Which Investors Matter for Equity Valuations and Expected Returns?*

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Abstract

We develop and estimate a characteristics-based demand system for financial assets to quantify the impact of changes in demand of various investors on asset prices and investors' wealth. We apply the model to understand the impact of the market trend from active to passive investing on asset prices and price informativeness. We find that there is a nontrivial impact on valuations, yet a small impact on price informativeness. To understand the mechanism, we develop a new investor-level measure of price informativeness and show that there is no systematic relation between changes in institutional flows from active to passive managers and and how informed investors are about future fundamentals. We also explore the impact of a shift in demand for green firms, either for a subset of investors as a result of climate-related regulations or for a broad group of institutional investors due to overall increased awareness. This shift in demand benefits long-term investors such as pension funds and insurance companies, banks, and passive investment advisors at the expense of hedge funds and small-active investment advisors.

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Many questions in financial economics and in the policy sphere are about understanding how a shift in demand for specific assets or how a group of investors will affect asset prices and investors' wealth and welfare. Examples include: What is the impact of the broad market trend from active to passive investing on equity prices and price informativeness? What is the effect of socially responsible investing or climate-related regulation on equity prices, firms' cost of capital, and investors' capital positions?

Market equilibrium requires that investors' asset demands be equal to the supply of various assets. Thus, asset demand systems play a critical role in determining asset prices and in answering these questions involving shifts in investors' demand. In recent years, the availability of portfolio holdings data and progress on longstanding identification challenges have revealed an important fact: asset demand for financial assets is much less elastic than standard asset pricing models predict.This calls for new tools to analyze the effect of broad market trends or changes in regulation.

In this paper, we use a characteristics-based demand system for financial assets to answer these questions. To motivate our empirical work, we develop a simple model in which investors use a set of characteristics to estimate a firm's expected future profitability and riskiness. We allow investors to have subjective beliefs and they may disagree about which characteristics are important for a firm's expected future profitability and riskiness. Optimal portfolio choice implies that demand curves depend on prices, characteristics, and latent demand. Latent demand captures additional information that investors use to predict profitability or riskiness that is unobserved to the econometrician.[1] In equilibrium, asset prices depend on characteristics and latent demand. The coefficients on characteristics and latent demand are a weighted average of the preferences of individual investors, weighted by their assets under management. This implies that changes in demand or capital flows from one group of investors to another change the link between those characteristics and asset prices, as well as latent demand.

We estimate the model using quarterly, investor-level portfolio holdings data in the U.S. from 2000 to 2019. In estimating the model, we allow for rich heterogeneity across investors,

[1]Latent demand also captures other factors driving investors' demand such as fluctuations in sentiment (Barberis, Shleifer, and Vishny, 1998) or funding constraints of institutional investors (Brunnermeier and Pedersen, 2009).

as well as within institutional type.[2] This turns out to be important, as our estimates reveal substantial heterogeneity in demand curves of institutional investors both within and across groups (e.g. hedge funds, mutual funds, and broker dealers), with significant deviations from the market portfolio.

We then use our framework to address two broad questions that relate to policy. We first analyze how firm valuations and price informativeness are affected by the broad market trend from active to passive management. To study this trend, we start by documenting two stylized facts. First, the aggregate active share across institutional investors dropped from 45% in the early 1980s to a little over 25% at the end of our sample in 2019. Second, during the relevant part of our sample period from 2007 to 2016, which matches the long-run trend, most of the decline in the aggregate share was due to capital flows disproportionately to investors with lower active shares.

Based on the second stylized fact, we consider a counterfactual in which capital is redistributed such that the size distribution in 2016 matches the one in 2007, while investors' demand curves are unaffected. Given this new size distribution, we compute new equilibrium asset prices. We define a measure of repricing, which is the sum of the absolute value of changes in firms' market capitalization normalized by the total market capitalization in 2016. The total repricing is 14% in our counterfactual, which is nontrivial.

We then ask whether these prices computed under the alternative size distribution are more informative about future fundamentals. We follow Bai, Philippon, and Savov (2016) and compute their measure of price informativeness in 2016, which shows how valuation ratios in 2016 are cross-sectionally related to earnings three years into the future. We find that the price informativeness coefficient is very similar when using the actual or the counterfactual prices. To understand the mechanism, we show how we can use the model to estimate how informed each individual investor is. We then use this new investor-level measure of price informativeness to document that during the period from 2007 to 2016 capital did not flow systematically to those investors who have superior information about future fundamentals.

[2]We group institutional investors by type: investment advisors, hedge funds, long-term investors, private banking, and brokers. Investment advisors are further broken down by size and the active share, as this is a large category of institutional investors that includes mutual funds. Long-term investors include pension funds and insurance companies.

This explains why the trend from active to passive management has a significant impact on valuations but a negligible impact on price informativeness.

In our second application, we explore the impact of climate-related regulations or shifts in demand. This question is also of interest to policymakers, who wonder about the impact on asset prices and firms' cost of capital as well investors' welfare and overall financial stability. Quantifying such effects is challenging, in part because of the different dimensions of risk such as physical damages, policy and regulatory risks, and changes in consumer preferences, among others. While a comprehensive analysis of all risks is beyond the scope of this paper, we can use our framework to quantify two key dimensions of climate-related risks. Our focus is guided by a recent survey of Stroebel and Wurgler (2021), which shows that the respondents consider regulatory risk as the main risk over the next five years, followed by "stakeholder risk," which includes changing preferences of employees and customers.[3] We design two counterfactuals to capture regulatory risk for long-term investors (i.e., pension funds and insurance companies) and to capture stakeholder risk. In both cases, we compute effects on asset prices and investors' AUM (a measure of welfare).

As the environmental characteristic is only weakly correlated with all other characteristics, the impact of climate-related demand shifts on valuations is largely limited to valuation's regression coefficient on the environmental characteristic. More interestingly, in terms of investors' welfare, we find that long-term investors, banks, and passive investment advisors benefit from the transition, while active investment advisors and hedge funds would experience a decline in AUM. The mechanism in this case is straightforward: As we shift the demand curve along a particular characteristic, those investors who tilt their portfolios relatively more in this direction prior to the shift in demand stand to benefit. These calculations show how our framework can be used to develop and implement "climate stress tests."

Building on the insights from these counterfactuals, we show in the last part of the paper how our characteristics-based demand system can be used to understand the role of different investors in connecting asset prices to characteristics and, analogously to connect expected returns to characteristics. As in the first counterfactual, we consider how asset

[3]Over longer horizons, which in the survey corresponds to the next 30 years, physical risks are considered to be most important.

prices change if capital is reallocated from one group of investors to other institutions. We then regress the counterfactual prices on characteristics, which provides a simple way to quantify the relative importance of different investor groups. This can answer a long-standing question in finance of why certain characteristics are related to the cross-section of valuation ratios and expected returns (e.g., Fama and French (1995), Daniel and Titman (2006), and Campbell, Polk, and Vuolteenaho (2010)).

Our paper relates to a literature on "demand system asset pricing," which directly models the asset demand system. This literature has roots going back to (at least) Brainard and Tobin (1968), Tobin (1969), and Friedman (1977, 1978), and has recently been revived by Koijen and Yogo (2019). They show how demand system asset pricing can be implemented using the high-quality holdings data that are now available and taking advantage of modern econometric tools.

Our main contribution is to show how the characteristics-based demand system can be used to answer questions of policy relevance related to broad market trends, such as the transition from active to passive investing, and changes in regulation, for instance on climate-related risks. We make several methodological contributions as well that are important in answering these questions. First, we endogenize investors' assets in the counterfactuals, which has been kept fixed in earlier work, which allows us to analyze welfare implications. Second, we show how to measure the effect of such market trends or regulatory changes on price informativeness, and how to explore the mechanism by measuring how informed each investor is. Our new investor-level measure of price informativeness has broader applicability beyond this paper in answering questions related to informed investors and uninformed noise traders. Third, we develop an instrumental variables shrinkage estimator, which allows us to estimate investor-specific demand curves, even when an investor holds a concentrated portfolio. Lastly, we improve upon the earlier data through new information on institutional types. In particular, our classification identifies hedge funds who play an important role in numerous parts of the analysis.

1. An Asset Pricing Model

We develop an asset pricing model that illustrates how an asset demand system can be used for general equilibrium analysis of regulation or secular trends in asset demand such as the growth of passive management. The model is intentionally simple and stylized to illustrate the core economic mechanisms that underly a broader class of asset pricing models. We use the model to explain the empirical applications in the subsequent sections.

We present the assumptions and the results in this section and leave all derivations for Appendix C. 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 the identity matrix as $\mathbf{I}$ and a vector with the nth element equal to one and other elements equal to zero as $\boldsymbol{e}_n$.

1.1. Assumptions about preferences, beliefs, and technology

We start with a two-period model with time indexed by $t = 0, 1$. There are N assets indexed by $n = 1, \ldots, N$. We normalize the supply of each asset to one share. Let $\boldsymbol{P}$ be an N-dimensional vector of asset prices in period 0. Let $\boldsymbol{B}$ be an N-dimensional vector of book values in period 0. Let $\boldsymbol{D}$ be an N-dimensional vector of terminal dividends in period 1. For each asset n, we define the market-to-book ratio as $MB(n) = P(n)/B(n)$ and the return on equity (ROE) as $d(n) = D(n)/B(n)$. Thus, the N-dimensional vectors corresponding to the market-to-book ratio and the ROEs are $\boldsymbol{MB}$ and $\boldsymbol{d}$, respectively.

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

$$\begin{aligned} A_{i,0} =& \boldsymbol{q}_i'\boldsymbol{P} + O_i \\ =& \boldsymbol{Q}_i'\boldsymbol{MB} + O_i, \end{aligned}$$

where O_i is the dollar investment in an outside asset. To simplify notation, we assume that the outside asset is a cash account that earns no interest. The investor's wealth in period 1 is

$$\begin{aligned} A_{i,1} = & A_{i,0} + \boldsymbol{q}_i'(\boldsymbol{D} - \boldsymbol{P}) \\ = & A_{i,0} + \boldsymbol{Q}_i'(\boldsymbol{d} - \boldsymbol{M}\boldsymbol{B}). \end{aligned}$$

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

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

Investors have heterogeneous coefficients of absolute risk aversion, which we parameterize as $\gamma_i = 1/(\tau_i A_{i,0})$. 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 heterogenous beliefs about ROEs. We assume that investors have full information about other investors' beliefs and agree to disagree.

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

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

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

Investors form expectations based on asset characteristics, which are public information. We denote a vector of observed (to the econometrician) characteristics of asset n as $\boldsymbol{x}(n)$. We order the characteristics so that the first element is book value and the last element is a constant. We denote unobserved characteristics of asset n regarding expected growth and factor exposure as ν_i^μ and ν_i^ρ, respectively. Thus, investor i's beliefs about expected growth and factor exposure are given by

$$\mu_i(n) = \boldsymbol{\lambda}_i^{\mu\prime} \boldsymbol{x}(n) + \nu_i^{\mu}(n), \tag{1}$$

$$\rho_i(n) = \boldsymbol{\lambda}_i^{\rho\prime} \boldsymbol{x}(n) + \nu_i^{\rho}(n). \tag{2}$$

We assume that both observed and unobserved characteristics are exogenous and mutually uncorrelated.

1.2. Optimal portfolio choice

As we show Appendix C, investor i's optimal demand for asset n is

$$Q_i(n) = -\frac{1}{\gamma_i \sigma^2} \left(MB(n) + \underbrace{(\boldsymbol{\lambda}_i^{\mu} - c_i \boldsymbol{\lambda}_i^{\rho})'}_{\boldsymbol{\beta}_i'} \boldsymbol{x}(n) + \underbrace{\nu_i^{\mu}(n) - c_i \nu_i^{\beta}(n)}_{\epsilon_i(n)} \right), \tag{3}$$

where c_i is a scalar that does not vary across assets. The first term in equation (3) says that asset demand is decreasing in the market-to-book ratio, or equivalently, the price. The second term in equation (3) says that asset demand is increasing in characteristics that are associated with higher expected growth 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 towards a particular characteristic because of beliefs about expected growth or risk. We refer to the last term in equation (3) as latent demand because it is unobserved to the econometrician. Again, the relation between asset demand and unobserved characteristics could arise because of beliefs about expected growth or risk.

Equation (3) establishes a cross-sectional relation between an investor's asset demand and asset characteristics. In Section 4, we estimate asset demand for the cross section of institutional investors and households. The interesting empirical implication of equation (3) is that investors with heterogenous risk preferences and beliefs could have different elasticities with respect to price and observed characteristics. Asset demand is less price elastic for investors with higher risk aversion γ_i. Asset demand is more elastic to environmental scores for investors with stronger views about the implications of climate change for expected growth and risk (due to uncertainty about the transition to a green economy or government policy).

Equation (3) could arise from microfoundations other than heterogenous beliefs. In Appendix C, 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 green firms (Pástor, Stambaugh, and Taylo 2021; Pedersen, Fitzgibbons, and Pomorski, 2021). Asset holdings data are not sufficient to disentangle whether demand for a particular characteristic arises from beliefs about expected growth or risk, hedging motives, or nonpecuniary benefits. Survey data are promising for this purpose (Bauer, Ruof, and Smeets, 2021; Krueger, Sautner, and Starks, 2020).

1.3. Equilibrium asset prices

Market clearing for each asset n is $\sum_{i=1}^{I} Q_i(n) = B(n)$. Substituting optimal demand (3) into market clearing, we express equilibrium asset prices in terms of market-to-book ratios:

$$MB(n) = \overline{\boldsymbol{\beta}}'\boldsymbol{x}(n) + \overline{\epsilon}(n), \tag{4}$$

where[4]

$$\begin{aligned}
\overline{\boldsymbol{\beta}} &= \sum_{i=1}^{I} a_i \boldsymbol{\beta}_i - \frac{\sigma^2 \boldsymbol{e}_1}{\sum_{i=1}^{I} \tau_i A_{i,0}} \\
\overline{\epsilon}(n) &= \sum_{i=1}^{I} a_i \epsilon_i(n), \\
a_i &= \frac{\tau_i A_{i,0}}{\sum_{j=1}^{I} \tau_j A_{j,0}}.
\end{aligned}$$

Equation (4) establishes a cross-sectional relation between market-to-book ratios and asset characteristics. The vector $\overline{\boldsymbol{\beta}}$ is a weighted average of the coefficients on observed characteristics in the investors' demand (3). Investors with more extreme beliefs about expected growth or risk with larger $\boldsymbol{\beta}_i$ have a greater impact on asset prices. In addition, investors with more wealth or higher risk tolerance have a higher weight a_i and have a

[4]Recall that book value is the first element of $\mathbf{x}(n)$, which explains $\boldsymbol{e}_1$ in the expression for $\overline{\boldsymbol{\beta}}$.

greater impact on asset prices. The term $\overline{\epsilon}(n)$ is a weighted average of latent demand across investors. Investors with more extreme beliefs about expected growth or risk with larger latent demand have a greater impact on asset prices.

1.4. Applications of the asset demand system

In the subsequent sections, we estimate this characteristics-based demand system to understand the general equilibrium impact of regulation that shift investors' demand curves or of broad market trends that involve flows across investors (e.g., capital flows from active to passive institutions). We now briefly illustrate how to interpret those exercises in the model.

First, we consider the case in which a regulatory change shifts investors' demand for a particular characteristic, say the k-th characteristic. An example is a characteristics that captures a firm's impact on the environment. Formally, this corresponds to changing $\frac{1}{\gamma\sigma^2}\boldsymbol{\beta}_i$ in (3) to $\frac{1}{\gamma\sigma^2}\boldsymbol{\beta}_i + \eta_i \boldsymbol{e}_k$, where η_i, which captures the intensity of the regulation, may vary across investors. Substituting this shift of the demand curve into (4) implies that the loadings on characteristics change to $\overline{\boldsymbol{\beta}} + \frac{\sigma^2}{\sum_{i=1}^{I}\tau_i A_{i,0}}\sum_{i=1}^{I}\eta_i \boldsymbol{e}_k$. In this expression, $\frac{\sigma^2}{\sum_{i=1}^{I}\tau_i A_{i,0}}$ measures the price impact of demand shocks and $\sum_{i=1}^{I}\eta_i \boldsymbol{e}_k$ corresponds to the shift in the demand curve.

Second, we consider the case in which capital flows from one group of institutions to another group of institutions, for instance from active to passive institutions. This capital flow changes the relative weights a_i in computing $\overline{\boldsymbol{\beta}}$ and $\overline{\epsilon}(n)$. In this case, the investor-level demand curve is unaffected in terms of their appetite for characteristics and latent demand, but the relative importance of investors shifts.

In both types of counterfactuals, some investors realize capital gains on their existing portfolio, while others experience capital losses, as prices change due to a shift in demand curves or due to capital flows. In addition to the impact on asset prices, we also measure the impact on investors' wealth and the wealth distribution.

1.5. Extenstions

In solving the model, we assume that the characteristics do not depend on prices. While this assumption is reasonable for characteristics that measure a firm's productivity and market power, it may be too strong for some characteristics that capture corporate actions, like a firm's payout policy, which can depend on equity valuations. To capture such dependencies, we consider an extension of the model,

$$x_k(n) = h_{0,k} + h_{1,k} MB(n) + \nu_k^x(n),$$

where $h_{1,k}$ captures the feedback from valuation ratios to the characteristic and $\nu_k^x(n)$ is a policy shock. In Appendix C.3, we provide the solution for asset prices in this extended model.

2. Data and summary statistics

Data on firm characteristics and stock prices are from CRSP, Compustat, ISS, and Sustainalytics. Portfolio holdings are from FactSet and sourced from regulatory 13-F filings. The details on the data construction can be found in Appendix A.

2.1. Investor types

We classify investors into eight groups. We use FactSet's classification of investor types to assign institutions to institutional groups. We first form the following groups: Investment Advisors, Long-Term Investors, Hedge Funds, Private Banking, Brokers, and Households. The group Long-Term includes primarily insurance companies and pension funds, and the group Investment Advisors includes investment advisors and mutual funds.[5] Next, as the group of investment advisors is large, we further split this group by assets under management and active share as we discuss in more detail in Appendix A. Our final groupings are given by Investment Advisors – Large-Passive, Investment Advisors – Small-Passive, Investment Advisors – Small-Active, Investment Advisors – Large-Active, Hedge Funds, Long-Term, Private Banking, Brokers, and Households. FactSet also provides data on the location of the investor, which we use to study whether domestic and foreign investors behave differently.

The household sector is constructed as the difference between the total shares outstanding

[5]FactSet classifies an investment firm as an Investment Advisor when the majority of its investments are not in mutual funds and when it is not a subsidiary of a bank, brokerage firm, or insurance company. If the majority of its investments are in mutual funds, it is instead classified as Mutual Fund. As this classification is economically quite arbitrary, we group investment advisors and mutual funds together.

and the total holdings of all institutions. In rare instances, the total holdings exceed the market cap of a company, in which case we scale the holdings back proportionally. One reason why this may happen is due to short-selling activity, which are not covered in our data as 13-F filings only measure the long positions (Lewellen, 2011).[6]

Figure 1 reports the ownership shares by institutional type, which have been fairly stable during our sample. Table 2 lists the largest investor by type in 2000 and in 2019 to provide some perspective on the types of institutions that populate the groups. The distribution of ownership is concentrated as well (e.g., Azar, Schmalz, and Tecu (2018)), and this concentration has increased over time (Ben-David, Franzoni, Moussawi, and Sedunov, 2016). Part of this concentration is driven by the increased popularity of passive indexing strategies, which we explore in more detail in Section 5.

