression relates the environment coefficient, $b_{i,t}(env)$, to $PRIdummy_{i,t}$ and additional variables reflecting size and investor origin, while controlling for type- and time-fixed effects. Table 7 reports the results in column (1). For readability, we drop the coefficients on investor types and time dummies.

The coefficient on *PRI dummy* is positively significant at the 1% level, indicating a positive impact of PRI membership on the green demand of large institutional investors. Moreover, the relationship is significant in size. A coefficient of 0.028 indicates that PRI investors in our sample have, on average, a green demand coefficient that is 0.028 larger than their non-PRI counterparts. This translates into a 0.028 higher demand increase for an asset whose environment score increases by one standard deviation. Comparing this to an equal-weighted average coefficient of -0.0104 across all investors in the sub-sample, the magnitude becomes apparent: Controlling for size, origin, type- and time-fixed effects, a PRI membership increases green demand, on average, by more than 250%.

Next to the *PRI dummy*, Table 7 also reveals a significant negative impact of investor size on sustainability demand. All else equal, a 10% AUM increase corresponds to a

0.0022 decrease in the demand for sustainability, which follows from the properties of log variables in level regressions. This indicates that, in our sample, larger investors demand less green assets, confirming the intuition provided by the distribution plots. Among potential reasons are that the largest investors in our sample are mutual funds, which tend to act as natural arbitrageurs, focusing on generating abnormal returns for their clients at the expense of investing responsibly (Hong & Kacperczyk, 2009). On the other side, larger investors might more likely be index funds, which, due to the nature of their mandate, have limited flexibility to tilt their portfolios excessively towards green assets. The results reported for size do not align with Brandon et al. (2022) and Noh and Oh (2023). For their respective measures of environmental sustainability (we compare to Noh and Oh (2023)'s *Environment Score*), they find the opposite impact of size. This likely has two reasons: One, they use different samples. Brandon et al. (2022) use global investor holdings, and Noh and Oh (2023) do not restrict their estimation to large 13(f) investors. Two, they use different measurements of environmental sustainability. Brandon et al. (2022) construct a blend of three sustainability scores (MSCI ESG, Sustainalytics, Refinitiv ESG), while Noh and Oh (2023) leverage MSCI ESG. Considering the large divergence found across ESG ratings (Berg, Kölbel, & Rigobon, 2022), this has the potential to tilt results significantly. For a further discussion of result divergences between comparable studies, we refer to Section 6.

The variable *foreign*, which reflects investors headquartered outside of the U.S., does not prove to be significant. This indicates that, in our sample, there is no difference in green demand related to investors being domestic or foreign. Without providing further proof, we suspect that headquarters play a minor role for very large investors, which operate on a global scale to a considerable extent, causing country-specific influences to diminish. Our findings are contrary to those of Brandon et al. (2022) and Noh and Oh (2023). However, due to the limited amount of foreign investors in our sample, we do not see ground to oppose those findings on the basis of this study.

While we find significant relationships, the adjusted R^2 remains at a low level of 7.4%, showing that a large portion of variance in $b_{i,t}(env)$ is still unexplained. We, therefore, include additional regressors in the following regressions.

B. Regression 2: PRI dummy and additional variables

As specified in Equation (4.29), the second PRI regression adds the additional variables turnover, active share (AS), number of holdings ($LNnhold$) and average share size (*avgss*) to the previous model.[19] We report the results in column (2) of Table 7.

First and most importantly, we see that the *PRI dummy* maintains its statistical and economic significance. This shows that the relationship of PRI membership and green demand is robust to a set of variables that have been shown to be explanatory of investors' green asset preferences.

Moreover, we identify four more variables being important determinants of institutions' green demand. To start, *turnover* negatively influences $b_{i,t}(env)$ at the 1% level. Specifically, an increase in turnover by 10% is associated with a 0.0146 decrease in green demand. As such, investors with longer investment horizons (lower portfolio turnover) show a higher demand for green assets, which is significant in magnitude. This confirms the findings reported by Starks et al. (2017) and Gibson and Krueger (2017). Among potential explanations is that long-term investors evaluate different information than their short-term counterparts. For instance, they are less influenced by negative earnings surprises, which might occur for ESG-focused firms that aim to create value in the long-term. Other reasons could be that arbitrage opportunities for short-term investors are limited for ESG assets, or that long-term investors serve a different clientele (Starks et al., 2017). The higher green demand for long-term investors is also consistent with the results reported in Brandon et al. (2022) and Noh and Oh (2023).

We also find that active investors in our sample demand less green assets. Albeit being less significant, the coefficient on $AS_{i,t}$ is negative at the 5% level. While this is somewhat opposite to what L. Chen et al. (2020) and Noh and Oh (2023) find, it confirms the findings in Brandon et al. (2022), and is consistent with the hypothesis that active investors take advantage of cheap *brown* assets in their tendency to prioritize positive abnormal returns over non-pecuniary benefits.

Lastly, we observe that both the number of holdings and average share size impact green demand negatively at the 1% level. Therefore, in our sample, investors that hold more and larger assets (measured by market capitalization) exhibit a lower demand for green assets. The negative coefficient on number of holdings is consistent with the coefficient reported on size: A higher AUM is likely to go hand-in-hand with a higher number of holdings. In fact, we find a correlation of 0.54 between *LNaum* and

[19] We report the correlation matrix of the variables in Appendix D.3 and find that the correlation coefficients between variables fall well within the collinearity threshold of $r < |0.7|$ (Dormann et al., 2013).

LNnhold in our sample. Moreover, it suggests that investors holding more concentrated portfolios exhibit a higher green demand, which is consistent with the intuition of more diversified investors showing less extreme portfolio tilts. The negative influence of stock size could be due to larger stocks having generally worse environment scores. This would, however, be surprising, considering that large firms are found to possess an edge in ESG reporting and tend to outperform smaller firms in corporate sustainability in previous studies (Artiach, Lee, Nelson, & Walker, 2010). We can also not confirm this intuition based on the cross-section of Sustainalytics scores and market equity in our stock data. While remaining to be somewhat puzzling, the relationship between share size and sustainability demand is consistent with the results reported by Brandon et al. (2022). Noh and Oh (2023) find a positive, but weak, relationship.

Overall, by including the additional variables, we are able to increase the explanatory power of the model considerably, reaching an adjusted R^2 of 13.7%. However, this still leaves a large chunk of variation unexplained, which we aim to reduce further by including additional variables.

C. Regression 3: PRI dummy and extended variables

In this regression, we extend the analysis conducted by Brandon et al. (2022), and test hypotheses that are, to our knowledge, new in the application of asset demand systems and PRI membership. Specifically, we add three variables to the previous regression model: The first two are the estimated demand coefficients $b_{i,t}(ei)$ on the entrenchment index and $b_{i,t}(LNme)$ on log market(-to-book) equity, and the third one is an indicator for the PRI *match types*. The results are reported in column (3) of Table 7.

Again, we find that the coefficient on *PRI dummy* remains to be statistically significant and relevant in size. In fact, it even increases slightly, from 0.028 to 0.029. Thus, in our sample, the positive influence of PRI membership on green demand is robust to an even larger set of variables. We conjecture that this serves as sufficient evidence for arguing that, in our sample, PRI investors have, all else equal, a higher demand for sustainability than their non-PRI peers. We recall the first two principles of PRI, which state that investors should incorporate ESG in their investment decision and push for ESG considerations in their portfolio companies. While we cannot, based on the current analysis, distinguish which principle is the driving force in the higher sustainability preferences, we can argue that these principles seem to be somewhat manifested in the investment and portfolio management behavior of large members, at least with respect to the environmental dimension.

Table 7: PRI regressions

	Dependent variable: $b_{i,t}(env)$		
	(1)	(2)	(3)
const	0.186***	1.135***	0.862***
	(0.021)	(0.210)	(0.209)
PRI dummy	0.028***	0.028***	0.029***
	(0.005)	(0.005)	(0.006)
LNaum	-0.022***	-0.024***	-0.019***
	(0.001)	(0.002)	(0.002)
foreign	-0.007	0.001	0.002
	(0.006)	(0.006)	(0.006)
turnover		-0.146***	-0.120***
		(0.011)	(0.011)
AS		-0.044**	-0.056***
		(0.020)	(0.020)
LNnhold		-0.057***	-0.041***
		(0.014)	(0.013)
avgss		-0.052***	-0.036***
		(0.014)	(0.014)
b(ei)			-0.264***
			(0.026)
b(LNme)			-0.046***
			(0.012)
PRIsubs			-0.030***
			(0.008)
13Fsubs			0.005
			(0.007)
Observations	3,870	3,752	3,752
R^2	0.085	0.148	0.179
Adjusted R^2	0.074	0.137	0.167
Type-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes

Note: Regressions of the environment coefficient on PRIdummy, including additional variables. The numbers (1), (2) an (3) correspond to the regression models 1, 2, and 3 specified in Section 4.3.2. Statistical significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

What we cannot yet say is whether the PRI membership is actually driving the above-mentioned behavior. One could hypothesize that PRI investors have been environmentally conscious before joining the initiative, in which case it would not be the signature that makes them demand more green assets. We test the robustness of our *PRI dummy* to this hypothesis based on a difference-in-difference approach and report the results in the subsequent section. Compared to Noh and Oh (2023) and Brandon et al. (2022), we report contrary results. Controlling for a similar set of variables, Noh and Oh (2023) find no significant impact of PRI membership on their environment coefficient at all, while Brandon et al. (2022) arrive at even *negative* influences of a PRI membership when looking at U.S. investors in isolation. Like before, we relate the result discrepancies to differences in samples and data sources, and refer to Section 6 for implications of our analysis in the light of previous findings.

Next to the *PRI dummy*, we find three more significant relationships. First, we report a significantly (1% level) negative impact of *PRIsubs* on green demand. Thus, in-sample institutions which signed PRI on a lower entity level than the one we have estimated demand functions for exhibit lower green demand than their *perfectly* matched counterparts. In fact, *PRI subsidiary* matches have, on average and all else equal, an environment demand coefficient which is 0.03 lower, thereby entirely eradicating the positive effect stemming from the *PRI dummy.* In other words, signing PRI at a subsidiary level seems to not have any impact on the green demand at group level. We infer that the reach of a PRI membership, i.e., the breadth of the implementation of the PRI principles, is limited to the (sub-)entity in which the initiative was signed. Conversely, the spill-over effects of one subsidiary entity joining PRI on the rest of the organization seem to be limited. Consistent with that, we do not find a significant difference in sustainability demand between *Perfect matches* and *13F subsidiary matches*, indicating that the effects of a group-level signature trickle down into the subsidiaries, but not the other way around. The takeaways from these results are two-fold. First, this aligns with findings in Brandon et al. (2022), which report substantially lower *ESG footprints* for signatories who commit only parts of their AUM to the initiative. Second, this supports the intuition that PRI signatories show distinct behavior towards sustainability, since the positive effect in the *PRI dummy* is isolated to the entity which signed the initiative.

