Which Investors Matter for Equity Valuations and Expected Returns?*

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Abstract

Based on an asset demand system, we develop a framework to quantify the impact of market trends and changes in regulation on asset prices, price informativeness, and the wealth distribution. Our leading applications are the transition from active to passive investment management and climate-induced shifts in asset demand. The transition from active to passive investment management had a large impact on equity prices but a small impact on price informativeness because capital did not flow from more to less informed investors on average. This finding is based on a new measure of investor-level informativeness that identifies which investors are more informed about future profitability. Climate-induced shifts in asset demand have a potentially large impact on equity prices and the wealth distribution, implying capital gains for passive investment advisors, pension funds, insurance companies, and private banking and capital losses for active investment advisors and hedge funds.

Key words: Asset demand system, Asset pricing, Climate risk, Passive investment management, Price informativeness

JEL Codes: G12, G23, Q54

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1. Introduction

Many questions in financial economics with policy relevance require an understanding of how capital flows across investors and how shifts in asset demand for a group of investors affect asset prices, price informativeness, and the wealth distribution. For example, how does the transition from active to passive investment management affect the cross section of equity prices and expected returns? Do equity prices become less informative when passive investors own a larger share of the market? How do climate-induced shifts in asset demand in response to sustainable investing or changes in climate regulation affect the cross section of equity prices and the firms' cost of capital? How do these capital flows and shifts in asset demand affect the wealth distribution across institutional investors and thereby financial stability?

Market trends and changes in regulation induce capital flows across investors or shifts in asset demand. By market clearing, asset prices adjust so that supply is equal to the aggregate demand across all investors. Thus, asset demand systems play a fundamental role in determining how asset prices respond to market trends and changes in regulation. Moreover, asset demand systems have become a practical reality due to the availability of portfolio holdings data and recent progress on longstanding identification challenges. Building on an earlier literature on index effects (Harris and Gurel, 1986; Shleifer, 1986), more recent papers find demand elasticities that are much lower than those predicted by traditional asset pricing models (Chang et al., 2014; Koijen and Yogo, 2019; Pavlova and Sikorskaya, 2022). Our contribution is to develop a new framework to quantify the impact of market trends and changes in regulation on asset prices, price informativeness, and the wealth distribution. We apply the framework to study the transition from active to passive investment management, climate-induced shifts in asset demand, and the relative importance of institutional investors for cross-sectional asset pricing. Although the set of policy-relevant questions will change over time, the framework that we develop could be generally useful for counterfactual analysis of financial markets.

We start with a simple asset pricing model that illustrates the framework. Investors have heterogeneous beliefs or sentiment about future profitability and agree to disagree. Investors believe that expected profitability and profitability risk depend on observed characteristics and unobserved (to the econometrician) characteristics that we call latent demand. Latent demand could also arise from investor sentiment (e.g., Barberis et al., 1998) or portfolio constraints (e.g., Brunnermeier and Pedersen, 2009) that are not easily modeled as a function of observed characteristics. Thus, optimal portfolio choice implies that asset demand is a linear function of asset prices, characteristics, and latent demand. Market clearing implies that asset prices are a linear function of characteristics and the weighted average of latent demand, where the slope on characteristics are weighted averages of the investors' demand elasticities. The model delivers three insights. First, capital flows change asset prices by changing the relative importance of investors in the weighted average. Second, asset prices change when the elasticities of demand to characteristics change in response to market trends and regulation. Third, the degree to which capital flows and shifts in asset demand affect asset prices depends on heterogeneity in asset demand and demand elasticities.

We estimate the asset demand system by instrumental variables using quarterly U.S. institutional holdings data from 2000 to 2019. The estimated demand system reveals rich heterogeneity across institutional investors, even conditional on investor type and wealth.[1] For example, the wealth-weighted semi-elasticity of demand to the environmental score is 3.07% for small-passive investor advisors and −1.25% for hedge funds per one standard deviation change in the environmental score. The price elasticity of demand is low on average and varies from zero to one across investors. Even hedge funds, which are the most elastic among institutional investors, have a wealth-weighted demand elasticity around 0.5.

Based on the estimated demand system, we answer two questions of current policy interest. The first question is how the transition from active to passive investment management affects the cross section of equity prices and price informativeness. We start by documenting two key facts. First, the aggregate active share of institutional investors declined from 34.5% in 2007 to 29.9% in 2016, which is a similar rate to a longer decline from 45% in 1980 to 25% in 2019. Second, the capital flows from active to passive investors, rather than the investment strategies becoming more passive, explain most of the decline in the aggregate active share from 2007 to 2016. Based on these facts, we compute counterfactual equity prices in 2016 if the wealth distribution across institutional investors were to remain the same as that in 2007. Equity prices change as the active investors' portfolio strategies become more influential in the counterfactual market. The value-weighted absolute percentage change in equity prices, which we call *equity repricing* throughout the paper, is quite large at 14%. However, the transition from active to passive investment management has little impact on price informativeness, as measured by a cross-sectional regression of future profitability on market-to-book equity (Bai et al., 2016). To explain this finding, we develop a new measure of investor-level informativeness that identifies which institutional investors are more informed about future profitability. The intuition is that a more informed investor has demand shifters, which are outputs of the demand estimation, that predict future profitability

[1] We group institutional investors into investment advisors (including mutual funds), hedge funds, long-term investors (i.e., pension funds and insurance companies), private banking, and brokers. We further split investment advisors by wealth and the active share into large-passive, small-passive, large-active, and small-active.

in the cross section of its equity holdings. Using the investor-level informativeness, we find that capital did not flow from more to less informed investors on average, which explains the small impact on price informativeness.

The second question is how climate-induced shifts in asset demand due to sustainable investing or changes in climate regulation affect equity prices. Such shifts could change the wealth distribution across institutional investors and ultimately affect financial stability. Thus, the framework has potential policy relevance as a basis for implementing climate stress tests. Based on a survey by Stroebel and Wurgler (2021), we focus on stakeholder risk (i.e., changing preferences of customers and employees) and regulatory risk as the primary sources of risk at a five-year horizon. We model realized stakeholder risk as an increase in the elasticity of demand to the environmental score for all institutional investors. Because of the initial heterogeneity in portfolio strategies along the environmental score, realized stakeholder risk has a large impact on the wealth distribution across institutional investors. On the one hand, passive investment advisors, pension funds, insurance companies, and private banking earn capital gains. On the other hand, active investment advisors and hedge funds earn capital losses. In contrast to realized stakeholder risk, realized regulatory risk that affects only pension funds and insurance companies has a small impact on equity prices and the wealth distribution.

Building on the two policy-relevant applications, we use the asset demand system to study the relative importance of institutional investors for cross-sectional asset pricing. A long-standing question in financial economics is why characteristics are priced in the cross-section of equity valuations and expected returns (e.g., Fama and French, 1995; Daniel and Titman, 2006; Campbell et al., 2010). Asset pricing theory tells us that characteristics relate to differences in beliefs or sentiment about future profitability, and the asset demand system allows us to infer these beliefs from investor portfolios. Analogous to the first application of the transition from active to passive investment management, we compute counterfactual equity prices in response to capital flows from a group of investors to other institutional investors. Relative to their size, hedge funds play an outsized role with equity repricing of \$3.58 per dollar of wealth, followed by small-active investment advisors with equity repricing of \$2.28 per dollar of wealth. The magnitude of the equity repricing depends on two factors. First, the equity repricing is larger for capital flows from investors who have asset demand that is more different from the other investors. Second, the equity repricing is larger for capital flows from investors who are relatively price elastic because the outflow faces relatively inelastic demand, resulting in a higher price impact. In terms of the relation between market-to-book equity and characteristics, a notable finding is that small-active investment advisors and foreign investors have opposite effects on the pricing of the environmental score. On the one hand, the cross-sectional slope between market-to-book equity and the environmental score would steepen in the absence of small-active investment advisors. On the other hand, the cross-sectional slope would flatten in the absence of foreign investors.

An older literature estimated asset demand systems on sector-level portfolio holdings (Brainard and Tobin, 1968) and inferred the importance of heterogeneous expectations for asset prices (Friedman, 1977, 1978). Building on this tradition, Koijen and Yogo (2019) developed demand system asset pricing as a systematic approach to studying asset prices using portfolio holdings data. Relative to this literature, our contribution is to develop a new framework to quantify the impact of market trends and changes in regulation. Along the way, we make four methodological contributions. First, we endogenize the investors' wealth in counterfactual analysis, allowing us to study the wealth distribution. Second, we incorporate price informativeness as a policy-relevant outcome and develop a measure of investor-level informativeness that allows us to understand the mechanism behind the counterfactual analysis. The investor-level informativeness allows us to identify which investors are more informed about future profitability and could have broader application in studying price discovery and market efficiency. Third, we develop an instrumental variables ridge estimator that allows us to estimate asset demand for investors with concentrated portfolios. This estimator allows for more heterogeneity in asset demand, which is important for the quantitative results. Fourth, we improve the classification of investor types and separate hedge funds, which play an important role in our analysis.

2. Asset pricing model

We develop an asset pricing model that illustrates how we use an asset demand system to quantify the impact of market trends and changes in regulation. The model delivers three insights. First, capital flows change asset prices by changing the relative importance of investors. Second, asset prices change when the elasticities of demand to characteristics change in response to market trends and regulation. Third, the degree to which capital flows and shifts in asset demand affect asset prices depends on heterogeneity in asset demand and demand elasticities. We use the model to explain the applications in the subsequent sections. The model is static and intentionally stylized to focus on the core economic mechanisms. We leave extensions, such as a dynamic model of portfolio choice with income shocks or liquidity effects, for future research.

We present the assumptions and the results in this section and leave all derivations for Appendix A. To summarize the notation, we denote vectors and matrices in bold and index their elements in parentheses (e.g., $x(n)$ is the nth element of the vector $\boldsymbol{x}$). We denote an identity matrix as $\mathbf{I}$. We denote a vector with the first element equal to one and other elements equal to zero as $\boldsymbol{e}(1)$. We use the subscript 1 to denote all variables in period 1 and omit the subscript for all variables in period 0.

2.1. Financial market

There are two periods indexed by $t = 0, 1$. There are N stocks, indexed by $n = 1, \ldots, N$, with the supply of each stock normalized to one. There is also a riskless asset in perfectly elastic supply with a constant interest rate normalized to zero. Let $\boldsymbol{P}$ be an N-dimensional vector of equity prices in period 0. Because the supply is normalized to one, $\boldsymbol{P}$ is also the vector of market equity in period 0. Let $\boldsymbol{B}$ be an N-dimensional vector of book equity in period 0. Let $\boldsymbol{D}_1$ be an N-dimensional vector of terminal dividends in period 1. For each stock n, we define market-to-book equity as $\mathrm{MB}(n) = P(n)/B(n)$ and profitability as $d_1(n) = D_1(n)/B(n)$. Thus, the N-dimensional vectors corresponding to market-to-book equity and profitability are $\mathbf{MB}$ and $\boldsymbol{d}_1$, respectively.

2.2. Portfolio-choice problem

There are I investors indexed by $i = 1, \ldots, I$. The investors choose an optimal portfolio in period 0 and receive the dividends in period 1. Let $q_i(n)$ be the number of shares of stock n that investor i holds in period 0. Equivalently, we express the investor's holdings of stock n in units of book equity as $Q_i(n) = B(n)q_i(n)$. Let O_i be the dollar investment in the riskless asset. Thus, the investor's wealth in period 0 is

$$\begin{aligned} A_i =& \boldsymbol{P}'\boldsymbol{q}_i + O_i \\ =& \mathbf{MB}'\boldsymbol{Q}_i + O_i. \end{aligned}$$

The investor's wealth in period 1 is

$$\begin{aligned} A_{i,1} =& A_i + (\boldsymbol{D}_1 - \boldsymbol{P})'\boldsymbol{q}_i \\ =& A_i + (\boldsymbol{d}_1 - \mathbf{MB})'\boldsymbol{Q}_i. \end{aligned} \tag{1}$$

Investors choose an optimal portfolio in period 0 to maximize expected constant absolute risk aversion (CARA) utility over wealth in period 1:

$$\max_{\boldsymbol{Q}_i} \ \mathbb{E}_i[-\exp(-\gamma_i A_{i,1})]. \tag{2}$$

Investors have heterogeneous coefficients of absolute risk aversion, which we parameterize as $\gamma_i = 1/(\tau_i A_i)$. This assumption delivers the desirable implications of a constant relative risk aversion model while maintaining the tractability of a CARA-normal model (Makarov and Schornick, 2010). As the subscript i on the expectations operator denotes, investors have heterogeneous beliefs or sentiment about future profitability. We assume that investors agree to disagree.

2.2.1. Heterogeneous beliefs about profitability

We model investor i's beliefs about future profitability through a factor model:

$$\boldsymbol{d}_1 = \boldsymbol{\mu}_i + \boldsymbol{\rho}_i F_1 + \boldsymbol{\eta}_1.$$

The vector $\boldsymbol{\mu}_i$ represents the investor's beliefs about expected profitability. The vector $\boldsymbol{\rho}_i$ represents the investor's beliefs about exposures to a systematic factor F_1, which is a standard normal random variable. The vector $\boldsymbol{\eta}_1$ is a normally distributed idiosyncratic shock (i.e., uncorrelated with the factor) with a mean of zero and a diagonal covariance matrix $\mathrm{Var}(\boldsymbol{\eta}) = \sigma^2 \mathbf{I}$. We assume constant idiosyncratic variance across stocks to simplify notation.

Investors form expectations based on asset characteristics, which are public information. We denote a vector of observed (to the econometrician) characteristics of stock n as $\boldsymbol{x}(n)$. We order the characteristics so that the first element is book equity and the last element is a constant. We denote unobserved characteristics of stock n that relate to expected profitability and factor exposure as $\phi_i^{\mu}(n)$ and $\phi_i^{\rho}(n)$, respectively. Thus, investor i's beliefs about expected profitability and factor exposure are

$$\mu_i(n) = \boldsymbol{\Phi}_i^{\mu\prime} \boldsymbol{x}(n) + \phi_i^{\mu}(n), \tag{3}$$

$$\rho_i(n) = \boldsymbol{\Phi}_i^{\rho\prime} \boldsymbol{x}(n) + \phi_i^{\rho}(n). \tag{4}$$

In the spirit of asset pricing in an endowment economy (Lucas, 1978), we assume that both observed and unobserved characteristics are exogenous.

2.2.2. Optimal portfolio choice

As we show in Appendix A, investor i's optimal demand for stock n is

$$Q_i(n) = \frac{1}{\gamma_i \sigma^2} \left(-\mathrm{MB}(n) + (\underbrace{\boldsymbol{\Phi}_i^{\mu} - c_i \boldsymbol{\Phi}_i^{\rho}}_{\boldsymbol{\beta}_i})' \boldsymbol{x}(n) + \underbrace{\phi_i^{\mu}(n) - c_i \phi_i^{\rho}(n)}_{\epsilon_i(n)} \right), \tag{5}$$

where c_i is a scalar that does not vary across stocks. The first term in equation (5) implies that asset demand is downward sloping and decreasing in market-to-book equity. The second term in equation (5) implies that asset demand is increasing in observed characteristics that are associated with higher expected profitability or lower risk. However, the expression for $\boldsymbol{\beta}_i$ shows that the relation between asset demand and observed characteristics does not reveal whether an investor tilts toward a particular characteristic because of expected profitability, risk, or sentiment. We refer to the last term in equation (5) as latent demand because it is unobserved to the econometrician. Again, the relation between asset demand and unobserved characteristics could arise from expected profitability, risk, or sentiment.

Equation (5) is an asset demand function that relates the cross section of equity holdings to characteristics. Equation (5) implies that investors with heterogeneous risk preferences and beliefs could have different elasticities with respect to equity prices and characteristics. Asset demand is less price elastic for investors with higher risk aversion γ_i. Asset demand is more elastic to the environmental score for investors with stronger beliefs about the impact of climate change on expected profitability or risk.

Equation (5) could arise from microfoundations other than heterogeneous beliefs. In Appendix A, we extend the model to background risk, such as income that is correlated with climate risk. Alternatively, investors could have direct tastes for characteristics (Fama and French, 2007), such as nonpecuniary benefits that arise from investing in greener firms (Pástor et al., 2021; Pedersen et al., 2021). Portfolio holdings data are not sufficient to disentangle whether the demand for a particular characteristic arises from beliefs or sentiment about future profitability, hedging motives, or nonpecuniary benefits. Survey data are promising for making progress on this issue (Krueger et al., 2020; Bauer et al., 2021).

2.3. Equilibrium equity prices

Market clearing for each stock n is

$$B(n) = \sum_{i=1}^{I} Q_i(n). \tag{6}$$

That is, supply is equal to aggregate demand across all investors. Substituting optimal demand (5) in market clearing (6), we solve for the equilibrium equity prices as

$$\mathrm{MB}(n) = \overline{\boldsymbol{\beta}}' \boldsymbol{x}(n) + \overline{\epsilon}(n), \tag{7}$$

where

$$\begin{aligned}
\overline{\boldsymbol{\beta}} =& \sum_{i=1}^{I} a_i \boldsymbol{\beta}_i - \frac{\sigma^2 \boldsymbol{e}(1)}{\sum_{i=1}^{I} \tau_i A_i}, \\
\overline{\epsilon}(n) =& \sum_{i=1}^{I} a_i \epsilon_i(n), \\
a_i =& \frac{\tau_i A_i}{\sum_{j=1}^{I} \tau_j A_j}.
\end{aligned} \tag{8}$$

The second term with $\boldsymbol{e}(1)$ in equation (8) arises from the assumption that the book equity is the first element of $\mathbf{x}(n)$.

Equation (7) establishes a cross-sectional relation between market-to-book equity and characteristics. The vector $\overline{\boldsymbol{\beta}}$ is a weighted average of the coefficients on characteristics in asset demand (5). Investors with larger $\boldsymbol{\beta}_i$ have more extreme beliefs or sentiment about future profitability based on characteristics and consequently have a larger impact on equity prices. The scalar $\overline{\epsilon}(n)$ is a weighted average of latent demand across investors. Investors with larger latent demand have a larger impact on equity prices.

Investor i is more influential for equity prices if its relative weight a_i is larger. The relative weight depends on three factors. First, the relative weight increases in wealth A_i. Second, the relative weight increases in the risk tolerance τ_i because the investor trades more aggressively along its beliefs. Third, the relative weight increases if the other investors have lower risk tolerance. This effect arises from the fact that the investor faces a less elastic demand curve on its trades, which results in a larger price impact.

By equation (1), the definition of return on stock n is $R_1(n) = d_1(n) - \mathrm{MB}(n)$. Taking the expectation and rearranging, we have

$$\begin{aligned}
\mathrm{MB}(n) =& \mathbb{E}[d_1(n)] - \mathbb{E}[R_1(n)] \\
=& \overline{\boldsymbol{\beta}}' \boldsymbol{x}(n) + \overline{\epsilon}(n).
\end{aligned}$$

The first line is a present-value formula. A high market-to-book equity signals either high expected profitability or low expected returns. The second line, which repeats equation (7), states that market-to-book equity is a linear combination of characteristics and the weighted average of latent demand in period 0. Combining the two lines, the same characteristics that explain market-to-book equity predict either future profitability or stock returns. We will test this implication of the model in Section 3.

2.4. Applications of the asset demand system

In Section 5, we estimate asset demand for all institutional investors and households. We then use the estimated demand system to quantify the impact of capital flows and shifts in asset demand on equity prices, price informativeness, and the wealth distribution. We describe the applications in the context of the simple asset pricing model in this section.

2.4.1. Capital flows across investors

According to equation (7), market-to-book equity depends on $\overline{\boldsymbol{\beta}}$, the weighted average of the coefficients on characteristics, and $\overline{\epsilon}(n)$, the weighted average of latent demand. Investors with more wealth are more important in the weighted average. Therefore, equity prices change when capital flows across investors change the wealth distribution. A stock becomes more expensive if it has characteristics or latent demand that are more highly valued by investors who become larger. In Section 6, we study capital flows from active to passive investors. In Section 8, we study capital flows across different types of institutional investors.

The capital flows from active to passive investors could also affect price informativeness. Bai et al. (2016) define price informativeness based on a cross-sectional regression of future profitability on market-to-book equity. Let $E_1(n)$ be future earnings before interest and taxes. Equity prices are more informative when the regression coefficient on market-to-book equity is higher in

$$\begin{aligned}\frac{E_1(n)}{B(n)} =& \alpha + \pi \mathrm{MB}(n) + \nu_1(n) \\ =& \alpha + \pi \sum_{i=1}^{I} a_i(\boldsymbol{\beta}_i' \boldsymbol{x}(n) + \epsilon_i(n)) - \frac{\pi \sigma^2}{\sum_{i=1}^{I} \tau_i A_i} B(n) + \nu_1(n). \end{aligned} \tag{9}$$

The second line follows from equation (7).

Equation (9) shows why the asset demand system is important for understanding price informativeness. Investor i's demand shifters $\boldsymbol{\beta}_i' \boldsymbol{x}(n) + \epsilon_i(n)$ vary across stocks, reflecting beliefs or sentiment about future profitability. A more informed investor has demand shifters that predict future profitability in the cross section of its equity holdings. Therefore, the capital flows from active to passive investors could decrease price informativeness if passive investors have less informative demand shifters. This insight leads to a measure of investor-level informativeness that allows us to understand the mechanism through which the capital flows affect price informativeness. We estimate the demand shifters based on the characteristics and the estimated demand coefficients and latent demand. We then estimate price informativeness for each investor through a cross-sectional regression of future profitability on the demand shifters. The investor-level regression coefficients identify which investors are more informed about future profitability.