2.2. Selection of firms

We focus on the largest 90% of firms to make sure that we focus on stocks that are sufficiently liquid (see also Asness, Moskowitz, and Pedersen (2013)). We group the bottom 10% into a small-cap portfolio that becomes an outside asset for the investors.

Table 1 documents firm characteristics along the firm size distribution, as measured by market capitalization. The top panel is for 2019.Q4 and the bottom panel for 2000.Q1. In 2019.Q4, the top 90% of total market capitalization is accounted for by only 541 firms. The largest 57 firms already account for 50% of the total market capitalization. The largest 50% of firms account for only 34% of sales yet 46% of profits. This implies that profits are highly concentrated among the largest firms. By comparing the distribution to 2000.Q1, we see that this concentration appears to have increased over the past two decades. Table 1 shows that the economic impact of the bottom 10% of firms is small among all listed firms.

2.3. Selection of characteristics

We consider eight characteristics. The first characteristic is log book equity (LNbe), which captures size effects. To measure future productivity and profitability, we use the sales-to-

[6]As we cannot observe short positions at the investor-level, we estimate the model on long positions only. This results in a selected sample, but there is unfortunately little that we can do about this given data limitations.

book equity ratio, the foreign sales share, the dividend-to-book equity ratio, and the Lerner index. Our use of the foreign sales share is motivated by models such as Melitz (2003) in which only the most productive firms export to other countries. The Lerner index is a simple measure of markups that is also used in the recent literature on industry concentration and the rise of superstar firms (see for instance Gutiérrez and Philippon (2017)). The Lerner index is calculated as operating income after depreciation divided by sales. Next, we include a stock's market beta, measured relative to the market return, as the canonical measure of stock market risk.

In addition to characteristics constructed using data from firms' income statements and balance sheets, we use scores that reflect their performance in terms of the environment and governance. For the environmental score, we rely on Sustainalytics. There are various environmental ratings used in the industry and they are not always strongly correlated. Sustainalytics is one of the major environmental rating agencies and is, for instance, used by Morningstar. The Sustainalytics ratings are therefore an important driver of flows (Hartzmark and Sussman, 2019). One aspect worth noting is that Sustainalytics provides industry-adjusted ratings, and environmental ratings therefore do not simply reflect differences across industries.

For the governance index, we follow the influential study by Bebchuk, Cohen, and Ferrell (2009). They study how different provisions in the index constructed by Gompers, Ishii, and Metrick (2003) matter for valuations and emphasize six entrenchment provisions. We use their entrenchment index as an additional characteristic. We also construct dummy variables that take the value of one when the environmental score or the governance score is missing.

We construct a quarterly sample that begins in 2000 and ends in 2019. We also study a subsample that runs from 2010 until 2019 where the starting point is dictated by the availability of the environmental and governance scores. We cross-sectionally standardize all characteristics, by quarter, by removing the mean and dividing by the standard deviation.

2.4. Explaining valuation ratios using characteristics

We now show that a small set of characteristics explains the majority of the cross-sectional variation in valuation ratios. We use this fact in the specification of our asset demand system.

We start with the following panel regression of valuation ratios on the characteristics

$$mb_t(n) = a_t + \boldsymbol{\lambda}'_{mb}\boldsymbol{x}_t(n) + \epsilon_t(n), \tag{5}$$

where a_t are year fixed effects. For these regressions we use annual end of year data. The results are reported in Table 3. Environment and governance characteristics are only available beginning in 2010 so we study two samples: 2000 to 2019 and 2010 to 2019.

First, we find that the coefficient on log book equity is negative, while the productivity and markup variables all enter positively. The negative coefficient on book equity is consistent with equation (4) and points to downward-sloping demand curves for individual stocks. The coefficient on the environmental score is positive. A one standard deviation increase in the environmental score is associated with a 17% increase in a firm's market-to-book ratio, all else equal. We find that a one standard deviation increase in the governance score is associated with an 10% lower valuation ratio. Recall that the governance score is an entrenchment index, implying that higher values are associated with weaker governance.

Second, these characteristics account for a large fraction of the cross-sectional variation in prices using a small set of characteristics, which is consistent with Asness, Frazzini, and Pedersen (2019). We explain 64% of the variation in the panel of valuation ratios after projecting out year fixed effects. As we can explain a substantial fraction of the variation in prices, it is natural to ask which investors account for this information in forming their portfolios.

As further evidence that these eight characteristics form a reasonable basis, in Appendix F.2 we present valuation regresions including three additional characteristics that have been shown to be strong predictors of returns (Daniel, Hirshleifer, and Sun, 2020). In particular, we show that when further including investment, net repurchases, and earnings surprises the R-squared only increases from 64% to 68%.

Table 3 shows that the same eight characteristics also explain a substantial fraction of the cross-sectional variation in future profitability,[7] often with similar coefficients in terms of sign

[7] We construct earnings adjusted for issuances and repurchases using the clean-surplus accounting identity: $X_t = B_t - B_{t-1} + NR_t + D_t$, where X_t denotes earnings, B_t book equity, NR_t net repurchases, and D_t cash dividends. We then define $e_t = \ln(1 + X_t/B_{t-1})$ and use as our earnings measure $\sum_{i=1}^{5} \rho^i e_{t+i}$ with $\rho = 0.95$.

and magnitude as in the valuation regressions.[8] We do note that our sample is short, which makes it challenging to accurately estimate expected future earnings. However, our decomposition of the market-to-book-ratio also implies a decomposition of long-horizon expected returns, once combined with a model for expected earnings via the present-value identities developed in Cohen, Polk, and Vuolteenaho (2003) and Campbell, Polk, and Vuolteenaho (2010). As such, a decomposition of valuations, combined with a model of earnings expectations, yields a decomposition of expected returns. We explore this in more detail in Section 7.

3. An empirically-tractable model of the asset demand system

Building on the insights developed in the previous section, we now outline an empirically-tractable asset demand system that allows for rich heterogeneity in demand curves across investors. Our model builds on the asset demand system developed in Koijen and Yogo (2019).

3.1. Notation

There are N assets, indexed by $n = 1, \ldots, N$. Lowercase letters denote the logarithm of the corresponding uppercase variables. As before, we denote the vector of characteristics of asset n in period t as $\boldsymbol{x}_t(n)$. The financial assets are held by I investors, indexed by $i = 1, \ldots, I$. One of the investors is a household sector, which holds all remaining shares that are not held by institutional investors.

3.2. The universe of assets and asset demand

Financial markets are highly concentrated, as we show in Section 2. We therefore define the top 90% of stocks by market capitalization as the universe of assets. This ensures that our model focuses on pricing the largest firms in the economy that capture almost all of the economic activity among listed firms and it avoids that our estimates are driven by a large

[8] Kacperczyk, Sundaresan, and Wang (2021) show that price informativeness is increasing in the fraction of equity held by foreign investors, in particular in developed economies (see also Bena, Ferreira, Matos, and Pires (2017).

number of micro-cap or small firms. We refer to stocks within an investor's choice set as inside assets. There is also an outside asset, which is all stocks that are not part of the top 90% by market capitalization. The outside asset is indexed by $n = 0$.

Each investor allocates assets $A_{i,t}$ in period t across the stocks in its choice set $\mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$. An investor's choice set is a subset of assets that the investor considers or is allowed to hold. Restrictions on the choice set may be driven by investment mandates, benchmarking or informational frictions that limit an investor's ability to analyze a large universe of stocks (Merton, 1987).

We model an investor's portfolio weight on stock n as

$$w_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m \in \mathcal{N}_i} \delta_{i,t}(m)}, \tag{6}$$

where

$$\delta_{i,t}(n) = \exp\left\{b_{0,i,t} + \beta_{0,i} mb_t(n) + \boldsymbol{\beta}'_{1,i}\boldsymbol{x}_t(n)\right\} \epsilon_{i,t}(n), \tag{7}$$

and $b_{0,i,t}$ are investor-time fixed effects. An investor's demand depends on the log market-to-book ratio, firm characteristics, and latent demand, $\epsilon_{i,t}(n)$. Investors with lower values of $\beta_{0,i}$ have more elastic demand curves. Latent demand captures the part of investor i's demand that is not captured by observed (to the econometrician) characteristics. Zero holdings, within an investor's choice set, correspond to $\epsilon_{i,t}(n) = 0$.

This demand curve is motivated by the simple model in Section 1 and accounts for the observation that portfolio holdings are log-normally distributed in the data. We normalize the mean of latent demand, $\epsilon_{i,t}(n)$, to one so that the intercept $b_{0,i,t}$ in equation (7) is identified. This implies that the error terms, by construction, average to one for a given investor across stocks in each period, but the error terms typically do not average to one across investors for a given stock. Indeed, the residual variation in market-to-book ratios beyond characteristics is due to latent demand, see equation (4).

3.3. Market clearing

We complete the model with the market clearing condition for each asset n,

$$ME_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n). \tag{8}$$

The market value of shares outstanding must equal the asset-weighted sum of portfolio weights across all investors. In solving for equilibrium asset prices, we follow the literature on asset pricing in endowment economies (Lucas, 1978) and assume that shares outstanding and the characteristics are exogenous.

Koijen and Yogo (2019) show that $\beta_{0,i} < 1$, for all investors, is a sufficient condition for both individual and aggregate demand to be downward sloping. We impose this condition in estimating the demand system.

3.4. Computing counterfactuals

We consider two types of counterfactuals. First, we consider changing the coefficients of the demand curve, $\boldsymbol{\beta}_{1,i}$, for instance to increase investors' demand for firms with green characteristics. Second, we consider a set of capital flows, $F_{i,t}$. The counterfactual assets under management, $A_{i,t}^{CF}$, are then

$$A_{i,t}^{CF} = A_{i,t} R_{i,t}^{P} + F_{i,t}. \tag{9}$$

The portfolio return is given by $R_{i,t}^{P} = \sum_n w_{i,t}(n) \frac{ME_t^{CF}(n)}{ME_t(n)}$. In computing this return, we use the portfolio weights $w_{i,t}(n)$ as observed in the data, as the portfolio is determined before the change in demand and flows occur. An innovation relative to the existing literature is that we endogenize the distribution of assets.[9] This allows us to explore the impact on investors' assets and thus a measure of welfare.

[9]Koijen and Yogo (2019) keep the distribution of assets fixed in their counterfactuals.

We then solve for prices so that markets clear, as in (8),

$$ME_t^{CF}(n) = \sum_{i=1}^{I} A_{i,t}^{CF} w_{i,t}^{CF}(n),$$

where the counterfactual portfolio weights, $w_{i,t}^{CF}(n)$, reflect counterfactual prices. In the counterfactuals, we assume that investors do not vary the fraction that they hold in the outside assets. We solve for market clearing prices, $ME_t^{CF}(n, c)$ using the algorithm in Koijen and Yogo (2019), where we update the distribution of assets in each iteration using (9).

4. Estimating the asset demand system

In this section, we discuss how we estimate the asset demand system, as summarized by equations (6) and (7).

4.1. The estimating equation

Our goal in this section is to estimate the demand curve of investor i, which can be written as

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left\{b_{0,i,t} + \beta_{0,i} mb_t(n) + \boldsymbol{\beta}_{1,i}' \boldsymbol{x}_t(n)\right\} \epsilon_{i,t}(n), \tag{10}$$

where, as before, we standardize all the characteristics cross-sectionally by quarter.

For our benchmark results, we assume that characteristics are exogenous to latent demand,

$$\mathbb{E}_t\left[\epsilon_{i,t}(n) \mid \boldsymbol{x}_t(n)\right] = 1. \tag{11}$$

In Section 4.5, we explore an extension in which we relax this assumption and allow characteristics to respond to prices.

There are two challenges in estimating asset demand curves. First, prices are endogenous to latent demand. We therefore construct an instrumental variable, $z_{i,t}(n)$, which we discuss in Section 4.2. Second, as some investors hold portfolios consisting of relatively few stocks, we may not be able to estimate all coefficients precisely. We propose a new shrinkage estimator of the coefficients in Section 4.3 to estimate the demand curves for each investor separately.

4.2. Construction of the instrument

We cannot simply estimate investors' demand curves using nonlinear least squares, as latent demand is likely correlated with prices, that is, $\mathbb{E}\left[\epsilon_{i,t}(n) \mid mb_t(n)\right] \neq 0$. This correlation may arise if latent demand is correlated across investors or if some investors are large and their individual latent demand impacts prices.

To construct an instrument, we follow Koijen and Yogo (2019) and use exogenous variation in investors' investment mandates to generate exogenous variation in demand. The key economic idea is that investors restrict attention to a subset of all stocks, for instance because of institutional constraints or because of limited information processing capacity. Consistent with this idea, Koijen and Yogo (2019) show that the set of stocks held by investors is quite small and very stable over time.

While the existence of mandates is plausible, measuring the precise boundaries of the investment mandate is more challenging. Let $\mathcal{S}_{i,t}$ denote the stocks held in period t. In any given period, investors may drop certain stocks due to variation in latent demand, that is, $\epsilon_{i,t}(n)$ and $\mathcal{S}_{i,t}$ are correlated.

For our main estimation, we assume that any stock that the investor holds during the current year, or any of the previous two years, is part of the choice set, $\mathcal{N}_{i,t} = \cup_{k=0}^{11}\mathcal{S}_{i,t-k}$. The number of stocks in an investor's choice set is denoted by $|\mathcal{N}_{i,t}|$.

To construct an instrument that relies only on the investment universe, and not the precise holdings within the investment universe, we compute counterfactual prices when investors all hold an equal-weighted portfolio of the stocks in their universe. We exclude the investor's own holdings and the holdings of the household sector:

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

While the look-back period of three years mitigates concerns about endogeneity of the universe, we ultimately have to estimate this universe as we do not have direct information on it. We therefore explore the robustness of our demand elasticity estimates to the choice of the window, by varying the look-back period and also expanding the window into the future, in Section 4.5.[10]

4.3. A ridge instrumental variables estimator of the demand curve

The second empirical challenge in estimating the asset demand system is most asset managers hold fairly concentrated portfolios. While this is useful in constructing an instrument, as we discussed in the previous section, it also implies that we have limited data to estimate demand curves investor-by-investor and period-by-period. This challenge is even more relevant in our setting in which we focus on the largest 90% of stocks, which further shrinks the number of stocks held by investors.

One approach to estimate demand curves is to pool investors by institutional type or investment style (Koijen and Yogo, 2019). However, this imposes substantial homogeneity in demand curves that we wish to avoid for the purposes of this paper. We propose an alternative econometric strategy by augmenting the standard GMM moment conditions derived from (11) with a ridge penalty (Hoerl and Kennard, 1970). We provide the main intuition here and leave the details of the estimation procedure, including a fast numerical procedure to implement the estimator, for Appendix D.

A ridge estimator shrinks the estimated coefficients of an investor's demand curve towards a target by adding a quadratic penalty to the objective that is minimized by the estimator.[11] We therefore need to choose a shrinkage target and how much shrinkage to apply. To determine the shrinkage target, we group investors by type and size, ensuring that each group has at least 2,000 positions, which includes zeroes, in their choice set in a given year. We pool all quarters of a given year and include quarter fixed effects. This determines the shrinkage target. We then estimate the demand curve for each investor, while fixing the estimate of $\beta_{0,i,t}$. We do this to avoid that the instrument is weak in case an investor holds

[10] Koijen and Yogo (2019) also explored the impact of including dummy variables for widely-used benchmark, such as the S&P500, and found that they do not affect the demand elasticity estimates much. One reason for this is that the 13-F data that we use to estimate the model is at the level of the institution, which aggregates across different funds that are compared to different benchmarks.

[11] Or, equivalently, by adding a linear term to the first-order condition that is solved by the estimator.

few positions in a given year.

We determine the shrinkage parameter using cross-validation, as is common practice in the machine learning literature. We split the holdings randomly in half for each investor by year. We then estimate the model on one sample for each investor and compute the mean-squared error on the left out sample. The shrinkage penalty is selected to minimize the model's out-of-sample performance. We specify the penalty as $\lambda_{i,t} = \lambda|\mathcal{N}_{i,t}|^{-\xi}$, implying that the shrinkage declines if an investor has a larger number of holdings. The cross-validation procedure selects $\lambda = 120$ and $\xi = 0.7$.

4.4. Demand estimation results

We present the asset demand estimation results in Figure 2, Figure 3, and Table 4. To estimate the model, we use quarterly data. To summarize each investor's demand curve, we compute the time-series average of coefficients. In Figure 2, we plot the distribution of demand coefficient estimates for each of the characteristics across investors. The vertical lines correspond to the size-weighted average across investors by institutional type for each of the coefficients.[12]

An important first takeaway is that there is significant heterogeneity across investors, beyond institutional type. This highlights the relevance of our ridge estimator that allows for more heterogeneity across investors compared o simply pooling investors by size and institutional type. There is also significant heterogeneity in demand elasticities across investors, which is determined by the coefficient on the market-to-book ratio — see the top-right panel. This implies that the same shift in demand may have a different impact on prices depending on which investor's demand curve shifts. This difference is a result of the residual demand curve being more or less elastic.

In Table 4, we summarize the heterogeneity in demand curves in two different ways. In Panel A, we regress the demand coefficients, averaged across time for each manager, on institutional-type fixed effects. Demand coefficients are multiplied by 100 for readability, with the exception of the coefficient on $mb_t(n)$. This implies that the coefficients can be

[12]To average the coefficients, we first compute the AUM-weighted average for a given investor group and year. We then average these across years for a given investor group.

interpreted as the percentage increase in demand for a one standard deviation change in the characteristic.

For the environmental score, we find stronger demand for large investment advisors (both active and passive) as well as brokers. In terms of a firm's governance, small-active investors and brokers have the strongest tilt away from firms with entrenched management. For the coefficient on $mb_t(n)$, where lower coefficients correspond to more elastic demand, we find that the asset demand curve of hedge funds and small-active investors is most elastic, while the demand of large investment advisors, brokers, and long-term investors is most inelastic. Even though we can relate some variation in the estimated coefficients to institutional type, the R-squared values of these regressions are quite low. This implies that there is a lot of heterogeneity in demand curves that cannot be captured by institutional type alone. An exception is the coefficient on $mb_t(n)$, which determines the demand elasticity, and the coefficient on log book equity, which is a measure of firm size. Those R-squared values are 48% and 59%, respectively.

In Panel B of Table 4, we regress the same coefficients on an investor's log AUM, active share, and an indicator variable that takes the value of one in the case of a foreign investor. We do not add institutional-type fixed effects as we already sort by size and active share for investment advisors.

For the environmental score, we find that larger, passive, and foreign investors have a stronger demand for greener firms. Foreign investors tend to tilt away from firms with entrenched management, while the opposite is true for larger investors, and there is no strong link to active share. That said, the R-squared values of these regressions are low, pointing to a lot of unexplained heterogeneity across investors. As before, the coefficients on $mb_t(n)$ and log book equity form the exception. The estimates imply that demand is more elastic for smaller and for more active investors. These intuitive relations lend further credibility to the demand estimates.