We furthermore find important relationships between estimated demand coefficients. The demand coefficient on the entrenchment index, $b_{i,t}(ei)$, is negatively significant at the 1% level. As such, in our sample, lower demand for entrenched firms (that is, poor governance) is associated with higher demand for green assets. In other words, investors that demand good governance also demand green assets. This effect comes at a relevant magnitude. An increase in $b_{i,t}(ei)$ by 0.01 (roughly 5% of the average) translates into a decrease in $b_{i,t}(env)$ of 0.003 (roughly 30% of the average). The relationship confirms the presence of holistic ESG investment strategies within ESG-conscious investors, at least on the E and G dimensions. While this insight makes intuitive sense, it also raises concerns about the simultaneity of governance and environment demand. We will discuss this issue in more detail in Section 6.

The demand coefficient on log market(-to-book) equity, $b_{i,t}(me)$, is negatively significant at the 1% level. This indicates that more price-inelastic investors in our sample exhibit a lower demand for sustainability. Specifically, an increase of $b_{i,t}(me)$ by 0.1, which relates to a higher price inelasticity of about 11% (coming from an equal-weighted average of 0.88 in the institution-level sub-sample), corresponds to a lower sustainability demand coefficient of 0.0046 (roughly 46% of the average). Considering that ESG performance tends to pay off in the long-term and is preferred by long-term investors, which we would expect to react less drastically to price changes, the effect found here is somewhat puzzling, albeit consistent with the results in Noh and Oh (2023). Taking the alternative interpretation of $b_{i,t}(me)$ (see Section 4.3.2), we could make more intuitive sense out of the results. If we view $b_{i,t}(me)$ as the demand for market-to-book equity, lower values correspond to more value-like investing. The negative coefficient on $b_{i,t}(me)$ in this present regression would thereby indicate that value-like investors have a higher demand for sustainability, which is consistent with the long-term attributes of value investing and the findings in Kaiser (2020). We leave a deeper discussion of the influence of $b_{i,t}(me)$ for further research, but will touch upon the limitations of the findings presented here in Section 6.

Overall, the extended set of variables enables us to boost the explanatory power of our model to an adjusted R^2 of 16.7%. While this is a substantial increase compared to the results of the type-only (Appendix D.2) and baseline variables (column (1)) models, and slightly exceeds what Noh and Oh (2023) report for their regression on the environment score coefficient, it still leaves a large portion of variance unexplained. Due to data limitations, we refrain from investigating further variables and instead drill deeper on the relationships found so far, especially with regards to the *PRI dummy*.

5.3.3 Difference-in-Difference Regressions

As touched upon in the previous section, we find evidence that PRI investors in our sample exhibit stronger preferences for sustainability than their non-PRI peers. In the coming section, we want to test whether the higher green demand is actually rooted in the PRI signature, or if PRI investors have already been into sustainability before signing the initiative. To conduct this test, we employ a difference-in-difference approach as outlined in Section 4.3.3. We report the results from the difference-in-difference regressions excluding and including control variables in column (1) and (2) of Table 8, respectively.

A. Difference-in-difference excluding control variables

From the first difference-in-difference regression excluding controls, we find that the interaction effect (*signing effect*), as measured by the *PRI dummy*, is not statistically different from zero on any significance levels. That is, we do not observe that the institutional investors in our sample systematically alter their demand for green assets post-signing relative to the control group. This finding is consistent with Brandon et al. (2022), who likewise report that the signing effect is not statistically significant with respect to the environmental footprint of an investor's portfolio.

Interestingly, the constant is statistically significant on all levels. This implies that, holding everything else equal, the control group is associated with an average green demand coefficient of -0.059 pre-treatment, which ranges considerably below both the AUM- and equal-weighted average demand coefficients reported in Table 4. This observation reflects the composition of the control group being mainly comprised by larger investors. As we have shown previously, there are many more determinants of green demand than only PRI membership. To reflect these influences and increase the robustness of our findings, we control for a number of relevant investor-specific characteristics in the second regression.

B. Difference-in-difference including control variables

We add dummy variables for each investor type as well as investor controls on portfolio characteristics given by active share, turnover, average stock size, the log of AUM, and the log of the number of holdings to the regression.

Including controls, we still find no evidence of a PRI signing effect on the demand for green assets. That is, the *PRI dummy* coefficient is still not statistically different

Table 8: Difference-in-difference regression

	Dependent variable: b_env	
	(1)	(2)
const	-0.059***	4.824***
	(0.013)	(1.160)
Treatment	0.027	0.024
	(0.018)	(0.016)
post	0.004	0.006
	(0.018)	(0.016)
PRI_dummy	-0.029	-0.033
	(0.025)	(0.020)
Observations	240	240
R^2	0.012	0.469
Adjusted R^2	-0.000	0.362
Investor controls	No	Yes
Type-fixed effects	No	Yes

Note: Difference-in-difference regressions comparing PRI investor's demand for environmental sustainability pre- and post signature, benchmarked with their non-PRI peers. Statistical significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

from zero, meaning that we fail to reject the null hypothesis that investors joining the PRI do not change their demand for green assets relative to the control group post-signing. Tying the lack of a signing effect to the findings from Section 5.3.2 on the positive relationship between PRI membership and green demand, it suggests that the in-sample PRI investors are systematically different in other ways than their PRI membership. That is, other factors could have driven them to be more environmentally-conscious prior to joining the PRI. In this interpretation, the PRI membership appears like a "low-hanging fruit" for already-sustainable investors, which could undertake the signing for reputational purposes, to attract new business, or because it aligns with their organizational values (Majoch et al., 2017).

5.3.4 PRI vs. Non-PRI

Following the results from the previous section, we aim to understand more about the structural differences between PRI and non-PRI investors: If they are distinct with respect to their sustainability demand, but this distinction does not stem from the PRI signature, where else might it come from?

To start, we want to understand what kind of investors in our sample join PRI. Table 9 reports the results for the regression specified in Equation (4.33). Column (1) and (2) are the same models except for the PostParis (1) and PostUSA (2) dummy variables, which indicate observations after the Paris 2015 agreement and after the announcement of the U.S. drop-out, respectively. We find that, in our sample, larger investors with more diversified portfolios containing larger stocks are more likely to be part of PRI. Interestingly, these investors also exhibit *higher* turnover. All these relationships are contrary to the influences we found for those variables in the $b_{i,t}(env)$ regressions. We interpret this as PRI investors in our sample demand green assets *despite* their characteristics, which do not predispose them to do so. This way, PRI could be seen as a tool for these investors to learn responsible investment practices (Sievänen et al., 2013).

On top of that, we see that the *foreign* dummy variable becomes significant in this regression, at the 1% level. Despite the small number of foreign investors in our sample, we still observe that those are more likely to be part of PRI. This aligns with the PRI summary statistics in Brandon et al. (2022), which state that the majority of PRI signatories are based outside of the U.S.

Lastly, we observe an increase in PRI membership after the 2015 Paris Agreement, albeit not being significant. We do not see a drop in PRI memberships after the 2017 announcement of the U.S. to pull out of the agreement. The coefficients and standard errors of those two dummies being equal indicates that we are lacking observations of PRI joiners in the time period between the beginning of 2016 and 2017, potentially explaining the absence of significance.

We now compare the two sub-groups of PRI and non-PRI investors in our sample more closely. We start out by testing the hypothesis that PRI investors exhibit a smaller dispersion in their green demand coefficients. This is motivated by the idea that for a homogeneous group of environmentally-conscious investors, we would expect a larger consensus in valuing sustainability. We run a Levene-test to compare the sub-

Table 9: PRI dummy regressions

	Dependent variable: PRI dummy	
	(1)	(2)
Constant	-3.437***	-3.437***
	(1.018)	(1.018)
LNaum	0.099***	0.099***
	(0.005)	(0.005)
foreign	0.188***	0.188***
	(0.020)	(0.020)
turnover	0.090**	0.090**
	(0.037)	(0.037)
AS	-0.331***	-0.331***
	(0.067)	(0.067)
LNnhold	0.121**	0.121**
	(0.056)	(0.056)
avgss	0.154**	0.154**
	(0.074)	(0.074)
PostParis	0.137	
	(0.091)	
PostUSA		0.137
		(0.091)
Observations	3,752	3,752
R^2	0.235	0.235
Adjusted R^2	0.225	0.225
Time-fixed effects	Yes	Yes
Type-fixed effects	Yes	Yes

Note: Regression of PRI dummy on investor-specific variables. Column (1) includes a PostParis dummy, indicating observations after the 2015 Paris Agreement (PA), and column (2) contains a PostUS dummy, marking observations after the U.S. announced their pull-out of PA in January 2017. Statistical significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

group variances, and recover a p-value of 0.087, which ranges above the critical value of 0.05. As such, there is no significant difference in the dispersion of sustainability demand between PRI and non-PRI investors. We infer that PRI investors misalign on sustainability demand to the same extent as non-PRI investors do, albeit at a higher level. Moreover, with a similar level of demand variance, this result raises the question which investors among the PRI group are driving the higher environmental consciousness we observe. The following regressions will give some insights into this.

We regress the environment coefficient on the same set of variables as in column (3) of Table 7, except for the PRI-specific variables (*PRIsubs*, *13Fsubs* and *Subs*), which we exclude for the non-PRI sub-group. In addition, we include the *PostParis* dummy from the previous analysis as well as a *Signature Year* variable for the PRI sub-group. We report the results in Table 10, where column (1) and (2) give the regression output for the PRI and non-PRI sub-groups, respectively. Inspecting column (1), we observe that among the PRI investors in our sample, the ones with lower AUM, lower turnover, higher active share, less holdings, and holdings of smaller stocks exhibit higher green demand. All these effects align with the results for the total and non-PRI sub-group, albeit being stronger in the PRI group, except for turnover and AUM. We therefore cannot observe structural differences based on these variables.

For the governance demand coefficient, $b_{i,t}(ei)$, we obtain no significance in the PRI, but in the non-PRI group. It appears that demand for good governance does not coincide with green demand for PRI investors but does so strongly for non-PRI ones. We suspect this discrepancy to arise due to a more consistent demand for good governance in the PRI group, given that their membership in the initiative requires the implementation of holistic ESG investment strategies. In fact, running a levene test for $b_{i,t}(ei)$ comparing its variances in the two sub-groups of PRI and non-PRI investors reveals a significantly lower variance for PRI investors, thereby offering support for this intuition.