2.4.2. Shifts in asset demand

In Section 7, we quantify the impact of climate-induced shifts in asset demand. We model realized stakeholder risk as an increase in the coefficient on the environmental score in equation (5) from $\beta_i(k)$ to $\beta_i(k) + \Delta_i$, where $\Delta_i > 0$ for all institutional investors and $\Delta_i = 0$ for the household sector. We model realized regulatory risk as an increase the coefficient on the environmental score for only pension funds and insurance companies. Then equation (7) implies that the cross-sectional slope between market-to-book equity and the environmental score increases from $\overline{\beta}(k)$ to $\overline{\beta}(k) + \sum_{i=1}^{I} a_i \Delta_i$. That is, market-to-book equity increases for greener stocks and decreases for browner stocks. The linearity of the asset pricing model implies no impact on the cross-sectional slope between market-to-book equity and characteristics other than the environmental score.

These counterfactuals also have implications for the wealth distribution. Investors with different initial portfolios have different capital gains when equity prices change. For example, investors with an initial tilt toward greener stocks have higher capital gains than those with an initial tilt toward browner stocks. Depending on the particular investors that are affected, such shifts in the wealth distribution could affect financial stability. Thus, the framework has potential policy relevance as a basis for implementing climate stress tests.

2.5. Extension to endogenous characteristics

Our baseline model assumes that asset characteristics are exogenous. This assumption may be reasonable for characteristics that primarily relate to productivity and market power. However, it may be too strong for characteristics that relate to firm decisions that could depend on equity prices, such as capital structure and payout policy. In Appendix A.3, we extend the model to allow the characteristics to depend on market-to-book equity. The extended model has an important implication for the identification of asset demand, as we discuss in Appendix D.3.

3. Stock market data and motivating facts

We construct U.S. stock market data on institutional equity holdings, equity prices, and characteristics. We summarize the essential elements of the data construction and leave the details for Appendix B.

3.1. Institutional equity holdings

Data on quarterly U.S. institutional equity holdings from 2000.Q1 to 2019.Q4, based on Securities and Exchange Commission (SEC) Form 13F filings, and shares outstanding are from FactSet Ownership. We group institutional investors into investment advisors (including mutual funds), hedge funds, long-term investors (i.e., pension funds and insurance companies), private banking, and brokers.[2] Because investment advisors are a large group, we further split them into four subgroups: large-passive, small-passive, small-active, and large-active. At each date, we first split the investment advisors into two groups by wealth (i.e., total equity holdings), so that the total wealth is equal across the groups. Within each wealth group, we split the investment advisors into two groups at the median of the active share (Cremers and Petajisto, 2009). The active share is one-half times the sum of the absolute differences between an investor's portfolio weights and the market weights within the subset of stocks that it holds. The active share measures the total share of the investor's portfolio that deviates from the market weights.

We construct the household sector as shares outstanding minus the sum of institutional holdings. In rare cases, the sum of institutional holdings exceeds shares outstanding because SEC Form 13F does not report short positions and may contain reporting errors (Lewellen, 2011). If the sum of institutional holdings exceed shares outstanding, we rescale all institutional holdings proportionally to add up to shares outstanding.[3]

We identify foreign investors based on the investors' domicile reported by FactSet. For some of our analysis, we tabulate foreign investors separately to study whether they behave differently from domestic investors. For example, Norges Bank Investment Management is a long-term investor but also a foreign investor. Therefore, we include Norges Bank Investment Management in the tabulation for long-term investors as well as an additional tabulation for foreign investors.

Table 1 provides a perspective on the range of institutional investors by listing the largest investor by investor type. The largest passive investment advisor is Vanguard, managing \$2,494 billion in 2019.Q4. The largest hedge fund is Renaissance Technologies, managing \$89 billion in 2019.Q4. As documented in the literature, institutional ownership is concentrated among a small group of large investors (Gompers and Metrick, 2001), and this concentration has increased over time (Ben-David et al., 2016).

Figure 1 shows the ownership shares by investor type from 2000.Q1 to 2019.Q4. The

[2]Private banking includes private banking and wealth management, family offices, private equity, and venture capital.

[3]Our data construction implies that we estimate asset demand for institutional investors on long positions only, and the aggregate short position of institutional investors is lumped into the household sector.

institutional ownership share has increased over time. Part of this trend is due to a fixed reporting threshold of $100 million in total 13(f) securities, which implies increased coverage of institutional ownership over time. Passive investors account for a large share of institutional ownership, which has important asset pricing implications as we discuss in Section 6.

3.2. Sample of firms

Our sample consists of publicly traded firms with ordinary common shares that trade on the New York Stock Exchange, the American Stock Exchange, and Nasdaq. Table 2 reports summary statistics by deciles of market equity. In 2019.Q4, the largest 57 firms alone accounted for 50% of total market equity. The largest 541 firms that accounted for 90% of total market equity cover 81% of total sales and 87% of total net income. That is, market equity and net income are even more concentrated than sales. A comparison of 2000.Q1 and 2019.Q4 shows that the market concentration has increased among the largest 90% of firms by market equity.

We study the equity prices of the largest 90% of firms by market equity, which capture most of the economic activity among publicly traded firms. In modeling the asset demand system in Section 4, the largest 90% of firms are the inside assets. We aggregate the remaining 10% of firms into an outside asset. This treatment ensures that our estimates of the asset demand system are based on the largest and most liquid stocks (Asness et al., 2013).

3.3. Equity prices and characteristics

Data on equity prices, shares outstanding, and market equity are from FactSet Ownership.[4] Data on financial statements are from Compustat Fundamentals. Data on stock returns are from the Center for Research on Security Prices (CRSP) Monthly Stock Database. Guided by the asset pricing model in Section 2, we model expected profitability and profitability risk as a function of characteristics. We focus on eight characteristics in the baseline specification of asset demand: the environmental score, the governance index, log book equity, the foreign sales share, the Lerner index, the ratio of sales to book equity, the ratio of dividends to book equity, and market beta.

The environmental scores are from Sustainalytics, which is Morningstar's environmental rating agency. The environmental scores are industry adjusted, reflecting differences in environmental risk across firms within an industry. The environmental scores from Sustainalytics do not necessarily have high correlation with those from other environmen-

[4] We use FactSet instead of CRSP to more easily align the institutional holdings and shares outstanding with respect to stock splits.

tal rating agencies. However, Sustainalytics is an important driver of mutual fund flows (Hartzmark and Sussman, 2019).

Following Bebchuk et al. (2009), we construct the governance index as the total number of entrenchment provisions among six that include staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, supermajority requirements for mergers, and supermajority requirements for charter amendments. Bebchuk et al. (2009) find that these entrenchment provisions matter for equity valuations among the 24 governance provisions that Gompers et al. (2003) studied. A higher governance index means that the firm is more entrenched and has weaker governance.

Log book equity captures firm size. The foreign sales share relates to productivity since the most productive firms export their goods (Melitz, 2003). The Lerner index, which is the ratio of operating income after depreciation to sales, is a measure of profitability that relates to market power (e.g., Gutiérrez and Philippon, 2017). We use the market beta as a measure of risk, estimated from a 60-month rolling regression of excess stock returns on the excess market returns.

The sample period is 2000 to 2019. For part of the analysis that requires the environmental score or the governance index, we focus on a shorter sample from 2010 to 2019. For stocks that do not have an environmental score or a governance index, we construct a dummy variable that is equal to one if the corresponding variable is missing. We standardize all characteristics within each year to simplify the interpretation of the regression coefficients.

3.4. Relation between equity valuations and characteristics

An important issue in estimating the asset demand system is the choice of characteristics. The asset pricing model in Section 2 gives us guidance. According to equation (7), characteristics that enter asset demand have explanatory power for the cross section of market-to-book equity. Therefore, we estimate a panel regression of log market-to-book equity on the eight characteristics in the baseline specification:

$$\mathrm{mb}_t(n) = \alpha_t + \overline{\boldsymbol{\beta}}' \boldsymbol{x}_t(n) + \overline{\epsilon}_t(n),$$

where α_t are year fixed effects. Table 3 reports the regression coefficients for the baseline specification in an annual sample from 2010 to 2019. It also reports the regression coefficients for a specification without the environmental score or the governance index in a longer sample from 2000 to 2019.

The eight characteristics in the baseline specification explain most of the cross-sectional variation in market-to-book equity. The adjusted within R^2 is 64%, which excludes the explanatory power of the year fixed effects. The fact that a relatively small number of characteristics have explanatory power for the cross section of market-to-book equity is consistent with Asness et al. (2019). Market-to-book equity is increasing in the environmental score and decreasing in the governance index (i.e., less entrenchment). A standard deviation change in the environmental score is associated with a 17% change in market-to-book equity. A standard deviation change in the governance index is associated with a 10% change in market-to-book equity. The negative coefficient on log book equity means that smaller firms have higher market-to-book equity. The positive coefficients on the foreign sales share and the Lerner index mean that more productive and profitable firms have higher market-to-book equity.

In Table D1 of Appendix D, we test the robustness of the baseline specification by adding three characteristics: investment, the ratio of net repurchases to book equity, and earnings surprises. These characteristics are known to be strong predictors of stock returns (Daniel et al., 2020). We find that the adjusted within R^2 increases only modestly from 64% to 68%. The fact that the additional characteristics do not significantly increase explanatory power further supports the choice of eight characteristics in the baseline specification of the asset demand system.

3.5. Relation between profitability and characteristics

As we discussed in Section 2, the same characteristics that explain market-to-book equity predict either future profitability or stock returns. Let $e_{t,t+5}(n)$ be five-year future profitability, which we define in Appendix B. We estimate a panel regression of future profitability on the eight characteristics in the baseline specification:

$$e_{t,t+5}(n) = \alpha_t + \boldsymbol{\pi}'\boldsymbol{x}_t(n) + \nu_{t+5}(n),$$

where α_t are year fixed effects. In Table 3, we find that the characteristics have significant explanatory power for future profitability with an adjusted within R^2 of 45%. The regression coefficients have the same sign and similar magnitude to those for market-to-book equity. This finding supports the assumption in equation (3) that expected profitability is a function of characteristics. Nevertheless, we caution that expected profitability is challenging to estimate accurately in a short panel.

In Section 8, we use equation (7) to decompose the relative importance of institutional investors for the cross section of market-to-book equity. We also show that the same decomposition has immediate implications for the cross section of expected returns.

4. An empirically tractable asset demand system

The linear demand system in Section 2 is highly tractable for obtaining closed-form solutions for equity prices. For estimation, we use a corresponding logit demand system because the portfolio holdings data are much closer to a lognormal distribution (Koijen and Yogo, 2019). By market clearing, the logit demand system implies a unique solution for equity prices, analogous to equation (7). The only difference is that the solution is numerical instead of closed form.

4.1. *Investment universe*

Following the same notation as Section 2, there are N inside assets indexed by $n = 1, \ldots, N$. In addition, there is an outside asset $n = 0$ that consists of micro-cap stocks, as we described in Section 3. There are I investors indexed by $i = 1, \ldots, I$. Investor $i = 1$ is households, which is a residual sector that holds all remaining shares that are not held by the institutional investors.

Each investor i allocates wealth $A_{i,t}$ in period t across its investment universe $\mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$ and the outside asset. The investment universe is a subset of stocks that an investor is allowed to hold, determined by its investment mandate or benchmarking. For example, an S&P 500 index fund is only allowed to hold stocks in the index. Alternatively, the investment universe could arise from informational frictions that limit an investor's choice set to a subset of stocks (Merton, 1987).

4.2. *Asset demand*

Based on equation (5), we model asset demand to be loglinear in characteristics. Investor i's portfolio weight on asset $n \in \mathcal{N}_{i,t}$ in period t is

$$w_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)}, \tag{10}$$

where

$$\delta_{i,t}(n) = \exp(\alpha_{i,t} + \beta_{0,i,t}\mathrm{mb}_t(n) + \boldsymbol{\beta}'_{1,i,t}\boldsymbol{x}_t(n))\epsilon_{i,t}(n). \tag{11}$$

The portfolio weight depends on investor-time fixed effects $\alpha_{i,t}$, log market-to-book equity $\mathrm{mb}_t(n)$, a vector of observed (to the econometrician) characteristics $\boldsymbol{x}_t(n)$, and latent demand $\epsilon_{i,t}(n)$. Since portfolio weights must add up to one, the portfolio weight on the outside asset is

$$w_{i,t}(0) = \frac{1}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)}. \tag{12}$$

Investors with lower values of $\beta_{0,i,t}$ have more elastic demand, and their portfolio weights vary more with log market-to-book equity. That is, more price elastic investors tilt their portfolios toward stocks with lower market-to-book equity, holding other characteristics constant.

Latent demand $\epsilon_{i,t}(n) \geq 0$ is the part of investor i's demand for asset n that arises from unobserved (to the econometrician) characteristics. Within its investment universe, the investor endogenously chooses a zero portfolio weight for asset n when $\epsilon_{i,t}(n) = 0$. We normalize the mean of latent demand across an investor's investment universe to one so that the intercept $\alpha_{i,t}$ in equation (11) is identified. However, the mean of latent demand across investors need not equal one for a given asset. According to equation (7), any variation in market-to-book equity that characteristics do not explain is due to the weighted average of latent demand. In equilibrium, market-to-book equity is higher for stocks that have higher weighted average of latent demand due to beliefs or sentiment about future profitability.

4.3. Market clearing

Let $P_t(n)$ be market equity for asset n in period t, which is also the equity price because we normalize shares outstanding to one. Market clearing for each asset n is

$$P_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n; \mathbf{P}_t). \tag{13}$$

Market equity is equal to the sum of asset demand, which is wealth times the portfolio weight, across all investors. In equation (10) for the portfolio weight, we can write log market-to-book equity as log market equity minus log book equity. Thus, the notation in equation (13) emphasizes that the portfolio weight for asset n depends on the N-dimensional vector of equity prices $\mathbf{P}_t$.

Market clearing (13) is a system of N nonlinear equations in N equity prices. Koijen and Yogo (2019) show that $\beta_{0,i,t} < 1$ for all investors is a sufficient condition for the system of equations to have a unique solution. Therefore, we impose the coefficient restriction $\beta_{0,i,t} < 1$ in the demand estimation.

4.4. *Counterfactuals with endogenous wealth*

As we explained in Section 2, we consider two types of counterfactuals. The first is capital flows from a group of investors to other investors, such as from active to passive investors. The second is a shift in asset demand through a change in the coefficient for a particular characteristic, such as the environmental score. We solve for the counterfactual equity prices by market clearing, maintaining the assumption in Section 2 that shares outstanding and characteristics do not change in the spirit of an endowment economy. However, we allow the investors' wealth to change endogenously with equity prices, which is a contribution relative to Koijen and Yogo (2019). Thus, the counterfactuals have implications for the wealth distribution, which is an important part of welfare analysis.

Let the superscript C denote the counterfactual values of the corresponding variables. Investor i's wealth in the counterfactual market is

$$A_{i,t}^{C}\left(\mathbf{P}_{t}^{C}\right) = \underbrace{A_{i,t}\left(w_{i,t}(0) + \sum_{n \in \mathcal{N}_{i,t}} \frac{P_{t}^{C}(n)}{P_{t}(n)} w_{i,t}(n)\right)}_{\text{capital gain}} + F_{i,t}. \tag{14}$$

The first term is the investor's initial portfolio revalued at the counterfactual vector of equity prices $\mathbf{P}_{t}^{C}$. The second term is the capital flow $F_{i,t}$. We can specify the set of capital flows and compute the counterfactual wealth distribution by equation (14). Equivalently, we can specify the counterfactual wealth distribution directly and implicitly define the set of capital flows that supports that distribution.

The counterfactual equity prices are a solution to market clearing:

$$P_{t}^{C}(n) = \sum_{i=1}^{I} A_{i,t}^{C}\left(\mathbf{P}_{t}^{C}\right) w_{i,t}^{C}\left(n; \mathbf{P}_{t}^{C}\right). \tag{15}$$

We assume that investors maintain the same outside portfolio weights in the counterfactual market (i.e., $w_{i,t}^{C}(0) = w_{i,t}(0)$), which ensures that our results are not driven by substitution into the outside asset (i.e., micro-cap stocks). We solve for the counterfactual equity prices by iterating on equation (15) until convergence, using the algorithm in Koijen and Yogo (2019, Appendix C). Equation (14) at the converged vector of equity prices implies the counterfactual wealth distribution.

5. Estimating the asset demand system

We face two main challenges in the demand estimation. First, market-to-book equity and latent demand are jointly endogenous, which we address through instrumental variables. Second, many investors do not have enough observations in the cross section of equity holdings for accurate demand estimation, which we address through a ridge estimator. After estimating the asset demand system, we summarize the evidence on heterogeneity in asset demand and low demand elasticities across institutional investors. Finally, we test the robustness of our identifying assumptions.

5.1. *Estimation equation*

For each investor i, we divide the portfolio weight for asset n (10) by the outside portfolio weight (12) to obtain a nonlinear regression equation:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_{i,t}(n) = \exp(\alpha_{i,t} + \beta_{0,i,t}\mathrm{mb}_t(n) + \boldsymbol{\beta}'_{1,i,t}\boldsymbol{x}_t(n))\epsilon_{i,t}(n), \tag{16}$$

The cross-sectional relation between the portfolio weights and the characteristics identifies the demand coefficients. More price elastic investors tilt their portfolios toward stocks with lower market-to-book equity, controlling for other characteristics. Investors who tilt their portfolios toward greener stocks have larger coefficients on the environmental score, controlling for other characteristics.

We use two estimation samples for the demand estimation. The first is quarterly data from 2000.Q1 to 2019.Q4, for which we use six characteristics: log book equity, foreign sales share, the Lerner index, the ratio of sales to book equity, the ratio of dividends to book equity, and market beta. The second is quarterly data from 2010.Q1 to 2019.Q4, for which we add the environmental score and the governance index as additional characteristics.

5.2. *Instrumental variables*

Our baseline assumption is that the observed characteristics $\boldsymbol{x}_t(n)$ are exogenous in the spirit of an endowment economy. However, we discuss how to relax this assumption to allow for endogenous characteristics in Appendix D.3. Even with exogenous characteristics, log market-to-book equity and latent demand are jointly endogenous. This correlation could arise for larger investors with price impact or smaller investors with correlated latent demand that have price impact in the aggregate.

Following Koijen and Yogo (2019), we construct an instrument under the assumption that investors have an exogenous component of demand that arises from predetermined investment mandates. For example, mutual funds have investment mandates or an effective investment universe that arises from benchmarking. Hedge funds, pension funds, and insurance companies also have investment mandates or an effective investment universe that arises from capital regulation and fiduciary rules. Alternatively, an investment universe could arise from informational frictions that limit an investor's choice set to a subset of stocks.

Although investment mandates and benchmarking are ubiquitous, they are not systematically disclosed except for some mutual funds and exchange traded funds. Following Koijen and Yogo (2019), we estimate the investment universe in each period as the set of stocks that an investor currently holds or has ever held in the past 11 quarters. Consistent with the notion that the investment universe is predetermined and exogenous to contemporaneous demand shocks, Koijen and Yogo (2019) show that this empirical estimate of the investment universe is very stable over time. In Appendix D, we test the robustness of our estimates to changing the definition of the investment universe in various ways.

Let $\mathcal{N}_{i,t}$ be the investment universe of investor i in period t. Let $|\mathcal{N}_{i,t}|$ be the number of stocks in the investment universe. Let $\mathbb{1}_i(n)$ be an indicator function that is equal to one if stock n is in investor i's investment universe. Under the assumption that our empirical estimates of the investment universe are exogenous, we construct an instrument for log market equity of asset n as

$$z_{i,t}(n) = \log\left(\sum_{j \notin \{i,1\}} A_{j,t} \frac{\mathbb{1}_j(n)}{1 + |\mathcal{N}_{j,t}|}\right).$$

This instrument corresponds to log market equity for stock n in a counterfactual market if investors were to hold an equal-weighted portfolio within their investment universe. The instrument is investor specific (and thus indexed by i) because we exclude own holdings and the household sector (i.e., $j = 1$). The identifying assumption is that the investment universe of other institutional investors affects the portfolio choice of investor i only through prices.

5.3. Estimation methodology

Another challenge in the demand estimation is that most institutional investors hold concentrated portfolios. Thus, many investors do not have enough observations in the cross section of equity holdings for accurate demand estimation. This challenge is especially relevant since we define inside assets as the largest 90% of firms by market equity, which makes the cross section smaller than the universe of all U.S. stocks. In estimating equation (16), we pool the data across the four quarters of a given year and assume that the demand coefficients are constant within each year. However, we allow the intercept $\alpha_{i,t}$ to vary across quarters.

For investors with fewer than 2,000 holdings across the four quarters (inclusive of the zero holdings), we estimate their demand coefficients through a two-step instrumental variables ridge estimator (Hoerl and Kennard, 1970). In the first step, we estimate the shrinkage target. We sort the investors by investor type and average wealth over the four quarters. We group the investors so that there are at least 2,000 holdings per group. Let $\mathbf{0}$ be a vector of zeros. Let $\boldsymbol{e}_t$ be a four-dimensional vector of time fixed effects, where the t-element is one and the other elements are zero. We estimate the demand coefficients through the moment condition:

$$\mathbb{E}\left[\left(\underbrace{\delta_{i,t}(n)\exp(-\beta_{0,i}\mathrm{mb}_t(n)-\boldsymbol{\alpha}_i'\boldsymbol{e}_t-\boldsymbol{\beta}_i'\boldsymbol{x}_t(n))}_{\epsilon_{i,t}(n)}-1\right)\begin{pmatrix} z_{i,t}(n)\\ \boldsymbol{e}_t \\ \boldsymbol{x}_t(n)\end{pmatrix}\right]=\mathbf{0}. \tag{17}$$

We denote the estimated coefficients for log market-to-book equity and other characteristics as $\widehat{\beta}_0$ and $\widehat{\boldsymbol{\beta}}_1$, respectively.