In Figure 3, we zoom in on the differences in demand across domestic and foreign investors. The first two panels of the first row reveal that foreign investors tilt their portfolios more strongly towards greener and less entrenched firms. This highlights an interesting role that foreign investors play in US financial markets as this lowers the cost of capital for greener firms. Also, foreign investors put more weight on firms with a larger fraction of sales from foreign markets, perhaps because of familiarity with those firms. Lastly, the bottom right panel shows that foreign investors also prefer to hold safer firms relative to domestic investors, where risk is measured by a firm's equity beta.

Taken together, our new estimator uncovers rich heterogeneity in demand that can only be partially explained by simple investor characteristics such as institutional type, size, activeness, and geography. It raises a new set of research questions to explain this heterogeneity using more granular information about investors, for instance, regarding their regulation, investment mandates, funding structure, et cetera.

4.5. Robustness and potential threats to identification

We made a number of assumptions when estimating the asset demand system. To ensure that our findings are robust, we study a number of variants of our estimation and identication procedure. We focus on the robustness along three dimensions. For each of these three dimensions we demonstrate that our demand curve estimates and, importantly, our key results presented in the following sections remain very similar across the alternative specifciations. We summarize the dimensions we study robustness over here and provide the details in Appendix F.

First, we assumed the existence of an investment universe that can be measured using the stocks an investor holds at any point during the last three years. To alleviate concerns regarding measurement of the investment universe we: (1) construct our instrument omitting hedge funds, (2) vary the window over which we measure investor's universes, and (3) randomly increase the size of investor's universes. Second, we used a set of eight characteristics in estimating investor's demand curves. To alleviate concerns with using this specific set of characteristics, we produce results including three additional characteristics which have been shown to be powerful predictors of returns (Daniel, Hirshleifer, and Sun, 2020): investment, repurchases, and earnings surprises. Third, we assumed that latent demand is exogenous to characteristics, which rules out that characteristics may depend on prices. To alleviate concerns with this assumption, we extend our model to allow characteristics, such as firm's dividend policies, to depend on prices. For all three of these dimensions we find that our key findings remain qualitatively and quantitatively similar.

5. The impact of the transition from active to passive management

We now use the estimated asset demand system to analyze the impact of the transition from active to passive management on equity valuations and price informativeness.

5.1. *Understanding the trend towards passive management*

We focus on the active share as our measure of active portfolio management (Cremers and Petajisto, 2009). We define an aggregate measure of active risk taking by institutions as

$$AS_t = \sum_{i,i \neq HH} S^{in}_{i,t} AS_{i,t},$$

where $S^{in}_{i,t} = A^{in}_{i,t}/(\sum_{j,j\neq HH} A^{in}_{jt})$ is the relative size of investor i based on inside assets, $AS_{i,t} = \frac{1}{2}\sum_n \mid w^{\star}_{i,t}(n) - w^{m}_{i,t}(n) \mid$ the active share of investor i, $w^{\star}_{i,t}(n) = \frac{\delta_{i,t}(n)}{\sum_m \delta_{it(m)}}$ the investor's portfolio weight in stock n using inside assets only, and $w^{m}_{i,t}(n)$ the market portfolio weights based on the stocks held by investor i.

In the right panel of Figure 4, we show that AS_t declines strongly during our sample period. In the left panel, we plot the same statistic, but now using a sample starting in 1980 based on data used in Koijen and Yogo (2019). This illustrates a longer-run trend during the last 40 years during which the aggregate active share has been declining. We focus on the period between 2007.Q4 and 2016.Q4, which captures the long-run trend within our sample well. This sample also allows us to measure price informativeness during the subsequent period, as we do in the next subsection. During this period, the aggregate active share declined from 35.2% to 30.5%.

The aggregate active share can decline for two reasons. First, investors can reallocate capital from institutions with high active shares to those with low active shares. Second, institutions can change their investment strategies over time and lower their active share. To measure the relative importance of these two forces, we focus on all institutions that are present in both 2007 to 2016.[13]

[13] These institutions manage 89.8% of all institutional assets in 2016. Also, using data on these institutions,

We decompose the change in the active share as

$$AS^{\#}_{2016} - AS^{\#}_{2007} = \sum_i S^{\#}_{i,2007} \left(AS_{i,2016} - AS_{i,2007}\right) + \sum_i (S^{\#}_{i,2016} - S^{\#}_{i,2007}) AS_{i,2016}, \tag{12}$$

where variables with an # are computed for institutions that exist in both 2007.Q4 and 2016.Q4.

We find that the first term in (12) equals -0.9%, while the second equals -3.7%. This implies that most of the decline in active share is due a reallocation of capital from active institutions to more passive institutions, instead of institutions changing their investment strategies during the last decade.

5.2. *The impact on firm valuations and price informativeness*

We now design a counterfactual based on the insights of the previous section to explore the implications of this trend for valuations and price informativeness. Specifically, we change the size distribution of institutions that are active in 2007.Q4 and 2016.Q4 from the distribution in 2016.Q4 to the distribution in 2007.Q4. For institutions that only exist in 2016.Q4 as well as for the household sector, we fix their AUM values.[14]

We recursively switch the distribution of a group of investors to see the relative impact of different institutional types. We index institutional types by $k = 1, \ldots, 8$. We define $\mathcal{G}(j)$ to include all institutions in groups $k = 1, \ldots, j$. We then compute the counterfactual size distribution, $\tilde{S}^{(j)}_{i,2016}$, in each of the $j = 1, \ldots, 8$ steps as

$$\tilde{S}^{(j)}_{i,2016} = S_{i,2007} \frac{\sum_{i \in \mathcal{G}(j)} S_{i,2016}}{\sum_{i \in \mathcal{G}(j)} S_{i,2007}},$$

where the second term simply ensures that the shares still add to one across all investors. An investor's AUM in the counterfactual is then given by $\tilde{A}_{i,2016} = \tilde{S}^{(j)}_{i,2016} \sum_i A_{i,2016}$.

For each counterfactual size distribution, we compute equilibrium asset prices and mea-

the active share declined from 34.5% to 29.9%, which closely mimics the aggregate decline from 35.2% to 30.5%.

[14]By fixing the wealth distribution, we implicitly define a set of flows as in (9).

sure the average change in valuations

$$\theta = \frac{\sum_{n=1}^{N} \mid ME_t^{CF}(n) - ME_t(n) \mid}{\sum_{n=1}^{N} ME_t(n)}. \tag{13}$$

In addition, we explore implications of the trend from active to passive for price informativeness. Prices may become more informative if capital flows from uninformed investors (that is, noise traders or sentiment investors) to passive investors, while the opposite is true if capital flows from active, informed investors to passive investors.

We follow Bai, Philippon, and Savov (2016) in measuring price informativeness using the following regression:[15]

$$\frac{EBIT_{t+3}(n)}{A_t(n)} = a + b_t \log\left(\frac{ME_t(n)}{A_t(n)}\right) + c_t \left(\frac{EBIT_t(n)}{A_t(n)}\right) + e_t(n). \tag{14}$$

The coefficient of interest is b_t, which measures how valuations today predict profitability in three years. We run this regression in 2016.Q4 and find a slope of 0.049 with a standard error of 0.0033. Their measure of price informativeness is then given by $b_t \times \sigma_t \left(\log\left(\frac{ME_t(n)}{A_t(n)}\right)\right)$, which equals 0.049. To assess how the trend from active to passive management has changed price informativeness, we replace the observed valuations in (14) with those that we compute in the counterfactuals.

Figure 5 presents the results. The top left panel plots managers log AUM shares in 2007 and 2016 and shows that there was substantial reallocation of capital between managers over this period. The top right panel plots firm-level log market equity after reallocating all institutional types AUM. This top right panel shows that there is substantial repricing, especially among smaller firms. Using the measure as in (13), the total repricing is 14% (in terms of the market capitalization of 2016) when the size distribution of 2007 is used instead of the one observed in 2016. The bottom left panel of Figure 5 quantifies the impact on price informativeness. The first point presents the actual price informativeness, and each of the following points is a step where we additionally reset the AUM distribution from its 2016

[15]We use EBIT for earnings to remain consistent with the specification used by Bai, Philippon, and Savov (2016). When computing future earnings in the regressions in Table 3 we used clean-surplus earnings to adjust for issuances and repurchases. That said, when using EBIT to compute future earnings we find a similar relation to characteristics as in Table 3.

value to the 2007 value. The ordering is descending by the institutional type's AUM shares in 2016. The bars correspond to the 95% confidence intervals.

The main takeaway is that, while the reallocation of capital from active to passive institutions has a nontrivial impact on firm-level valuations, price informativeness is affected very little. To understand why this is the case, we construct an *investor-level* measure of price informativeness, which is a new metric that the demand system allows us to construct. As can be seen from (4), valuations are a (size-weighted) average of individual investors' valuations. We can compute each of those contributions to the valuation, $\exp\left\{\boldsymbol{\beta}'_{1,i}\boldsymbol{x}_t(n)\right\}\epsilon_{i,t}(n)$, and use these instead of $ME_t(n)$. Intuitively, $\exp\left\{\boldsymbol{\beta}'_{1,i}\boldsymbol{x}_t(n)\right\}\epsilon_{i,t}(n)$ is the market value (up to a constant) if investor i is the representative investor and we can therefore use it just as we usually use a firm's market value itself in estimating price informativeness in (14). This provides an investor-level measure of price informativeness, $b_{i,t}\sigma(\exp\left\{\boldsymbol{\beta}'_{1,i}\boldsymbol{x}_t(n)\right\}\epsilon_{i,t}(n))$. We then ask whether there is a systematic relation between capital flows between 2007 and 2016 and the investor-level measure of price informativeness. The panel in the bottom right shows that there is no such link, explaining why overall price informativeness is unaffected by the trend from active to passive investing despite the nontrivial impact on valuations.

6. Impact of climate-related shifts in asset demand on prices and welfare

6.1. Assessing the impact of climate-related risks

Investors and regulators are increasingly concerned about the impact of climate-related risks on asset prices, investors' welfare, and overall financial stability. Quantifying such effects is challenging, in part because of the different dimensions of risk such as physical damages, policy and regulatory risks, and shifts in preferences, among others.

While a comprehensive analysis of all risks is beyond the scope of this paper, we can use our framework to quantify two key dimensions of climate-related risks. Our focus is guided by a recent survey of Stroebel and Wurgler (2021) among 861 academics, professionals, public sector regulators, and policy economists. The survey shows that the respondents consider regulatory risk as the main risk over the next five years, followed by "stakeholder risk," which includes changing preferences of employees and customers. Over longer horizons, which in the survey corresponds to the next 30 years, physical risks are considered to be most important.

Regulatory risks can take various forms. One example is a carbon tax, which can be modeled as a change in characteristics (for instance, a change in profitability where the tax depends on carbon emissions). Another example includes capital regulation that applies only to certain groups of institutions, such as insurance companies, pension funds, and banks. Such regulation can be motivated by the long-term financial risks to which brown firms are exposed. As asset demand strongly responds to capital charges, we consider a counterfactual in which the element of $\boldsymbol{\beta}_{i,t}$ associated with the environmental score increases by 0.1 for long-term investors, which include pension funds and insurance companies. A shift of 0.1 implies that the portfolio weight increases by 10% for a one standard deviation change in the environmental score, thus from a baseline level of 5%, say, to 5.5%. A 0.1 adjustment in the coefficient is a reasonable magnitude and corresponds approximately to one standard deviation in the cross-sectional distribution of this estimated coefficient across investors (see Figure 2). We could calculate the counterfactual for values other than 0.1, depending on the specific regulation that is being considered.

The second counterfactual is designed to capture stakeholder risk. As preferences of consumers and employees change, households and asset managers (who ultimately manage households' assets) may also change their asset demand and tilt their portfolios to greener firms. In this counterfactual, we increase the element of $\boldsymbol{\beta}_{i,t}$ associated with the environmental score by 0.1 for all institutional investors.

6.2. Empirical results

In Table 6, we show the impact on firm valuations. The first column shows the benchmark results using the actual log market-to-book ratios in 2019. In the second and third columns we report results from regressions with changes in log market-to-book, $mb_t^{CF}(n) - mb_t(n)$ in each of the two counterfactuals. The second column reports the stakeholder risk counterfactual in which all investors increase their demand for green firms. The third column reports the regulatory risk counterfactual in which insurance companies and pension funds only increase their demand for green firms. As is clear from the table, the effect is noticeable only for the environmental score. As this characteristic is not strongly correlated with the other characteristics, the other coefficients are minimally affected.

In the stakeholder risk counterfactual, the coefficient increases by 0.57 from its original value of 0.23, which is a large effect. If only long-term investors shift their demand, and thus a smaller group of investors is impacted, the effect is much smaller and the coefficient increases by 0.03 from 0.23.

This is an important insight as insurance regulators are concerned about how transition risk may affect the highly-levered insurance sector.[16] These calculations imply that one could potentially regulate insurance companies without much of an impact on asset prices, yet it may have important financial stability advantages in the insurance sector.

Figure 6 then translates the counterfactuals to gains and losses per investor sector. The two counterfactuals are essentially scaled versions of each other, where the regulatory risk of long-term investors is much less consequential compared to a broad shift in preferences. The main beneficiaries of the transition are long-term investors, banks, and passive investors. Those exposed to climate-related transition risk are hedge funds and active investors.

7. Measuring the impact of investors on asset prices

Building on the insights from the counterfactuals in the previous sections, in this final section we show how our characteristics-based demand system can be used to understand the role of different investors in connecting asset prices to characteristics and, analogously to connecting expected returns to characteristics.

Following the intuition discussed in Section 1, we consider a flow from one group of investors to other institutional investors. For expositional simplicity, we consider a single investor k. We refer to counterfactual values with a superscript "CF." To measure the impact of investor k, we measure a flow that takes the assets of investor k and reallocates those funds to all other investors in proportion to their assets. The demand curve of investors is unchanged in this counterfactual. The counterfactual assets of the investors are then $A_{kt}^{CF} = 0$ for investor k and (9) defines the assets for all other institutional investors with

[16] For instance, the National Association of Insurance Commissioners (NAIC) has set up a task force on Climate and Resiliency to explore such questions.

$F_{i,t} = A_{k,t} \times \frac{A_{i,t}}{\sum_{j,j\neq k,HH} A_{j,t}}$ and HH indexes households.

7.1. The impact of different types of institutional investors on asset prices

We report the results in Table 5 and in Figure 7. In the first column, we report the actual distribution of AUM across investor type. In the second column, we report the repricing measure, θ, when we reallocate the assets of one group of investors to all others, as described in (13). In the last column, we report the ratio of the repricing measure relative to the AUM share to adjust for size differences across investor types.

The results indicate that there are large differences across investor types, with small-active investment advisors and hedge funds having the largest impact on prices. If the assets of small-active investment advisors get reallocated, the total repricing in the market amounts to 26.7%. Long-term investors, as one would expect, have a modest impact on prices and move prices only by 3.9%. Interestingly, reallocating the assets of brokers only moves prices by 1.8%. This small direct impact is largely the result of their size, which is just over 1% of the US stock market.

By comparing the first two columns, it is clear that there is a strong correlation between the AUM share and the repricing measure. In the last column, we compute the ratio, which is the repricing per dollar of AUM. We find, quite strikingly, that hedge funds play an outsized role with a ratio equal to 3.58. By contrast, passive investment advisors, be it large or small, and long-term investors have the smallest impact per dollar of assets that they manage with ratios around one.

In Figure 7, we open the black box and explain the mechanism in detail. The top panels summarize the information in Table 5. The top left panel plots the overall repricing measure and the size distribution. The top right panel plots the repricing measure scaled by each type's AUM share. The bottom two panels explain the mechanism behind the result in the top right panel.

In our counterfactual, we explore a flow from one group of institutional investors to all other institutions. This has a large impact on prices when the group experiencing an outflow has preferences (both in terms of characteristics and in terms of latent demand) that differ from all other investors. A simple reduced-form statistic is an investor's active share that we used in Section 5, which compares the distance between an investor's portfolio weights and market weights. As market weights summarize the demand curves of all investors, the active share measures the difference in preferences of, say hedge funds, relative to all other investors. Consistent with this logic, the bottom left panel shows a strong correlation between the repricing measure per dollar of AUM and each type's active share. More active investors who have more dissimilar demand curves from other investors (which may be driven by information or sentiment) have a larger impact on prices.

The second important input into the calculation are investors' demand elasticities. If hedge funds reduce their positions due to outflows, other investors need to be motivated to purchase those securities for markets to clear. If other investors' demand curves are more inelastic, a larger move in prices is required for them to purchase the shares sold by hedge funds. In the model, the demand elasticity is determined by $1 - \beta_{0,i}$. Consistent with this intuition, the bottom right panel shows a strong correlation between the repricing measure per dollar of AUM and each type's demand elasticity. In summary, when hedge funds sell their shares, they face a more inelastic demand curve compared to when, for instance, passive investment advisors sell their shares (as elastic hedge funds and small active investment investors quickly step in).

Both of these two effects combined explain the heterogeneity in the repricing measure per dollar of AUM.

7.2. Understanding the link between asset prices and characteristics

We now study the link between prices and characteristics, analogous to Table 3. Large literatures in accounting and finance discover characteristics that are linked to valuation ratios or expected returns. Oftentimes, economists provide narratives, and suggestive supporting evidence, to link characteristics to the demand of different investors; for instance, the sentiment of retail investors, smart money (e.g., hedge funds), or pension funds and sovereign wealth funds with ESG objectives. We provide a framework to assess these narratives quantitatively.

As before, we consider a flow from one group of investors to all other investors. We compute counterfactual equilibrium prices and valuation ratios and re-run the regressions in (5). In the first column of Table 7, we replicate the benchmark regression using actual valuation ratios, which is identical to the first column of Table 3. In the subsequent columns we consider a different type of institutions as well as the foreign sector. The coefficients are directly comparable across columns.

If we first focus on the pricing of the environmental index, we see that the coefficient increases the most from 0.17 to 0.21 in case of small-active investment advisors, while it decreases the most in case of foreign investors from 0.17 to 0.14. Hence, if foreign investors would leave the US and their assets are allocated to all other domestic institutions, a one standard deviation increase in the environmental score would move prices only by 14% instead of 17%.

For the governance index, we find the largest change from -0.10 to -0.09 for small-active investment advisors and hedge funds. Hence, if the assets of small-active investment advisors or hedge funds are assigned to other institutions, a one standard deviation change in the entrenchment index would only lead to a 9% in a firm's valuation ratio as opposed an 10% decline. Hence, small-active investment advisors and hedge funds are important for the pricing of governance in US markets.