Within the PRI group, we observe that the signature year negatively impacts investors' demand for green assets. This suggests that, in our sample, the early signatories are the ones driving the higher green demand observed for PRI members. To understand the influence of *Signature Year* in more detail and analyse which other subsets of PRI investors are responsible for the significant PRI effect, we group PRI investors into cohorts based on *Signature Year* cut-offs and percentiles of variables that are determinants of green demand. Specifically, we include indicators marking investors which are within the bottom five deciles of *turnover*, *AS*, *LNaum*, *avgss* and *LNnhold* or which signed PRI in the early years into regressions of $b_{i,t}(env)$ on the *adj PRI dummy*, investor controls, and type- and time-fixed effects. We report the results in Appendix D.4, where the *Bottom group* line indicates whether the bottom-decile or early-signature PRI investors significantly alter the PRI effect. Testing multiple cut-off years, we recover a significantly positive impact of *Signature Year* on the PRI effect for all signatures before 2010. This finding relates well to the intuition provided by Majoch et al. (2017), who report that the signing of early joiners is more prominently driven by value alignment between the investor and PRI, which is associated with a higher degree of implementation of the initiative's principles. Interestingly, we observe that PRI investors with *higher* turnover positively impact the PRI effect. We see this as a confirmation of the intuition derived from the regressions in Table 9 in the sense that short-term investors, which are typically unlikely to demand greenness, are substantially greener when being part of PRI. Conversely, long-term PRI investors, which already demand more greenness, differ less from their non-PRI peers. Apart from investment horizon, the significantly negative (positive) coefficients for *avgss* (*LNnhold*) indicate that investors holding larger shares (more concentrated portfolios) drive the PRI effect. This is consistent with previous findings of larger firms showing ESG out-performance (Artiach et al., 2010), and the intuition that more concentrated portfolios correlate with more "extreme" tilts towards a certain characteristic.

Going back to the sub-group regression of Table 10 and inspecting the *PostParis* dummy, we obtain significantly positive coefficients in both sub-groups (see Table 10). As such, in our sample, green demand increased substantially in the period after the agreement. This is consistent with the end-2015 spike observed in the time-series plots of the environment coefficient (Figure 5). Interestingly, the coefficient for PRI investors is more than nine-fold the one of non-PRI investors, which could indicate that PRI investors increased their green demand more excessively following the agreement. To test this and analyze whether PRI investors react differently to a major climate-related event, we run a similar difference-in-difference approach as in Section 5.3.3, using (1) the PA and (2) the U.S. PA pull-out announcement as climate-related events. We describe the methodology in detail in Section 4.3.4. If PRI investors behave more environmentally conscious, we would expect them to react more strongly to a climate push (like the PA) and less strongly to a climate setback (like the U.S. pull-out announcement). Appendix D.5 reports the results. We obtain slightly negative, but insignificant, coefficients on the DID estimator in both regression models, and therefore reject the hypothesis that PRI investors reacted more positively (less negatively) to the PA (U.S. PA pull-out announcement) event. The negative coefficient of the DID estimator in the *PostParis* model could even indicate the opposite, potentially pointing towards a larger "catch-up" needed by non-PRI investors post-Paris in terms of environmental sustainability.

Table 10: PRI regressions for PRI and non-PRI sub-groups

	Dependent variable: $b_{i,t}(env)$	
	(1)	(2)
const	22.471***	2.050***
	(3.060)	(0.320)
LNaum	-0.017***	-0.025***
	(0.004)	(0.002)
foreign	-0.006	0.006
	(0.013)	(0.007)
turnover	-0.054*	-0.147***
	(0.030)	(0.012)
AS	-0.151***	-0.074***
	(0.051)	(0.022)
LNnhold	-0.358***	-0.064***
	(0.042)	(0.018)
avgss	-0.281***	-0.152***
	(0.062)	(0.023)
b(ei)	0.089	-0.311***
	(0.062)	(0.029)
b(LNme)	-0.123***	-0.045***
	(0.033)	(0.013)
PostParis	1.084***	0.181***
	(0.140)	(0.030)
Signature Year	-0.009***	
	(0.002)	
Observations	749	3,003
R^2	0.278	0.223
Adjusted R^2	0.239	0.207
Time-fixed effects	Yes	Yes
Type-fixed effects	Yes	Yes

Note: Regression of the environment coefficient on a set of investor-specific variables. Column (1) and (2) run the regression for the PRI and non-PRI sub-groups, respectively. Statistical significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

We conclude the analysis with a brief recap of our main findings. Studying the estimated demand curves, we obtain similar coefficients to previous studies, reaffirming the specification of our asset demand system. Regressing stock characteristics on valuation ratios and the estimation of a hypothetical index fund further strengthen the validity of our model. Inspecting differences between AUM- and equal-weighted coefficients, we see that large investors mostly tilt coefficients towards less extreme values, reflecting their highly diversified portfolios. Overall, institutional investors prefer firms with better environment scores, better governance, lower systematic risk, higher productivity, and higher profitability. For the environment score, investors' demand peaks coincidentally with the 2015 Paris Agreement.

Proceeding to investor heterogeneity, we show that asset demand is highly dispersed and unexplained by investor type. Long-term oriented investors, like pension funds and insurance companies, demand more sustainability than natural arbitrageurs like mutual funds. However, those differences only explain 1.9% and 2.1% of $b_{i,t}(env)$'s variance in the full- and institution-level sub-sample, respectively. Moreover, differences in AUM- and equal-weighted average coefficients point towards the importance of size as a determinant of demand heterogeneity.

Limiting the analysis to large investors covered by the institution-level estimation, we show that PRI investors have significantly higher demand for green assets, which is relevant in size and contradicts results of previous studies. This effect appears to be restricted to the entity-level in which the institution signs the initiative. We find evidence that demand for governance positively impacts green demand, supporting the presence of holistic ESG mandates. Next to that, our sample indicates that smaller, more active, value-liking long-term investors who hold less and smaller assets exhibit a higher demand for green assets. When attempting to isolate the PRI effect, we neither find evidence that a signature of PRI elevates green demand nor that PRI investors react differently to broad climate-related shocks like the PA. Moreover, green demand appears to be as dispersed among PRI investors as it is among their non-PRI peers, and we are at most able to explain about a quarter of this dispersion with the variables we use. Inspecting PRI signatories in our sample, we see indications that investors who would typically be less likely to demand green assets sign PRI. In fact, the positive PRI effect seems to be driven by early and short-term oriented signatories holding larger stocks in more concentrated portfolios. As the last results paint a somewhat ambivalent picture, we suspect structural differences between PRI and non-PRI investors, apart from the signature, which remain unexplained based on the data at hand.

6 Discussion

As we have touched upon previously, the purpose of this discussion is to put our findings into perspective. This generally has four dimensions: the result itself, a comparison to previous research, potential limitations and corresponding mitigations, and theoretical and practical implications. We will discuss the main categories of findings corresponding to the subquestions of this paper, namely Asset Demand System, Investor Heterogeneity, and Green Demand, along these four dimensions.

6.1 Asset Demand System

In this paragraph, we briefly summarize the main findings from the estimation of the characteristics-based demand. Firstly, we found, on average, a positive demand for productive, profitable, and environmentally friendly assets yet a negative demand for bad governance and market risk. Moreover, the average institutional investor seems to have a highly inelastic demand, while the opposite goes for households. In terms of time trends, both the AUM- and equal-weighted average environment score coefficients are subject to a significant increase towards the end of 2015. Lastly, we observed that the AUM-weighted average coefficients were generally smaller than the equal-weighted coefficients in absolute terms, which suggests that larger investors take less extreme positions in their portfolios.

A. Comparison to previous research

The inelastic demand, as inferred from the high log market-to-book equity coefficients, aligns neatly with the emerging body of literature refuting the common assumptions from neoclassical asset pricing models holding that demand is elastic (Petajisto, 2011, 2009; Da et al., 2018; Koijen & Gabaix, 2021). Since they are either using partly different characteristics or types, the easiest way to match our demand coefficients with KY19 and KRY22 is by comparing estimates for the household sector, as it is the residual investor (i.e. if not specified correctly, we would expect significant deviations from the two papers). We infer that the household sector is the most elastic investor and has the highest demand for green assets as well as good governance in all instances. Similar to KY19, we observe that the demand elasticity of the household sector takes a dip around 2015, which is likely attributable to changes in their latent demand or that they react more to feedback trading around this time (Gabaix et al., 2022).

Given that KRY22 use the same set of characteristics, we can draw comparisons to their distribution of demand coefficients. Here, we note that their environment and governance coefficients follow a normal distribution and that the distribution of their log book equity coefficient has a negative skew. This is consistent with our histograms in Figure 7. Moreover, we also seem to, generally, have similar demand coefficients as Noh and Oh (2023) as illustrated by their AUM- and equal-weighted demand coefficients. Contrary to our results, they report that the AUM-weighted average for the environment coefficient is slightly higher than the equal-weighted one. However, given that the AUM- and equal-weighted environment coefficients are almost identical, we regard this divergence as a minor issue, which is likely to be induced by differences in data sources.

The fact that our demand coefficients relate closely to Noh and Oh (2023), KY19, and KRY22 imposes two important implications regarding the validity of our findings: First, it validates the specification of our demand system. Second, it implies that we have sourced, cleaned, and treated our data correctly.

B. Limitations

To test the validity of our non-linear GMM estimator and the specification of the demand system, we have adopted two approaches suggested by KY19 and KRY22. First, we estimate demand coefficients of a hypothetical index fund as described in Section 4.1.4 and hereby assert that the estimator is valid. Second, we regress our nine asset characteristics on the valuation ratio and get an adjusted R^2 close to Noh and Oh (2023), yet smaller than KRY22. We attribute the difference to KRY22 to their smaller selection of stocks, which focuses exclusively on the 90% largest assets as measured by their market capitalization. Given that we produce a lower adjusted R^2 than Noh and Oh (2023), one could adopt their additional environment asset characteristics (carbon emission and green patents) or attempt to use multiple providers of environment scores as suggested by Brandon et al. (2022) to complement missing data points. Moreover, to get a more holistic representation of ESG in valuation ratios, it would be interesting to add an asset characteristic measuring social responsibility. For example, Iliev and Roth (2021) use five different social commitment indicators of firms to score their social performance: Community, diversity, employee relations, human rights, and products. We are, however, largely constrained by access to data and while it would be interesting to study if other characteristics are more suitable for explaining variation in valuation ratios, it deems out of scope for this thesis.