In the second step, we estimate the demand coefficients for each investor, using the group-level estimates as the shrinkage target. We impose an infinite penalty on the coefficient for log market-to-book equity to avoid weak identification, which is conceptually related to two-sample instrumental variables estimation (Angrist and Krueger, 1992). We estimate the coefficients on the other characteristics through the moment condition:

$$\mathbb{E}\left[\left(\widehat{\delta}_{i,t}(n)\exp(-\boldsymbol{\alpha}_i'\boldsymbol{e}_t-\boldsymbol{\beta}_i'\boldsymbol{x}_t(n))-1\right)\begin{pmatrix}\boldsymbol{e}_t\\ \boldsymbol{x}_t(n)\end{pmatrix}\right]-\frac{\lambda}{|\mathcal{N}_i|^{\xi}}\begin{pmatrix}\mathbf{0}\\ \boldsymbol{\beta}_i-\widehat{\boldsymbol{\beta}}_1\end{pmatrix}=\mathbf{0}, \tag{18}$$

where $\widehat{\delta}_{i,t}(n)=\delta_{i,t}(n)\exp(-\widehat{\beta}_0\mathrm{mb}_t(n))$. A quadratic penalty on the generalized method of moments objective function leads to a linear term in the moment condition (18). The penalty is inversely related to $|\mathcal{N}_i|$, which is the number of investor i's holdings across the four quarters. The penalty shrinks the demand coefficients toward the group-level estimator $\widehat{\boldsymbol{\beta}}_1$.

We select the penalty parameters by cross validation. For each investor, we randomly split the estimation sample in half within each quarter. We estimate asset demand in the first subsample and compute the mean squared error of predicted demand in the second subsample. We select the penalty parameters to minimize the mean squared error, which turn out to be $\lambda=120$ and $\xi=0.7$. In Appendix C, we describe a fast numerical algorithm to compute the instrumental variables ridge estimator.

For investors with at least 2,000 holdings across the four quarters (inclusive of the zero holdings), we estimate their demand coefficients individually by generalized method of moments through the moment condition (17).

5.4. Estimated demand system

The demand coefficients are too numerous to report, so we summarize their distribution in various ways. Except for log market-to-book equity, we standardize and multiply the demand coefficients by 100, so that they can be interpreted as the percentage change in demand per one standard deviation change in the characteristic.

For each investor type, we compute the wealth-weighted average of the demand coefficients by year and then average across years. The wealth-weighted demand coefficients, represented by the colored vertical lines in Figure 2, vary across investor types. For example, the wealth-weighted coefficient on the environmental score is 3.07% for small-passive investor advisors and −1.25% for hedge funds. A coefficient of 3.07 on the environmental score means that demand changes by 3.07 percentage points per one standard deviation change in the environmental score.

Figure 2 also shows significant heterogeneity in the demand coefficients across investors, beyond the heterogeneity across investor types. For each investor, we compute the time-series average of the demand coefficients. We then plot the cross-sectional distribution of the average demand coefficients. The average coefficient on log market-to-book equity varies from 1 (i.e., inelastic demand) to 0 (i.e., approximately unit elasticity) across investors. This coefficient determines the price elasticity of demand, which is approximately $1 - \beta_{0,i,t}$. Even hedge funds, which are the most elastic among institutional investors, have a wealth-weighted demand elasticity around 0.5.

Table 4 summarizes the cross-sectional variation in the demand coefficients across investors. For each investor, we compute the time-series average of the demand coefficients. Panel A reports a regression of the average demand coefficients on investor-type fixed effects. Passive investment advisors (both large and small) and brokers have a higher demand for stocks with higher environmental scores. Small-active investment advisors and brokers have a higher demand for stocks with lower governance indices (i.e., less entrenchment). On the one hand, hedge funds and small-active investment advisors have lower coefficients on log market-to-book equity, implying higher demand elasticities. On the other hand, large investment advisors (both passive and active), long-term investors, and brokers have higher coefficients on log market-to-book equity.

Panel A of Table 4 also reports the adjusted R^2 for the regression of the demand coefficients on investor-type fixed effects. Log market-to-book equity, which determines the demand elasticity, has an adjusted R^2 of 48%. Log book equity, which captures demand for firm size, has an adjusted R^2 of 59%. Except for these two characteristics, the demand coefficients have a low R^2. The investor type alone does not explain much of the heterogeneity in asset demand across investors.

Panel B of Table 4 reports a regression of the average demand coefficients on the log wealth share, the active share, and a foreign-investor dummy. Larger, passive, and foreign investors have a higher demand for stocks with higher environmental scores. Smaller and foreign investors have a higher demand for stocks with lower governance indices (i.e., less entrenchment). Smaller and more active investors have lower coefficients on log market-to-book equity, implying higher demand elasticities. Except for log market-to-book equity and log book equity, the demand coefficients have a low R^2.

Figure 3 summarizes the differences in the demand coefficients between domestic and foreign investors. For each group of investors, we compute the wealth-weighted average of the demand coefficients by year and then average across years. Foreign investors have a higher demand for stocks with higher environmental scores and lower governance indices (i.e., less entrenchment). This finding suggests that foreign investors play an important role in lowering the cost of capital for greener U.S. firms. Foreign investors also have a higher demand for stocks with a higher foreign sales share, perhaps due to more familiarity with those firms. Finally, foreign investors have a higher demand for safer stocks with a lower market beta.

In summary, we find rich heterogeneity in asset demand across investors that are not well captured by simple characteristics such as investor type, wealth, activeness, and geography. This finding has several important implications. First, it highlights the relevance of the instrumental variables ridge estimator that allows for heterogeneity in asset demand within investor type and wealth group. Second, it opens a new research agenda to explain the heterogeneity using more granular information about investors such their capital regulation, investment mandates, and funding structure. Third, the heterogeneity in asset demand implies that ownership could have an important impact on equity prices, as we study in Sections 6–8.

5.5. Robustness of the identifying assumptions

We have made a number of choices in the identifying assumptions and in specifying asset demand. We would like to ensure that our results are robust to reasonable variation in these assumptions. In particular, we test whether our results are robust to the definition of the investment universe, the choice of characteristics, and the exogeneity of characteristics. Our criteria for robustness are the estimated demand coefficients and their impact on the counterfactual equity prices, price informativeness, and the wealth distribution in the applications of Sections 6–8. We summarize the results here and leave the full presentation for

Appendix D.

Although investment mandates and benchmarking are ubiquitous, estimating the investment universe is challenging. The baseline definition of the investment universe is the set of stocks that an investor currently holds or has ever held in the past 11 quarters. We test whether our results are robust to changing the definition in three ways. First, we construct the instrument without hedge funds to address the concern that their investment mandates may be more flexible than those of other institutional investors. Second, we change the window for estimating the investment universe, both backward and forward by up to five years. Third, we randomly increase the number of stocks in the investment universe by up to 100%. Our results are robust to each of these alternative assumptions.

We have eight characteristics in the baseline specification of asset demand. We test whether our results are robust to the choice of characteristics by adding three characteristics: investment, the ratio of net repurchases to book equity, and earnings surprises. These characteristics are known to be strong predictors of stock returns (Daniel et al., 2020). Our results are robust to the additional characteristics, suggesting that the baseline specification is not especially sensitive to the choice of characteristics.

The baseline assumption is that characteristics other than log market-to-book equity are exogenous. However, some firm decisions, such as dividend policy, could depend on equity prices. Our results are robust to an alternative estimator of asset demand that allows the ratio of dividends to book equity to be endogenous.

6. Transition from active to passive investment management

The estimated demand system reveals rich heterogeneity in asset demand across investors. The heterogeneity between active and passive investors is one dimension that is of current policy interest because of the transition from active to passive investment management. We first show that the decline in the aggregate active share is mostly due to the capital flows from active to passive investors, rather than the investment strategies becoming more passive. Based on this fact, we design a counterfactual to quantify the impact of the transition from active to passive investment management on equity prices and price informativeness.

6.1. Trend in the aggregate active share

We use the active share, appropriately modified for our application, as a measure of active investment management (Cremers and Petajisto, 2009). Let $A^I_{i,t} = A_{i,t}(1 - w_{i,t}(0))$ be investor i's wealth excluding the outside assets (i.e., micro-cap stocks). Let $w^I_{i,t}(n) = P_t(n)q_{i,t}(n)/A^I_{i,t}$ be the investor's portfolio weight on stock n among the inside assets only.

Let $\mathcal{M}_{i,t}$ be the subset of the inside assets with positive holdings in period t. Let $w_{i,t}^M(n) = P_t(n)/\sum_{m\in\mathcal{M}_{i,t}} P_t(m)$ be the corresponding portfolio weight if the investor were to hold the market portfolio among its inside assets. We define investor i's active share in period t as

$$\text{AS}_{i,t} = \frac{1}{2}\sum_{n\in\mathcal{M}_{i,t}} \left|w_{i,t}^I(n) - w_{i,t}^M(n)\right|. \tag{19}$$

The active share measures the total share of the investor's portfolio that deviates from the market weights. The division by two avoids double counting and ensures the active share is between zero (most passive) and one (most active).

We then define the aggregate active share as a wealth-weighted average of the active shares across all institutional investors, excluding the household sector (i.e., $i = 1$):

$$\text{AS}_t = \sum_{i=2}^{I} a_{i,t}\text{AS}_{i,t},$$

where $a_{i,t} = A_{i,t}^I/\sum_{j=2}^I A_{j,t}^I$ is the wealth share. Panel A of Figure 4 shows that the aggregate active share declined from 2000 to 2019, based on our sample from FactSet Ownership. Panel B shows a longer decline from 45% in 1980 to 25% in 2018, based on the Thomson Reuters Institutional Holdings Database. We focus our analysis on 2007.Q4 to 2016.Q4, which is a subperiod that has a similar rate of decline to the overall trend from 1980 to 2018. During this period, the aggregate active share declined from 34.5% to 29.9%, for the subset of institutional investors who exist in both 2007.Q4 and 2016.Q4.[5]

For this subset of institutional investors, we decompose the change in the aggregate active share as

$$\text{AS}_{2016}^B - \text{AS}_{2007}^B = \sum_{i=2}^{I} a_{i,2007}^B(\text{AS}_{i,2016} - \text{AS}_{i,2007}) + \sum_{i=2}^{I}\left(a_{i,2016}^B - a_{i,2007}^B\right)\text{AS}_{i,2016},$$

where the variables with the superscript B are defined over investors who exist in both 2007.Q4 and 2016.Q4. The aggregate active share can change for two reasons. The first term captures the change in the investment strategies, holding the wealth distribution constant. The second term is the change in the wealth distribution, holding the investment strategies constant. We find that the change in the aggregate active share is the sum of -0.9% for the first term and -3.7% for the second term. Thus, the decline in the aggregate active share is

[5]This subset of investors managed 89.8% of all institutional equity holdings in 2016. In addition, the decline in the aggregate active share from 34.5% to 29.9% closely matches 35.2% to 30.5%, which are the corresponding estimates without conditioning on the subset of investors.

mostly due to the capital flows from active to passive investors, rather than the investment strategies becoming more passive.

6.2. Impact on equity prices

Based on this fact about the aggregate active share, we design a counterfactual to quantify the impact of the transition from active to passive investment management on equity prices and price informativeness. Within the subset of institutional investors who exist in both 2007.Q4 and 2016.Q4, we replace their wealth distribution in 2016.Q4 with that in 2007.Q4.[6] However, we do not change their asset demand functions (i.e., the demand coefficients and latent demand) in 2016.Q4. For the household sector and the institutional investors who exist only in 2016.Q4, we do not change their wealth or asset demand functions. As we discussed in Section 4, this change in the wealth distribution defines a set of capital flows across investors by equation (14). By market clearing, we compute counterfactual equity prices in 2016.Q4 if the wealth distribution across institutional investors were to remain the same as that in 2007.Q4.

Panel A of Figure 5 is a scatter plot that compares the wealth distribution in 2007.Q4 and 2016.Q4. Both axes are in units of log wealth shares. Above the 45-degree line are investors whose wealth share increased from 2007.Q4 and 2016.Q4. These investors are more passive on average and would have a lower wealth share in the counterfactual market.

Panel B of Figure 5 is a scatter plot of the actual log market equity in 2016.Q4 versus the counterfactual log market equity. Equity prices change substantially, especially among smaller stocks. Above the 45-degree line are stocks that become more expensive in the counterfactual market. These stocks have characteristics or latent demand that are more highly valued by investors who become larger in the counterfactual market. We summarize Panel B by defining equity repricing as the value-weighted absolute percentage change in equity prices:

$$\frac{\sum_{n=1}^{N} \left| P_t^C(n) - P_t(n) \right|}{\sum_{n=1}^{N} P_t(n)}, \tag{20}$$

where $P_t^C(n)$ is the counterfactual market equity for stock n. We find an economically significant estimate of 14%.

[6] We have verified that the results in this section are robust to an alternative counterfactual that isolates the capital flows that correlate with the active share. We run a cross-sectional regression of the log difference in wealth shares between 2007.Q4 and 2016.Q4 on the active share in 2016.Q4. We then multiply the wealth shares in 2016.Q4 by the exponential of the predicted values from the regression to obtain the counterfactual wealth distribution in 2007.Q4.

6.3. *Impact on price informativeness*

The transition from active to passive investment management could have implications for price informativeness. Equity prices could become less informative if capital flowed from more to less informed investors. We first estimate how the change in the wealth distribution from 2007.Q4 to 2016.Q4 affected price informativeness. We then investigate the mechanism with a measure of investor-level informativeness.

Let $E_t(n)$ be earnings before interest and taxes for stock n in year t.[7] Let $A_t(n)$ be book assets for stock n in period t. Following Bai et al. (2016), we measure price informativeness based on a cross-sectional regression:

$$\frac{E_{t+3}(n)}{A_t(n)} = \alpha + \pi \log\left(\frac{P_t(n)}{A_t(n)}\right) + \rho\left(\frac{E_t(n)}{A_t(n)}\right) + \nu_t(n). \tag{21}$$

This regression asks whether the ratio of market equity to book assets predicts future profitability, which is the ratio of three-year ahead earnings to book assets. The regression coefficient π measures price informativeness, where a higher coefficient implies that equity prices are more informative. In 2016.Q4, we estimate a standardized coefficient of 0.049 with a standard error of 0.003. This estimate implies that a standard deviation change in the ratio of market equity to book assets predicts a 4.9 percentage point change in profitability.

We quantify the impact of the change in the wealth distribution from 2007.Q4 to 2016.Q4 on price informativeness. We reestimate the cross-section regression (21), replacing the actual market equity in 2016.Q4 with the counterfactual market equity under the wealth distribution in 2007.Q4. Panel C of Figure 5 shows that the regression coefficient for price informativeness hardly changes. The first bar in Panel C represents the regression coefficient 0.049 estimated on actual data, together with a 95% confidence interval. The second bar shows the impact of changing the wealth distribution for only large-passive investment advisors to that in 2007.Q4. The third bar shows the cumulative impact of changing the wealth distribution for small-passive and large-passive investment advisors to that in 2007.Q4. We keep adding investor types sequentially until the final bar, which shows the cumulative impact of changing the wealth distribution for all institutional investors to that in 2007.Q4.[8]

[7] Following Bai et al. (2016), we use this measure that is different from the clean-surplus earnings that we used in Table 3. However, we have checked that the results in Table 3 are similar when we use earnings before interest and taxes.

[8] In each step, we rescale total wealth by investor type so that the relative size of the investor types match the actual distribution in 2016.Q4.

6.4. *Investor-level informativeness*

To investigate why the change in the wealth distribution had a small impact on price informativeness, we develop a measure of investor-level informativeness. We are guided by equation (9), which shows that the investors' demand shifters reflect beliefs or sentiment about future profitability. A more informed investor has demand shifters that predict future profitability in the cross section of its equity holdings. Thus, we identify which investors are more informed about future profitability to directly test whether capital flowed from more to less informed investors.

For each investor in 2016.Q4, we estimate the demand shifters based on the characteristics and the estimated demand coefficients and latent demand. We then estimate a cross-sectional regression of future profitability on the demand shifters:

$$\frac{E_{t+3}(n)}{A_t(n)} = \alpha + \pi_i \log\left(\frac{\exp(\boldsymbol{\beta}'_{1,i,t}\boldsymbol{x}_t(n))\epsilon_{i,t}(n)}{A_t(n)}\right) + \rho\left(\frac{E_t(n)}{A_t(n)}\right) + \nu_t(n).$$

The investor-level informativeness is the standardized version of the regression coefficient π_i. A higher coefficient implies that the investors' demand shifters are more informative about future profitability. We focus on the subsample of investors with at least 30 positive holdings. Nevertheless, we caution that expected profitability is challenging to estimate accurately in a single cross section. Future research could extend our estimation exercise to the entire panel to systematically study price discovery and market efficiency.

Panel D of Figure 5 is a bin scatter plot of the changes in the log wealth share from 2007.Q4 to 2016.Q4 versus the investor-level informativeness. There is little correlation between the two variables, which implies that capital did not flow from more to less informed investors on average. Thus, the transition from active to passive investment management did not reduce price informativeness, despite the large effect that it had on equity prices.

7. Climate-induced shifts in asset demand

Stroebel and Wurgler (2021) surveyed 861 finance academics, policy economists, professionals, and public sector regulators regarding climate risk. Over a shorter horizon of five years, the survey finds that regulatory risk is the primary source of climate risk. The survey also identifies stakeholder risk as a secondary source of climate risk, which includes the changing preferences of customers and employees. Over a longer horizon of 30 years, the survey finds that physical risk is the primary source of climate risk. By an overwhelming margin, the respondents believe that asset prices underestimate climate risk.

Based on this survey, we focus on regulatory and stakeholder risks. A comprehensive analysis of these risks on asset prices, firms, and the macroeconomy is beyond the scope of this paper. We focus on one important aspect of this problem, which is the potential impact on equity prices and the wealth distribution across institutional investors. Our counterfactual analysis could be a building block in a more comprehensive climate stress test of the financial sector.

7.1. Modeling the impact of climate risk on asset demand

We focus on one aspect of regulatory risk, which is a tighter constraint on the portfolio choice of long-term investors (i.e., pension funds and insurance companies). Pension and insurance regulators could become increasingly concerned that some firms are exposed to greater stakeholder or physical risk. Alternatively, some firms are exposed to greater uncertainty over a carbon tax. To limit the climate risk exposure, pension and insurance regulators could change the investment mandates to favor green firms or increase the capital charges on brown firms as part of risk-based capital regulation. For example, the National Association of Insurance Commissioners has set up a Climate and Resiliency Task Force to explore the impact of climate risk on the insurance industry.

We model realized regulatory risk as an increase in the coefficient on the environmental score for long-term investors by 0.1, which is approximately one standard deviation in its cross-sectional distribution (see Figure 2). A increase of 0.1 implies that the portfolio weight changes by 10% (e.g., from 5% to 5.5% of wealth) per one standard deviation change in the environmental score. We assume that the coefficients on the other characteristics remain constant because the environmental score is only weakly correlated with the other characteristics. However, we could choose a value different from 0.1 or allow the coefficients on the other characteristics to change to tailor the counterfactual to a particular policy proposal.

Stakeholder risk arises from the possibility that many institutional investors unexpectedly shift their portfolios toward greener firms in response to the changing preferences of customers and employees. We model realized stakeholder risk as an increase in the coefficient on the environmental score for all institutional investors by 0.1. An important caveat is that the counterfactual only captures the short-run effects on equity prices, holding the composition of firms and their environmental scores fixed. In the long-run, the composition of firms and their policies could change with climate-induced shifts in asset demand.

7.2. Impact on equity prices

As a reference point, the first column of Table 5 reports a regression of log market-to-book equity on characteristics in 2019. This regression is essentially the same as that in Table 3, except that we limit the sample to a single cross section.

The second column of Table 5 reports the change in the regression coefficients in response to realized stakeholder risk, when the elasticity of demand to the environmental score increases for all institutional investors. We estimate the second column through a regression of the difference between counterfactual and actual log market-to-book equity on the characteristics. The regression coefficient on the environmental score increases by 0.57. That is, market-to-book equity changes by 57% more per one standard deviation change in the environmental score. As we explained Section 2, the regression coefficients on the other characteristics do not change in a linear asset pricing model. Thus, the fact that the regression coefficients on the other characteristics hardly change implies approximately linear effects in the counterfactual.

The third column of Table 5 reports the change in the regression coefficients in response to realized regulatory risk, when the elasticity of demand to the environmental score increases for long-term investors only. The regression coefficient on the environmental score increases by 0.03, which is a much smaller effect because the regulation applies to a smaller group of investors. This finding implies that pension funds and insurance companies could reduce climate risk exposure without a large impact on the stock market. An important caveat is that pension funds and insurance companies are larger in fixed income markets, so the overall impact on financial markets could be larger than the limited scope of our analysis.

7.3. Impact on the wealth distribution

Because of initial heterogeneity in portfolio strategies along the environmental score, the wealth distribution across institutional investors changes when equity prices change. Panel A of Figure 6 is a bin scatter plot of the coefficient on the environmental score versus the percent change in wealth in response to realized stakeholder risk. Investors whose initial portfolios tilt toward greener stocks benefit when these stocks become more expensive in the counterfactual market.