7.3. Understanding the link between expected returns and characteristics

To map changes in valuations, and their connection to characteristics, to expected returns, we use the valuation model of Cohen, Polk, and Vuolteenaho (2003) and Campbell, Polk, and Vuolteenaho (2010). We write the log market-to-book ratio of firm n, $mb_t(n)$, as

$$mb_t(n) = \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t \left[e_{t+s}(n) \right] - \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t \left[r_{t+s}(n) \right], \tag{15}$$

where

$$e_t(n) = \ln \left(1 + \frac{\Delta BE_t(n) + D_t(n)}{BE_{t-1}(n)} \right), \tag{16}$$

$$r_t(n) = \ln \left(1 + \frac{\Delta ME_t(n) + D_t(n)}{ME_{t-1}(n)} \right), \tag{17}$$

and $BE_t(n)$ a firm's book equity, $ME_t(n)$ its market equity, and $D_t(n)$ its dividend.[17]

To convert these estimates to expected returns, we make the simplifying assumption that expected growth rates, g_t, and expected returns, μ_t, are random walks, which is not unreasonable given the extreme persistence in these series. The expression for the market-to-book ratio now simplifies to

$$mb_t(n) = C + \frac{g_t}{1-\rho} - \frac{\mu_t}{1-\rho}.$$

If the link between characteristics and expected growth rates does not change in the counterfactuals, the change in valuation ratios links one-to-one to changes in expected returns, with a scaling coefficient of $(1-\rho)^{-1}$. Using a typical value of $\rho = 0.95$, we obtain a scaling factor around 20 in mapping changes in valuations to changes in expected returns. The impact on expected returns would be larger in case expected returns are persistent but not a random walk.[18]

Hence, in case of small-active investment advisors, a one standard deviation change in the environmental index changes valuation ratios by 4%, which translates to 20bp per annum. If expected returns are less (more) persistent, for instance because characteristics are less (more) persistent, these effects would be larger (smaller).

8. Conclusion

In this paper we develop and estimate a characteristics-based demand system for financial assets to quantify the impact of changes in demand of various investors on asset prices and investors' wealth. We apply the model to understand the impact of the market trend from active to passive investing on asset prices and price informativeness. We find that there is a nontrivial impact on valuations, yet a small impact on price informativeness. We also explore the impact of a shift in demand for green firms, either for a subset of investors as a result of climate-related regulations or for a broad group of institutional investors due to overall

[17]As we use characteristics throughout this paper, Appendix E shows how one could compute variance decompositions in characteristics space.

[18]Alternatively, the scaling coefficient equals $(1-\rho\varphi_\mu)^{-1}$ if expected returns follow an AR(1) with autoregressive parameter φ_μ. Using the estimates in Binsbergen and Koijen (2010), the scaling coefficient is $(1 - 0.932 \times 0.969)^{-1} \simeq 10$.

increased awareness. This shift in demand benefits long-term investors such as pension funds and insurance companies, banks, and passive investment advisors at the expense of hedge funds and small-active investment advisors.

We motivate the characteristics-based demand system with a static model of utility-maximizing agents in Section 1 of the paper. In future work, it would be interesting to explore dynamic extensions of the model. For instance, in understanding the impact of the transition from active to passive management, it may be worthwhile to explore models in which investors are potentially hit by (correlated) liquidity shocks. As the trend to passive management may impact the market's liquidity, the welfare of investors may be affected by these broad trends. We leave such extensions for future research.

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Table 1
Firm size distribution

Mkt Pct	Number of Firms	Sales Pct	NI. Pct
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
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

Each row presents the number of companies as well as the fraction of sales and net income represented by the top deciles of market cap. Firm-level fundamentals are annual from CRSP and Compustat.

Table 2
Largest investors by type

Type	Investor	AUM
Households	Households	8553
Inv. Large Passive	The Vanguard Group, Inc.	2494
Inv. Large Active	T. Rowe Price Associates, Inc. (Investment Management)	659
Long-Term	Norges Bank Investment Management	292
Inv. Small Passive	Charles Schwab Investment Management, Inc.	162
Inv. Small Active	PRIMECAP Management Co.	117
Private Banking	Goldman Sachs & Co. LLC (Private Banking)	112
Hedge Funds	Renaissance Technologies LLC	89
Brokers	Schweizerische Nationalbank (Investment Portfolio)	84
Foreign	Norges Bank Investment Management	292

Largest investors by assets under management for each institutional type in 2019 Q4. Equity holdings data are from FactSet.

Table 3
Valuation and earnings regressions

	2010 - 2019		2000 - 2019	
	mb	e^5	*mb*	e^5
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)
Dividend 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)
Adj. R^2	0.65	0.45	0.57	0.34
Within Adj. R^2	0.64	0.45	0.55	0.33
Num. obs.	6399	2143	13664	6699

Regressions of end of year valuation ratios on firm-level characteristics. Columns 1 and 2 present regressions from 2010 to 2019 when Environment and Governance data are available. Columns 3 and 4 present regressions from 2000 to 2019. All regressions include year fixed effects. mb is the log market-to-book ratio at time t. e^5 is cumulative earnings growth t to $t+5$ adjusted for repurchases. Characteristics are standardized cross-sectionally by year. Environmental scores are from Sustainalytics, Governance Scores are the entrenchment index from Bebchuk, Cohen, and Ferrell (2009), Foreign sales is the fraction of ales from abroad, Lerner is operating income after depreciation divided by sales, and market beta is 60-month rolling market beta. Regressions in columns 1 and 2 include dummy variables for when Governance and Environmental scores are missing. Firm-level fundamentals are from CRSP and Compustat. T-statistics clustered by year in parentheses.

TABLE 4
Explaining demand curves

Panel A: Institutional Type

	Environment	Governance	Log Market-to-Book	Log Book Equity	Foreign Sales	Lerner	Sales to Book	Dividend to Book	Market Beta
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)
Inv. 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)
Inv. 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)
Inv. 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)
Inv. 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)
Adj. R^2	0.08	0.08	0.48	0.59	0.05	0.15	0.07	0.16	0.14
Num. obs.	6560	6560	7959	7959	7959	7959	7959	7959	7959

Panel B: Size, Active Share, and Foreign

	Environment	Governance	Log Market-to-Book	Log Book Equity	Foreign Sales	Lerner	Sales to Book	Dividend to Book	Market Beta
log(AUM Share)	0.47	0.71	0.06	6.98	0.30	−1.08	0.08	−1.66	1.34
	(7.99)	(13.33)	(52.71)	(49.47)	(7.26)	(−23.76)	(1.42)	(−19.20)	(23.52)
Active Share	−8.19	0.27	−0.45	−96.71	−0.47	1.28	−10.18	−31.16	2.37
	(−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)
Adj. R^2	0.10	0.05	0.55	0.67	0.02	0.11	0.06	0.14	0.09
Num. obs.	6560	6560	7959	7959	7959	7959	7959	7959	7959

Regressions of average demand curve coefficients on institutional type dummies and manager characteristics. Average demand curve coefficients are the time-series average of estimated yearly demand curve coefficients by manager. Demand curve coefficients are estimates using the cross-section of holdings data for each manager by year. Demand coefficients are multiplied by 100 except for Log Market-to-Book. Panel A uses dummy variables for each manager type and Panel B uses manager characteristics. Environmental scores are from Sustainalytics, Governance Scores are the entrenchment index from Bebchuk, Cohen, and Ferrell (2009), Foreign sales is the fraction of sales from abroad, Lerner is operating income after depreciation divided by sales, and market beta is 60-month rolling market beta where the market is the local MSCI index. Holdings data are from FactSet. Firm-level fundamentals are from CRSP and Compustat. The sample runs from 2000 to 2019. T-statistics in parentheses.

Table 5
Repricing by institutional type in flow counterfactuals

	Share AUM	Repricing	Repricing AUM Scaled
Inv. Large Passive	17.7	15.9	0.90
Inv. Small Passive	16.4	17.2	1.05
Inv. Small Active	11.7	26.7	2.28
Inv. 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

Statistics on repricing in flow counterfactuals as decscribe in Section 7. Share AUM is the percent of assets under management for each investor type. Total repricing is the percent change in market cap if the assets of an investor are reallocated as flows to all other institutional investors in proportion to their assets. Repricing AUM scaled is total repricing divided by the share of assets under management. Each value is the time series average of the quarterly values. Holdings data are from FactSet. Firm-level fundamentals are from CRSP and Compustat. The sample runs from 2000 to 2019.

Table 6

Change in valuation regression coefficients ESG counterfactuals

	Original	Change (All)	Change (LT)
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)
Dividend 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)
Adj. R^2	0.65	0.92	0.81
Num. obs.	540	540	540

The first column is a regression of log market-to-book ratios on characteristics. The second and third columns are regressions of changes in log market-to-book ratios on characteristics. The new market-to-book ratios are calculated in scenarios where institutions care more about environmental scores of companies as described in Section 6. In column 2 instituions increase their coefficient on environment by 0.1. In column 3 only long-term investors increase their coefficient on environment by 0.1. Characteristics are standardized cross-sectionally by year. Environmental scores are from Sustainalytics, Governance Scores are the entrenchment index from Bebchuk, Cohen, and Ferrell (2009), Foreign sales is the fraction of sales from abroad, Lerner is operating income after depreciation divided by sales, and market beta is 60-month rolling market beta where the market is the local MSCI index. Regressions include dummy variables for when governance or environment scores are missing. Holdings data are from FactSet. Firm-level fundamentals are from CRSP and Compustat. Data is end of year for 2019.

Table 7

Change in valuation regression coefficients in flow counterfactuals by institutional type

	Original	Inv. Large Passive	Inv. Small Passive	Inv. Small Active	Inv. 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)
Dividend 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 Adj. R^2	0.64	0.61	0.61	0.45	0.65	0.57	0.63	0.63	0.64	0.63
Num. obs.	6399	6399	6399	6399	6399	6399	6399	6399	6399	6399

Each column is a regression of log market-to-book ratios on characteristics. Data is end of year from 2010 to 2019. Original is as observed in the data and the remaining columns are under counterfactual market-to-book ratios. The new market-to-book ratios are calculated under the assumption that each investor types' assets are reallocated as flows to all other institutional investors in proportion to their assets as described in Section 7.1. All regressions include year fixed effects. Characteristics are standardized cross-sectionally by year. Environmental scores are from Sustainalytics, Governance Scores are the entrenchment index from Bebchuk, Cohen, and Ferrell (2009), Foreign sales is the fraction of sales from abroad, Lerner is operating income after depreciation divided by sales, and market beta is 60-month rolling market beta where the market is the local MSCI index. Regressions include dummy variables for when governance or environment scores are missing. Holdings data are from FactSet. Firm-level fundamentals are from CRSP and Compustat.

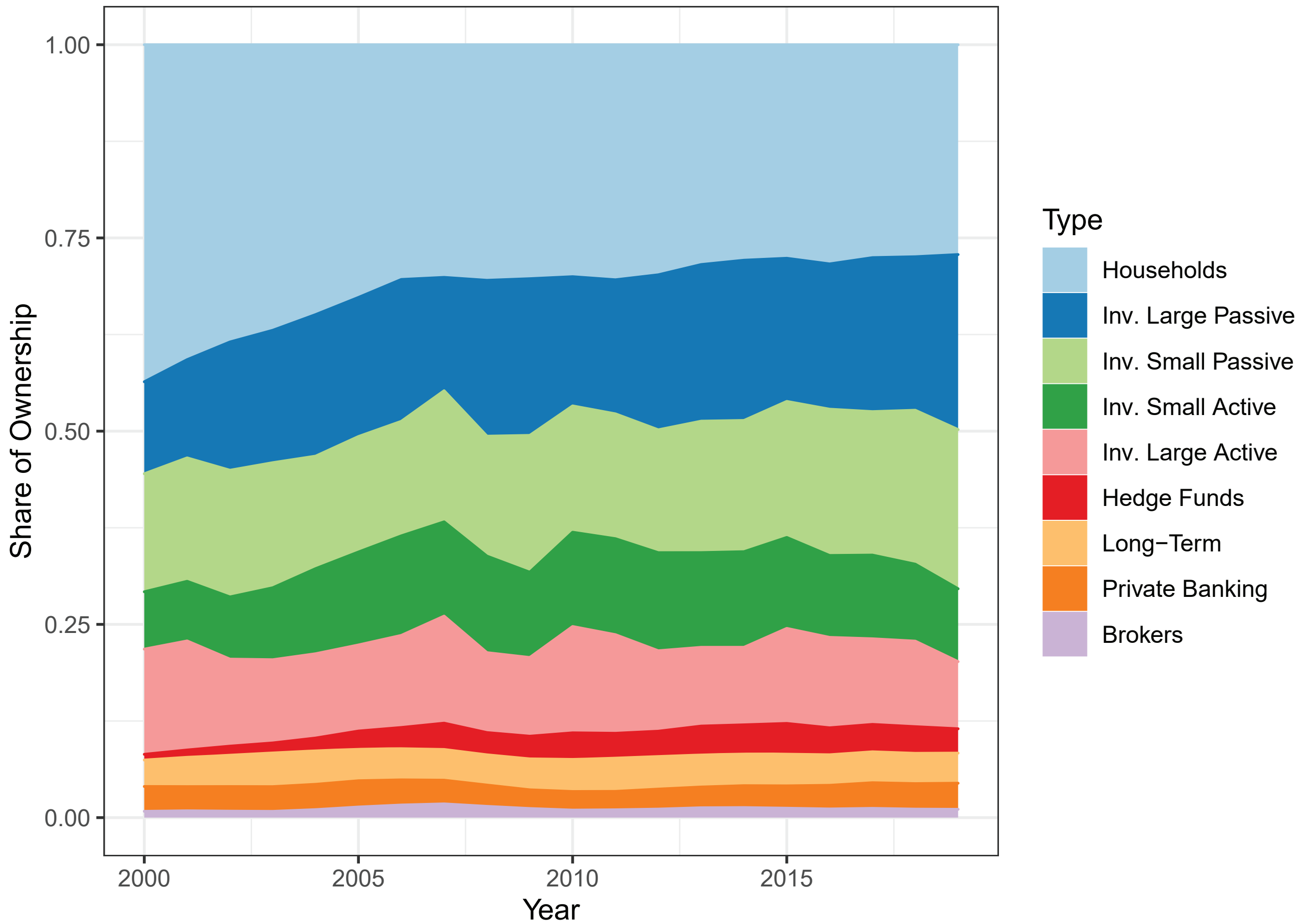

FIGURE 1
Time series of ownership by institutional type

Share of total ownership by type of institution by year. Equity holdings data are from FactSet. Share of ownership is the annual average by institution type. Holdings data is quarterly from FactSet from 2000 to 2019.

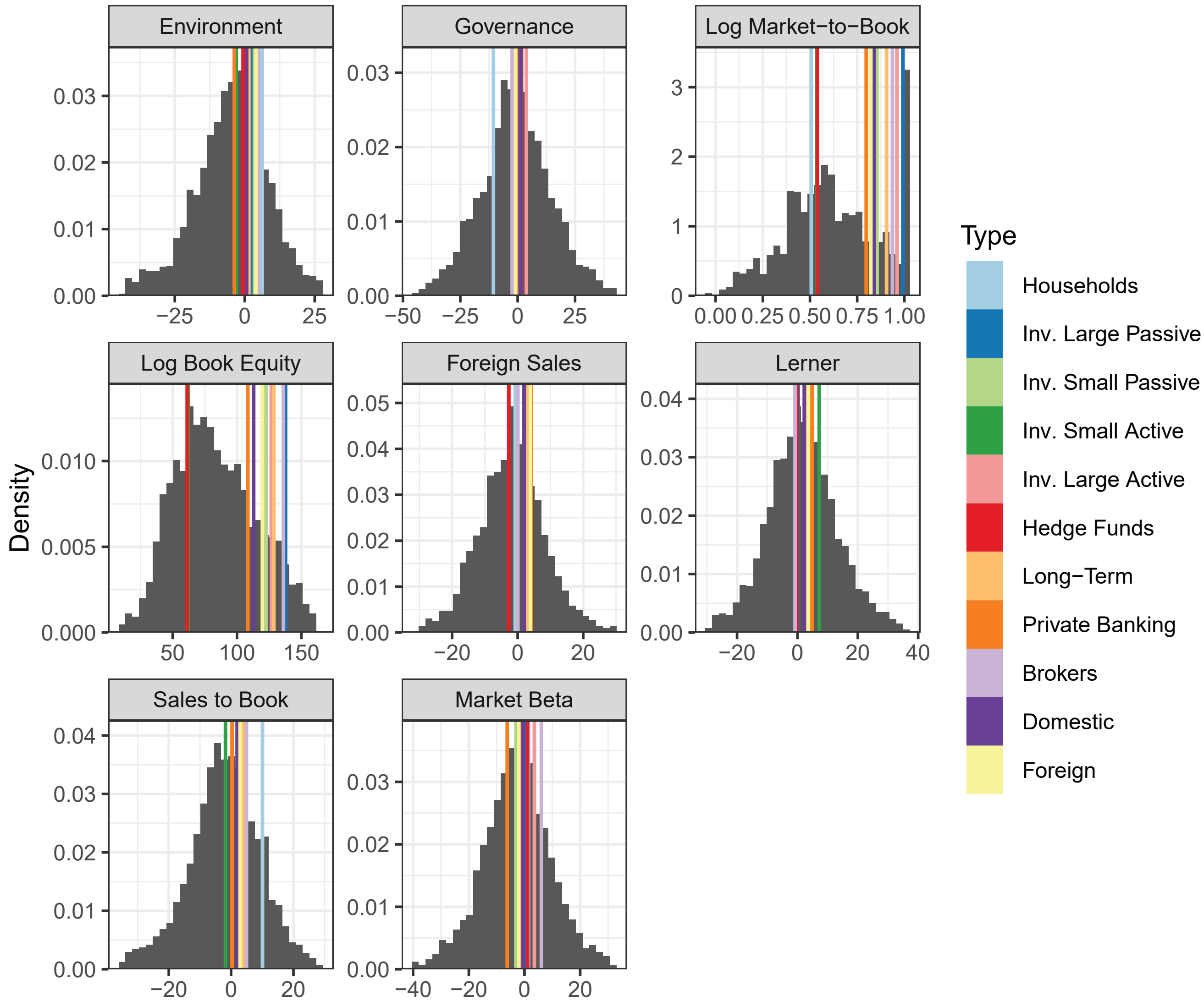

FIGURE 2

Demand curve summary by investor type

Summary of demand curves by investor type. Each panel is a histogram of the time-series average of each institution's demand curve estimate. The vertical lines report the weighted average of the estimates for each investor type. To average the coefficients, we first compute the AUM-share average for a given investor group and year. We then average these across years for a given investor group. Demand oefficients are multiplied by 100 except for $LNmebe$. Environmental scores are from Sustainalytics, Governance Scores are the entrenchment index from Bebchuk, Cohen, and Ferrell (2009), Foreign sales is the fraction of sales from abroad, Lerner is operating income after depreciation divided by sales, and market beta is 60-month rolling market beta where the market is the local MSCI index. Firm-level fundamentals are from CRSP and Compustat. Holdings data are from FactSet. The sample runs from 2000 to 2019. Governance and Environment data begins in 2010.