As KY19 argue that asset prices are not exogenously determined, we adapt their approach and instrument market equity building on investors' mandates as explained in Section 4.1.2. We also test for instrument relevance and reject the null of irrelevance on the 5% significance level. However, it might be that other instrumental variables for market equity are more suitable for the construction of asset demand systems. Accordingly, KY19 also acknowledge the inherent limitations of their instrument and call for new research to improve their framework using new data or methodologies (e.g. using exchange-traded funds). In an attempt to do so, van der Beck (2022) instruments market equity using demand shocks from mutual fund flows. He argues that the cross-sectional identification of the market equity instrument using holdings data, as suggested by KY19, is likely subject to some omitted variable bias in that unobservable investment mandates are potentially correlated with prices. Even though we do acknowledge the proposed limitations of the instrumental variable used for this thesis, it has been, and still is, used extensively in academia, assigning it additional credibility (Noh & Oh, 2023; Haddad et al., 2021; Koijen et al., 2022; van der Beck & Jaunin, 2021). Regardless, it would be interesting for future research to adopt the new market equity instrumental variable suggested by van der Beck (2022), or potentially other instruments, to test their implications for our findings.

Throughout this thesis, the focus has been limited to U.S. investors and the market for equities. In terms of the former limitation, KRY22, Noh and Oh (2023), and Brandon et al. (2022) mitigate this problem using global holdings data as sourced through FactSet. Access to this data would allow us to produce even more granular findings on the heterogeneity of institutional investors due to an increase in the sample size, positively impacting the generalizability of our results. For the latter limitation, the fact that we are limited to the market for equities restricts us from studying if the green demand of institutional investors differs across asset classes. For example, an increasing amount of literature studies the direct investment of institutional investors into real assets and green infrastructure (e.g., wind and solar projects) (Kaminker & Stewart, 2012; Kaminker, Kawanishi, Stewart, Caldecott, & Howarth, 2013), as well as the implications of investor's ESG considerations for debt instruments (Baker et al., 2018; Zerbib, 2019). Hence, studying if and how demand differs across asset classes other than equities represents an interesting and highly relevant addition to the research about investor demand heterogeneity. However, getting institutional-level ownership data for other asset classes is challenging, given that institutional investors only report equity holdings under Form 13(f).

C. Implications

From the estimation of the asset demand system, a number of apparent implications arise. First, the demand coefficients estimated from the asset demand system deem robust as they resemble those produced by KY19, KRY22, and Noh and Oh (2023). This implies that they offer reliable insights into the preferences of large financial intermediaries in the U.S. Second, governance and environmental characteristics are factored in by investors as we find that their inclusion increases the adjusted R^2 of the valuation ratio regression. Third, we observe that demand is indeed inelastic, which not only aligns with a large body of emerging literature, but it also refutes the simplifying assumption from neoclassical asset pricing models that demand is elastic. This also suggests that investors *can* exert influence on equity prices through their (collective) changes in holdings. Lastly, possible extensions for further research could entail the implementation of alternative market equity instruments (van der Beck, 2022), and the inclusion of a social asset characteristic to the specification of characteristics-based demand to reflect the entire ESG front in investor demand.

6.2 Investor Heterogeneity

The first important finding from analyzing the heterogeneity in characteristics-based demand is that there seems to be plenty of heterogeneity to uncover given the large dispersion in the distribution of coefficients. From regressing demand coefficients on type, we primarily find that type indeed remains a statistically significant indicator of differences in demand, but that it only explains little of the variation in demand coefficients. By recovering the lowest adjusted R^2 for the regression on the green demand coefficient, we show that demand is especially dispersed for the environmental characteristic. We also observe that large investors, generally, pull the AUM-weighted average coefficients towards zero, arguing for the importance of size as a determinant of demand heterogeneity.

A. Comparison to previous research

The dispersion in the distribution of the green demand coefficients suggests, similar to Noh and Oh (2023) and KRY22, that institutional investors differ in their demand for green assets. Consistent with Hong and Kacperczyk (2009) and their notion of mutual funds as natural arbitrageurs in the marketplace, we observe the lowest absolute demand for green assets and good governance for this investor type. We also find that pension funds and insurance companies have a positive demand for green assets, which aligns with Bolton and Kacperczyk (2021) as well as Hong and Kacperczyk (2009), who argue that these two types are more exposed to social norms and are thus subject to litigation risks if not holding a green portfolio.

Comparing our type-regressions to KRY22, we get similar adjusted R^2 for all characteristics except for the log market-to-book and log book equity demand coefficients. Here, we get a substantially lower adjusted R^2, which we attribute to the fact that KRY22 use only the 90% largest firms and group investors using different traits (e.g. long-term, large-passive, small-active, etc.).

B. Limitations

Given the fact that we are using pooled estimation, we are likely losing out on a substantial amount of heterogeneity for two reasons: First, as we pool investors with less than 1,000 quarterly holdings by type and size, we assume that smaller investors have similar preferences as their peers. This assumption is critical for our estimation, but it also implies that we infer homogeneous preferences of smaller investors. Second, the pooled estimation limits us to study the heterogeneity of only the *largest* institutional investors, which decreases the generalizability of our findings. There are a number of ways to mitigate this problem and thus squeeze out as much heterogeneity from the asset demand system as possible. For an in-depth coverage of potential mitigation strategies, we refer to the discussion of our findings related to green demand (Section 6.3).

As expressed in Section 3.1, the type codes from the Thomson Reuters holdings database contain substantial errors, which we attempt to mitigate to the best of our ability using the steps outlined by KY19 and WRDS Research (2008). However, since this alternative assignment of type codes is not free from errors, it might be that the low adjusted R^2 for the type regression stems from assigning wrong type codes. For less erroneous type distinctions, the holdings database provided by FactSet could be leveraged. To completely resolve this problem, one could, potentially, disregard the conventional type distinction of institutional investors (e.g., banks, insurance companies, pension funds, etc.), and group investors by more quantifiable characteristics (KRY22).

C. Implications

First of all, given that we observe rich heterogeneity in demand curves, one ought to refute the assumption arising from traditional asset pricing models, such as CAPM, which holds that asset demand is largely homogeneous. That is, institutional investors do indeed differ in their demand preferences as we see from the highly dispersed demand coefficients. These differences can, to some extent, be explained by investor type, but this only captures little of the variation in demand - implying that there seem to be plenty of other reasons why investors differ in their characteristics preferences.

The fact that institutions differ in their demand beyond what can be explained by type also has interesting implications in a regulatory and business setting. For the former setting, our findings suggest that it deems inefficient for policymakers to target a distinct type of institutional investor if attempting to infer a specific behavior. In a recent action, for example, the SEC amended the Investment Advisers Act of 1940 to make investment advisors provide additional information regarding ESG practices to clients and shareholders (SEC, 2022). According to our findings, this atomistic approach of targeting investment advisors alone is inefficient. For the latter setting, it is important for firms to understand the preferences and behavior of their investors to adjust their investment strategy and risk management practices accordingly. This implies that firms should look towards other characteristics than type to better understand institutional investors' appetite for risk, greenness, dividends, etc. This can help firms cater to their investors' needs, attract and retain investors, and, ultimately, improve their performance.

6.3 Green Demand

We start by briefly recapping our main findings. In our regression analyses, we observe higher green demand for smaller, long-term oriented, less active, value-preferring investors with less and smaller holdings. Moreover, we find a substantially positive impact of membership in the PRI on green demand in the (sub-)entity that signed, which is driven by earlier, short-term oriented signatories that hold larger assets in more concentrated portfolios. However, we do not find evidence that signing PRI changes an investor's behavior. We conjecture that PRI investors are likely to exhibit unobserved attributes beyond their signature which makes them distinct in terms of green demand.

A. Comparison to previous research

As previously mentioned, our study is most closely related to the ones of Brandon et al. (2022) and Noh and Oh (2023), who both scrutinize the holdings of institutional investors with regards to their greenness. While Brandon et al. (2022) analyze plain holdings and deep-dive on PRI, Noh and Oh (2023) estimate an asset demand system and focus more broadly on green demand heterogeneity. Most strikingly, our results contradict the findings of both papers in such that neither of them finds a significant effect of PRI membership on green demand. Moreover, both studies report a *positive* impact of investor size on green demand, which is also confirmed by KRY22.

We generally propose three explanations for these deviations: data, sample selection, and conceptual reasons. The first one primarily concerns data for investor holdings and ESG ratings. While both papers use FactSet as the source of holdings data, the source of ESG ratings differs among all studies. Due to the reported issues on holdings data in the Thomson Reuters database (see Section 3.1) and the divergence in ESG ratings (Berg et al., 2022), these discrepancies in data sourcing have the potential to induce variation in results. The second one concerns our limited view on larger investors. In essence, our study deep-dives exclusively on the top-end of the AUM distribution, whereas Noh and Oh (2023) and Brandon et al. (2022) consider the entire AUM spectrum. Our findings suggest that the relationship between investor size and greenness is not entirely linear, but alters when zooming in on the upper-AUM-end. The third explanation concerns the analysis of Brandon et al. (2022), where deviations might occur based on how they observe an investor's greenness. Their measure, the *Environmental Footprint*, is exclusively derived from the greenness of an investor's portfolio, and thereby neglects the true motivation of an investor to hold green stocks, which might stem from other characteristics (e.g., better return profiles). This could cause instances of an investor's greenness to be over- or understated. By estimating characteristics-based demand, we control for other stock characteristics, and thus use a potentially more precise measure of investor greenness.

Apart from size and the *PRI dummy*, our results mostly align with the two other studies. Both find a higher green demand for long-term investors. Brandon et al. (2022) report lower green demand for active investors, and do not observe a PRI signing effect with respect to the environmental footprint of investor's portfolios. Similar to us, Noh and Oh (2023) find a higher green demand for price elastic investors. We view these similarities as a confirmation that increases the robustness of previous results.

B. Limitations

Albeit being significant, our findings are subject to some important limitations, which we want to discuss in the following. The primary limitation stems from our limited sample of institutions, which we obtain due to data restrictions regarding ESG scores and estimation restrictions regarding our estimator's minimum observation threshold.

Apart from reducing the sample size, the short time frame from 2010 to 2019 has two major implications for our analysis: First, we do not observe green demand pre- and post-PRI signature for early signatories, which exhibit different behavior (Majoch et al., 2017), and seem to be driving the PRI effect. Possibly, this explains the lack of a signing effect observed in the DID regressions. Second, we miss out on more recent observations of green demand. While the availability of holdings and stock data would allow for the estimation of demand curves up until end-2021, the Sustainalytics dataset dictates a cut-off at the end of 2019. As such, we cannot study more recent trends in green demand, for example the implications of economy-wide environmental shocks like the COVID-19 crisis (Albuquerque, Koskinen, Yang, & Zhang, 2020).