Panel B of Figure 6 shows the percent change in wealth in response to climate-induced shifts in asset demand. Stakeholder risk has a larger impact on the wealth distribution than regulatory risk because of larger changes in equity prices. On the one hand, passive investment advisors, long-term investors, and private banking earn capital gains. On the other hand, active investment advisors and hedge funds earn capital losses. Thus, active investment advisors and hedge funds have the greatest exposure to climate risk.

8. Impact of institutional investors on equity prices

Building on the two policy-relevant applications in the previous sections, we use the asset demand system to study the relative importance of institutional investors for cross-sectional asset pricing. Our starting point is equation (7), which shows that market-to-book equity is a wealth-weighted average of the demand shifters across investors. The variation in the demand shifters across investors reflect heterogeneous beliefs or sentiment about future profitability. Consequently, equity prices change with the wealth distribution across institutional investors.

We quantify the relative importance of a group $\mathcal{G}$ of investors through a counterfactual flow from this group to other institutional investors in proportion to their wealth. In the counterfactual, we set $A_{k,t} = 0$ for all investors $k \in \mathcal{G}$ (e.g., hedge funds) and keep the household wealth $A_{1,t}$ constant. The other institutional investors receive an offsetting flow

$$F_{i,t} = \frac{A_{i,t}}{\sum_{j \notin \{\mathcal{G},1\}} A_{j,t}} \left(\sum_{k \in \mathcal{G}} A_{k,t} \right).$$

This flow defines a new wealth distribution across institutional investors through equation (14). We do not change the asset demand functions (i.e., the demand coefficients and latent demand) in this counterfactual. By market clearing, we compute counterfactual equity prices in response to capital flows from a group of investors to other institutional investors.

8.1. *Impact on equity prices*

In Table 6, the first column reports the wealth distribution as a share of total wealth. The second column reports equity repricing (20) in response to capital flows from the given group of investors to other institutional investors. Comparing the first two columns, the equity repricing is larger for capital flows from a larger group of investors. The largest equity repricing is 26.7% for capital flows from small-active investment advisors. The equity pricing is modest for smaller groups of investors including hedge funds, long-term investors, private banking, and brokers. For example, the equity pricing is 1.8% for brokers because they manage only 1.1% of the stock market.

In Table 6, the last column reports the ratio of equity repricing in the second column to the wealth share in the first column. Thus, the last column is the absolute dollar change in equity prices per dollar of wealth. Relative to their size, hedge funds play an outsized role with equity repricing of \$3.58 per dollar of wealth. Small-active investors also play an important role with equity repricing of \$2.28 per dollar of wealth. In contrast, passive investment advisors (both large and small) and long-term investors play a less important role with equity repricing of about $1 per dollar of wealth.

Figure 7 explains the mechanism behind the relative importance of institutional investors for equity prices. Panels A and B report the same information as Table 6. Panel A reports the wealth distribution and the equity repricing by investor type. Panel B reports the equity repricing per dollar of wealth by investor type. Panels C and D explain the two important inputs behind the equity repricing per dollar of wealth in Panel B. The first input is heterogeneity in asset demand. The equity repricing per dollar of wealth is larger for capital flows from a group of investors who have asset demand that is more different from the other investors. A simple statistic that captures the heterogeneity in asset demand is the active share (19). Panel C shows a positive correlation between the active share and the equity repricing per dollar of wealth across investor types. Hedge funds have the largest equity repricing per dollar of wealth because their portfolio strategies are the most different from the other investors.

The second input is the relative demand elasticities across investors. For a group of investors who have relatively elastic demand, their outflow faces the relatively inelastic demand of the other investors, leading to a larger price impact. A simple statistic that captures the demand elasticity by investor type is the wealth-weighted average of one minus the coefficient on log market equity (i.e., $1 - \beta_{0,i,t}$). Panel D shows a positive correlation between the wealth-weighted demand elasticity and the equity repricing per dollar of wealth across investor types. Hedge funds have the largest equity repricing per dollar of wealth because they have relatively elastic demand, so that their outflow faces the relatively inelastic demand of the other investors. In summary, the combination of more active portfolio strategies and more elastic demand implies that hedge funds have the largest impact on equity prices per dollar of wealth.

8.2. Relation between equity valuations and characteristics

Table 3 shows that characteristics explain a large share of the variation in market-to-book equity. Financial analysts, economists, and reporters sometimes provide narratives for the relation between equity valuations and characteristics. One narrative is that retail investors and hedge funds drove up the prices of growth stocks during the dot-com bubble and COVID-19. Another narrative is that pension funds and sovereign wealth funds drive up the prices of sustainable or socially responsible firms. The asset demand system provides a framework to quantitatively assess these narratives, by allowing us to infer the investor's beliefs or sentiment about future profitability from their portfolios.

In Table 7, the first column reports the regression of actual log market-to-book equity on characteristics, which is identical to the first column of Table 3. The remaining columns reestimate the regression with counterfactual log market-to-book equity for capital flows from the given group of investors to other institutional investors. Small-active investment advisors and foreign investors have opposite effects on the pricing of the environmental score. On the one hand, the regression coefficient on the environmental score increases from 0.17 to 0.21 for capital flows from small-active investment advisors. That is, a standard deviation change in the environmental score would change equity prices by 21% instead of 17%. On the other hand, the regression coefficient on the environmental score decreases from 0.17 to 0.14 for capital flows from foreign investors.[9]

Small-active investment advisors and hedge funds are influential in pricing the governance index. The regression coefficient on the governance index increases from −0.10 to −0.09 for capital flows from small-active investment advisors or hedge funds. That is, a standard deviation decrease in the governance index (i.e., less entrenchment) would increase equity prices by 9% instead of 10%.

8.3. *Relation between expected returns and characteristics*

The decomposition of market-to-book equity into the relative importance of institutional investors has immediate implications for expected returns. Let r_t be the log stock return and e_t be log profitability in year t, which we define in Appendix B. Cohen et al. (2003) derive a present-value model for log market-to-book equity:

$$\mathrm{mb}_t = \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t[e_{t+s}] - \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t[r_{t+s}].$$

If expected returns were to follow an autoregressive process so that $\mathbb{E}_t[r_{t+s}] = \phi^{s-1}\mu_t$, this equation simplifies to

$$\mu_t = (1 - \rho\phi) \left(-\mathrm{mb}_t(n) + \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t[e_{t+s}] \right). \qquad (22)$$

Expected returns are high when log market-to-book equity is low or when expected profitability is high. The sensitivity of expected returns to log market-to-book equity is decreasing in the persistence of expected returns (i.e., decreasing in ϕ).

Suppose that the econometrician's forecast of expected profitability does not change in a counterfactual. We can use equation (22) to translate the counterfactual change in

[9] Future research could examine whether foreign ownership increases investment in greener technology, building on previous findings that foreign ownership increases long-term investment and price informativeness (Bena et al., 2017; Kacperczyk et al., 2021).

log market-to-book equity to the corresponding change in expected returns. For example, consider the counterfactual capital flow from small-active investment advisors in Table 7. Log market-to-book equity for a stock with the environmental score equal to one standard deviation increases by 0.04. Using an estimate $1 - \rho\phi = 1 - 0.932 \times 0.969 = 0.097$ (Binsbergen and Koijen, 2010), the annual expected return decreases by 39 basis points (i.e., 0.097×0.04). More generally, we can translate all of Table 7 to units of annual expected returns by simply multiplying each cell by -0.097.

9. Conclusion

We develop a new framework to quantify the impact of market trends and changes in regulation on asset prices, price informativeness, and the wealth distribution. We estimate an asset demand system to quantify the importance of capital flows and shifts in asset demand in two applications of current policy interest. First, we find that the transition from active to passive investment management has a large impact on equity prices but a small impact on price informativeness. To explain the latter result, we develop a measure of investor-level informativeness that allows us to identify which investors are more informed about future profitability. The investor-level informativeness could have broader application in studying price discovery and market efficiency. Second, climate-induced shifts in asset demand that affect all institutional investors have a large impact on equity prices and the wealth distribution. Such shifts imply capital gains for passive investment advisors, pension funds, insurance companies, and private banking and capital losses for active investment advisors and hedge funds.

The framework could be useful for future research because the set of policy-relevant questions changes over time. In addition, future research could extend the framework to study other policy-relevant outcomes. For example, the transition from active to passive investment management could reduce trading and liquidity. An analysis of liquidity would benefit from higher frequency transactions data, which are available in other countries such as Norway and Brazil (Betermier et al., 2022; Schmickler and Tremacoldi-Rossi, 2022).

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Table 1
Largest investors by investor type

Type	Investor	Wealth
Households		8553
Large-passive IA	The Vanguard Group, Inc.	2494
Large-active IA	T. Rowe Price Associates, Inc.	659
Long-term	Norges Bank Investment Management	292
Small-passive IA	Charles Schwab Investment Management, Inc.	162
Small-active IA	PRIMECAP Management Co.	117
Private banking	Goldman Sachs & Co. LLC	112
Hedge funds	Renaissance Technologies LLC	89
Brokers	Schweizerische Nationalbank	84
Foreign	Norges Bank Investment Management	292

Notes: Wealth is U.S. equity holdings in billions of U.S. dollars in 2019.Q4.

Table 2
Firm size distribution

Market equity percentile	Number of firms	Sales percentile	Net income percentile
Panel A: 2019.Q4			
10	3	4	6
20	9	12	16
30	19	21	27
40	34	29	40
50	57	34	46
60	97	44	57
70	159	56	67
80	278	68	77
90	541	81	87
100	2825	100	100
Panel B: 2000.Q1			
10	3	2	4
20	8	7	9
30	17	12	16
40	29	16	21
50	48	21	32
60	80	34	46
70	142	42	53
80	274	55	66
90	615	72	81
100	5137	100	100

Notes: This table reports summary statistics for U.S. firms by deciles of market equity.

Table 3

Explaining equity valuations and future profitability with characteristics

	2010–2019		2000–2019	
Characteristic	Market-to-book	Profitability	Market-to-book	Profitability
Environment	0.17	0.04		
	(8.08)	(7.27)		
Governance	−0.10	−0.08		
	(−6.35)	(−4.74)		
Log book equity	−0.65	−0.26	−0.55	−0.23
	(−24.59)	(−9.69)	(−30.04)	(−21.04)
Foreign sales	0.11	0.01	0.14	0.03
	(10.26)	(0.61)	(19.80)	(3.65)
Lerner	0.08	0.15	0.09	0.18
	(7.74)	(9.22)	(10.88)	(9.64)
Sales to book	0.22	0.26	0.21	0.21
	(22.81)	(9.16)	(22.45)	(14.32)
Dividends to book	0.17	0.07	0.19	0.06
	(20.34)	(12.96)	(29.55)	(5.29)
Market beta	−0.04	−0.05	0.02	−0.01
	(−2.38)	(−9.77)	(0.74)	(−0.84)
Adjusted R^2	0.65	0.45	0.57	0.34
Adjusted within R^2	0.64	0.45	0.55	0.33
Observations	6399	2143	13664	6699

Notes: Log market-to-book equity is at the end of year t. Clean-surplus profitability is from year t to $t+5$. All characteristics are measured in year t and standardized within each year. The environmental scores are from Sustainalytics. The governance index is the number of entrenchment provisions, following Bebchuk et al. (2009). The Lerner index is the ratio of operating income after depreciation to sales. All specifications include year fixed effects. The environmental scores and the governance indices are only available from 2010 to 2019. These specifications include dummy variables for a missing environmental score or governance index. The t-statistics clustered by year are reported in parentheses.

TABLE 4
Heterogeneity in asset demand by investor type, wealth, and active share

Investor characteristic	Environment	Governance	Log market-to-book	Log book equity	Foreign sales	Lerner	Sales to book	Dividends to book	Market beta
Panel A: Investor type									
Hedge funds	−1.25	0.96	0.48	55.42	−2.51	0.21	1.87	−14.01	1.17
	(−3.03)	(2.64)	(50.71)	(46.89)	(−8.22)	(0.63)	(4.65)	(−21.94)	(2.82)
Investment advisors:									
Large-passive	2.18	1.89	0.97	137.53	3.67	0.53	5.04	−0.11	1.45
	(11.03)	(10.89)	(232.35)	(260.12)	(26.85)	(3.53)	(28.01)	(−0.38)	(7.80)
Small-passive	3.07	1.09	0.84	116.14	3.09	3.76	1.76	−2.31	−3.41
	(16.48)	(6.66)	(216.88)	(238.53)	(24.54)	(27.30)	(10.61)	(−8.78)	(−19.97)
Small-active	−2.65	−2.68	0.52	64.03	2.76	7.68	−1.53	−8.48	−4.07
	(−11.76)	(−13.49)	(103.70)	(102.26)	(17.04)	(43.40)	(−7.16)	(−25.06)	(−18.51)
Large-active	0.65	3.79	0.95	125.32	3.63	0.07	2.02	−13.09	3.31
	(2.66)	(17.71)	(204.72)	(213.67)	(23.94)	(0.41)	(10.11)	(−41.29)	(16.08)
Long-term	1.05	−0.18	0.87	124.63	2.50	3.82	3.51	−2.08	−1.21
	(2.25)	(−0.44)	(83.07)	(94.53)	(7.35)	(10.23)	(7.82)	(−2.92)	(−2.61)
Private banking	−4.10	0.53	0.76	102.02	4.56	4.83	0.46	4.32	−8.61
	(−8.11)	(1.19)	(69.21)	(74.08)	(12.83)	(12.40)	(0.98)	(5.81)	(−17.83)
Brokers	4.22	−2.24	0.92	131.12	0.61	−1.12	3.51	−1.64	4.72
	(5.08)	(−3.06)	(52.01)	(58.90)	(1.07)	(−1.78)	(4.64)	(−1.36)	(6.05)
Adjusted R^2	0.08	0.08	0.48	0.59	0.05	0.15	0.07	0.16	0.14
Observations	6560	6560	7959	7959	7959	7959	7959	7959	7959
Panel B: Welath, active share, and foreign									
Log wealth share	0.86	1.30	0.11	12.36	0.53	−1.92	0.14	−2.94	2.38
	(7.99)	(13.33)	(52.71)	(49.47)	(7.26)	(−23.76)	(1.42)	(−19.20)	(23.52)
Active share	−1.28	0.04	−0.07	−14.85	−0.07	0.20	−1.56	−4.79	0.36
	(−14.11)	(0.51)	(−36.75)	(−65.28)	(−1.08)	(2.66)	(−18.00)	(−34.27)	(3.96)
Foreign	3.06	−0.94	0.03	9.82	1.84	−0.24	−0.17	0.73	−0.52
	(10.19)	(−3.47)	(5.38)	(12.72)	(8.10)	(−0.98)	(−0.58)	(1.54)	(−1.65)
Adjusted R^2	0.10	0.05	0.55	0.67	0.02	0.11	0.06	0.14	0.09
Observations	6560	6560	7959	7959	7959	7959	7959	7959	7959

Notes: Asset demand is estimated by investor and year, pooling across the investor's quarterly holdings within each year. For each investor, the demand coefficients are averaged in the time series between 2010 and 2019. This table reports regressions of the average demand coefficients on investor characteristics. The regression coefficients are multiplied by 100, except for that on log market-to-book equity. The environmental scores are from Sustainalytics. The governance index is the number of entrenchment provisions, following Bebchuk et al. (2009). The Lerner index is the ratio of operating income after depreciation to sales. The investor characteristics in Panel A are dummy variables for investor types. The investor characteristics in Panel B are the log wealth share, the active share, and a foreign-investor dummy. The log wealth share and the active share are standardized. The t-statistics are reported in parentheses.

Table 5
Impact of climate risk on valuation regressions

		Counterfactual	
Characteristic	Actual	Stakeholder	Regulatory
Environment	0.23	0.57	0.03
	(4.61)	(50.47)	(32.29)
Governance	−0.14	−0.01	−0.00
	(−1.97)	(−0.43)	(−1.65)
Log book equity	−0.74	−0.01	−0.00
	(−19.91)	(−1.06)	(−1.63)
Foreign sales	0.11	0.00	−0.00
	(3.49)	(0.29)	(−0.40)
Lerner	0.11	0.02	−0.00
	(3.45)	(2.20)	(−0.42)
Sales to book	0.22	−0.00	−0.00
	(6.18)	(−0.38)	(−2.01)
Dividends to Book	0.16	0.01	0.00
	(4.47)	(0.94)	(1.97)
Market beta	−0.04	0.00	0.00
	(−1.27)	(0.60)	(1.68)
Adjusted R^2	0.65	0.92	0.81
Observations	540	540	540

Notes: The first column is a regression of log market-to-book equity on characteristics in 2019. The second and third columns are regressions of the difference between actual and counterfactual log market-to-book equity on characteristics. For stakeholder risk, asset demand for all institutional investors shifts as the coefficient on the environmental score increases by 0.1. For regulatory risk, asset demand for only long-term investors shifts as the coefficient on the environmental score increases by 0.1. All characteristics are standardized. All specifications include dummy variables for a missing environmental score or governance index. The t-statistics are reported in parentheses.

Table 6

Equity repricing for counterfactual outflows by investor type

Investor type	Wealth share (%)	Repricing	Repricing per dollar wealth
Investment advisors:			
Large-passive	17.7	15.9	0.90
Small-passive	16.4	17.2	1.05
Small-active	11.7	26.7	2.28
Large-active	11.1	18.4	1.65
Hedge funds	3.2	11.5	3.58
Long-term	3.9	3.9	1.01
Private banking	2.9	5.3	1.81
Brokers	1.1	1.8	1.56
Foreign	6.1	8.0	1.31

Notes: The first column reports the total wealth shares by investor type. The second column reports the equity repricing for capital flows from the given group of investors to other institutional investors. The last column reports the ratio of equity repricing in the second column to the wealth share in the first column. Each cell is a time-series average of the quarterly estimates from 2000.Q1 to 2019.Q4.

Table 7

Valuation regressions for counterfactual outflows by investor type

		Investment advisors								
Characteristic	Actual	Large-passive	Small-passive	Small-active	Large-active	Hedge funds	Long-term	Private banking	Brokers	Foreign
Environment	0.17	0.17	0.14	0.21	0.16	0.18	0.17	0.17	0.17	0.14
	(8.08)	(7.51)	(6.67)	(9.81)	(7.87)	(7.85)	(8.47)	(7.87)	(7.88)	(8.48)
Governance	−0.10	−0.11	−0.11	−0.09	−0.12	−0.09	−0.10	−0.10	−0.10	−0.10
	(−6.35)	(−6.02)	(−4.90)	(−7.86)	(−6.53)	(−6.28)	(−6.52)	(−6.22)	(−6.40)	(−6.31)
Log book equity	−0.65	−0.69	−0.73	−0.44	−0.66	−0.59	−0.67	−0.66	−0.65	−0.69
	(−24.59)	(−28.20)	(−23.06)	(−16.64)	(−23.75)	(−27.63)	(−25.66)	(−23.82)	(−25.03)	(−31.61)
Foreign sales	0.11	0.13	0.11	0.07	0.10	0.12	0.10	0.11	0.11	0.09
	(10.26)	(10.69)	(11.17)	(5.75)	(13.28)	(9.08)	(9.44)	(9.76)	(9.79)	(7.14)
Lerner	0.08	0.08	0.05	0.05	0.09	0.09	0.07	0.07	0.08	0.06
	(7.74)	(7.23)	(6.42)	(2.70)	(9.93)	(8.99)	(6.88)	(6.53)	(7.96)	(6.75)
Sales to book	0.22	0.21	0.21	0.26	0.22	0.20	0.21	0.21	0.21	0.21
	(22.81)	(24.76)	(29.43)	(18.55)	(22.48)	(18.34)	(22.53)	(23.66)	(21.62)	(19.51)
Dividends to book	0.17	0.12	0.10	0.27	0.19	0.23	0.15	0.14	0.17	0.14
	(20.34)	(17.33)	(10.31)	(20.41)	(16.60)	(27.61)	(19.24)	(15.93)	(19.45)	(15.17)
Market beta	−0.04	−0.03	−0.03	−0.05	−0.04	−0.06	−0.04	−0.04	−0.04	−0.03
	(−2.38)	(−1.56)	(−1.86)	(−3.26)	(−2.76)	(−2.56)	(−2.22)	(−2.15)	(−2.43)	(−1.74)
Within adjusted R^2	0.64	0.61	0.61	0.45	0.65	0.57	0.63	0.63	0.64	0.63
Observations	6399	6399	6399	6399	6399	6399	6399	6399	6399	6399

Notes: The first column is a regression of the actual log market-to-book equity on characteristics. The remaining columns are regressions of the counterfactual log market-to-book equity on characteristics. Each column corresponds to capital flows from the given group of investors to other institutional investors. All characteristics are standardized within each year. All specifications include year fixed effects and dummy variables for a missing environmental score or governance index. The sample period is 2010 to 2019. The t-statistics clustered by year are reported in parentheses.