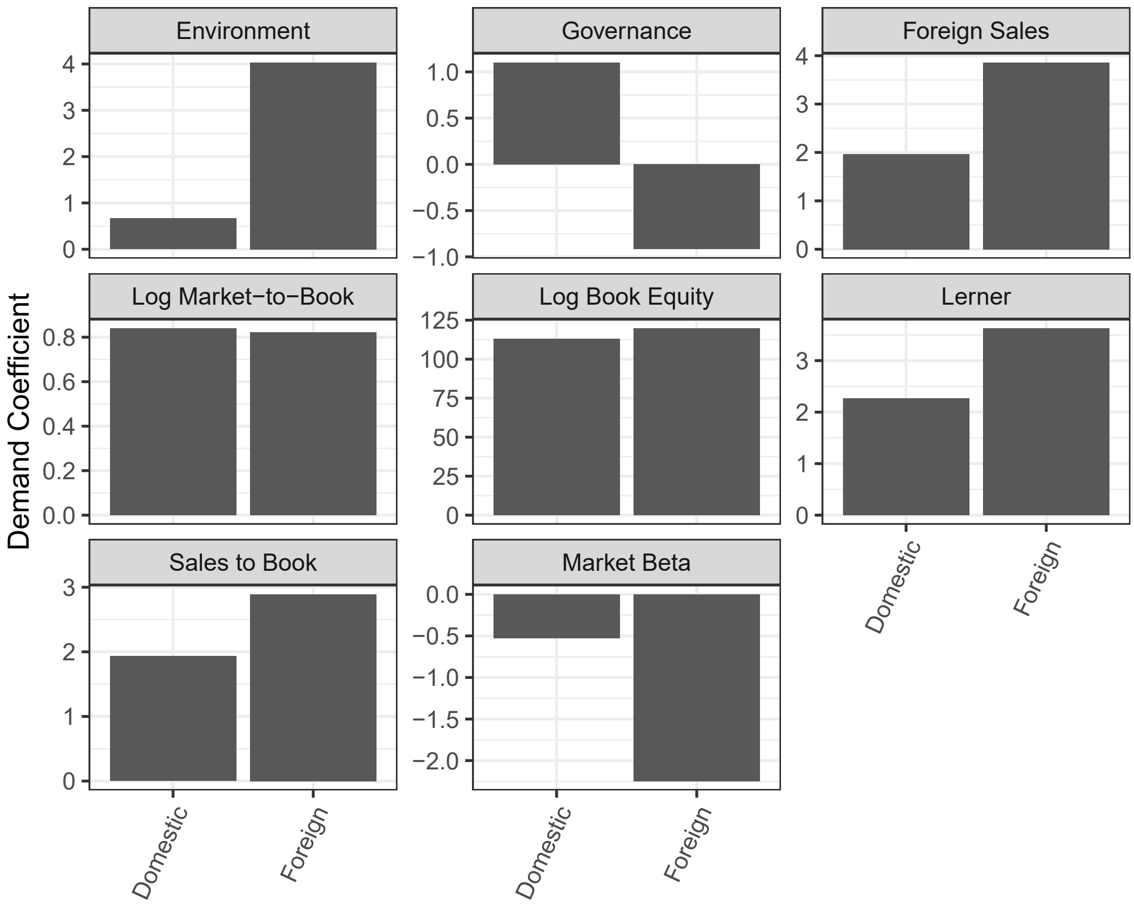

FIGURE 3

Demand curve summary by domestic/foreign

Summary of demand curves by investor domicile. We report the weighted average of the parameter estimates for each investor in that group. To average the coefficients, we first compute the AUM-share weighted average for a given investor group and year. We then average these across years for a given investor group. Demand oefficients are multiplied by 100 except for $LNmebe$. Environmental scores are from Sustainalytics, Governance Scores are the entrenchment index from Bebchuk, Cohen, and Ferrell (2009), Foreign sales is the fraction of sales from abroad, Lerner is operating income after depreciation divided by sales, and market beta is 60-month rolling market beta where the market is the local MSCI index. Firm-level fundamentals are from CRSP and Compustat. Holdings data are from FactSet. The sample runs from 2000 to 2019. Governance and Environment data begins in 2010.

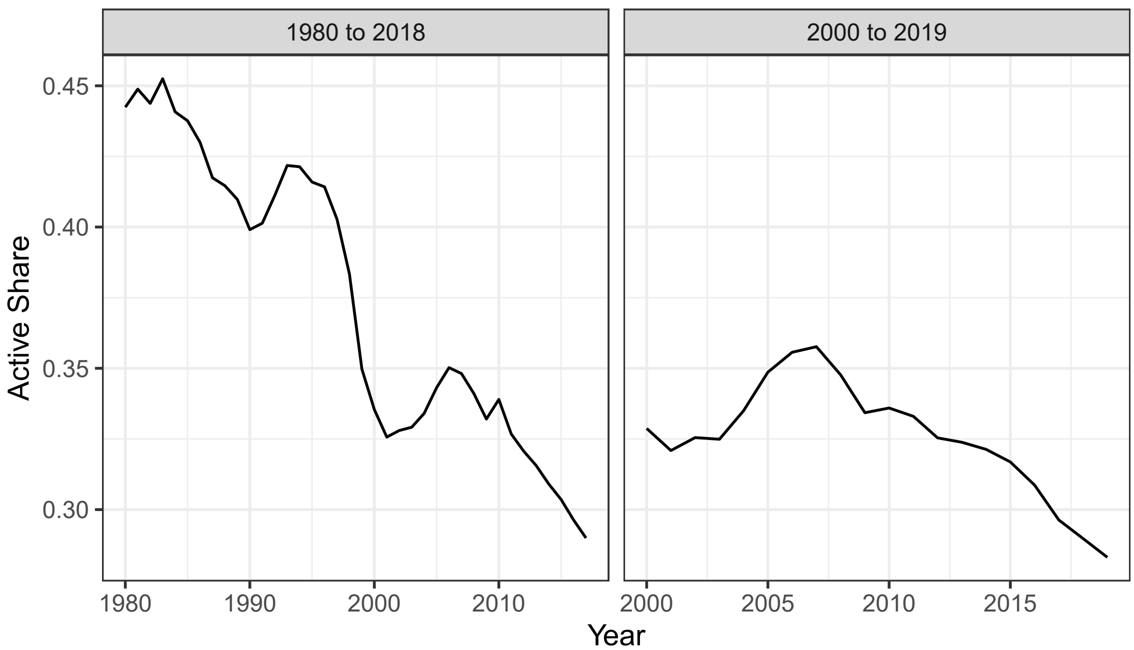

FIGURE 4
Aggregate active share over time

Trend in the active share over time for two sample periods. Aggregate active share is calculated as the AUM weighted active share across all institutional investors. Active share is one-half times the sum of the absolute value of active weights. Active weights are portfolio weights minus market weights within the set of stocks held for each manager. This figure presents the yearly average of quarterly aggregate active share. Data in the left panel are from Koijen and Yogo (2019). Data in the right panel uses holdings data from FactSet.

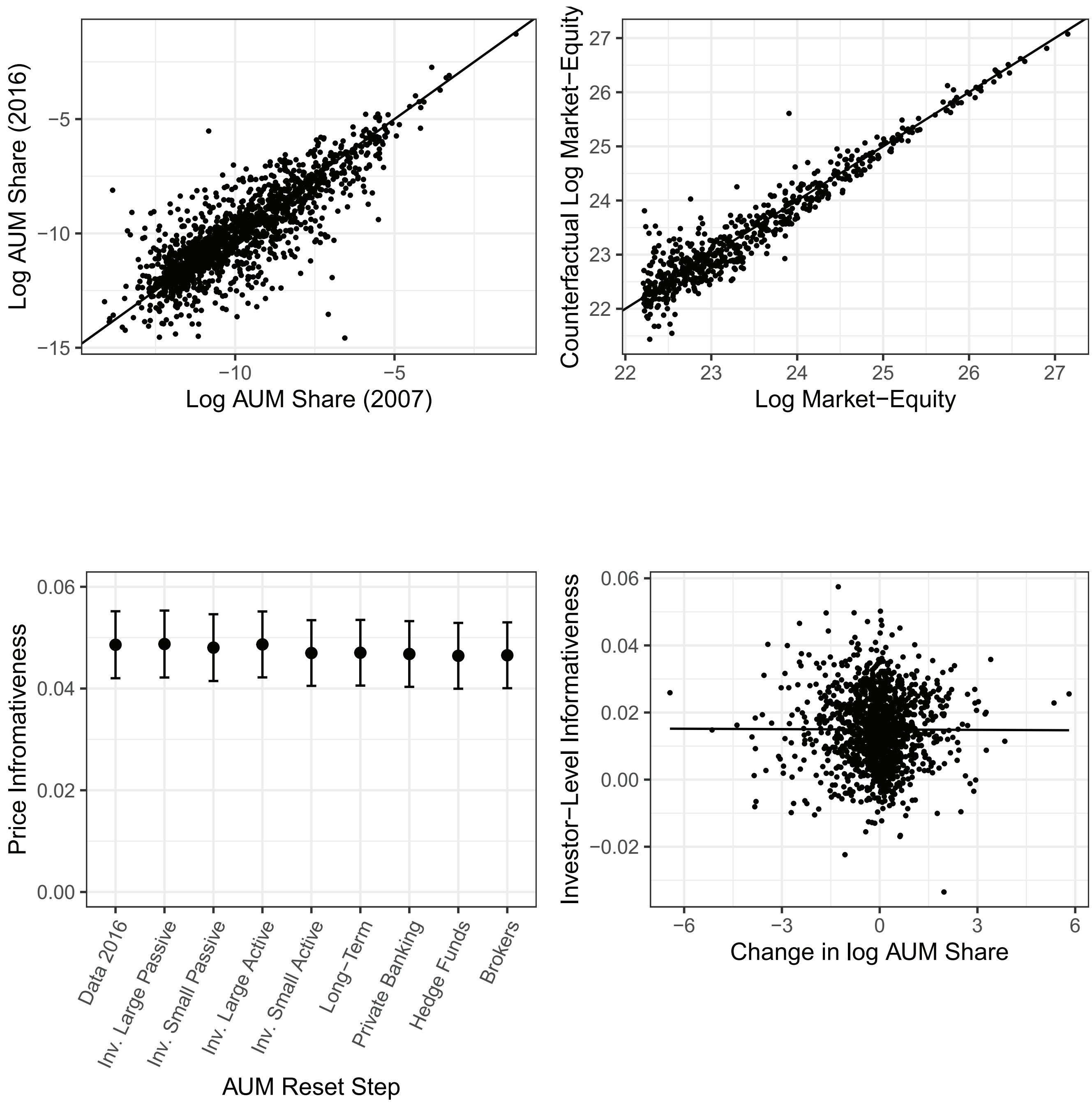

Figure 5

Price informativeness by institutional type when resetting AUM distribution

This figure reports results in 2016 Q4 from scenarios where the AUM distribution is reset to the AUM distribution in 2007 Q4 as described in Section 5. The top left panel presents the log aum share in 2016 Q4 versus 2007 Q4 for institutions that exist in both periods. We only reset the AUM distribution for these institutions. The top right panel presents log market-equity in the redistributed AUM scenario versus actual market-equity. The bottom left panel presents price informativeness coefficients as in Bai, Philippon, and Savov (2016). The first point is the price informativeness in the data and the remaining points sequential reset the AUM distribution to that in 2016 Q4 for each of the instituional types. The bottom right panel reports the investor-level price informativeness coefficient versus log change in AUM share between 2007 and 2016 Q4.

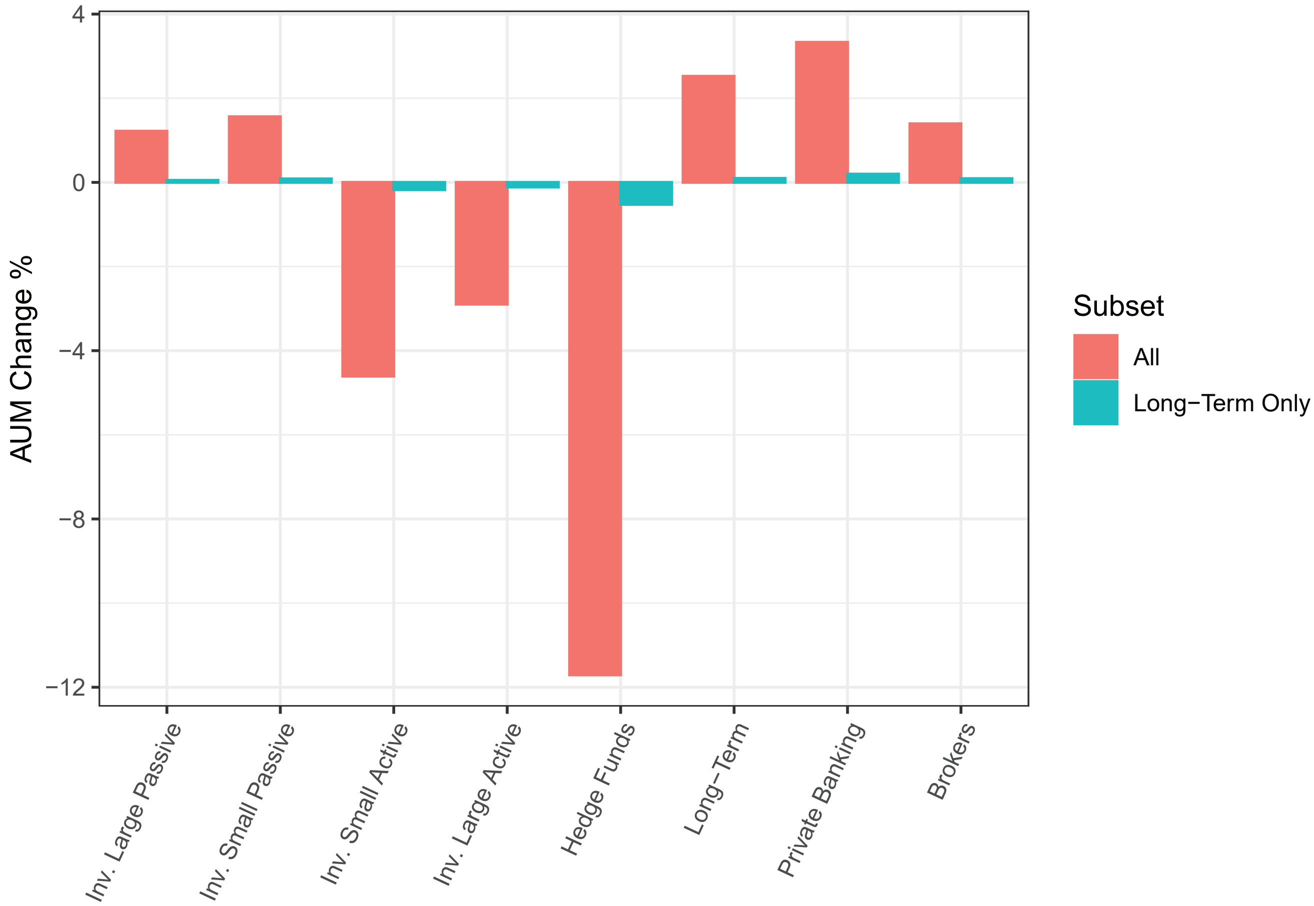

FIGURE 6
AUM change in ESG counterfactuals

Figure presents the percent change in AUM for each institution type in scenarios where institutions care more about environmental scores of companies as described in Section 6. In the red bars all instituions increase their coefficient on environment by 0.1. In the blue bars only long-term investors increase their coefficient on environment by 0.1. Each bar is the AUM share weighted log change in AUM for institutions of that type. Quarterly observations are averaged to present a single yearly observations for 2019. Firm-level fundamentals are from CRSP and Compustat. Holdings data are from FactSet.

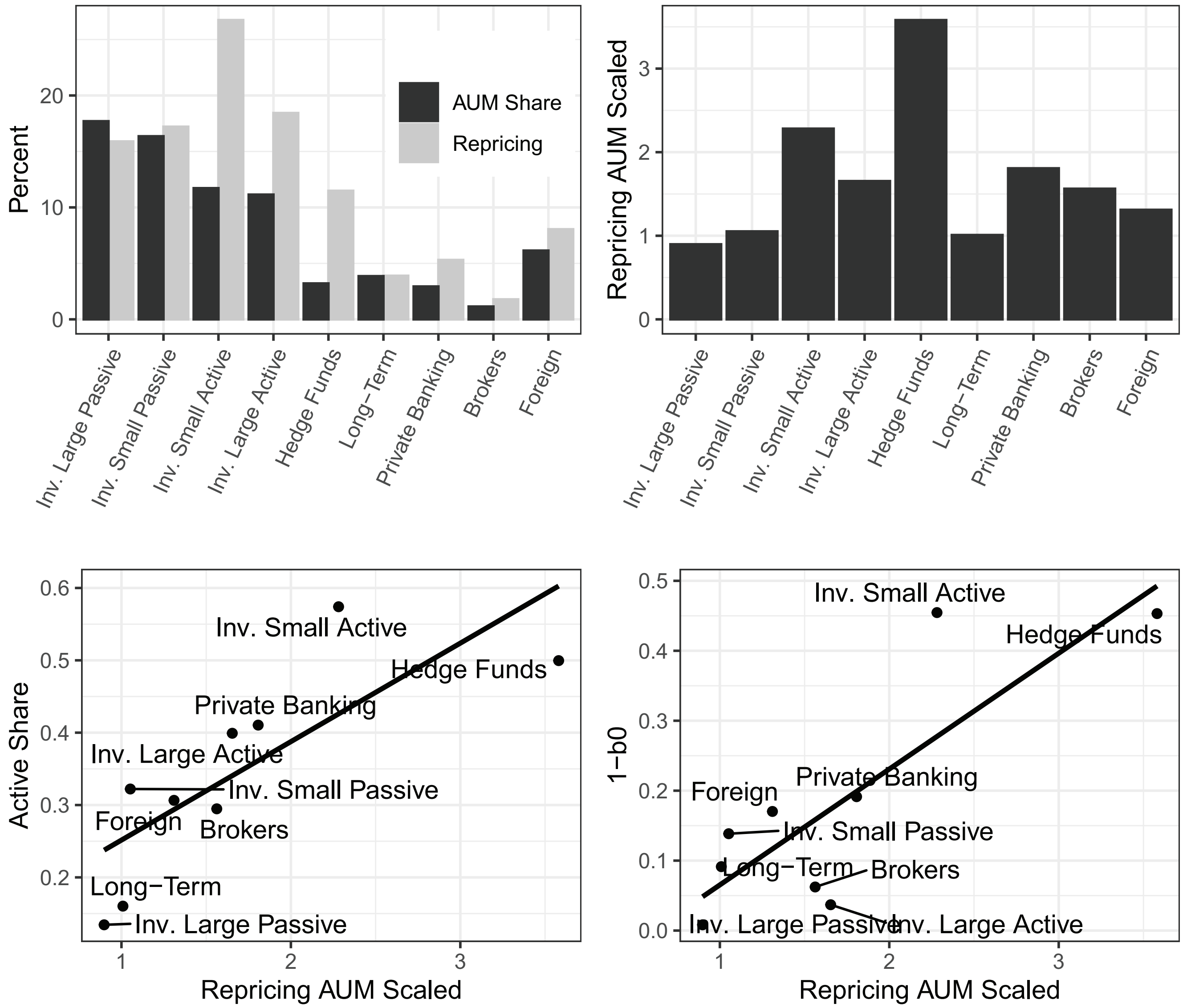

FIGURE 7

Repricing by institutional type in flow counterfactuals

The top left panel reports the fraction of assets under management and repricing. Repricing is the percent change in market cap if the assets of an investor are reallocated as flows to all other institutional investors in proportion to their assets as described in Section 7.1. The top right panel reports the change in market cap normalized by the fraction of ownership. Each bar is the time series average of the quarterly values. The bottom left panel reports the aum weighted active share by institutional type versus repricing scaled by AUM. The bottom right panel reports the aum weighted average of 1 minus the coefficient on log market-equity versus repricing scaled by AUM. Firm-level fundamentals are from CRSP and Compustat. Holdings data are from FactSet. The sample runs from 2000 to 2019.