The implications from the estimation restrictions are, however, more severe for our analysis. By having to pool the portfolios of investors with less than 1,000 quarterly holdings, we miss out on a substantial part of the institutional investor spectrum. In fact, our study focuses exclusively on the top AUM decile. Accordingly, our representation of PRI signatories is, albeit the over-representation of large investors in the initiative, slightly size-skewed. Moreover, the lower number of institutions causes our sample size to be smaller, which is most severe for the DID regressions of Section 5.3.3, where the investor sample of the treatment and control group contains only 30 individual entities. Apart from sample implications, pooling investors conditional on investor type and AUM implicitly assumes homogeneity within these groups. This assumption is, on the basis of the analysis of institution-level demand, questionable. The heterogeneity we find in Section 5.2 is thereby likely to be understated.

While the mitigation of the data restriction is limited to the access to additional ESG data, we discuss multiple viable strategies to deal with the estimation restriction. A first apparent way to obtain more investors for the PRI analysis within the bounds of the current methodology would be to pool investors not only conditional on size and AUM, but also on PRI membership. This would allow one to extend the number of PRI observations by additional pooled PRI investors. While requiring limited effort, this method would be subject to strong assumptions on the homogeneity of PRI investors, which are hard to justify based on our results.

To avoid the assumptions about homogeneity of investors along certain characteristics, KRY22 propose to augment the GMM estimator of KY19 with a ridge penalty. Initially proposed by Hoerl and Kennard (1970), the ridge penalty adds a linear term to the GMM estimator's goal function. Since this linear penalty term decreases in the number of available holdings per investor-quarter observation, the less robust demand coefficients obtained from more concentrated portfolios are reduced in magnitude, thereby limiting their impact on the overall results. By employing the ridge estimator, KRY22 are able to increase the number of demand curves substantially. While we operate with roughly 4,000 demand curves, KRY22 report approximately 6,500. We conjecture that the ridge estimator represents an exciting extension to our analysis.

Next to adjusting the non-linear GMM estimator, one could also attempt to use different estimators, which are potentially less liable to convergence issues and thus allow for lower holdings thresholds. KY19 show that, if investor holdings are limited to strictly positive values, characteristics-based demand (Equation 4.10) can be reduced to a linear regression model by taking logarithms of the equation. They estimate this linear regression model using both an OLS and a linear GMM estimator. Since OLS assumes exogeneity of all regressors, it returns positively biased results for the log-market-equity coefficient and is thereby deemed unsuitable. In contrast, the linear GMM estimator seems to perform well for larger institutions and less so for smaller ones. While this could argue for an application in our study, we still refrain from using this estimator due to the assumption of strictly positive holdings, which neglects important information contained in zero holdings. In a green investment context, the assets an investor decides to divest or intentionally not invest (e.g., because of a polluting business model) are of equal importance as the assets in the investor's portfolio. In line with our prioritization of precision over breadth, we thereby value this information higher than a potentially larger number of observations and avoid an application of the linear GMM estimator.

On top of what is induced by the sample size and selection, we want to acknowledge a few more remaining limitations. As the moderate adjusted R^2s of our PRI regressions indicate, we still leave a fair portion of the variation in institutions' green demand unexplained. Consequently, we cannot exclude the possibility of biased estimators in our regressions due to omitted variable bias. For instance, one could suspect that memberships in other responsible investing initiatives (e.g., Net Zero Asset Owner Alliance, Climate Action 100+), which partially require harsher commitments by its members (e.g., commitment to net zero portfolios), are important drivers of green demand that correlate with PRI membership. We argue that, for the time frame we are inspecting, PRI is the most prevalent initiative regarding responsible investing (Hoepner et al., 2021), and thereby encapsulates most investors' responsible investment efforts. Moreover, the limited breadth, historical importance, and data availability of other initiatives make it challenging to study them in detail.

Next to omitted variable bias, our analysis is not entirely free from simultaneity concerns. In the PRI regressions, these mainly surround two relationships: *PRI dummy* and green demand as well as governance demand and green demand. In the former case, the non-existent signing effect could suggest that investors have been environmentally-conscious before signing the initiative, thereby pointing towards *PRI dummy* being endogenous to green demand. To mitigate this concern, we have tried various approaches on instrumenting *PRI dummy*. Following an intuition provided by Brandon et al. (2022), we experimented with the staggered introduction of investor stewardship codes, which are governing principles for institutional investors put forth on a national basis, as well as external climate-related events like the PA or the U.S. PA pull-out announcement. However, none of those instruments proved to be relevant, which we attribute to the limited global dispersion of our investor sub-sample or the short time frame for stewardship codes and ESG events, respectively. Other instruments we hypothesized, such as the publication of an investor's ESG-strategy, could not be tested due to a lack of data. As such, the endogeneity of *PRI dummy* remains a concern in our analysis. We encourage future research to identify relevant instruments, which could improve the robustness of our results.

Regarding governance demand, we interpret the significant influence of $b_{i,t}(ei)$ on green demand as evidence for the presence of holistic E(S)G mandates within green investors. However, this interpretation also gives rise to the argument that green and governance demand are jointly endogenous. To address this concern, one could, again, attempt to instrument governance demand. We propose, for instance, an instrument based on the level of regulatory oversight in an investor's home country, as measured by the number of regulatory bodies or stringency of the regulatory environment. Due to a lack of data, we are unable to test this instrument, but remain confident in our interpretation of the relationship, which is not severely threatened by the endogeneity concerns.

Further limitations we want to reflect here include the analysis of relationships based on estimated variables. In contrast to Brandon et al. (2022), we do not observe investors' green demand directly, but through estimated variables, which are naturally subject to errors. Moreover, in the cases of governance demand and price in-elasticity, we also attempt to establish relationships between *two* estimated variables, which further adds to the potential error. To mitigate this, one could replace the estimated with directly observable variables. For instance, the *Governance Footprint* as measured by Brandon et al. (2022) could replace $b_{i,t}(ei)$. While we do not implement such variables due to data limitations, we make the case for our estimated variables based on two arguments. First, as previously mentioned, the demand coefficients we estimate control for other characteristics that drive an investor's demand, thereby increasing their precision of measuring an investor's actual motivation of demanding a characteristic. Second, the coefficients are rooted in a well-specified, micro-founded, and validated model of asset demand, that has been widely applied in research, also for similar purposes like ours (see Noh and Oh (2023)).

Another limitation is the extent to which we can observe the implementation of PRI's principles within investors. Arguably, green demand as measured by the coefficient $b_{i,t}(env)$ can only measure the implementation of the first two principles, and, to some extent, the third.[20] As such, we potentially miss out on green efforts of investors which are rooted in the execution of the remaining three principles, which aim to make investors active promoters of PRI's principles. A way to measure these efforts could be analyzing PRI survey data (Brandon et al., 2022). We argue, however, that, due to the nature of the principles, it is unlikely for an investor to implement principle four to six without acting on principle one to three themselves. This could pose threats to the investor's legitimacy. Based on this argument, we infer that we do not miss out on any green investors, but only allow for the possibility to underestimate their green efforts in cases where investors additionally implement principles three to four. Therefore, the lack of measurement of some PRI principles does not question the influence of *PRI dummy* on green demand, but makes it at most more conservative.

Recapping the limitations we have discussed surrounding our analysis of investors' green demand, the sample selection and endogeneity concerns are arguably the most impactful ones. We present potential strategies to mitigate these, including a ridge estimator (KRY22) and an instrumental variable approach. However, since an implementation of these mitigation strategies is outside the scope of this study, our results have to be carefully interpreted in light of their limitations. We will summarize the implications of our analysis of investors' green demand in the coming paragraph.

[20]For an overview of the principles, we refer to section 3.3.

C. Implications

The implications of our findings are two-fold as we offer important insights for both academia and practice. In the academic dimension, we contribute to research on sustainable finance, more specifically on investors' preferences for green assets and the drivers of those. We can confirm the previously established positive impact of long-term-ism (see, for instance, Starks et al. (2017)), and the negative impact of active share (see, for example KRY22), on green demand, thereby increasing the robustness of these relationships. Moreover, we add more color to the common view on size. While most studies agree that size positively influences an investor's green demand (Brandon et al. (2022), (Noh & Oh, 2023), KRY22), our results suggest that this relationship changes in the top AUM decile of investors, possibly due to more index-like, less focused investment styles among the largest investors. We furthermore add evidence to the field which indicates that large investors who care about their portfolio companies' governance also care about environmental performance, arguing for the presence of holistic E(S)G mandates.

Next to the research on investors' preferences for green assets, we contribute to the related field of research on the PRI and its effectiveness. In contrast to Noh and Oh (2023) and Brandon et al. (2022), our results suggest that there are instances in which PRI investors *do* exhibit a higher green demand, which is robust to other influences. Specifically, we show that this effect seems to appear among large investors, trickles down in the signatories' organization (but not upwards), and is driven by early, short-term oriented signatories with holdings of larger assets in more concentrated portfolios. However, due to the lacking evidence of a signing effect and distinct behavior of PRI investors, we cannot entirely deny endogeneity concerns of the PRI effect and leave the question open if it is actually the PRI signature that induces this behavior. This ambiguity within our findings, combined with the moderate explanatory power of our models on green demand and a similarly large dispersion of green demand for PRI and non-PRI investors, suggests that there are other influences beyond the ones we have studied which can potentially explain the PRI effect for large investors. We therefore encourage further research in this direction, since, in opposition to the concurring findings of Noh and Oh (2023) and Brandon et al. (2022), the full story of PRI's impact on investor greenness does not seem to be told yet.

Our findings also have relevant implications for practical fields of finance. On the one side, they provide insights for the initiators of PRI. Most importantly, we offer evidence that holds against the critique of PRI being a *greenwash* (see, for instance,

N. Eccles (2010)), by arguing that there can be instances in which PRI signatories exhibit superior environmental performance. Moreover, our insights on the drivers of the PRI effect could encourage the PRI to review their policies. The exemplary behavior of early signatories argues for a revision of PRI's policy changes since 2010, for example the introduction of membership fees in 2011 (Hoepner et al., 2021), and their effectiveness for inducing responsible investment within signatories. Considering that short-term investors and investors with more concentrated portfolios stand out compared to their non-PRI peers suggests that some PRI investors exert stronger efforts or take higher risks, which should be rewarded by the initiative, for example through additional certifications. Because the PRI effect seems to be limited to the (sub-)entity which signed, investors should be encouraged to sign on a group level, and any advertisement of a membership should be restricted to the signed (sub-)entity. The fact that green demand still shows a large dispersion among PRI investors indicates that the PRI contains investors which lack implementation of the principles, at least on the environmental dimension. While they might perform well on environment compared to their non-PRI peers, there is still room for improvement, where they can potentially benefit from best practices of PRI investors in the right-tail of the green demand distribution.