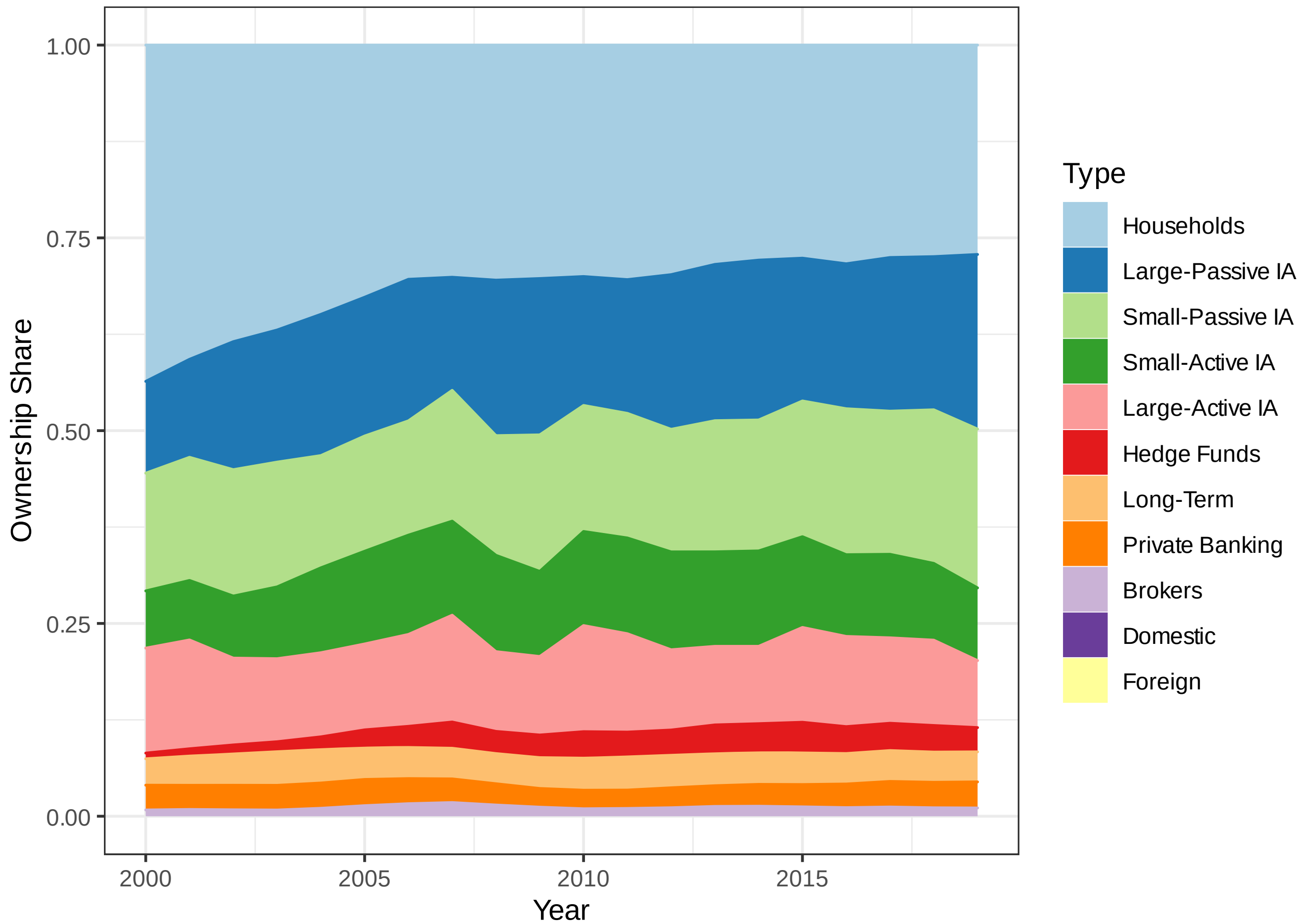

FIGURE 1
Ownership shares by investor type

Notes: This figure shows the ownership shares by investor type for the U.S. stock market. The household share is based on shares outstanding minus institutional ownership. The quarterly sample period is 2000.Q1 to 2019.Q4.

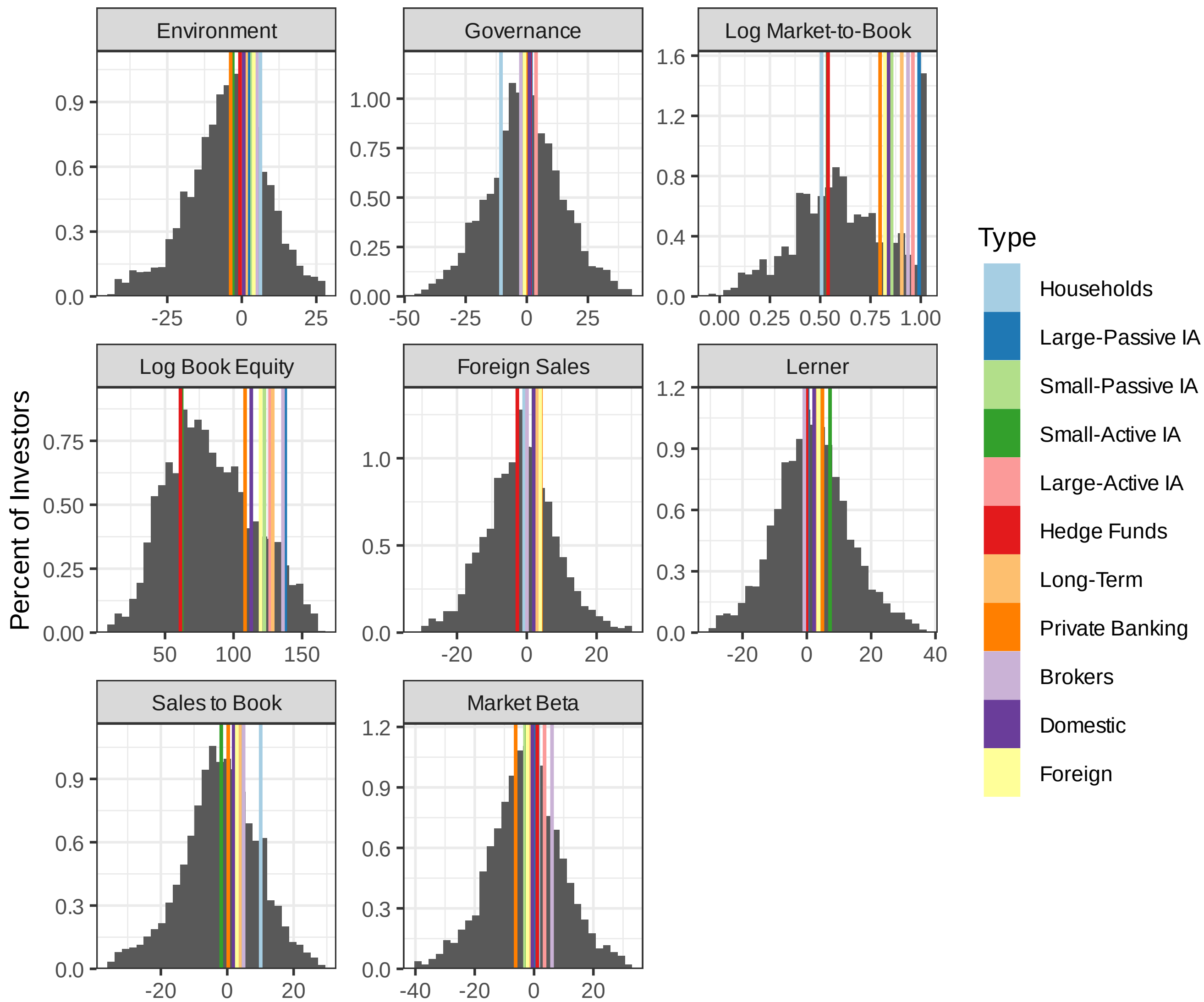

FIGURE 2

Heterogeneity in asset demand by investor type

Notes: Asset demand is estimated by investor and year, pooling across the investor's quarterly holdings within each year. For each investor, the demand coefficients are averaged in the time series between 2010 and 2019. The panels show histograms of the average demand coefficients for each characteristic. The colored vertical lines represent the time-series average of the wealth-weighted demand coefficients by investor type. Except for log market-to-book equity, the demand coefficients are standardized and multiplied by 100. The environmental scores are from Sustainalytics. The governance index is the number of entrenchment provisions, following Bebchuk et al. (2009). The Lerner index is the ratio of operating income after depreciation to sales.

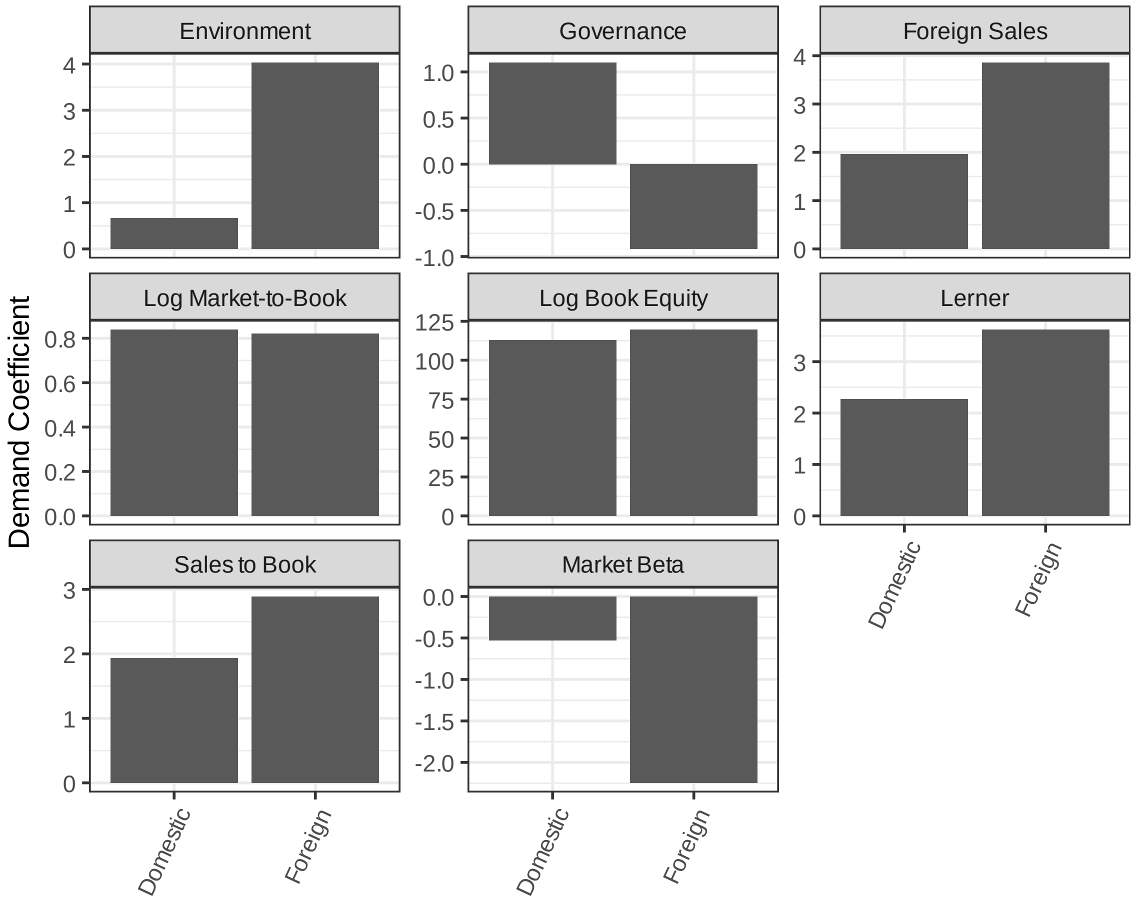

FIGURE 3

Heterogeneity in asset demand between domestic and foreign investors

Notes: Asset demand is estimated by investor and year, pooling across the investor's quarterly holdings within each year. The bars represent the time-series average of the wealth-weighted demand coefficients for domestic and foreign investors. Except for log market-to-book equity, the demand coefficients are standardized and multiplied by 100. The environmental scores are from Sustainalytics. The governance index is the number of entrenchment provisions, following Bebchuk et al. (2009). The Lerner index is the ratio of operating income after depreciation to sales.

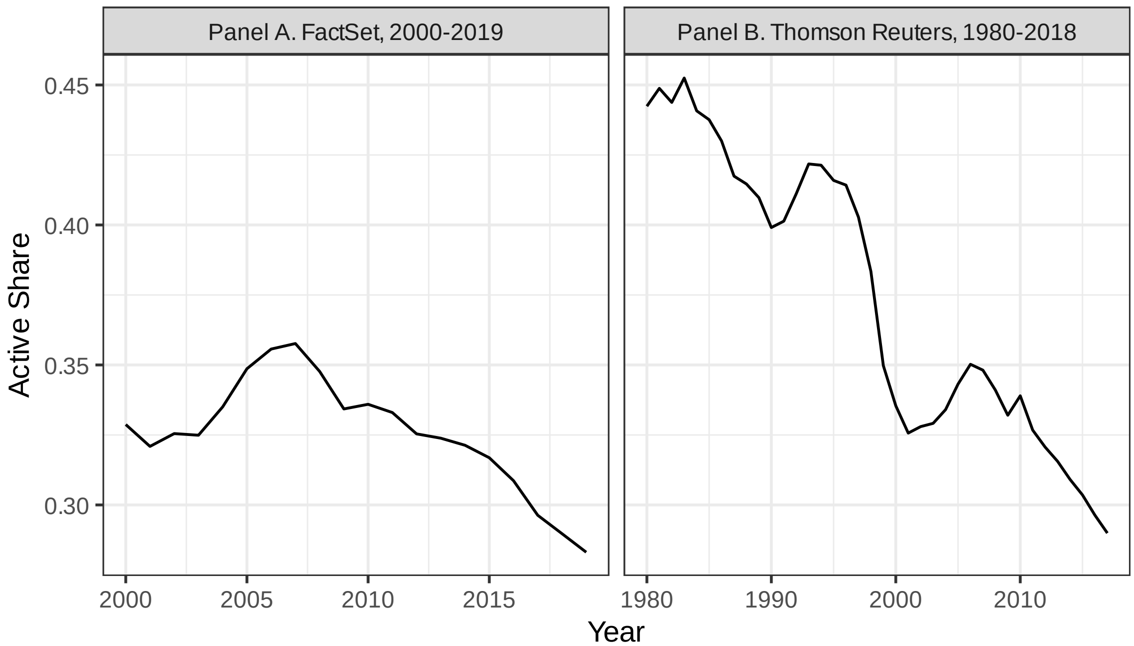

FIGURE 4
Aggregate active share

Notes: For each investor, the active share is one-half times the sum of the absolute differences between the portfolio weights and the market weights within the set of stocks that are held. The aggregate active share is a weighted average of the active shares across all institutional investors. The quarterly estimates are averaged within year. Panel A is based on FactSet Ownership from 2000.Q1 to 2019.Q4. Panel B is based on the Thomson Reuters Institutional Holdings Database for 1980.Q1 to 2018.Q4 (Koijen and Yogo, 2019).

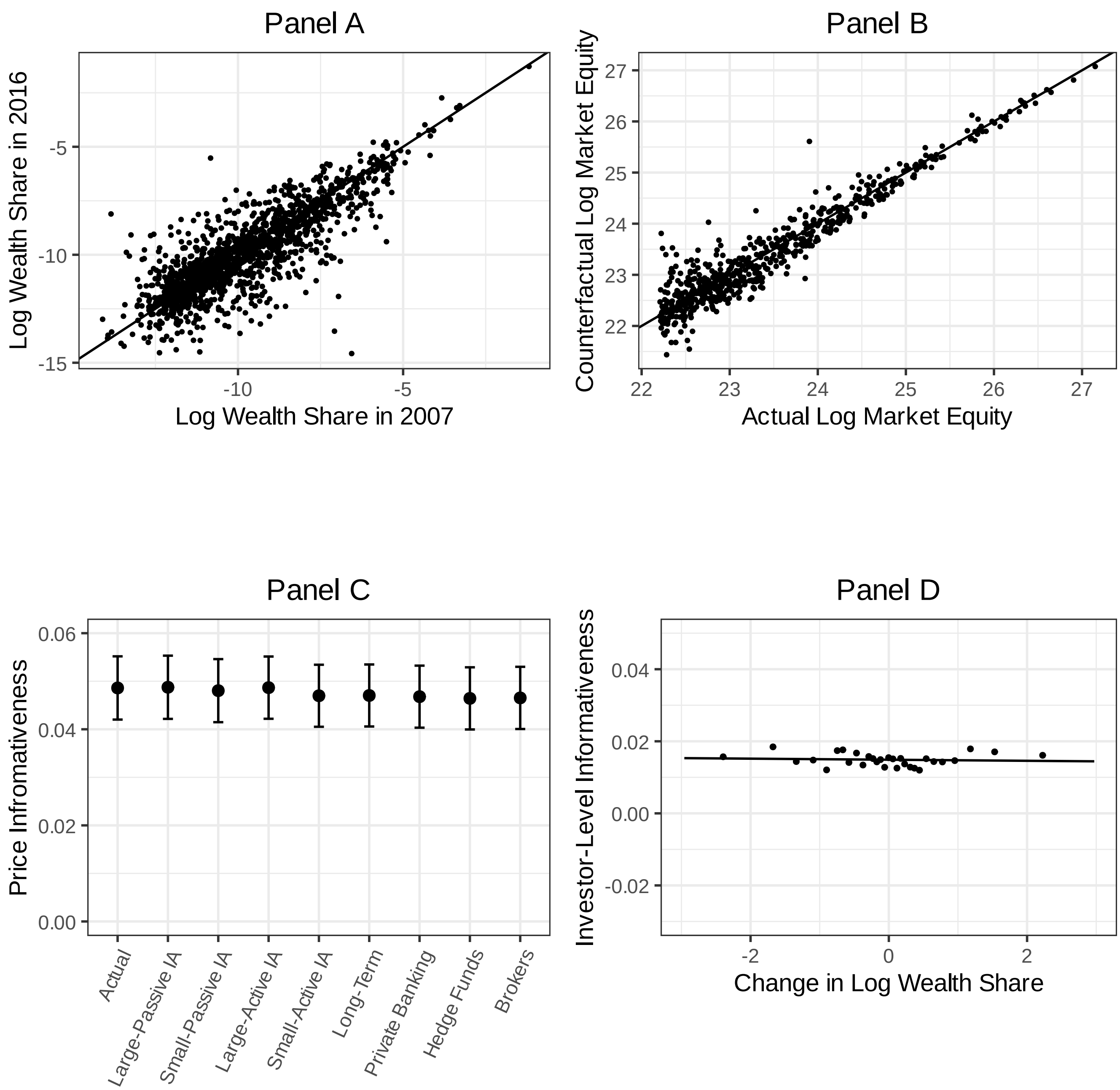

FIGURE 5

Counterfactual market in 2016 under the 2007 wealth distribution

Notes: Panel A is a scatter plot of the log wealth shares in 2007.Q4 versus 2016.Q4. Panel B is a scatter plot of the actual log market equity in 2016.Q4 versus the counterfactual log market equity under the wealth distribution in 2007.Q4. In the counterfactual, wealth changes only for institutional investors who exist in both periods. Panel C shows the cumulative effects on price informativeness when the wealth distribution is changed sequentially by adding each investor type. The range around the point estimate represents the 95% confidence interval. Panel D is a bin scatter plot of the changes in the log wealth share from 2007.Q4 to 2016.Q4 versus the investor-level informativeness in 2016.Q4.

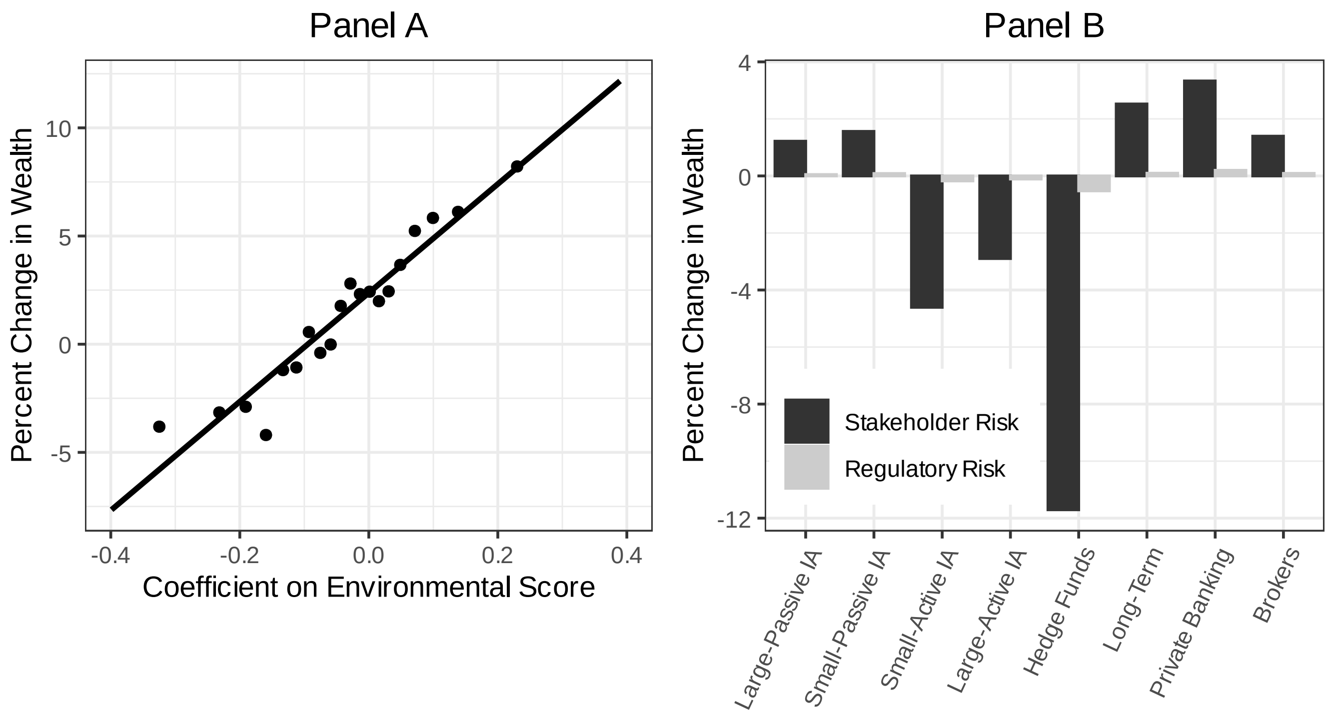

Figure 6

Impact of climate risk on the wealth distribution across institutional investors

Notes: Panel A is a bin scatter plot of the coefficient on the environmental score versus the percent change in wealth in response to realized stakeholder risk. Panel B shows the percent change in total wealth by investor type in response to a climate-induced shift in asset demand. For stakeholder risk, asset demand for all institutional investors shifts as the coefficient on the environmental score increases by 0.1. For regulatory risk, asset demand for only long-term investors shifts as the coefficient on the environmental score increases by 0.1.