A. Empirical appendix

B. Data appendix

B.1. Holdings data

We build a panel of end-of-quarter equity holdings of US companies using FactSet 13F holdings data. Our FactSet holdings data covers the period from 2000 Q1 until 2019 Q4.

13F data are from mandatory 13F reports on US-traded equities held by institutions managing more than $100 million in US-traded securities. data is in own_inst_13f_detail_eq.

We merge on prices from own_sec_prices_eq and calculate dollar values of holdings for holdings of each security.

We drop holdings for the following factset_entity_ids due to known errors when comparing the data with EDGAR 13F reports: 0FSVG4-E, 000V4B-E.

We classify institutions into types using FactSet's investor_sub_type in sym_entity. Hedge Fund=AR, FH, FF, FU, FS; Broker=BM, IB, ST, MM; Private Banking=CP, FY, VC; Investment Advisor=IC, RE, PP, SB, MF; Long-term=FO,SV,IN;.

We construct the Household sector so that total holdings of institutions and household are equal to each firm's market cap. On occasion, total holdings of institutions are greater than the market cap, in which case we proportionally scale back all institution's holdings.

We classify the outside asset as any firm which is outside of the top 90% of market cap or is missing any of the following characteristics (defined below): book equity, profit, foreign sales share, lerner, sales-to-book, market-to-book, or beta. Any institution which has less than $1m in holdings in the outside asset, $10mm in total holdings, or has less than 10 holdings in a given quarter is merged into the household sector.

We split investment advisors into four groups. We first split into two groups of equal size (as measured by total assets under management) in a given quarter. Within each size group, we split investors into two groups which are above and below the median active share in a given quarter. The active share is defined as the sum of the absolute value of the differences between the actual portfolio weights of an investor and a market-weighted portfolio based on the stocks held by the same investor within the subset of inside assets, divided by two to avoid double-counting.

B.2. Fundamentals and prices

We calculate firm-level market capitalization using FactSet prices and shares outstanding data. We use these FactSet market capitalization measures throughout the paper.

Our construction of firm-level fundamentals follows the procedure in Fama and French (2015). Accounting data are from the Compustat Fundamentals Annual and Quarterly databases. We start from Annual Compsutat data and supplement with the quarterly filings when Annual reports are missing for a given quarter end. We merge the CRSP data with the most recent Compustat data as of at least 6 months and no more than 18 months prior to the trading date. The lag of 6 months ensures that the accounting data were public on the trading date.

We restrict our sample of companies to ordinary common shares (share codes 10, 11) that trade on the New York Stock Exchange (NYSE), the American Stock Exchange, and Nasdaq (exchange codes 1, 2, and 3).

We measure our characteristics as follows:

- Dividends to book equity is the ratio of annual dividends per split-adjusted share times shares outstanding to book equity.

- Foreign sales share is calculated using Compustat segments data. We select domestic and non-domestic types (geotp either 2 or 3). Total domestic and foreign sales are the sum of sale and salexg. Foreign sales share is foreign sales divided by the sum of foreign plus domestic sales. Missing values are set to 0.

- Lerner is operating income before depreciation minus depreciation divided by sales.

- Sales to book is sales divded by book equity.

- Betas are from 60-month rolling regressions of excess returns on the excess returns of the CRSP Value Weighted index. Excess returns are calculated using 1-month treasury bill rates from Ken French's website.

- Investment is log changes in assets (at).

- Net repurchases are purchases of common and preferred stock (prstkc) minus sale of common and preferred stock (sstk) where missing values for either are set to 0.

- EBIT is calculated as sales minus cost-of-goods sold minus SG&A expenses minus depreciation (sale-cogs-xsga-dp) from Compustat.

- Earnings adjusted for issuances and repurchases using the clean-surplus accounting identity are calculated as: $X_t = B_t - B_{t-1} + NR_t + D_t$, where X_t denotes clean-surplus earnings, B_t book equity, NR_t net repurchases, and D_t dividends.

We winsorize beta, investment, and lerner at the 2.5% and 97.5% levels and winsorize dividend-to-book and sales-to-book at the 97.5% level by quarter. We set values of Lerner that are less than -1 to -1.

We merge our fundamentals data from CRSP and Compustat to FactSet by selecting the CUSIP in FactSet sym_cusip_hist that overlaps with the end-of-quarter in CRSP and Compustat.

B.3. Environment scores data

We obtain environmental scores from Sustainalytics. We merge data from Sustainalytics on CUSIP by taking the most recent observation up to 18 months before the end of the quarter. We set missing values for environment score to zero and include dummy variables for when these values are missing in our regressions.

B.4. Governance data

Our data on governance is from Institutional Shareholder Services (ISS). We follow Bebchuk, Cohen, and Fe (2009) and use six key entrenchment provisions: staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and supermajority (at least 2/3) requirements for mergers and charter amendments. We merge the governance data to our fundamentals data from CRSP and Compustat using CUSIP. We use the most recently available governance data for each quarter with a maximum gap of 18 months. We set missing values for governance score to zero and include dummy variables for when these values are missing in our regressions.

B.5. Earnings Surprise data

We construct earnings surprises using IBES unadjusted detail files following Livnat and Mendenhall (2006).[19]

We select the latest estimate for each analyst-quarter and require the forecast be made within 90 days of the earnings announcement. We define standardized unexpected earnings in each quarter as the actual earnings per share minus the median forecast, scaled by the price per share. Our procedure is as follows:

- Retrieve the list of US firm ibes tickers and CUSIPs from ibes.id. Keep only the most recent sdates by ticker, cusip pair. Merge on permno from crsp.stocknames by cusip. Merge on gvkey from crsp.ccmxpf_linktable by permno where usedflag=1 and linkprim is P or C.
- Using the ibes unadjusted file (ibes.detu_epsus) select quarterly forecasts for the current and the next fiscal quarter "fpi in (6,7)".
- Merge ibes unadjusted with CRSP/compustat on CUSIP and ensure linkdt≤anndats and anndats≤linkenddt.
- Select the latest estimate for a firm within broker-analyst group: Group by company,fpedats,estimator,analys then pick the last record in the group.
- Link Unadjusted estimates with Unadjusted actuals and CRSP permnos. Keep only the estimates issued within 90 days before the report date
  - From ibes.actu_epsus select 'QTR' pdicity and merge onto ibes unadjusted by ticker and fpedats.
  - Keep observations where $0 <$ repdats-anndats ≤ 90.

[19] Details are available at `https://wrds-www.wharton.upenn.edu/pages/support/applications/portfolio-construct`

- Put the estimate on the same per share basis as company reported EPS using CRSP Adjustment factors (cfacshr from crsp.dsf). To do so, adjust all estimate and earnings announcement dates to the closest preceding trading date in crsp daily to ensure that adjustment factors for shares won't be missing.

- Select unique ticker, fpedats, estimator, analys and compute the median by ticker, fpedats, act (medest)

- Merge with compustat fundamentals quarterly, ensuring datadate is within the linkdt and linkenddt. Compute and compute sue as (act-medest)/prccq where prccq is the price per share from Compustat.

We set missing values for earnings surprises to zero and include dummy variables for when these values are missing in our regressions.

C. Model derivations

In this appendix, we provide the solutions to the model in Section 1. We provide a solution of more general version of the model with background risk. We change the objective to

$$\max_{\boldsymbol{q}_i} \mathbb{E}\left[-\exp\left(-\gamma_i A_{i,1} + Y_{1,i}\right)\right],$$

where $Y_{1,i}$ represents other risk factors that impact the investor such as benchmarking, outside income, and time-varying investment opportunities.

We assume that the background risk factor $Y_{1,i}$ is normally distributed, $Y_{1,i} \sim N(\mu_{Yi}, \sigma^2_{Yi})$, and

$$2\mathrm{Cov}_i\left(Y_{1,i}, d(n)\right) = y_i(n) = \boldsymbol{\lambda}_i^{Y\prime}\boldsymbol{x}(n) + \nu_i^Y(n), \tag{18}$$

where $\mathrm{Cov}_i(V, W)$ denotes the covariance between V and W according to investor i's beliefs.

C.1. *First-order conditions*

The first-order condition of investor i is given by

$$(\boldsymbol{\mu}_i - \boldsymbol{M}\boldsymbol{B}) - \gamma_i \left(\boldsymbol{\rho}_i \boldsymbol{\rho}_i' + \sigma^2 \mathbf{I}\right) \boldsymbol{Q}_i + y_i = 0,$$

implying

$$\begin{aligned}
\boldsymbol{Q}_i =& \frac{1}{\gamma_i} \left(\boldsymbol{\rho}_i \boldsymbol{\rho}_i' + \sigma^2 \mathbf{I}\right)^{-1} (\boldsymbol{\mu}_i - \boldsymbol{M}\boldsymbol{B} + y_i) \\
=& \frac{1}{\gamma_i \sigma^2} \left(\mathbf{I} - \frac{\boldsymbol{\rho}_i \boldsymbol{\rho}_i'}{\boldsymbol{\rho}_i' \boldsymbol{\rho}_i + \sigma^2}\right) (\boldsymbol{\mu}_i - \boldsymbol{M}\boldsymbol{B} + y_i) \\
=& \frac{1}{\gamma_i \sigma^2} (\boldsymbol{\mu}_i - \boldsymbol{M}\boldsymbol{B} + y_i) - \frac{c_i}{\gamma_i \sigma^2} \boldsymbol{\rho}_i,
\end{aligned}$$

where $c_i = (\boldsymbol{\rho}_i' \boldsymbol{\rho}_i + \sigma^2)^{-1} \boldsymbol{\rho}_i' (\boldsymbol{\mu}_i - \boldsymbol{M}\boldsymbol{B} + y_i)$ is a scalar that is common across all stocks. Hence, an investor's demand for a given stock depends on its expected return (that is, the expected growth rate of fundamentals relative to the stock's current valuation), its riskiness, and the hedging benefit it provides. By substituting the assumptions that we made about expected growth rates and the stocks' riskiness in (1), (2), and (18) we obtain

$$\boldsymbol{Q}_i(n) = -\frac{1}{\gamma_i \sigma^2} \boldsymbol{M}\boldsymbol{B}(n) + \frac{1}{\gamma_i \sigma^2} \left(\boldsymbol{\lambda}_i^{\mu} - c_i \boldsymbol{\lambda}_i^{\rho} + \boldsymbol{\lambda}_i^{Y}\right)' \boldsymbol{x}(n) + \frac{1}{\gamma_i \sigma^2} \left(\nu_i^{\mu}(n) - c_i \nu_i^{\beta}(n) + \nu_i^{Y}(n)\right),$$

which is the expression announced in (3).

C.2. *Asset prices with exogenous characteristics*

By aggregating investors' demands and equating to supply, we solve for equilibrium asset prices,

$$\sum_{i=1}^{I} \boldsymbol{Q}_i = \boldsymbol{B},$$

where we use that the supply of each stock is normalized to one and $Q_i(n) = B(n)q_i(n)$. This implies

$$-\sum_{i=1}^{I}\frac{1}{\gamma_i\sigma^2}MB(n)+\sum_{i=1}^{I}\frac{1}{\gamma_i\sigma^2}\left(\boldsymbol{\lambda}_i^{\mu}-c_i\boldsymbol{\lambda}_i^{\rho}+\boldsymbol{\lambda}_i^{Y}\right)'x(n)+\sum_{i=1}^{I}\frac{1}{\gamma_i\sigma^2}\left(\nu_i^{\mu}(n)-c_i\nu_i^{\rho}(n)+\nu_i^{Y}(n)\right)=B(n),$$

that is,

$$MB(n)=\left(\sum_{i=1}^{I}a_i\boldsymbol{\beta}_{1,i}\right)'\boldsymbol{x}(n)+\sum_{i=1}^{I}a_i\epsilon_i(n)-\sigma^2\left(\frac{B(n)}{\sum_{i=1}^{I}\tau_iA_{i,0}}\right). \tag{19}$$

where $\boldsymbol{\beta}_{1,i}=\boldsymbol{\lambda}_i^{\mu}-c_i\boldsymbol{\lambda}_i^{\rho}+\boldsymbol{\lambda}_i^{Y}$, $\epsilon_i(n)=\nu_i^{\mu}(n)-c_i\nu_i^{\beta}(n)+\nu_i^{Y}(n)$, and

$$a_i=\frac{\gamma_i^{-1}}{\sum_{j=1}^{I}\gamma_j^{-1}}=\frac{\tau_iA_{i,0}}{\sum_{j=1}^{I}\tau_jA_j},$$

given our assumption that $\gamma_i=(\tau_iA_{i,0})^{-1}$.

C.3. Asset prices with endogenous characteristics

We now solve the model once more in the extended model as specified in equation (23). In vector notation, we have

$$\boldsymbol{x}(n)=\boldsymbol{h}_0+\boldsymbol{h}_1MB(n)+\boldsymbol{\nu}^x(n).$$

We substitute this expression into (19) and solve for the valuation ratio,

$$MB(n)=\Omega\left(\sum_{i=1}^{I}m_i\boldsymbol{\beta}_{1,i}\right)'(\boldsymbol{h}_0+\boldsymbol{\nu}^x(n))+\Omega\sum_{i=1}^{I}m_i\epsilon_i(n)-\Omega\sigma^2\left(\frac{B(n)}{\sum_{i=1}^{I}\tau_iA_{i,0}}\right), \tag{20}$$

where

$$\Omega=\frac{1}{1-\left(\sum_{i=1}^{I}m_i\boldsymbol{\beta}_{1,i}\right)'\boldsymbol{h}_1}.$$

The solution (20) highlights an important identification challenge in estimating equation (23) as valuation ratios depend on $\boldsymbol{\nu}^x(n)$. We therefore cannot estimate (23) and need to use an instrumental variables estimator instead. We implement this instrumental variables approach in Section 4.5.

D. A ridge-IV estimator of the demand curve

D.1. Moment conditions

We discuss how we modify the standard GMM moment conditions to impose a shrinkage penalty and how we choose the shrinkage target.

Before forming the moment conditions, we run a first-stage regression,

$$mb_t(n) = a_{0,i} z_{i,t}(n) + a'_{1,i} \boldsymbol{x}_t(n) + a_{2i} \boldsymbol{d}_t + e_t(n),$$

for each investor. We refer to the fitted value as $\widehat{z}_{i,t}(n)$. We then form the moment conditions based on (11),

$$\mathbb{E}_t \left[\left(\frac{w_{i,t}(n)}{w_{i,t}(0)} \exp\left\{ -\boldsymbol{\beta}_i' \boldsymbol{X}_t(n) \right\} - 1 \right) \boldsymbol{Z}_{i,t}(n) \right] = 0,$$

where $\boldsymbol{X}_t(n) = (mb_t(n), \boldsymbol{x}_t'(n), \boldsymbol{d}_t')'$, $\boldsymbol{\beta}_i = (\beta_{0,i}, \boldsymbol{\beta}_{1,i}', \boldsymbol{\beta}_{2,i}')'$, $\boldsymbol{Z}_{i,t}(n) = (\widehat{z}_{i,t}(n), \boldsymbol{x}_t'(n), \boldsymbol{d}_t')'$.

We implement the shrinkage estimator by adding a ridge penalty (Hoerl and Kennard, 1970) to the moment conditions:

$$\mathbb{E}_t \left[\left(\frac{w_{i,t}(n)}{w_{i,t}(0)} \exp\left\{ -\boldsymbol{\beta}_i' \boldsymbol{X}_t(n) \right\} - 1 \right) \boldsymbol{Z}_{i,t}(n) \right] - D(\boldsymbol{\Lambda}_i) \left(\boldsymbol{\beta}_i - \boldsymbol{\beta}_i^T \right) = 0. \tag{21}$$

The term $D(\boldsymbol{\Lambda}_i) \left(\boldsymbol{\beta}_i - \boldsymbol{\beta}_i^T \right)$ is the ridge penalty, where $D(\boldsymbol{v})$ denotes a diagonal matrix with the elements of the vector $\boldsymbol{v}$ on the diagonal.

For investors with more than 750 observations, across stocks and years, we can estimate $\boldsymbol{\beta}_i$ accurately without any shrinkage ($\boldsymbol{\Lambda}_i = \mathbf{0}$). For investors with fewer observations, we use as the shrinkage target $\boldsymbol{\beta}_i^T = \left(\beta_{0,i}^T, \boldsymbol{\beta}_{1,i}^T, \mathbf{0}_{1\times T} \right)'$, where the target parameters are (equal-weighted averages) across investors of the same institutional type who hold more than 750 stocks. We use a constant shrinkage parameter, λ, for $\left(\beta^T_{0,i}, \boldsymbol{\beta}^T_{1,i}\right)$ and no shrinkage for the time fixed effects.[20]

If the implied estimates result in an estimate of $\beta_{i,0}$ that exceeds 1, we increase the first element of $\boldsymbol{\Lambda}_i$ to ∞ to impose $\beta_{0,i} = 1$. Even though the moment conditions in (21) are nonlinear, we develop a simple numerical algorithm to solve them efficiently as we discuss in the next section.

To complete the estimation procedure, we need to determine λ. As is common practice in the machine learning literature, we choose this parameter using cross-validation. In particular, we split the holdings randomly in half for each investor by year. We then estimate the model on one sample for each investor and compute the mean-squared error on the left out sample. The mean-squared error is minimized for $\lambda = 0.2$ in the US and $\lambda = 0.3$ in GB.

D.2. Numerical algorithm to compute the ridge estimator

We start from

$$\mathbb{E}_t\left[\left(\delta_{i,t}(n)\exp\left\{-\boldsymbol{\beta}_i'\boldsymbol{X}_t(n)\right\} - 1\right)Z_t(n)\right] - D(\boldsymbol{\Lambda}_i)\left(\boldsymbol{\beta}_i - \boldsymbol{\beta}^T\right) = 0. \tag{22}$$

where $\delta_{i,t}(n) = \frac{w_{i,t}(n)}{w_{i,t}(0)}$. We start from an initial estimate, $\boldsymbol{\beta}_i^{(1)}$, which we discuss below. We then use a first-order Taylor expansion of the moment conditions around $\boldsymbol{\beta}_i^{(1)}$ to find $\boldsymbol{\beta}_i^{(2)}$

$$\begin{aligned}&\mathbb{E}_t\left[\left(\delta_{i,t}(n)\exp\left\{-\boldsymbol{\beta}_i^{(1)\prime}\boldsymbol{X}_t(n)\right\} - 1\right)Z_t(n)\right] - D(\boldsymbol{\Lambda}_i)\left(\boldsymbol{\beta}_i^{(1)} - \boldsymbol{\beta}^T\right) - \\ &\left[\mathbb{E}_t\left[\delta_{i,t}(n)\exp\left\{-\boldsymbol{\beta}_i^{(1)\prime}\boldsymbol{X}_t(n)\right\}Z_t(n)\boldsymbol{X}_t(n)'\right] + D(\boldsymbol{\Lambda}_i)\right]\left(\boldsymbol{\beta}_i^{(2)} - \boldsymbol{\beta}_i^{(1)}\right) \\ =&0,\end{aligned}$$

implying

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

[20] We also explored alternative penalty functions, such as $\lambda N^{-\xi}$, with $\xi > 0$, so that the penalty vanishes as $N \to \infty$. However, the cross-validation results show no substantial improvement from doing so and we therefore prefer the simpler penalty function.