On the other side, our findings also have implications for a wider range of market participants. For investors looking to assign funds to money managers, a PRI membership can serve as a sign of higher environmental consciousness, specifically when evaluating large managers in the top AUM decile. Among large PRI investors, especially the short-term oriented, early signatories with more concentrated portfolios and holdings of larger assets outperform their non-PRI peers in terms of environmental sustainability. Looking at the entire spectrum of large investors, long-termism, passiveness and portfolio concentration (size and average share size) serve as positive (negative) indicators of greenness, and can thereby all be relevant in the evaluation of large asset managers and in the design of effective policies aimed at promoting sustainable investing. Moreover, investors attempting to pick money managers that care about the environment *and* firm governance do not face an either/or decision, as both preferences are likely to go hand-in-hand.

We conclude the discussion of our findings related to green demand with a summary of topics for further research. To increase the robustness of our results, we suggest the replication of this analysis with broader (time, investors) data from potentially alternating sources (for holdings and ESG ratings). Moreover, addressing the main limitations of this study would be beneficial, especially concerning the identification of an instrument for *PRI dummy* and the implementation of an alternative estimation process. Going beyond the scope of the present analysis, further research on determinants of green demand and the effectiveness of PRI is highly encouraged, given that our results paint a somewhat different, but still incomplete, picture compared to what has been suggested by previous research. For example, since PRI addresses the entire ESG front, an investigation of its effect on investors' G and S demand using a similar approach could provide valuable insights into this direction. An initial analysis using $b_{i,t}(ei)$ as a dependent variable in the baseline PRI regression (Equation (4.25)) reveals promising results, returning a positive impact of PRI on demand for good governance. As another extension, one could leverage the properties of the asset demand system further and estimate the aggregate price impact of PRI investors using counterfactual experiments in the fashion of KRY22. This could help to assess the extent to which PRI investors are able to have an impact on firms' cost of capital, and thereby influence their behavior.

7 Conclusion

At the beginning of this paper, we raised the question: How can we describe green asset demand of U.S. institutional investors and explain the heterogeneity thereof? In an attempt to provide answers, we investigated three subquestions. For each of those, we described a theoretical-methodological approach, presented and interpreted empirical results, and comprehensively discussed findings and potential implications in light of their limitations and related research. This conclusion summarizes the findings of this paper along the three subquestions, before it points out the most important implications and areas for future research.

Using a demand-system approach grounded in the influential study of KY19, we show that large U.S. institutional investors demand firms with better environment scores, better governance, lower systematic risk, higher productivity, and higher profitability. Based on the consistency of these results with previous research and two successful validity tests, we argue for our estimates to be a sound representation of institutional asset demand.

Our results confirm the large heterogeneity previously found within institutional asset demand. In fact, we find that conventional investor types are able to explain merely 2% of the variation in green demand, despite them being important determinants. In line with previous literature, we find higher green demand for (large) long-term investors, like pension funds and insurance companies, and lower green demand for (large) mutual funds.

Investigating drivers of green demand, we observe that long-termism, passiveness, portfolio concentration, and value-like investing positively influence large investors' greenness, whereas size and average share size do so negatively. Importantly, large institutions with a PRI membership exhibit a significantly greater preference for green assets than those without. This *PRI effect* does not affect upstream entities in the signing organization, is robust to the aforementioned influences, and is driven by early, short-term oriented signatories with concentrated portfolios that contain smaller stocks. Due to the lack of conclusive evidence for either a signing effect or distinct PRI member behavior, the *PRI effect* is, however, not free from simultaneity concerns.

Our results have important implications for practice and academia. We confirm investment horizon, active share, and portfolio concentration as reliable signals of green investors, add more color to the influence of investor size on green demand in the upper AUM decile, and bring a new signal into the discussion: PRI membership. Our granular results surrounding the positive *PRI effect* for large institutions can help practitioners to identify truly green investors and should encourage the PRI initiators to pursue their mission whilst putting some of their policies under a critical review.

Although our findings are robust to a large set of variables, we still leave a fair portion of demand dispersion unexplained and fail to ultimately neglect the simultaneity concerns accompanying our PRI dummy. Accordingly, this study encourages further research, both on the heterogeneity of green demand and the effectiveness of PRI. Valuable arms-length extensions are, next to replications with different data, the application of an alternative GMM estimator, and the implementation of an instrumental variable approach for the *PRI dummy.* Upon a successful establishment of the *PRI effect* on green demand and the discovery of further determinants of investor greenness, the field could benefit from studies on the determinants of demand heterogeneity in other ESG dimensions and from a quantification of price pressure induced by green investors. Both times, PRI membership can play an important role.

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Appendix

A Data

A.1 Description of institutional investor types

Type	Description
Banks	Banks intermediate capital through the deposits of individuals, businesses, and governments, effectively pooling and mobilizing funds. They utilize these funds to provide loans, credit facilities, and other financial services to borrowers. Additionally, banks serve as custodians of money, offering safekeeping, payment processing, and financial advice to individuals and businesses.
Insurance companies	Insurance companies intermediate capital by providing coverage and financial protection against specified risks. They collect premium payments from individuals or businesses and pool the funds to create a reserve. In return, the insurance company offers compensation or benefits to policyholders in the event of covered losses or incidents, effectively managing and mitigating risks for individuals and businesses.
Investment advisors	An investment advisor intermediates capital by providing personalized financial advice and guidance to individuals or institutions. They assist clients in making informed investment decisions, helping to allocate their capital effectively and maximize returns based on their financial goals and risk tolerance.
Mutual funds	A mutual fund is an open-end investment company pooling money from private investors in stocks, bonds, short-term money-market instruments, other securities or assets, or some combination of these investments.
Pension funds	Pension funds pool and invest money from the pension plans of employers, unions, or other organizations in a promise of a certain level of retirement income in the future.

Note: This table provides a short description of the institutional investor types used for this paper.

A.2 Fundamentals data extended variables

The newly estimated variables are as follow:

- **Book equity**: $BE_t(n) = SEQ_t(n) + TXDITC_t(n) - PSTK_t(n)$
- **Market equity**: $ME_t(n) = price_t(n) * SHROUT_t(n)$
- **Log growth of shares outstanding** $= \ln CSHO_t - \ln CSHO_{t-1}$
- **Stock split adjustment factor**: $f_t(n) = \frac{(1+retx_t(n))P_{t-1}}{P_t}$
- **Dividend per share**: $div_t(n) = \frac{(ret_t - retx_t(n))P_{t-1}}{f_t(n)}$
- **Payout per share**: $pay_t(n) = \frac{ret_t - \frac{me_t}{me_{t-1}} P_{t-1}}{f_t(n)}$

Where the abbreviations follow Compustat's definitions: Stockholders sequity (SEQ), deferred taxes and investment tax credit (TXDITC), preferred/preference stock (PSTK), shares outstanding (SHROUT), Common shares outstanding (CSHO), holding period return without dividends (retx), holding period return (ret).

A.3 Exemplary PRI matches

Match case	*Exemplary institutions*		
	13F investor	PRI signatory	Parent entity
"Perfect match"	Credit Suisse Group AG	Credit Suisse Group AG	Credit Suisse Group AG
PRI subsidiary match	KBC Group NV	KBC Asset Management NV	KBC Group NV
13F subsidiary match	Russell Investment Trust Co	Russell Investment	Russell Investment
Subsidiary match	Nomura Securities Co., Ltd.	Nomura Asset Management Co., Ltd.	Nomura Holdings

Note: Exemplary matches between PRI signatories and 13F investors for the 4 different match cases.

B Extended Summary Statistics

B.1 Summary statistics of holdings data by investor type

Period	# of inst.	Mrkt share (%)	AUM (mUSD) Med.	AUM (mUSD) 90th perc.	Portfolio size (stocks) Med.	Portfolio size (stocks) 90th perc.	Size of inv. universe Med.	Size of inv. universe 90th perc.
Banks								
2000-04	154	11	458	21,630	219	1,365	322	1,780
2005-09	142	10	434	19,636	196	1,320	314	1,973
2010-14	134	10	433	20,510	172	1,121	272	1,686
2015-19	129	11	643	42,044	224	1,469	324	1,767
2020-21	136	10	776	41,777	204	1,550	358	1,814
Insurance companies								
2000-04	72	5	1,124	12,204	161	1,431	280	1,693
2005-09	120	4	513	11,504	82	1,061	150	1,373
2010-14	174	4	348	9,425	67	708	118	1,094
2015-19	189	4	499	12,062	64	736	129	1,090
2020-21	171	5	738	24,113	66	744	131	1,236
Investment advisors								
2000-04	1,130	9	264	1,689	68	218	116	418
2005-09	1,724	15	266	2,332	62	253	125	563
2010-14	2,178	18	260	2,760	57	264	106	539
2015-19	3,102	19	245	2,735	59	305	98	549
2020-21	4,204	19	221	2,510	58	286	97	534
Mutual funds								
2000-04	324	29	2,319	23,744	172	1,060	319	1,551
2005-09	270	30	2,911	41,159	176	992	388	1,770
2010-14	240	28	3,629	41,693	174	941	351	1,620
2015-19	217	30	4,916	51,816	179	1,095	360	1,622
2020-21	195	30	5,677	78,403	184	1,303	329	1,824
Pension funds								
2000-04	45	4	2,210	38,768	466	1,964	556	2,337
2005-09	55	4	3,195	34,169	444	2,002	732	2,437
2010-14	70	4	3,777	24,824	419	1,465	615	2,091
2015-19	81	3	4,314	32,032	322	1,453	515	1,898
2020-21	75	4	7,560	47,217	439	1,608	608	2,058
Other								

2000-04	82	0	157	1,024	46	190	77	292
2005-09	143	1	156	1,784	40	254	86	468
2010-14	98	2	188	3,051	55	489	98	756
2015-19	206	2	251	3,431	50	425	79	621
2020-21	265	2	347	5,799	43	387	76	641

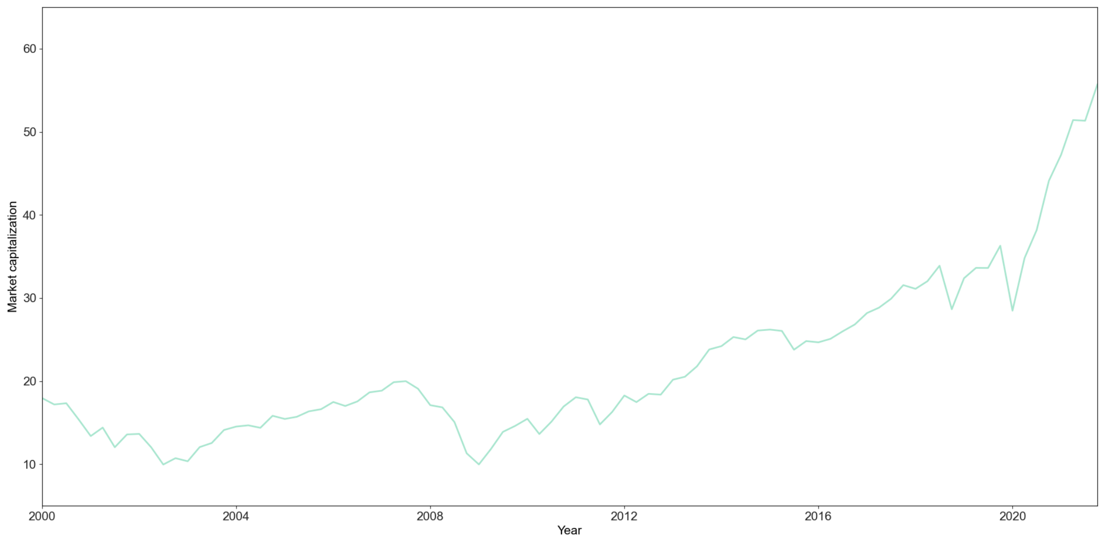
Note: This table represents the summary statistics for each type of institutional investor from 2000 to 2021

B.2 Securities Post Treatment

Year	Number of Securities
2010	4,883
2011	4,727
2012	4,618
2013	4,606
2014	4,718
2015	4,819
2016	4,761
2017	4,666
2018	4,703
2019	4,760

Note: Number of securities held by institutional investors and the household sector within our sample period.