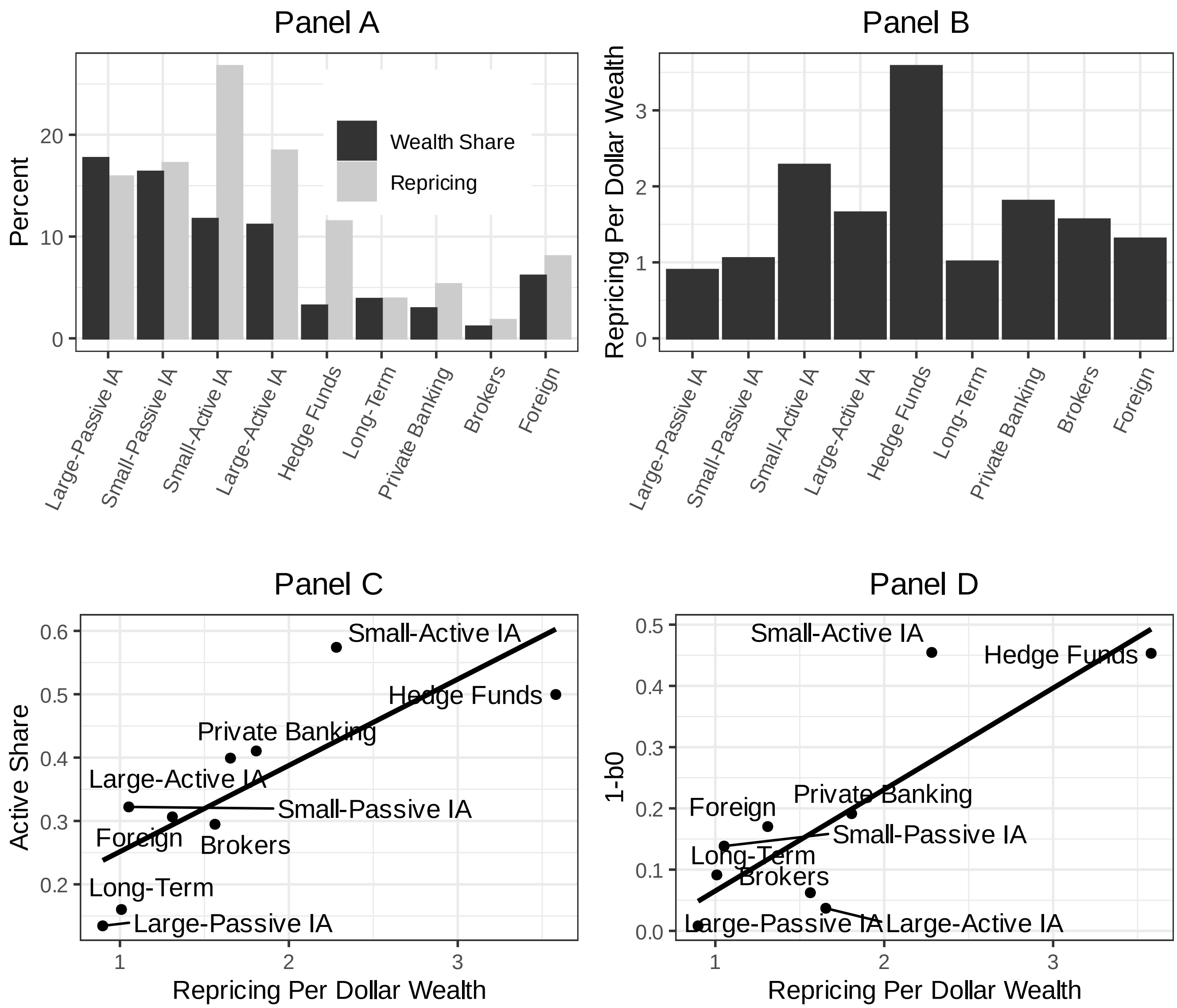

FIGURE 7

Equity repricing for counterfactual outflows by investor type

Notes: Panel A shows the total wealth share by investor type and the equity repricing for capital flows from the given group of investors to other institutional investors. Panel B shows the equity repricing per dollar of wealth, which is the ratio of equity repricing to the wealth share. Panel C is a scatter plot of the equity repricing per dollar of wealth versus the active share by investor type. Panel D is a scatter plot of the equity repricing per dollar of wealth versus the wealth-weighted average of one minus the coefficient on log market equity (i.e., $1 - \beta_{0,i,t}$). Each reported value is a time-series average of the quarterly estimates from 2000.Q1 to 2019.Q4.

Online Appendix

Appendix A. Model solution

We solve a more general version of the model in Section 2 with background risk. We change investor i's wealth in period 1 from equation (1) to

$$A_{i,1} = A_i + (\boldsymbol{d}_1 - \mathbf{MB})'\boldsymbol{Q}_i + Y_{i,1},$$

where $Y_{i,1}$ is exogenous income in period 1. Alternatively, $Y_{i,1}$ could represent other sources of background risk including benchmarking or time-varying investment opportunities. As stated in equation (2), investors choose an optimal portfolio in period 0 to maximize expected utility.

Investors have heterogeneous expectations about income and believe that it is normally distributed with mean $\mathbb{E}_i[Y_{i,1}]$ and variance $\mathrm{Var}_i(Y_{i,1})$. Analogously to beliefs about factor exposure (4), investor i's beliefs about the covariance between stock n's profitability and its income is

$$\mathrm{Cov}_i(d_1(n), Y_{i,1}) = \boldsymbol{\Phi}_i^{Y\prime}\boldsymbol{x}(n) + \phi_i^Y(n). \tag{A1}$$

The subscript i on the covariance operator represents heterogeneous beliefs. The investor forms beliefs based on a vector of observed characteristics $\boldsymbol{x}(n)$ and a scalar $\phi_i^Y(n)$, which represents unobserved characteristics of stock n that relates to background risk.

A.1. Optimal portfolio choice

Given the normality assumptions, we can write the investor's objective function as

$$\begin{aligned}\mathbb{E}_i[-\exp(-\gamma_i A_{i,1})] = &-\exp(-\gamma_i(A_i + (\boldsymbol{\mu}_i - \mathbf{MB})'\boldsymbol{Q}_i + \mathbb{E}_i[Y_{i,1}]) \\ &+\frac{\gamma_i^2}{2}(\boldsymbol{Q}_i'(\boldsymbol{\rho}_i\boldsymbol{\rho}_i' + \sigma^2\mathbf{I})\boldsymbol{Q}_i + \mathrm{Var}_i(Y_{i,1}) + 2\boldsymbol{Q}_i'\mathrm{Cov}_i(\boldsymbol{d}_1, Y_{i,1}))\Big)\end{aligned}$$

The first-order condition for optimal portfolio choice is

$$-(\boldsymbol{\mu}_i - \mathbf{MB}) + \gamma_i(\boldsymbol{\rho}_i\boldsymbol{\rho}_i' + \sigma^2\mathbf{I})\boldsymbol{Q}_i + \gamma_i\mathrm{Cov}_i(\boldsymbol{d}_1, Y_{i,1}) = \mathbf{0}.$$

We solve for the optimal demand as

$$
\begin{aligned}
\boldsymbol{Q}_i =& \frac{1}{\gamma_i}(\boldsymbol{\rho}_i\boldsymbol{\rho}_i' + \sigma^2\mathbf{I})^{-1}(\boldsymbol{\mu}_i - \mathbf{MB} - \gamma_i \mathrm{Cov}_i(\boldsymbol{d}_1, Y_{i,1})) \\
=& \frac{1}{\gamma_i\sigma^2}\left(\mathbf{I} - \frac{\boldsymbol{\rho}_i\boldsymbol{\rho}_i'}{\boldsymbol{\rho}_i'\boldsymbol{\rho}_i + \sigma^2}\right)(\boldsymbol{\mu}_i - \mathbf{MB} - \gamma_i \mathrm{Cov}_i(\boldsymbol{d}_1, Y_{i,1})) \\
=& \frac{1}{\gamma_i\sigma^2}(\boldsymbol{\mu}_i - \mathbf{MB} - \gamma_i \mathrm{Cov}_i(\boldsymbol{d}_1, Y_{i,1})) - \frac{c_i}{\gamma_i\sigma^2}\boldsymbol{\rho}_i.
\end{aligned} \tag{A2}
$$

The second line follows from the Woodbury matrix identity. The scalar

$$
c_i = \frac{\boldsymbol{\rho}_i'(\boldsymbol{\mu}_i - \mathbf{MB} - \gamma_i \mathrm{Cov}_i(\boldsymbol{d}_1, Y_{i,1}))}{\boldsymbol{\rho}_i'\boldsymbol{\rho}_i + \sigma^2}
$$

is investor specific but does not vary across stocks. According to equation (A2), asset demand is increasing in the expected return $\boldsymbol{\mu}_i - \mathbf{MB}$, decreasing in the background risk $\mathrm{Cov}_i(\boldsymbol{d}_1, Y_{i,1})$, and decreasing in the factor exposure $\boldsymbol{\rho}_i$ (if $c_i > 0$). Because of background risk, the investor decreases allocation to stocks that have a positive covariance with income. Conversely, the investor increases allocation to stocks that have a negative covariance with income because they provide hedging benefits.

Finally, we use the assumptions that expected profitability, factor exposure, and the background risk depend on observed and unobserved characteristics. Substituting equations (3), (4), and (A1) in equation (A2), we have

$$
\boldsymbol{Q}_i(n) = \frac{1}{\gamma_i\sigma^2}\left(-\mathbf{MB}(n) + (\underbrace{\boldsymbol{\Phi}_i^{\mu} - \gamma_i\boldsymbol{\Phi}_i^{Y} - c_i\boldsymbol{\Phi}_i^{\rho}}_{\boldsymbol{\beta}_i})'\boldsymbol{x}(n) + \underbrace{\phi_i^{\mu}(n) - \gamma_i\phi_i^{Y}(n) - c_i\phi_i^{\rho}(n)}_{\epsilon_i(n)}\right). \tag{A3}
$$

A special case of this equation without background risk is equation (5).

A.2. Equity prices with exogenous characteristics

Substituting optimal demand (A3) in market clearing (6), we solve for the equilibrium equity prices as

$$
\mathrm{MB}(n) = \left(\sum_{i=1}^{I}\frac{1}{\gamma_i\sigma^2}\right)^{-1}\left(\sum_{i=1}^{I}\frac{1}{\gamma_i\sigma^2}\boldsymbol{\beta}_i'\boldsymbol{x}(n) + \sum_{i=1}^{I}\frac{1}{\gamma_i\sigma^2}\epsilon_i(n) - B(n)\right).
$$

Equation (7) follows from the assumption that $\gamma_i = 1/(\tau_i A_i)$.

A.3. *Equity prices with endogenous characteristics*

In an extended version of the model, we allow the observed characteristics to depend on market-to-book equity as

$$\boldsymbol{x}(n) = \boldsymbol{\psi} + \boldsymbol{\Psi}\mathrm{MB}(n) + \boldsymbol{\nu}(n). \tag{A4}$$

The vector $\boldsymbol{\Psi}$ determines how the characteristics endogenously respond to equity prices. The vector $\boldsymbol{\nu}(n)$ represents an exogenous component of characteristics that relate to technology or other factors that the firm does not control. Substituting equation (A4) into equation (7), we solve for the equilibrium equity prices as

$$\mathrm{MB}(n) = \frac{\overline{\boldsymbol{\beta}}'(\boldsymbol{\psi} + \boldsymbol{\nu}(n)) + \overline{\epsilon}(n)}{1 - \overline{\boldsymbol{\beta}}'\boldsymbol{\Psi}}. \tag{A5}$$

This model has an important implication for the identification of asset demand (5). Equations (A4) and (A5) imply that the observed characteristics depend on $\overline{\epsilon}(n)$, which is the weighted average of latent demand. Consequently, the identification assumption that the observed characteristics are uncorrelated with latent demand is no longer justified. However, we could estimate asset demand through a two-step estimator that we describe in Appendix D.3. In the first step, we estimate equation (A4) with an instrument for market-to-book equity. In the second step, we estimate equation (5) by using the estimated residuals $\widehat{\boldsymbol{\nu}}(n)$ as instruments for $\boldsymbol{x}(n)$.

Appendix B. Data construction

B.1. *Institutional equity holdings*

We construct institutional equity holdings at the end of each quarter from 2000.Q1 to 2019.Q4, based on FactSet Ownership. The data come from SEC Form 13F filings, which are required for all institutional investment managers who exercise investment discretion on accounts holding 13(f) securities that exceed \$100 million in total market value. We exclude the holdings for two FactSet entity identifiers (0FSVG4-E and 000V4B-E), which contain known errors in comparison with the EDGAR 13F filings. We compute the dollar amount of holdings by multiplying the number of shares by the price per share.

We classify investors based on FactSet's investor subtype codes. They are investment advisors (IC, RE, PP, SB, and MF), hedge funds (AR, FH, FF, FU, and FS), long-term investors (FO, SV, and IN), private banking (CP, FY, and VC), and brokers (BM, IB, ST, and MM). FactSet classifies an investment firm as a mutual fund if the majority of its investments are in mutual funds. Otherwise, FactSet classifies an investment firm as an investment advisor if it is not a subsidiary of a bank, a brokerage firm, or an insurance company. We group mutual funds together with investment advisors because FactSet's distinction is not as economically meaningful.

We aggregate as an outside asset any firm that is in the bottom 10% of the market equity distribution or has a missing characteristic (i.e., book equity, foreign sales share, the Lerner index, the ratio of sales to book equity, the ratio of dividends to book equity, or market beta). We aggregate into the household sector any small institutional investor who has less than $10 million in total equity holdings, less than $1 million in the outside asset, or fewer than ten stocks.

B.2. Asset characteristics

Financial statements are from the Compustat Fundamentals Annual and Quarterly Databases. We use the financial statements closest to the end of each quarter, prioritizing the annual statements if available and otherwise using the quarterly statements. We merge the CRSP data in a given trading month to the Compustat data as of at least 6 months and no more than 18 months prior. The lag of at least 6 months ensures that the financial statements were publicly available on the trading date.

We merge the institutional holdings and shares outstanding from FactSet with the CRSP-Compustat data by CUSIP. We merge with the most recently available environmental score of no more than 18 months prior by Capital IQ identifier and CUSIP. We merge with the most recently available governance index of no more than 18 months prior by CUSIP.

We define the following characteristics, based on the definitions in Fama and French (2015). The Compustat item codes corresponding to the variables are in parentheses.

- Book equity: Stockholders equity (seq) plus deferred taxes and investment tax credit (txditc) minus preferred stock (pstk).

- Foreign sales share: Foreign sales divided by the sum of domestic and foreign sales. We identify domestic (geotp 2) and foreign (geotp 3) segments based on the Compustat Segments Database. Foreign sales are the sum of the export sales (salexg) of the domestic segments and the sales (sale) of the foreign segments. Total sales are the sum of sales (sale) and export sales (salexg) across all segments. We set missing values to zero.

- Lerner index: Operating income before depreciation (oibdp) minus depreciation (dp) divided by sales (sale).

- Ratio of sales to book equity: Sales (sale) divided by book equity.
- Ratio of dividends to book equity: Annual dividends per split-adjusted share times shares outstanding (csho) divided by book equity.
- Market beta: Estimated from a 60-month rolling regression of excess stock returns on the excess CRSP value-weighted index returns. Excess returns are relative to the one-month Treasury bill.
- Investment: Annual change in log assets (at).
- Ratio of net repurchases to book equity: Purchase of common and preferred stock (prstkc) minus sale of common and preferred stock (sstk) divided by book equity. If either the purchase or the sale of common and preferred stock is missing, we set it to zero.
- Earnings before interest and taxes: Sales (sale) minus the cost of goods sold (cogs) minus selling, general, and administrative expenses (xsga) minus depreciation (dp).
- Clean-surplus earnings: Change in book equity from year $t-1$ to t plus purchase of common and preferred stock (prsckc) minus sale of common and preferred stock (sstk) plus dividends.
- Profitability: Let E_t be clean-surplus earnings in year t. Let B_t be book equity at the end of year t. Log profitability in year t is $e_t = \log(1 + E_t/B_{t-1})$. Five-year future profitability in year t is $e_{t,t+5} = \sum_{s=1}^{5} 0.95^{s-1} e_{t+s}$.

We winsorize the ratio of dividends to book equity and the ratio of sales to book equity at the 97.5 percentile within each quarter. We winsorize the Lerner index, market beta, and investment at the 2.5 and 97.5 percentiles within each quarter. Furthermore, we truncate the left tail of the Lerner index at -1.

B.3. Earnings surprises

Following Livnat and Mendenhall (2006), we construct earnings surprises as the actual earnings per share minus the median forecast divided by the price per share. The actual earnings per share are from the IBES Actuals Database. The earnings forecasts are from the IBES Unadjusted Detail Database, where we select the latest forecast for each analyst within 90 days of the earnings announcement. The price per share is from the Compustat Fundamentals Quarterly Database. We construct the data through the following procedure.

1. Based on the ibes.id file, construct a list of IBES tickers and CUSIPs for U.S. firms. Keep only the most recent sdates for each ticker-CUSIP pair. Merge permno from the crsp.stocknames file by CUSIP. Merge gvkey from the crsp.ccmxpf_linktable file by permno if usedflag is 1 and linkprim is P or C.

2. In the IBES Unadjusted Detail file (ibes.detu_epsus), select quarterly forecasts for the current and the next fiscal quarter (i.e., fpi is 6 or 7).

3. Merge the data from steps 1 and 2 by CUSIP, ensuring that anndats is between linkdt and linkenddt.

4. Keep the latest forecast for each group formed by ticker, forecast period end date (fpedats), broker (estimator), and analyst (analys).

5. In the IBES Actuals file (ibes.actu_epsus), select quarterly earnings per share (i.e., pdicity is QTR) and merge with the data from step 4 by ticker and forecast period end date. Keep only the forecasts issued within 90 days of the report date (i.e., $0 <$ repdats $-$ anndats ≤ 90).

6. Adjust the forecasts and the earnings per share to be in the same stock-split basis, using the CRSP adjustment factor (cfacshr in the ecrsp.dsf file). Align both the forecast date and the announcement date with the closest preceding trading date in CRSP.

7. Compute the median forecast by ticker and forecast period end date.

8. Merge the data from step 7 and the price per share (prccq) from the Compustat Fundamentals Quarterly file, ensuring that datadate is between linkdt and linkenddt. Compute the earnings surprise as the actual earnings per share minus the median forecast divided by the price per share.

For stocks that do not have earnings forecasts, we construct a dummy variable that is equal to one if the earnings surprise is missing. We set missing values to zero and include the dummy variable for a missing earnings surprise in the regressions.