We iterate on this procedure until convergence. Note that the numerator of the adjustment term are the moment conditions in (22), implying that upon convergence, the moment conditions are satisfied. For numerical stability, we limit the updating step for each of the coefficients to 1 or -1.

To obtain the initial estimate, $\boldsymbol{\beta}_i^{(1)}$, we omit the zero holdings and use the linear moment conditions

$$\mathbb{E}_t\left[\left(\ln \delta_{i,t}(n) - \boldsymbol{\beta}_i^{(1)\prime}\boldsymbol{X}_t(n)\right) Z_t(n)\right] - D(\boldsymbol{\Lambda}_i)\left(\boldsymbol{\beta}_i^{(1)} - \boldsymbol{\beta}^T\right) = 0,$$

implying

$$\boldsymbol{\beta}_i^{(1)} = \left[\mathbb{E}\left[Z_t(n)\boldsymbol{X}_t(n)'\right] + D(\boldsymbol{\Lambda}_i)\right]^{-1}\left[\mathbb{E}_t\left[Z_t(n)\ln \delta_{i,t}(n)\right] + D(\boldsymbol{\Lambda}_i)\boldsymbol{\beta}^T\right].$$

E. Variance decompositions using characteristics

We show how our valuation regressions and earnings predictability regressions connect to traditional variance decompositions. Starting from (15) without expectations, it holds

$$mb_t(n) = c + \sum_{s=1}^{\infty}\rho^{s-1}e_{t+s}(n) - \sum_{s=1}^{\infty}\rho^{s-1}r_{t+s}(n).$$

Consider a linear projection of both sides on a set of characteristics, $x_t(n)$ as well as a time fixed effect, which yields

$$a_{mb,t} + \lambda_{mb}' x_t(n) = a_{e,t} + \lambda_e' x_t(n) - \left(a_{r,t} + \lambda_r' x_t(n)\right),$$

implying

$$\begin{aligned} a_{mb,t} =& a_{e,t} - a_{r,t}, \\ \lambda_{mb} =& \lambda_e - \lambda_r. \end{aligned}$$

Hence, the fraction of market-to-book ratios that can be explained by characteristics, $\mathrm{Var}\left(\lambda_{mb}' x_t(n)\right)$, satisfies the variance decomposition

$$\mathrm{Var}\left(\lambda_{mb}' x_t(n)\right) = \mathrm{Cov}\left(\lambda_{mb}' x_t(n), \lambda_e' x_t(n)\right) - \mathrm{Cov}\left(\lambda_{mb}' x_t(n), \lambda_r' x_t(n)\right),$$

and the fraction due to returns therefore equals

$$\text{Fraction due to expected returns} = \frac{\lambda_{mb}' \Sigma_x (\lambda_{mb} - \lambda_e)}{\lambda_{mb}' \Sigma_x \lambda_{mb}},$$

and the fraction due to expected growth rates

$$\text{Fraction due to expected growth rates} = \frac{\lambda_{mb}' \Sigma_x \lambda_e}{\lambda_{mb}' \Sigma_x \lambda_{mb}},$$

with $\Sigma_x = \mathrm{Var}\left(\Sigma_x\right)$. As characteristics are cross-sectionally standardized, if the characteristics are also uncorrelated, the shares equal $\frac{\lambda_{mb}'(\lambda_{mb} - \lambda_e)}{\lambda_{mb}' \lambda_{mb}}$ and $\frac{\lambda_{mb}' \lambda_e}{\lambda_{mb}' \lambda_{mb}}$, respectively.

F. Robustness

In this Appendix we provide details of our robustness checks, as discussed in Section 4.5. We made a number of assumptions in estimating the asset demand system. First, we assumed the existence of an investment universe that can be measured using the stocks an investor holds at any point during the last three years. Second, we used a particular set of characteristics in estimating investor's demand curves. Third, we assumed that latent demand is exogenous to characteristics, which rules out that characteristics may depend on prices. In this section we demonstrate the robustness of our results to relaxing these assumptions in various ways.

F.1. Robustness to Measurement of Investment Universes

While investment mandates and restrictions are ubiquitous, measuring investment mandates is challenging. We first study the robustness of our findings to the measurement of investors' investment universes. To do so, we present results from three variants of the measurement of the investment universes: (1) omitting hedge funds when constructing the instrument for market equity; (2) varying the window over which we measure the investment universe; and (3) randomly increasing the size of the investment universe.

Omitting Hedge Funds. Of all investor types, it may be most challenging to identify the investment mandate of hedge funds given the flexibility that hedge funds have in selecting their investment strategies. As a robustness check, we exclude hedge funds in the construction of the instrument for market equity, as detailed in Section 4.2. In the top left panel of Figure F.2, we show a scatter plot of the coefficient on log market-to-book, $\beta_{0,i}$, from our benchmark estimates and from estimates constructing our instrument excluding hedge funds. We find that the two sets of estimates are highly correlated with a correlation of 0.985.

Varying the investment universe measurement window. Koijen and Yogo (2019) showed that the universe of stocks stabilizes if we expand the window back in time and this motivated the three-year window. We now show that our estimates are robust to varying the window, both back in time and into the future. More precisely, we consider a window $[t_B, t_F]$, where t_B is the number of years back, including the current year, and t_F are the number of years forward. Koijen and Yogo (2019) used $[3, 0]$, which is also what we use in our primary estimation. In Figure F.1, we consider windows looking back as far as 5 years and ahead as far as 5 years. The choice set is then defined to include any stock that an investor holds during that window. We report the average estimates of the coefficient on log market-to-book, $\beta_{i,0}$, by institutional type in 2010, which is in the middle of our sample, in Figure F.1. While there is some variation, the estimates are robust to varying the window to estimate the investment mandate.

Increasing the size of the investment universe. We also randomly increase the size of investors' investment universes by 10%, 25%, 50%, and 100% and recompute our results. Specifically, for each investor, we randomly sample from the set of inside assets which that investor does not hold and expand their investment universe to this random set of assets. We then recompute our instrument, estimation, and counterfactuals. The top right panel in Figure F.2 presents a scatter plot of the coefficient on log market-to-book, $\beta_{i,0}$, for one sample where we expand investment universes by 25% versus our baseline estimates. We find that even when randomly expanding the investment universe, the demand elasticity estimates remain quite stable with a correlation of 0.921.

To further ensure that our results are robust to measurement of the investment universes, we recompute our three main counterfactuals in cases where we randomly increase the investment universe by certain amount. Given the computational complexity involved in computing our counterfactuals, we repeat this exercise 10 times.

We present the price informativeness coefficients from the active to passive transition counterfactuals (Section 5) in Figure F.3, the AUM change by investor type from the ESG counterfactuals (Section 6) in Figure F.4, and total repricing from measuring the importance of investors for asset prices (Section 7.1) in Figure F.5.

In each figure, the red line depicts the baseline calculated value as in the main paper. Each row of panels expands the universes by a different shares, as labeled on the panels on the right. Each column depicts the repricing, change in AUM share, and price informativeness measure for the particular insitutional type and counterfactual. The bars in each figure are for each of the 10 replications. We see that our results are robust to increasing the size of investor's investment universes across all samples, increase sizes, and counterfactual exercises.

F.2. Robustness to Inclusion of Additional Characteristics

As an additional robustness check, we include three additional characteristics (investment, repurchases, and earnings surprises) in the demand curve of investors. The three characteristics which we add are investment, net stock issuance, and earnings surprises. This set of characteristcs is motived by the fact that they are some of the most powerful predictors of returns (Daniel, Hirshleifer, and Sun, 2020). In Table F.1 we re-run our valuation and earnings regressions and show that these characteristics are important for explaining valuations and earnings, although they do not substantially increase the R^2 from our baseline set of characteristics.

In the bottom left panel of Figure F.2 we show a scatter plot of $\beta_{0,i}$ using our benchmark estimates and estimates from the model whcih includes three additional characteristics.

Overall we find that the estimated of $\beta_{0,i}$ are highly correlated between the two sets of estimates with a correlation of 0.964.

Using these estimates, we recompute our three key counterfacuals. We present the price informativeness coefficients from the active to passive transition counterfactuals (Section 5) in Figure F.6, the AUM change by investor type from the ESG counterfactuals (Section 6) in Figure F.7, and total repricing from measuring the importance of investors for asset prices (Section 7.1) in Figure F.8. Each figure contains a comparison to our "original" values in the paper. Overall, we see that including these additional characteristics does not substantially alter our key conclusions.

F.3. Robustness to Endogeneity of Characteristics

Finally, we study how our estimates vary when we relax the assumption that characteristics, $\boldsymbol{x}_t(n)$, are exogenous to latent demand. To do so, we extend our model so that some characteristics mary demend on prices. We split the characteristics into two groups, $\boldsymbol{x}_{1,t}(n)$ and $\boldsymbol{x}_{2,t}(n)$. The characteristics in the first group may respond to prices and thus latent demand, while we assume that the second group of characteristics are exogenous to latent demand. A firm's payout policy is an example of a characteristic that may respond to prices, while sales and the foreign sales share are more plausibly exogenous to latent demand and determined by a firm's productivity.

We model the dependence of $\boldsymbol{x}_{1,t}(n)$ on valuation ratios, $mb_t(n)$, as

$$x_{k,1,t}(n) = h_{0,k} + h_{1,k} mb_t(n) + \boldsymbol{h}_{2,k}' \boldsymbol{x}_{2,t}(n) + \nu^x_{k,t}(n), \tag{23}$$

where $\nu^x_{k,t}(n)$ is a technology or corporate policy shock. We complete the model with the following assumptions that replace and relax the earlier assumption $\mathbb{E}[\epsilon_{i,t}(n) \mid \boldsymbol{x}_t(n)] = 0$,

$$\begin{aligned}
\mathbb{E}[\boldsymbol{\nu}^x_t(n) \mid z_{i,t}(n), \boldsymbol{x}_{2,t}(n)] =& 0, \\
\mathbb{E}[\epsilon_{i,t}(n) \mid z_{i,t}(n), \boldsymbol{\nu}^x_t(n), \boldsymbol{x}_{2,t}(n)] =& 0.
\end{aligned}$$

The characteristics $\boldsymbol{x}_{1,t}(n)$ may depend on prices, but the corporate policy shocks, $\boldsymbol{\nu}^x_t(n)$, are assumed to be independent of latent demand. Under these assumptions, we can estimate investors' demand in two steps. First, we estimate $h_{0,k}$, $h_{1,k}$, and $\boldsymbol{h}_{2,k}$, using $z_{i,t}(n)$ as an instrument for $mb_t(n)$. Second, we compute the estimated residuals, $\nu^{x,e}_{k,t}(n) = x_{k,1,t}(n) - h^e_{0,k} - h^e_{1,k} mb_t(n) - \boldsymbol{h}^{e\prime}_{2,k} \boldsymbol{x}_{2,t}(n)$. We then use $\boldsymbol{\nu}^{x,e}_t(n)$ as instruments instead of $\boldsymbol{x}_{1,t}(n)$ in estimating the demand curve.

Of all characteristics included in our asset demand system, we are mostly concerned about the dependence of a firm's dividend policy on prices. As in the standard Q theory, investment responds to market-to-book ratios. As profits are used to invest, to pay dividends, or to save for the future via retained earnings, dividends plausibly respond to stock prices. Other characteristics in our demand system, such as sales, book equity, markups, and foreign sales are more closely tied to a firm's productivity and market power that are not directly influenced by equity valuations in standard production-based asset pricing models. That said, if one wants to explore models in which, for instance, a firm's export decision is endogenous, the general methodology that we develop here can be followed.

In the bottom right panel of Figure F.2, we show a scatter plot of $\beta_{0,i}$ using our benchmark estimator and using the estimator that we discussed in this section. The two sets of estimates have a correlation of 0.996, which illustrates the robustness of our estimates to this particular form of endogeneity. While firms' dividend policy responds to valuation ratios, the estimate of $h_{1,k}$ is relatively small. If we ignore the endogeneity of a firm's payout policy, the estimate of $\beta_{0,i}$ converges in probability to $\beta_{0,i} + \beta^{Div}_{1,i} h_{1,k}$, where $\beta^{Div}_{1,i}$ is the elasticity of an investor's demand with respect to a firm's dividend payout. As the estimate of $\beta^{Div}_{1,i} h_{1,k}$ is small, our estimate of $\beta_{0,i}$ is not much affected.

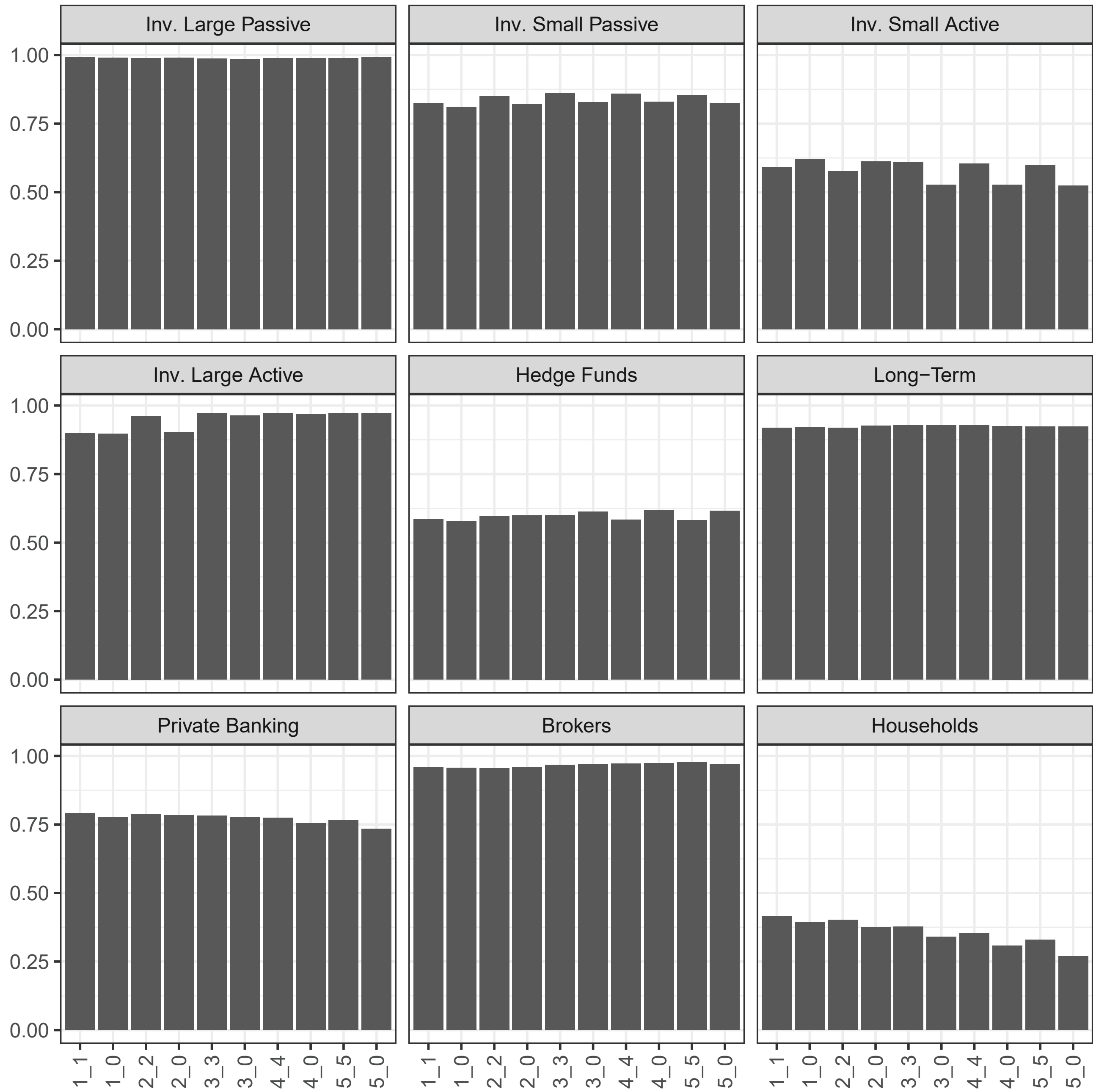

Figure F.1
Expanding window demand coefficients

Estimates of demand coefficients on log market-to-book for various constructions of the investment universe. Each bar is the time series average of the within year aum weighted coefficients for each institutional type. Yearly AUM is the average AUM for each institution in a given year across quarters. Investment universes are computed for varying backward and forward. The first number measures the trailing window in years and the second number the forward window in years. Baseline estimates in the paper are 3 years back and 0 years forward.

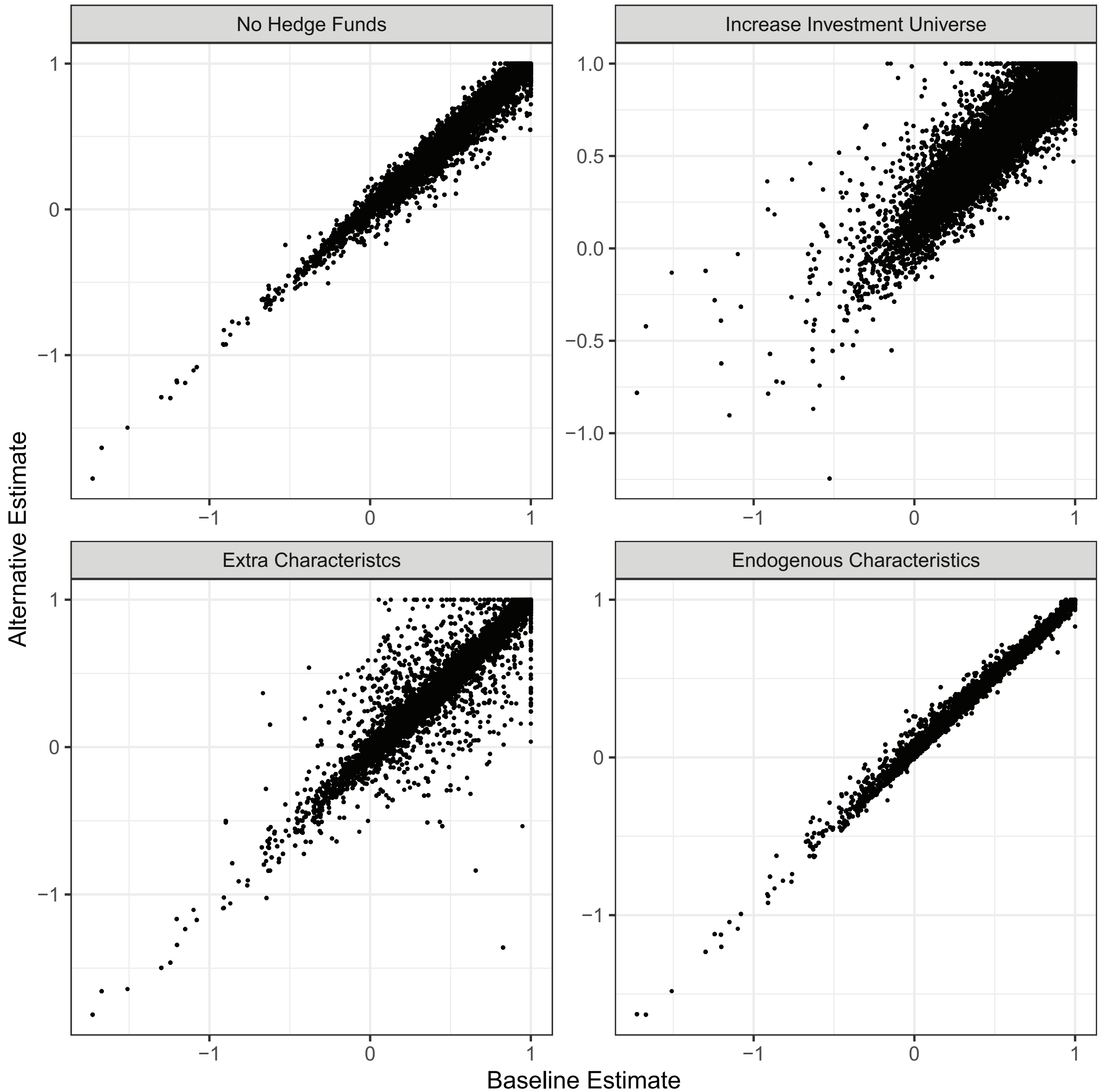

Figure F.2

Comparison of baseline estimates with alternative estimates

Coefficients on log market-to-book for four alternative estimates versus the baseline estimates. In the top left panel the instrument for market equity is constructed omitting hedge funds. In the top right panel we randomly expand each investor's investment universe by 25%. In the bottom left panel we add investment, repurchases, and earnings surprises as additional characteristics. In the bottom right panel the alternative estimates are from a model that allows for endogenous dividend-to-book.