B.3 Market capitalization



Note: The market capitalization is measured as the dollar value of the AUM for each institutional investor in the U.S. including the household sector

B.4 Summary statistics of investor-level sample

# of inst.	AUM (mUSD) Median	AUM (mUSD) 90th percentile	Portfolio size (stocks) Median	Portfolio size (stocks) 90th percentile	Size of inv. universe Median	Size of inv. universe 90th percentile
			Banks			
17	25,159	203,841	1,562	2,413	2,530	3,771
20	28,767	254,736	1,471	2,201	2,660	3,669
21	43,988	287,185	1,453	2,019	2,831	3,592
20	46,298	310,081	1,548	2,117	2,834	3,728
21	59,012	330,226	1,566	2,022	2,851	3,715
			Insurance companies			
16	10,076	67,074	1,1123	2,228	1,985	3,381
16	11,579	98,769	970	2,125	1,881	3,383
17	16,748	123,286	1,291	1,998	2,293	3,565
17	21,920	128,896	1,410	1,977	2,487	3,592
17	26,756	153,955	1,356	1,924	2,615	3,614
			Investment advisors			
58	2,915	20,781	948	1,655	1,853	3,068
64	3,359	26,878	943	1,567	1,880	2,933
76	3,875	35,675	896	1,531	1,936	3,128
81	3,592	38,472	993	1,623	2,034	3,142
87	3,820	45,670	1,021	1,613	2,246	3,220
			Mutual funds			
28	35,463	394,276	1,609	2,491	2,873	3,618
28	43,790	453,001	1,523	2,257	2,593	3,532
30	54,439	488,624	1,475	2,102	2,631	3,750
30	53,862	587,746	1,492	2,166	2,557	3,725
28	50,899	737,318	1,444	2,076	2,704	3,920
			Pension funds			
15	18,361	47,658	1,269	2,130	2,493	3,587
15	17,687	51,028	1,247	1,936	2,382	3,275
18	18,309	63,112	1,245	2,028	2,393	3,627
18	17,426	68,745	1,222	2,005	2,289	3,276
18	19,728	79,467	1,239	1,928	2,157	3,504
			Other			
3	28,839	143,533	923	2,125	1,932	3,404
4	30,061	177,170	1,139	2,000	1,805	3,196
6	23,672	213,773	1,352	1,863	2,172	3,245
6	23,521	133,760	1,289	1,631	2,425	3,022
6	28,728	227,256	1,218	1,752	2,594	2,844

Note: This table represents the summary statistics for each type of institutional investor for whom demand coefficients were estimated on an individual basis from 2010 to 2019.

B.5 Demand coefficients for investor-level sample

	AUM-weighted		Equal-weighted				
	Mean	SD	Mean	SD	Q10	Q50	Q90
Log market-to-book	0.874	0.242	0.879	0.202	0.577	0.990	0.990
Log book equity	1.185	0.146	1.087	0.311	0.715	1.094	1.471
Foreign sales share	0.036	0.059	0.015	0.109	-0.104	0.016	0.137
Lerner index	0.014	0.064	0.066	0.206	-0.176	0.054	0.310
Dividend-to-book	0.015	0.082	0.005	0.134	-0.133	-0.002	0.152
Market beta	0.007	0.046	-0.005	0.117	-0.145	0.006	0.130
Sales-to-book equity	0.076	0.071	0.062	0.118	-0.055	0.045	0.198
Environment score	-0.009	0.097	-0.008	0.129	-0.150	-0.016	0.155
Entrenchment index	0.004	0.064	0.019	0.080	-0.068	0.024	0.097

Note: This table represents the summary statistics of the demand coefficients for the investor-level subsample only.

C Asset Demand System

C.1 Derivation of market weights

This section shows the detailed steps to arrive at the specification of portfolio market weights given in Section 4.1.4. We start with the formula for investor i's weight in asset n, which is also stated in equation (4.9):

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

Moreover, we recall Equation (4.10):

$$\delta_{i,t}(n) = exp\left[\beta_{0,i,t} me_t(n) + \sum_{k=1}^{K-1} \beta_{k,i,t} x_{k,t}(n) + \beta_{K,i,t}\right] \epsilon_{i,t}(n),$$

In the case of an index fund, where the portfolio weights of an investor are solely determined by its market weights, we have $\beta_{0,i,t} = 1$, $\beta_{k,i,t} = 0$ for all $k = 1, ..., K-1$ and $\epsilon_{i,t}(n) = 1$. Applying this to the equations above, we obtain:

$$\begin{aligned} w_{i,t}(n) &= \frac{exp\left\{me_t(n) + \beta_{K,i,t}\right\} 1}{1 + \sum_{m \in \mathcal{N}_{i,t}} exp\left\{me_t(m) + \beta_{K,i,t}\right\} 1} \\ &= \frac{ME_t(n) exp\{\beta_{K,i,t}\}}{1 + \sum_{m \in \mathcal{N}_{i,t}} ME_t(m) exp\left\{\beta_{K,i,t}\right\}} \\ &= \frac{ME_t(n) exp\{\beta_{K,i,t}\}}{exp\left\{\beta_{K,i,t}\right\}\left(\frac{1}{exp\left\{\beta_{K,i,t}\right\}} + \sum_{m \in \mathcal{N}_{i,t}} ME_t(m)\right)} \\ &= \frac{ME_t(n)}{exp\left\{-\beta_{K,i,t}\right\} + \sum_{m \in \mathcal{N}_{i,t}} ME_t(m)} \end{aligned} \tag{C.1}$$

In the last equation, we can see how investor i's weight on asset n is determined by the share of this asset in the total market capitalization of his investment universe, which comprises the entire market in the case of an index fund. The term $exp\left\{-\beta_{K,i,t}\right\}$ scales this weight down proportionally depending on how much the investor holds in the outside asset.

We can proceed and do a similar exercise for the weight in the outside asset. From Equation (4.11), we recall:

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

Utilizing what we have stated above about the coefficients for an index fund gives:

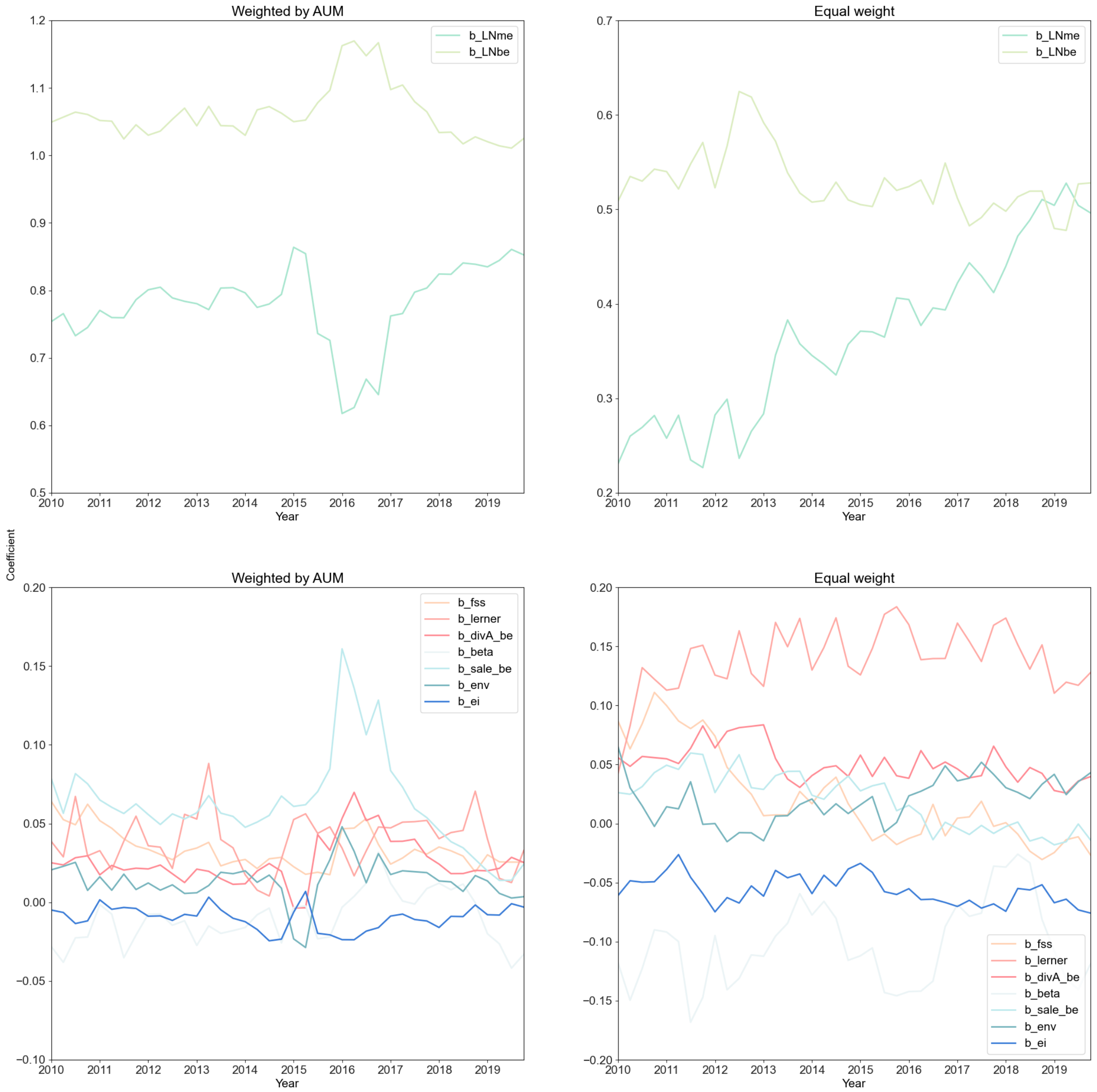
$$\begin{aligned} w_{i,t}(0) &= \frac{1}{1 + \sum_{m \in \mathcal{N}_{i,t}} exp\left\{me_t(m) + \beta_{K,i,t}\right\} 1} \\ &= \frac{1}{1 + exp\left\{\beta_{K,i,t}\right\} \sum_{m \in \mathcal{N}_{i,t}} ME_t(m)} \\ &= \frac{1}{exp\left\{\beta_{K,i,t}\right\} \left(exp\left\{-\beta_{K,i,t}\right\} + \sum_{m \in \mathcal{N}_{i,t}} ME_t(m)\right)}. \end{aligned} \tag{C.2}$$