Appendix C. Instrumental variables ridge estimator of asset demand

We rewrite equation (18) as

$$\mathbb{E}\left[\left(\widehat{\delta}_{i,t}(n)\exp(-\boldsymbol{\beta}_i'\boldsymbol{X}_t(n))-1\right)\boldsymbol{X}_t(n)\right]-\boldsymbol{D}_i\left(\boldsymbol{\beta}_i-\widehat{\boldsymbol{\beta}}\right)=\mathbf{0}, \tag{C1}$$

where

$$\boldsymbol{\beta}_i = \begin{pmatrix} \boldsymbol{\alpha}_i \\ \boldsymbol{\beta}_{1,i} \end{pmatrix}, \widehat{\boldsymbol{\beta}} = \begin{pmatrix} \mathbf{0} \\ \widehat{\boldsymbol{\beta}}_1 \end{pmatrix}, \boldsymbol{X}_t(n) = \begin{pmatrix} \boldsymbol{e}_t \\ \boldsymbol{x}_t(n) \end{pmatrix}, \boldsymbol{D}_i = \frac{\lambda}{|\mathcal{N}_i|^{\xi}} \begin{pmatrix} 0 & 0 \\ 0 & \mathbf{I} \end{pmatrix}.$$

Ignoring the zero holdings, we obtain an initial estimate $\boldsymbol{\beta}_i(1)$ by estimating asset demand (16) in logarithms. The corresponding moment condition is

$$\mathbb{E}\left[\left(\log\left(\widehat{\delta}_{i,t}(n)\right) - \boldsymbol{\beta}_i(1)'\boldsymbol{X}_t(n)\right)\boldsymbol{X}_t(n)\right] - \boldsymbol{D}_i\left(\boldsymbol{\beta}_i(1) - \widehat{\boldsymbol{\beta}}\right) = \mathbf{0}.$$

The estimator that solves this moment condition is

$$\boldsymbol{\beta}_i(1) = (\mathbb{E}[\boldsymbol{X}_t(n)\boldsymbol{X}_t(n)'] + \boldsymbol{D}_i)^{-1}\left(\mathbb{E}\left[\log\left(\widehat{\delta}_{i,t}(n)\right)\boldsymbol{X}_t(n)\right] + \boldsymbol{D}_i\widehat{\boldsymbol{\beta}}\right).$$

A first-order Taylor approximation of equation (C1) around $\boldsymbol{\beta}_i(2) \approx \boldsymbol{\beta}_i(1)$ is

$$\begin{aligned} &\mathbb{E}\left[\left(\widehat{\delta}_{i,t}(n)\exp(-\boldsymbol{\beta}_i(1)'\boldsymbol{X}_t(n)) - 1\right)\boldsymbol{X}_t(n)\right] - \boldsymbol{D}_i\left(\boldsymbol{\beta}_i(1) - \widehat{\boldsymbol{\beta}}\right) \\ &- \left(\mathbb{E}\left[\widehat{\delta}_{i,t}(n)\exp(-\boldsymbol{\beta}_i(1)'\boldsymbol{X}_t(n))\boldsymbol{X}_t(n)\boldsymbol{X}_t(n)'\right] + \boldsymbol{D}_i\right)(\boldsymbol{\beta}_i(2) - \boldsymbol{\beta}_i(1)) = \mathbf{0}. \end{aligned}$$

This equation implies that

$$\begin{aligned} \boldsymbol{\beta}_i(2) = &\boldsymbol{\beta}_i(1) + \left(\mathbb{E}\left[\widehat{\delta}_{i,t}(n)\exp(-\boldsymbol{\beta}_i(1)'\boldsymbol{X}_t(n))\boldsymbol{X}_t(n)\boldsymbol{X}_t(n)'\right] + \boldsymbol{D}_i\right)^{-1} \\ &\times\left(\mathbb{E}\left[\left(\widehat{\delta}_{i,t}(n)\exp(-\boldsymbol{\beta}_i(1)'\boldsymbol{X}_t(n)) - 1\right)\boldsymbol{X}_t(n)\right] - \boldsymbol{D}_i\left(\boldsymbol{\beta}_i(1) - \widehat{\boldsymbol{\beta}}\right)\right). \end{aligned}$$

We iterate on this equation until convergence, limiting the step size to the range $[-1, 1]$ for numerical stability. Note that the moment condition (C1) is satisfied upon convergence.

Appendix D. Robustness of the identifying assumptions

We test whether our results are robust to three components of the identifying assumptions: the definition of the investment universe, the choice of characteristics, and the exogeneity of characteristics. Our criteria for robustness are the estimated demand coefficients and their impact on the counterfactual equity prices, price informativeness, and the wealth distribution in the applications of Sections 6–8.

D.1. Definition of the investment universe

The baseline definition of the investment universe is the set of stocks that an investor currently holds or has ever held in the past 11 quarters. We test whether our results are robust to changing the definition in three ways. First, we construct the instrument without hedge funds to address the concern that their investment mandates may be more flexible than those of other institutional investors. Second, we change the window for estimating the investment universe, both backward and forward by up to five years. Third, we randomly increase the number of stocks in the investment universe by up to 100%.

D.1.1. Instrument without hedge funds

Hedge funds may have investment mandates that are more flexible than those of other institutional investors, so their investment universe may be the most challenging to identify. Therefore, we exclude hedge funds in constructing the instrument for log market equity. Panel A of Figure D2 is a scatter plot of the estimated coefficient on log market-to-book equity under the baseline instrument versus an alternative instrument without hedge funds. The two sets of estimated coefficients have a correlation of 0.985, which confirms that our estimates are robust to excluding hedge funds.

D.1.2. Changing the window for the investment universe

Koijen and Yogo (2019) chose a three-year window to estimate the investment universe, based on the fact that the set of stocks that an investor has ever held stabilizes with sufficient lags. We change the window for estimating the investment universe, both backward and forward by up to five years. Figure D1 shows the wealth-weighted coefficient on log market-to-book equity in 2010 by investor type for alternative windows. The alternative windows are labeled $[b, f]$, which means going back b years and going forward f years. The baseline window is $[3, 0]$, which means going back three years (or 12 quarters inclusive of the current quarter). Although we see small variation around the baseline window for small-active investment advisors and households, our estimates are sufficiently robust to changing the window for estimating the investment universe.

D.1.3. Expanding the investment universe

For each investor-quarter, we randomly increase the number of stocks in the investment universe by 10%, 25%, 50%, and 100%. For investors whose investment universe is already close to the entire market of inside assets (i.e., the largest 90% of firms by market equity), the investment universe is capped by the universe of all inside assets. Under the null hypothesis that the baseline investment universe is valid, adding a random set of stocks would only weaken the instrument. Panel B of Figure D2 is a scatter plot of the estimated coefficient on log market-to-book equity under the baseline instrument versus an alternative instrument with a 25% larger investment universe. The two sets of estimated coefficients have a correlation of 0.921, which confirms that our estimates are robust to expanding the investment universe.

For each expansion size, we reestimate the asset demand system on ten random samples to make sure that the results do not depend on a particular draw. Based on the reestimated demand system, we test the robustness of the three applications on the transition from active to passive investment management, climate-induced shifts in asset demand, and cross-sectional asset pricing. For the transition from active to passive investment management, Panel C of Figure 5 is the baseline result on price informativeness. Figure D3 shows that the results are robust to expanding the investment universe. The four rows correspond to expanding the investment universe by 10%, 25%, 50%, and 100%. The red line represents the baseline estimate. The ten bars in each panel correspond to the ten random samples.

For climate-induced shifts in asset demand, Figure 6 is the baseline result on the wealth distribution across institutional investors. Figure D4 shows that the results are robust to expanding the investment universe.

For cross-sectional asset pricing, Panel A of Figure 7 is the baseline result on equity repricing by investor type. Figure D5 shows that the results are robust to expanding the investment universe.

D.2. Choice of characteristics

We test whether our results are robust to the choice of characteristics by adding three characteristics: investment, the ratio of net repurchases to book equity, and earnings surprises. Appendix B describes how we construct these characteristics.

Table D1 adds the three characteristics to the panel regressions of log market-to-book equity and five-year future profitability in Table 3. The additional characteristics explain log market-to-book equity with statistically significant t-statistics. However, the adjusted within R^2 increases only modestly from 64% to 68%. Of the additional characteristics, only the ratio of net repurchases to book equity is a statistically significant predictor of future profitability. Moreover, the adjusted within R^2 increases only modestly from 45% to 46%. Thus, the additional characteristics do not significantly increase the explanatory power for log market-to-book equity and future profitability.

Panel C of Figure D2 is a scatter plot of the estimated coefficient on log market-to-book equity under the baseline specification versus an alternative specification with the additional characteristics. The two sets of estimated coefficients have a correlation of 0.994, which confirms that our estimates are robust to additional characteristics.

Based on the reestimated demand system, we test the robustness of the three applications on the transition from active to passive investment management, climate-induced shifts in asset demand, and cross-sectional asset pricing. For the transition from active to passive investment management, Panel C of Figure 5 is the baseline result on price informativeness. Figure D6 shows that the results are robust to additional characteristics.

For climate-induced shifts in asset demand, Figure 6 is the baseline result on the wealth distribution across institutional investors. Figure D7 shows that the results are robust to additional characteristics.

For cross-sectional asset pricing, Panel A of Figure 7 is the baseline result on equity repricing by investor type. Figure D8 shows that the results are robust to additional characteristics.

D.3. Identification with endogenous characteristics

We relax the baseline assumption that characteristics other than log market-to-book equity are exogenous. Our starting point is to split the characteristics into a subvector $\boldsymbol{x}_{1,t}(n)$ of endogenous characteristics and a subvector $\boldsymbol{x}_{2,t}(n)$ of exogenous characteristics. The endogenous characteristics relate to firm decisions that could depend on equity prices, such as capital structure and payout policy. The exogenous characteristics primarily relate to productivity and market power, which do not directly depend on equity prices.

We model the vector of endogenous characteristics as a function of log market-to-book equity and the exogenous characteristics as

$$\boldsymbol{x}_{1,t}(n) = \boldsymbol{\psi} + \boldsymbol{\Psi}_1 \mathrm{mb}_t(n) + \boldsymbol{\Psi}_2 \boldsymbol{x}_{2,t}(n) + \boldsymbol{\nu}_t(n). \tag{D2}$$

The vector $\boldsymbol{\nu}_t(n)$ represents an exogenous component of characteristics that relate to technology or other factors that the firm does not control. Then our identifying assumptions are

$$\begin{aligned} \mathbb{E}[\boldsymbol{\nu}_t(n) | z_{i,t}(n), \boldsymbol{x}_{2,t}(n)] &= \mathbf{0}, \\ \mathbb{E}[\epsilon_{i,t}(n) | z_{i,t}(n), \boldsymbol{\nu}_t(n), \boldsymbol{x}_{2,t}(n)] &= 1. \end{aligned} \tag{D3}$$

These moment conditions allow us to estimate asset demand consistently through a two-step estimator. In the first step, we estimate equation (D2) for each endogenous characteristic by instrumental variables, using $z_{i,t}(n)$ as the instrument for log market equity. We denote the vector of estimated residuals as $\widehat{\boldsymbol{\nu}}_t(n)$. In the second step, we estimate asset demand (16) by generalized method of moments based on moment condition (D3), using the estimated residuals $\widehat{\boldsymbol{\nu}}_t(n)$ as the instruments.

We test the importance of endogenous characteristics by treating the ratio of dividends to book equity as endogenous and the remaining characteristics as exogenous. In the Q-theory of investment, investment depends on the equity price. The firm saves profits net of investment as retained earnings or pays them out to shareholders. Thus, dividends plausibly depend on the equity price through investment. Other characteristics in our baseline specification, such as the foreign sales share or the Lerner index, relate to productivity and market power that are plausibly exogenous. Of course, one could argue that all characteristics are ultimately endogenous. Our goal here is to test the robustness of the baseline assumption to endogenizing one characteristic. However, our identification strategy is sufficiently general to apply to a model with more endogenous characteristics in future work.

Panel D of Figure D2 is a scatter plot of the estimated coefficient on log market-to-book equity under the baseline assumption versus an alternative assumption that is robust to endogeneity of the ratio of dividends to book equity. The two sets of estimated coefficients have a correlation of 0.996, which confirms that our estimates are robust to this form of endogeneity. When characteristic k is endogenous, the baseline assumption leads to a biased estimate $\beta_{0,i,t} + \beta_{1,i,t}(k)\Psi_1$ for the coefficient on log market-to-book equity. The bias is small as long as the endogenous response of the characteristic to log market-to-book equity (i.e., Ψ_1) is small. Consistent with this intuition, we find a small estimate of Ψ_1 when we estimate equation (D2) for the ratio of dividends to book equity by instrumental variables.

Table D1
Explaining equity valuations and future profitability with characteristics:
Robustness to additional characteristics

	Additional characteristics		Baseline characteristics	
Characteristic	Market-to-book	Profitability	Market-to-book	Profitability
Environment	0.15	0.04	0.17	0.04
	(10.06)	(11.96)	(7.98)	(7.24)
Governance	−0.08	−0.07	−0.10	−0.08
	(−6.92)	(−5.17)	(−6.32)	(−4.77)
Log book equity	−0.68	−0.28	−0.65	−0.26
	(−18.86)	(−7.76)	(−24.91)	(−9.63)
Foreign sales	0.09	−0.00	0.11	0.01
	(8.11)	(−0.11)	(10.31)	(0.60)
Lerner	0.06	0.15	0.08	0.15
	(4.37)	(8.82)	(7.65)	(9.20)
Sales to book	0.20	0.25	0.22	0.26
	(15.35)	(9.65)	(22.47)	(9.15)
Dividends to book	0.17	0.07	0.17	0.07
	(18.24)	(12.50)	(20.06)	(12.74)
Market beta	−0.03	−0.05	−0.04	−0.05
	(−2.27)	(−8.17)	(−2.37)	(−9.77)
Investment	0.14	0.02		
	(9.68)	(0.67)		
Repurchases	0.17	0.04		
	(8.12)	(3.11)		
Earnings surprises	−0.03	−0.02		
	(−3.90)	(−1.05)		
Adjusted R^2	0.69	0.46	0.65	0.45
Adjusted within R^2	0.68	0.46	0.64	0.45
Observations	6395	2142	6395	2142

Notes: Log market-to-book equity is at the end of year t. Clean-surplus profitability is from year t to $t+5$. All characteristics are measured in year t and standardized within each year. The additional characteristics are investment, the ratio of net repurchases to book equity, and earnings surprises. All specifications include year fixed effects and dummy variables for a missing environmental score, governance index, or earnings surprise. The sample is restricted to stocks with non-missing investment. The sample period is 2010 to 2019. The t-statistics clustered by year are reported in parentheses.

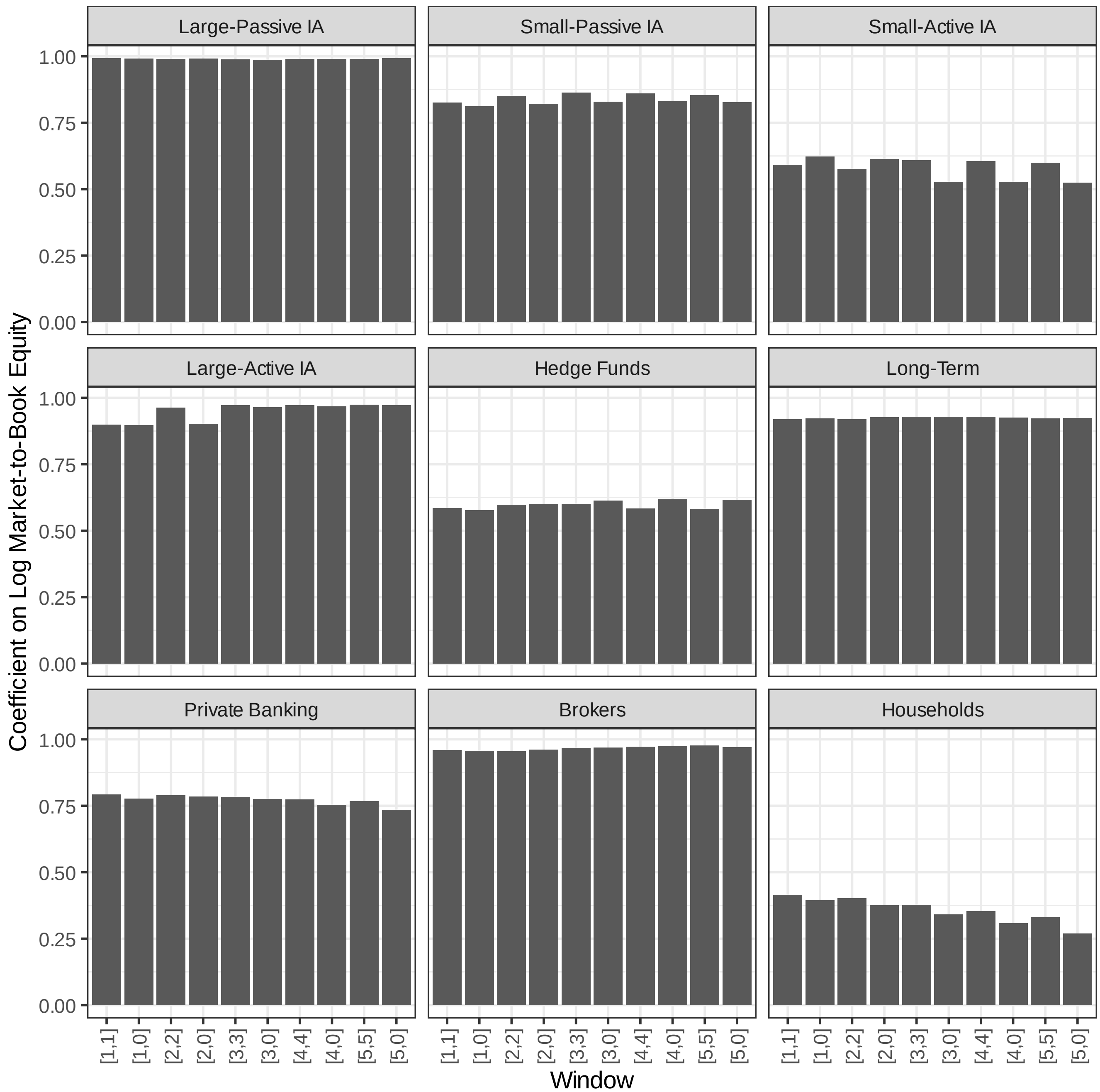

FIGURE D1
Coefficient on log market-to-book equity:
Robustness to expanding the investment universe

Notes: The asset demand system is reestimated by changing the window for estimating the investment universe to $[b, f]$ (i.e., going back b years and forward f years). The baseline window is $[3, 0]$, which means going back three years (or 12 quarters inclusive of the current quarter). Asset demand is estimated by investor and year, pooling across the investor's quarterly holdings within each year. The bars represent the time-series average of the wealth-weighted coefficient on log market-to-book equity.

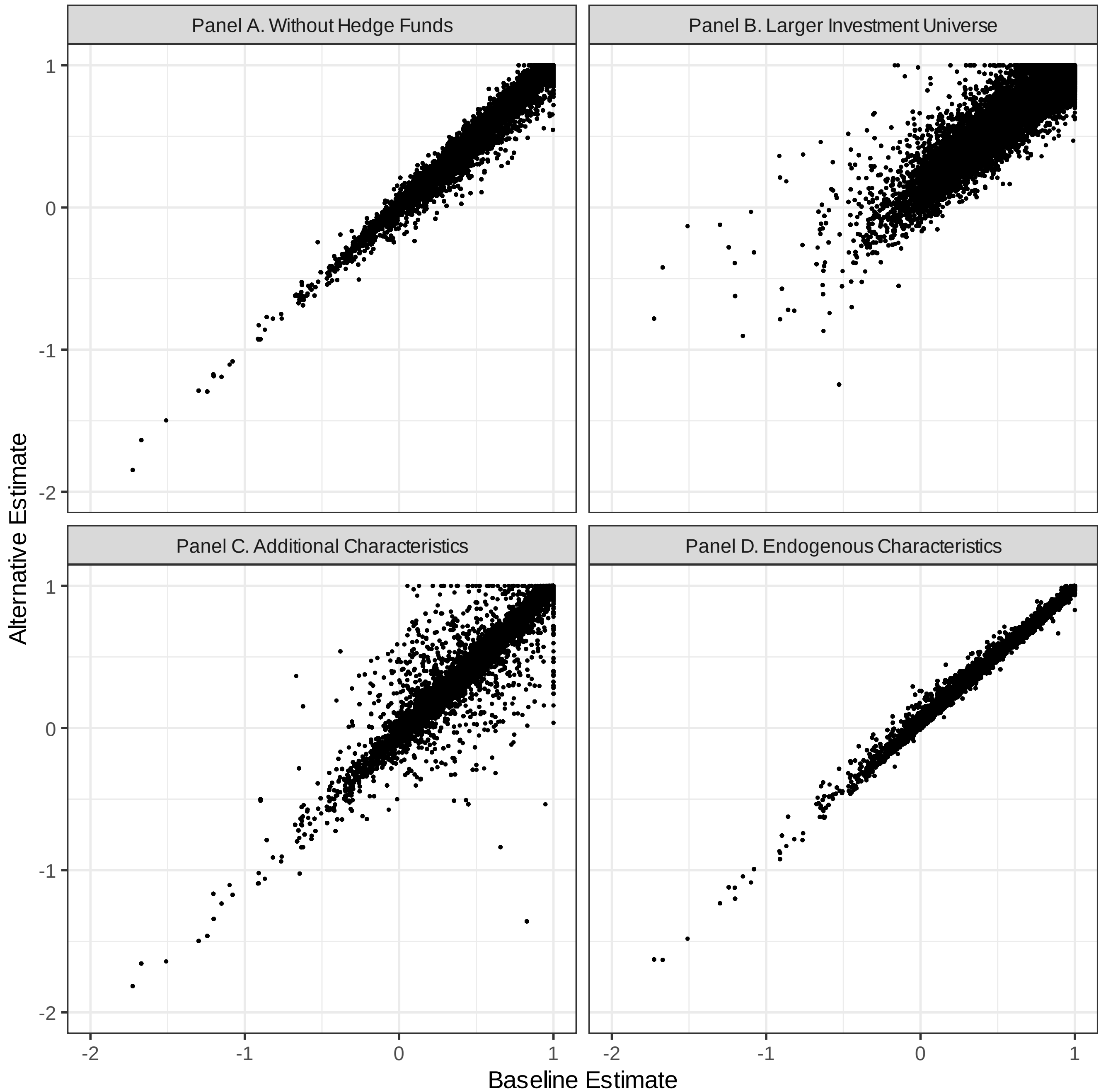

Figure D2

Baseline versus alternative estimates of the coefficient on log market-to-book equity

Notes: This figure compares the baseline estimates of the coefficient on log market-to-book equity versus four sets of alternative estimates. In Panel A, the instrument for log market equity is constructed without hedge funds. In Panel B, the number of stocks in the investment universe is randomly increased by 25%. In Panel C, investment, the ratio of net repurchases to book equity, and earnings surprises are added to the baseline specification. In Panel D, the identifying assumption is robust to endogeneity in the ratio of dividends to book equity.