Relating Equation (C.1) and (C.2) gives:

$$\begin{aligned} \frac{w_{i,t}(n)}{w_{i,t}(0)} &= \frac{ME_t(n)}{exp\left\{-\beta_{K,i,t}\right\} + \sum_{m \in \mathcal{N}_{i,t}} ME_t(m)} \left(exp\left\{\beta_{K,i,t}\right\} \left(exp\left\{-\beta_{K,i,t}\right\} + \sum_{m \in \mathcal{N}_{i,t}} ME_t(m) \right) \right) \\ &= ME_t(n) exp\left\{\beta_{K,i,t}\right\} \\ &= exp\left\{me_t(n) + \beta_{K,i,t}\right\}. \end{aligned} \tag{C.3}$$

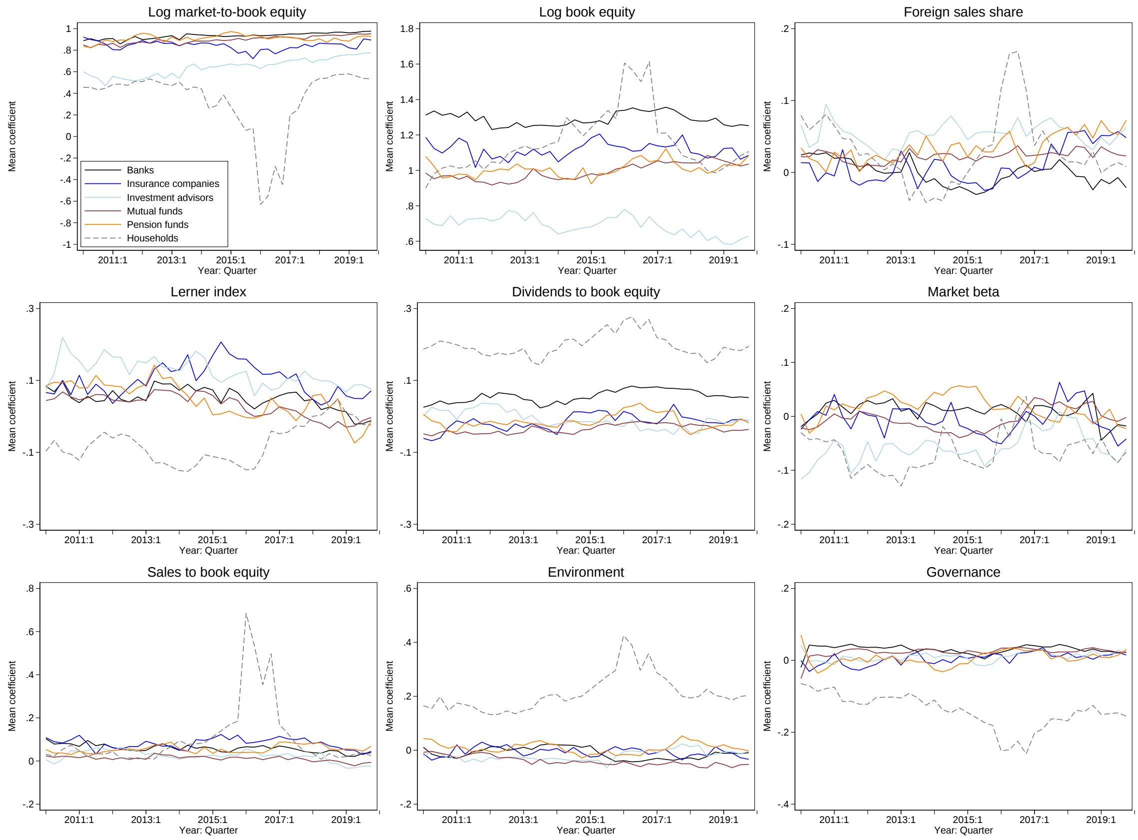
Which equals Equation (4.22). The same derivation can be applied to the alternative specification in Equation 4.23.

C.2 Evolution of aggregated demand coefficients



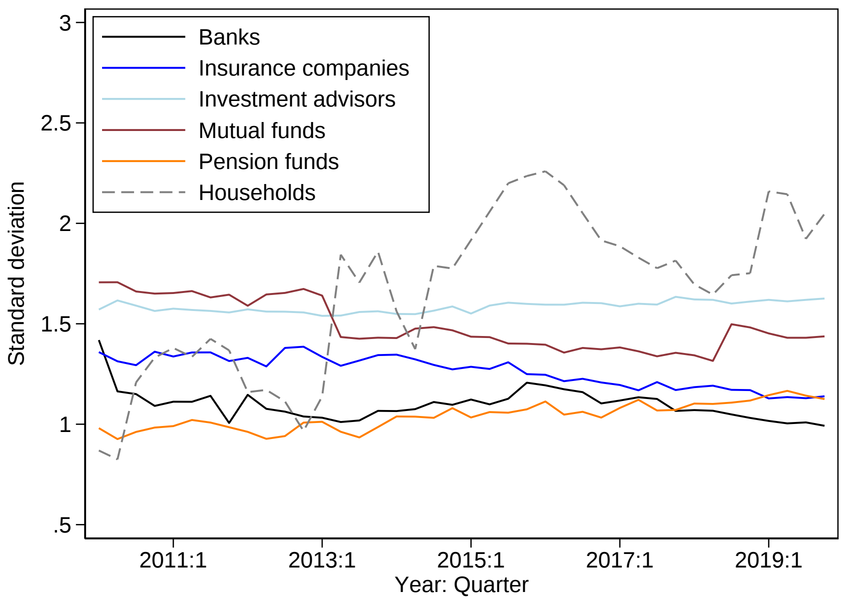
Note: AUM- and equal-weighted average demand coefficients for all institutional investors including the household sector

C.3 Evolution of AUM-weighted average demand coefficients by type



Note: AUM-weighted average demand coefficients for each type of institutional investor and characteristic

C.4 Latent demand



Note: This figure shows the AUM-weighted average residual demand for the entire sample including the pooled estimation and household sector.

D Regressions

D.1 Valuation regression

	Dependent variable: $mb_t(n)$	
	(1)	(2)
be	-0.251***	-0.602***
	(0.005)	(0.010)
Beta	0.033***	-0.015**
	(0.004)	(0.006)
Cons	0.841***	1.548***
	(0.020)	(0.023)
Div/be	0.202***	0.167***
	(0.004)	(0.006)
FSS	0.158***	0.109***
	(0.005)	(0.007)
Lerner	-0.040***	-0.068***
	(0.005)	(0.007)
Sale/be	0.228***	0.216***
	(0.004)	(0.006)
Entrenchment		-0.018**
		(0.008)
Environment		0.089***
		(0.010)
Observations	54,067	24,068
R^2	0.212	0.319
Adjusted R^2	0.211	0.319
Time-fixed effects	Yes	Yes
F Statistic	579.868***	593.330***

Note: Regressions of year-end market-to-book equity ratios on characteristics for the sample period 2000-2019 (1) and 2010-2019 (2). Both regressions include time-fixed effects. Regression (2) includes dummies for missing data in the environment score and entrenchment index. Statistical significance: **p<0.1;* ***p<0.05;* ****p<0.01*

D.2 Type regression for institution-level environment coefficients

	b_env
Pension funds	-0.001
	(0.013)
Insurance companies	-0.029**
	(0.013)
Banks	0.009
	(0.012)
Mutual funds	-0.014
	(0.012)
Investment advisors	0.015
	(0.012)
Other	-0.034**
	(0.015)
Observations	3,874
R^2	0.033
Adjusted R^2	0.021
Time-fixed effects	Yes

Note: Regression results for a regression of the environment coefficient on investor types using the institution-level demand curves only. Statistical significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

D.3 Correlation Matrix of Investor Characteristics

	LNaum	Turnover	actsh	avgss	LNnholding
LNaum	1	-0.288	-0.253	-0.265	0.540
Turnover	-0.288	1	0.558	-0.091	-0.196
actsh	-0.253	0.558	1	0.026	-0.343
avgss	-0.265	-0.091	0.026	1	-0.531
LNnholding	0.540	-0.196	-0.343	-0.531	1

Note: This table shows the correlation matrix of the signatory characteristics used for the PRI regression. actsh abbreviates active sales share, avgss is the average stock size, and LNnholding is the log of the number of holdings.

D.4 PRI regressions for investor cohorts

	PRI investor cohort:					
	turnover	AS	LNaum	avgss	LNnhold	Signature Year
	(1)	(2)	(3)	(4)	(5)	(6)
Bottom group	-0.0290***	0.0095	0.0142*	-0.0252***	0.0563***	0.0347***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	3,752	3,752	3,752	3,752	3,752	3,752
R^2	0.184	0.181	0.182	0.183	0.191	0.186
Adjusted R^2	0.172	0.169	0.170	0.171	0.179	0.174
Investor controls	Yes	Yes	Yes	Yes	Yes	Yes
Type-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Regressions of green demand coefficients on cohort indicator, adjusted PRI dummy, investor controls and type- and time-fixed effects. The top row states which cohort the indicator relates to. Statistical significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

D.5 Difference-in-difference regressions for ESG shocks (PA and U.S. pull-out)

	Dependent variable: $b_{i,t}(env)$	
	(1)	(2)
	PostParis	PostUSA
adj. PRI dummy	0.052***	0.022
	(0.013)	(0.014)
Post	0.773***	0.942***
	(0.141)	(0.148)
Interaction PostxPRI	-0.022	-0.004
	(0.016)	(0.017)
Observations	900	947
R^2	0.239	0.262
Adjusted R^2	0.220	0.244
Investor controls	Yes	Yes
Type-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes

*Note: Difference-in-difference regressions of the environment coefficient on a treatment (PRI dummy) and post (PostParis (1); PostUSA(2)) indicator as well as their interaction effect (Post x PRI). Both regressions include a constant, investor controls and type- and time-fixed effects. Statistical significance: *p<0.1; **p<0.05; ***p<0.01*