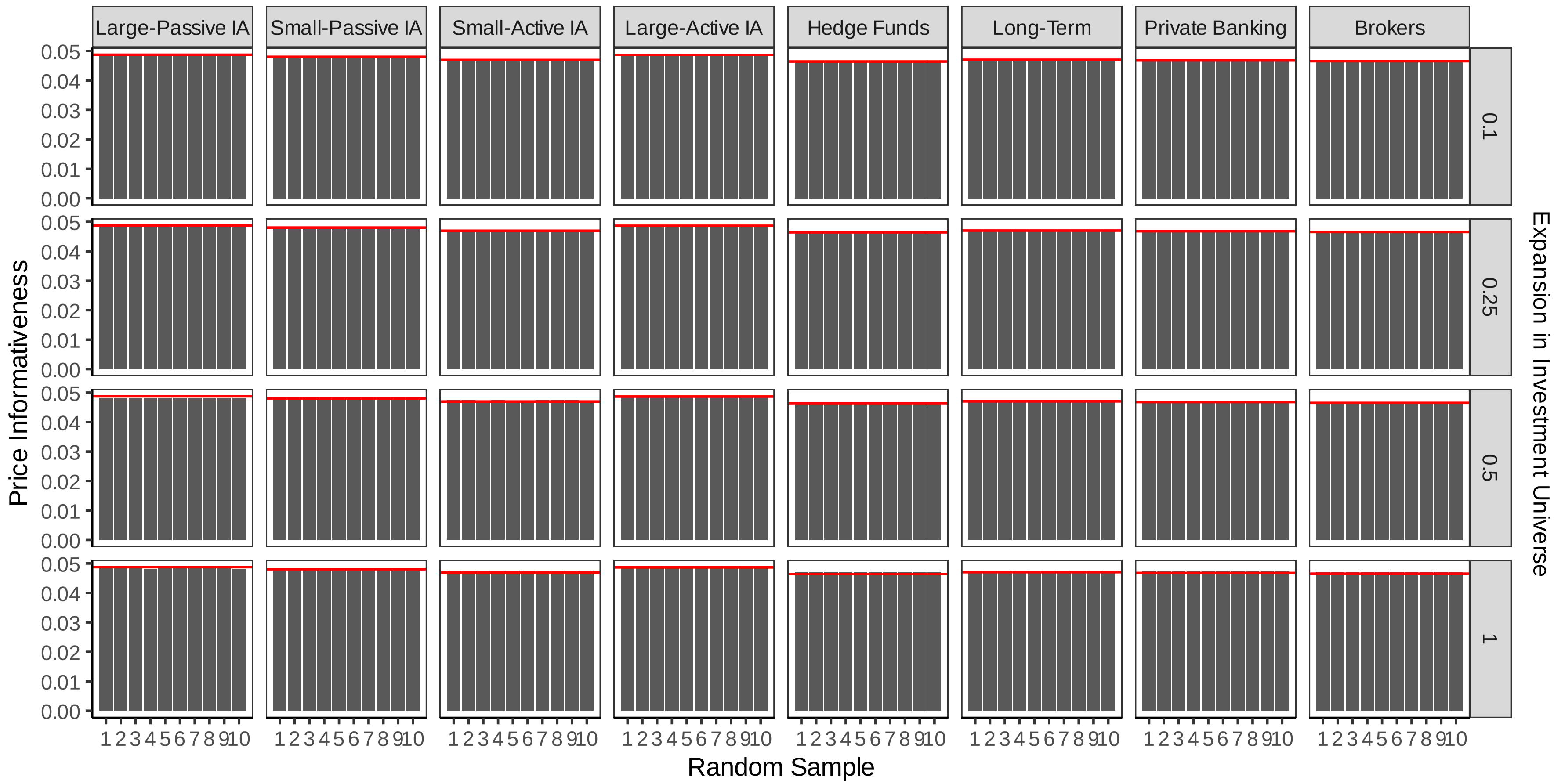

FIGURE D3

Counterfactual price informativeness in 2016 under the 2007 wealth distribution:
Robustness to expanding the investment universe

Notes: The asset demand system is reestimated by randomly increasing the number of stocks in the investment universe. The columns correspond to the cumulative effects on price informativeness when the wealth distribution is changed from that in 2016.Q4 to 2007.Q4 sequentially by adding each investor type. The rows correspond to expanding the investment universe by 10%, 25%, 50%, and 100%. The red lines represent the baseline estimates from Panel C of Figure 5. The ten bars in each panel represent ten random samples.

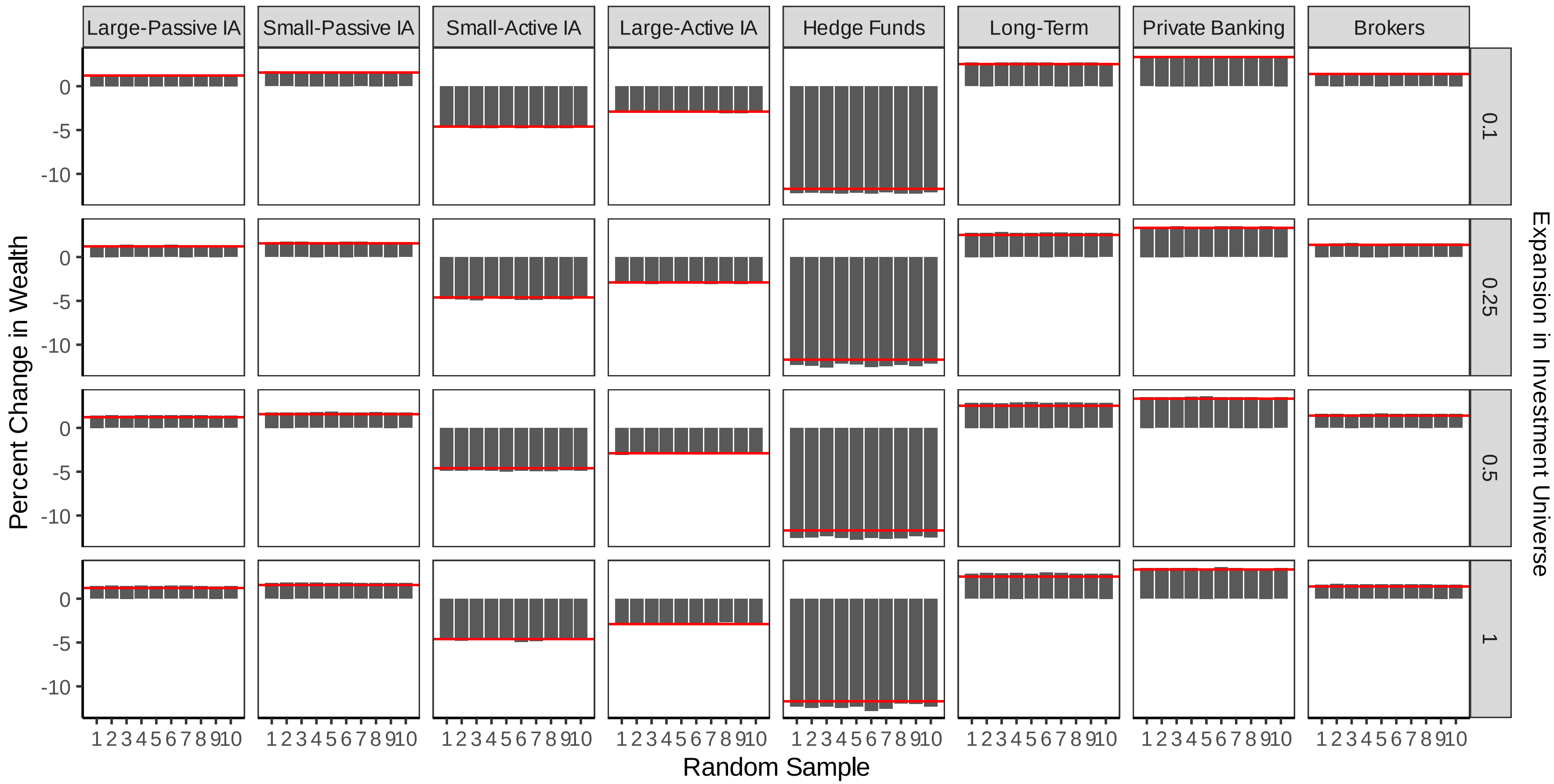

FIGURE D4

Impact of climate risk on the wealth distribution across institutional investors:
Robustness to expanding the investment universe

Notes: The asset demand system is reestimated by randomly increasing the number of stocks in the investment universe. The columns correspond to the percent change in total wealth by investor type in response to a climate-induced shift in asset demand due to stakeholder risk. The rows correspond to expanding the investment universe by 10%, 25%, 50%, and 100%. The red lines represent the baseline estimates from Figure 6. The ten bars in each panel represent ten random samples.

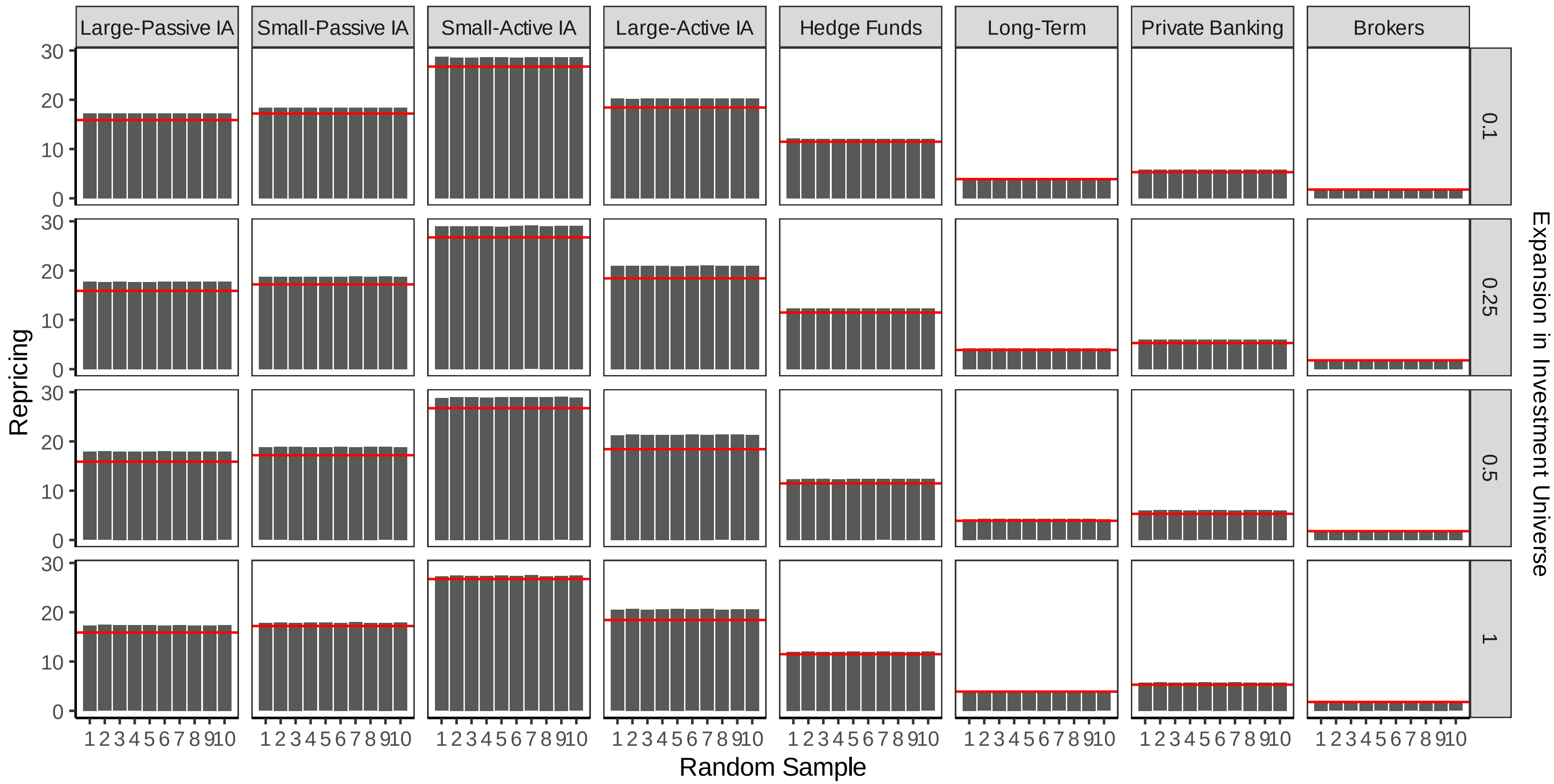

FIGURE D5

Equity repricing for counterfactual outflows by investor type:
Robustness to expanding the investment universe

Notes: The asset demand system is reestimated by randomly increasing the number of stocks in the investment universe. The columns represent the equity repricing for capital flows from the given group of investors to other institutional investors. The rows correspond to expanding the investment universe by 10%, 25%, 50%, and 100%. The red lines represent the baseline estimates from Panel A of Figure 7. The ten bars in each panel represent ten random samples.

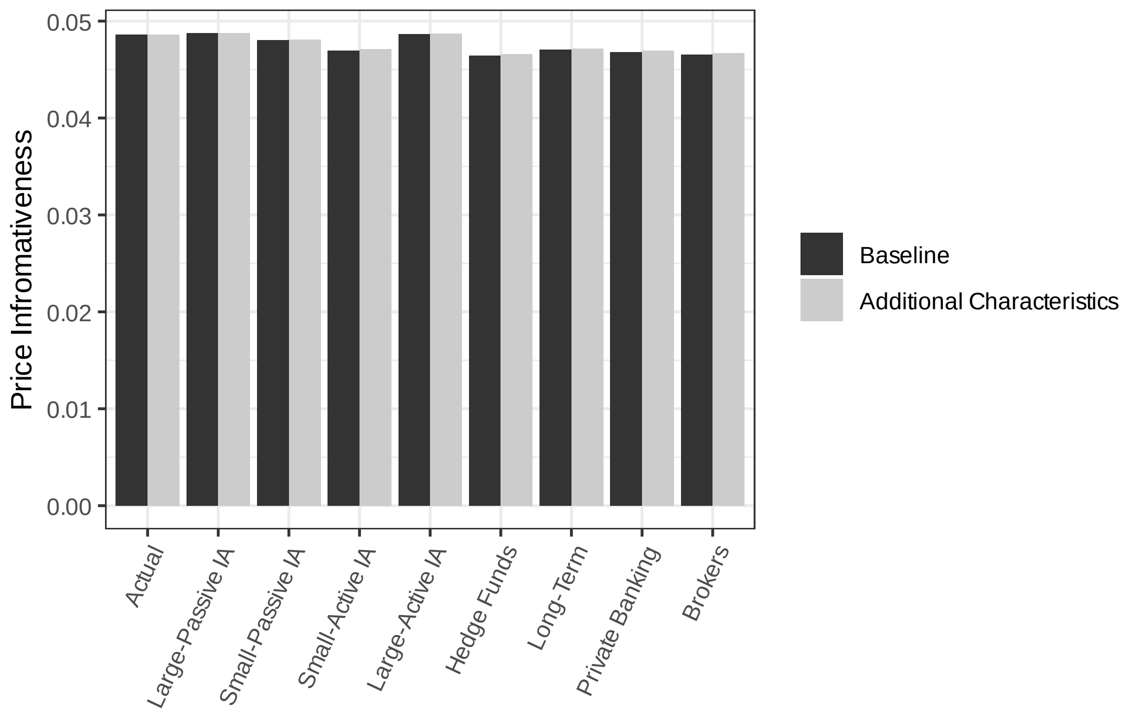

Figure D6
Counterfactual price informativeness in 2016 under the 2007 wealth distribution: Robustness to additional characteristics

Notes: The asset demand system is reestimated by adding investment, the ratio of net repurchases to book equity, and earnings surprises to the baseline specification. This figure shows the cumulative effects on price informativeness when the wealth distribution is changed from that in 2016.Q4 to 2007.Q4 sequentially by adding each investor type. The baseline estimates are from Panel C of Figure 5.

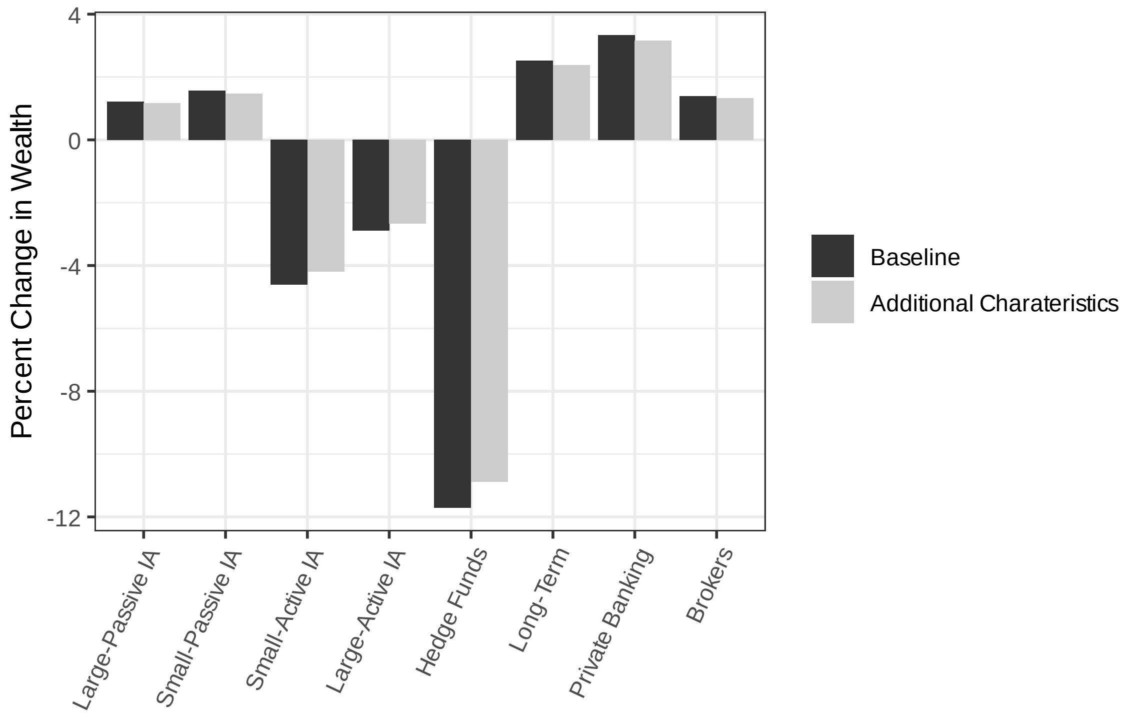

Figure D7

Impact of climate risk on the wealth distribution across institutional investors: Robustness to additional characteristics

Notes: The asset demand system is reestimated by adding investment, the ratio of net repurchases to book equity, and earnings surprises to the baseline specification. This figure shows the percent change in total wealth by investor type in response to a climate-induced shift in asset demand due to stakeholder risk. The baseline estimates are from Figure 6.

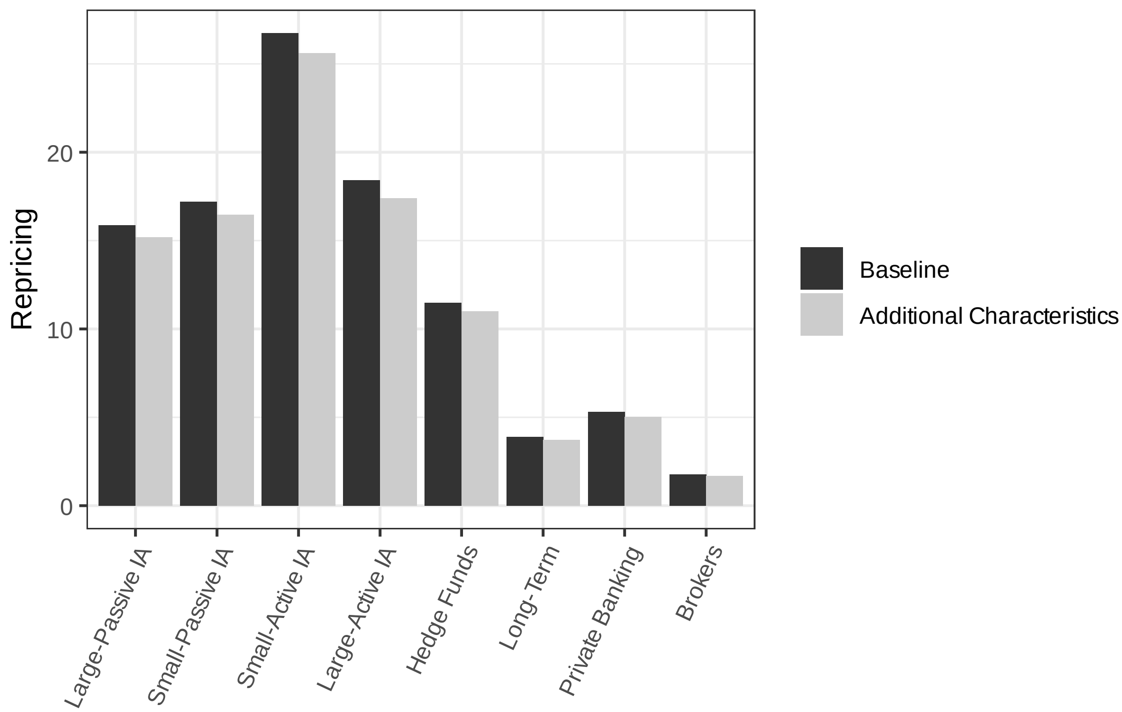

Figure D8
Equity repricing for counterfactual outflows by investor type:
Robustness to additional characteristics

Notes: The asset demand system is reestimated by adding investment, the ratio of net repurchases to book equity, and earnings surprises to the baseline specification. This figure shows the equity repricing for capital flows from the given group of investors to other institutional investors. The baseline estimates are from Panel A of Figure 7.