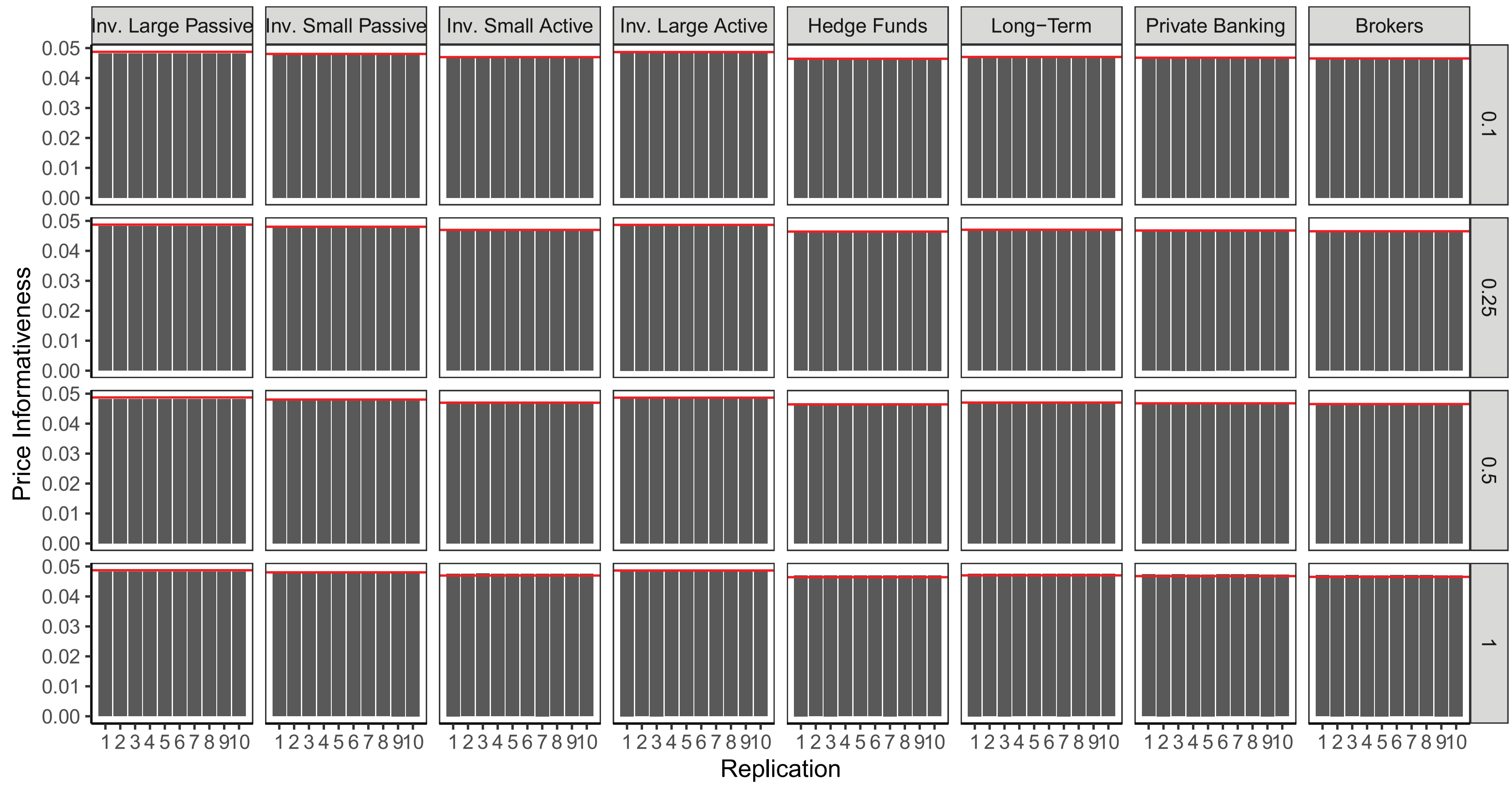

FIGURE F.3

Price informativeness by institutional type when resetting AUM distribution (robustness to varying investment universes)

Comparison of price informativeness coefficients where we reset the AUM distribution from 2016 Q4 to 2007 Q4 as in Figure 5 described in Section 5. Each bar represents a scenario where we randomly increase investor's investment universes within the set of inside assets by 10%, 25%, 50%, and 100%. The red line in each figure depicts the baseline calculated value in the paper. Each row of panels expands the universes by a different shares, as labeled on the panels on the right. Each column depicts the price informativeness measure for the particular insitutional type and counterfactual. The bars in each figure are for each of the 10 replications.

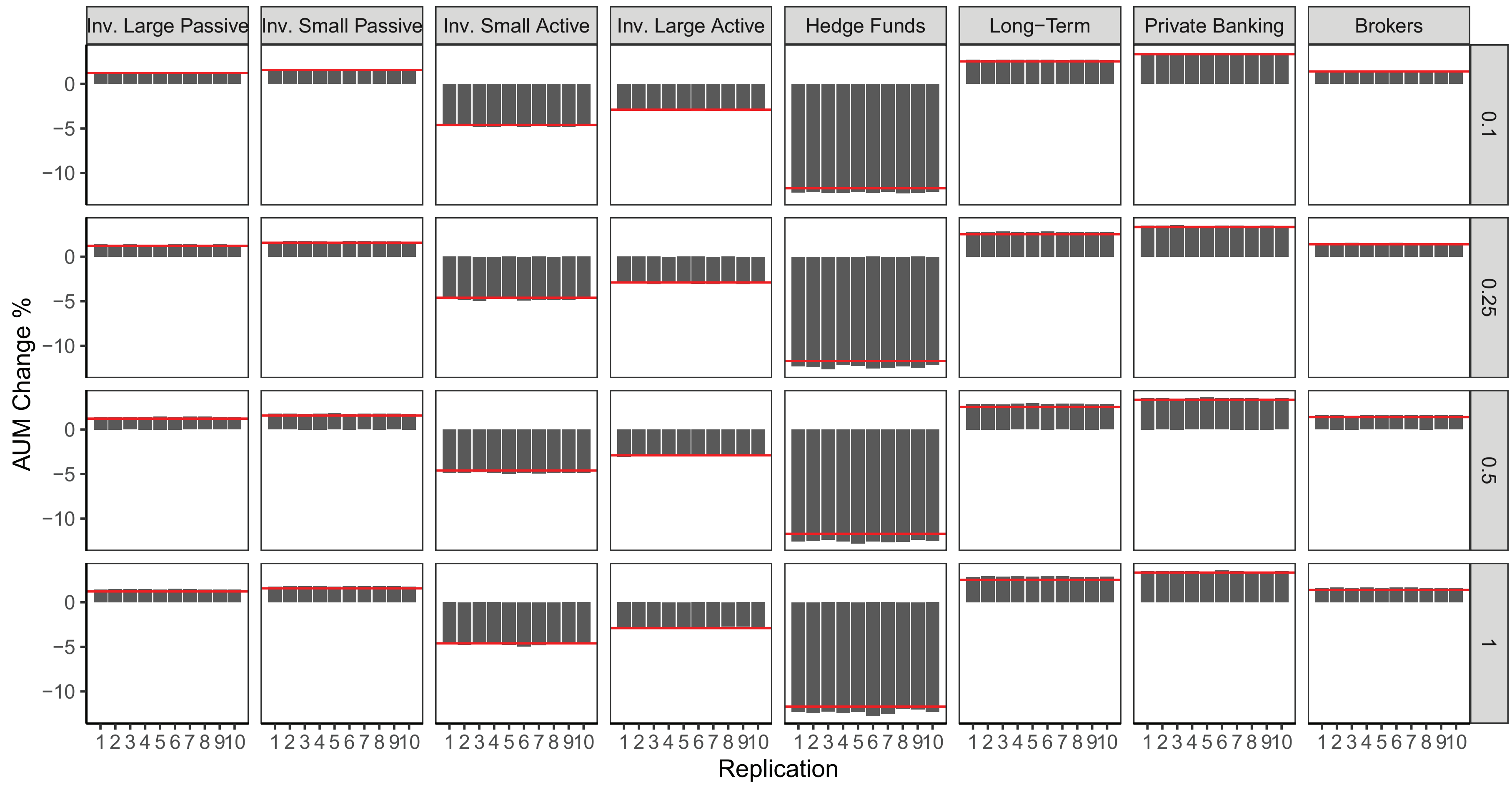

FIGURE F.4

AUM change in ESG counterfactual (robustness to varying investment universes)

Comparison of AUM change by investor type in ESG counterfactuals as in Figure 6 described in Section 6. Each bar represents a scenario where we randomly increase investor's investment universes within the set of inside assets by 10%, 25%, 50%, and 100%. The red line in each figure depicts the baseline calculated value in the paper. Each row of panels expands the universes by a different shares, as labeled on the panels on the right. Each column depicts the percent AUM change for the particular insitutional type and counterfactual. The bars in each figure are for each of the 10 replications.

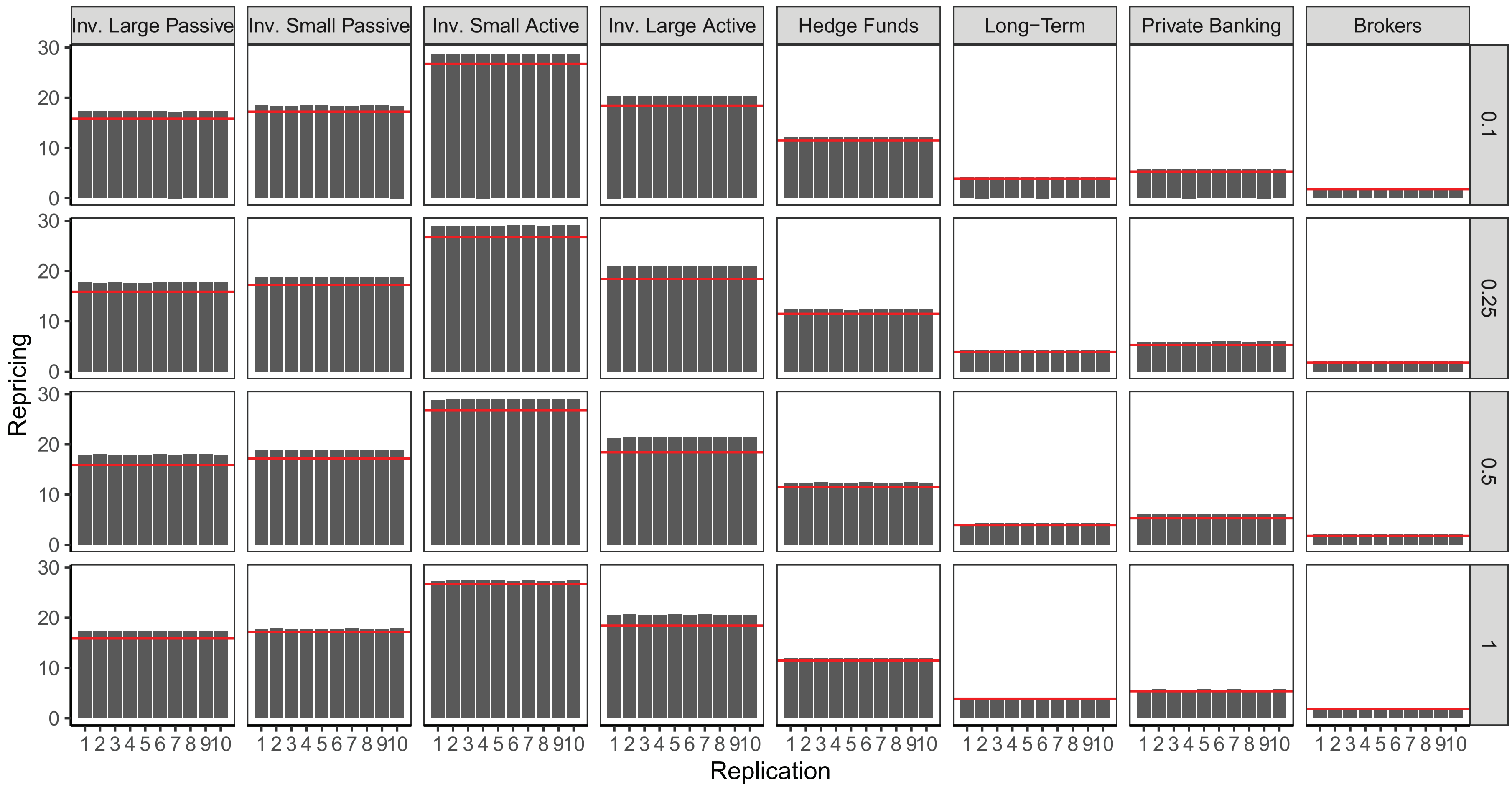

FIGURE F.5

Repricing by institutional type in flow counterfactuals (robustness to varying investment universes)

Comparison of total repricing in flow counterfactuals as in Figure 7 described in Section 7.1. Each bar represents a scenario where we randomly increase investor's investment universes within the set of inside assets by 10%, 25%, 50%, and 100%. The red line in each figure depicts the baseline calculated value in the paper. Each row of panels expands the universes by a different shares, as labeled on the panels on the right. Each column depicts the repricing measure for the particular insitutional type and counterfactual. The bars in each figure are for each of the 10 replications.

Table F.1
Valuation and earnings regressions with additional characteristics

	Extra Characteristics		Baseline Characteristics	
	mb	e^5	mb	e^5
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)
Dividend 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)
Earnings Surprise	−0.03	−0.02		
	(−3.90)	(−1.05)		
Repurchases	0.17	0.04		
	(8.12)	(3.11)		
Investment	0.14	0.02		
	(9.68)	(0.67)		
Adj. R^2	0.69	0.46	0.65	0.45
Within Adj. R^2	0.68	0.46	0.64	0.45
Num. obs.	6395	2142	6395	2142

Regressions of end of year valuation ratios on firm-level characteristics. Columns 1 and 2 present regressions from 2010 to 2019 with extra characteristics. Columns 3 and 4 present regressions from 2010 to 2019 using our baseline characteristics with a matched sample. All regressions include year fixed effects. mb is the log market-to-book ratio at time t. e^5 is cumulative earnings growth t to $t+5$ adjusted for repurchases. Characteristics are standardized cross-sectionally by year. Environmental scores are from Sustainalytics, Governance Scores are the entrenchment index from Bebchuk, Cohen, and Ferrell (2009), Foreign sales is the fraction of ales from abroad, Lerner is operating income after depreciation divided by sales, and market beta is 60-month rolling market beta. Firm-level fundamentals are from CRSP and Compustat. T-statistics clustered by year in parentheses.

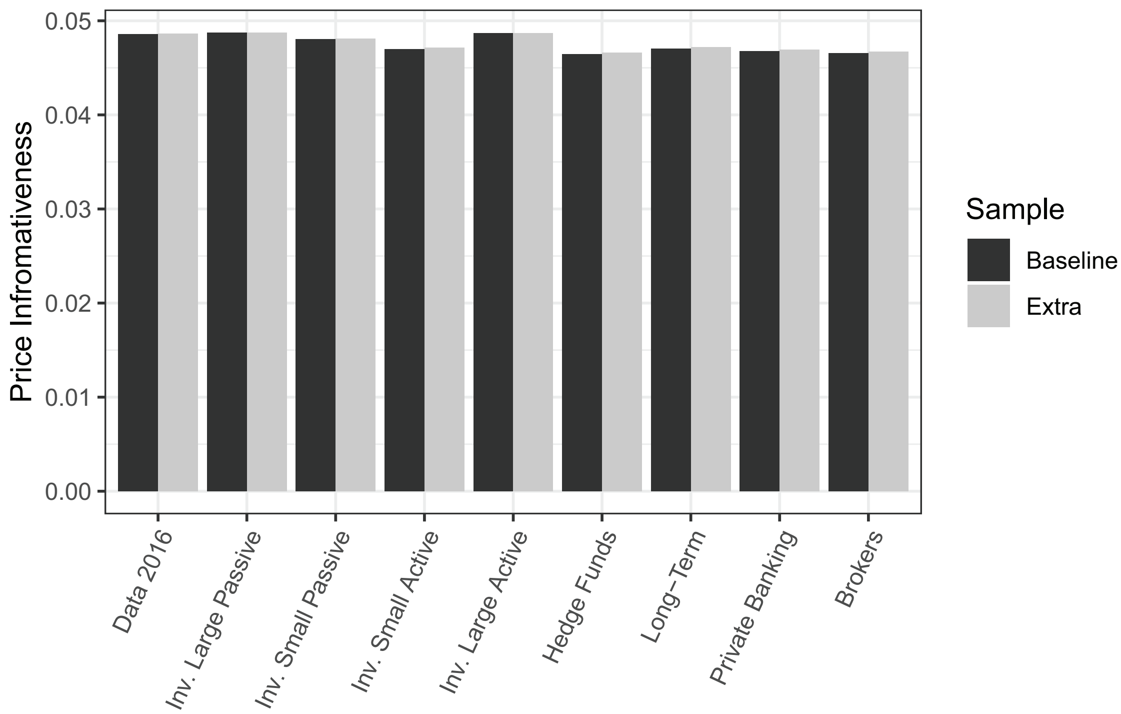

Figure F.6

Price informativeness by institutional type when resetting AUM distribution (robustness to including extra characteristics)

Comparison of price informativeness coefficients where we reset the AUM distribution from 2016 Q4 to 2007 Q4 as in Figure 5 described in Section 5. Baseline is the repricing in the baseline demand specification in the paper. Extra includes three additional characteristics in investor demand curves: investment, net repurchases, and earnings surprises.

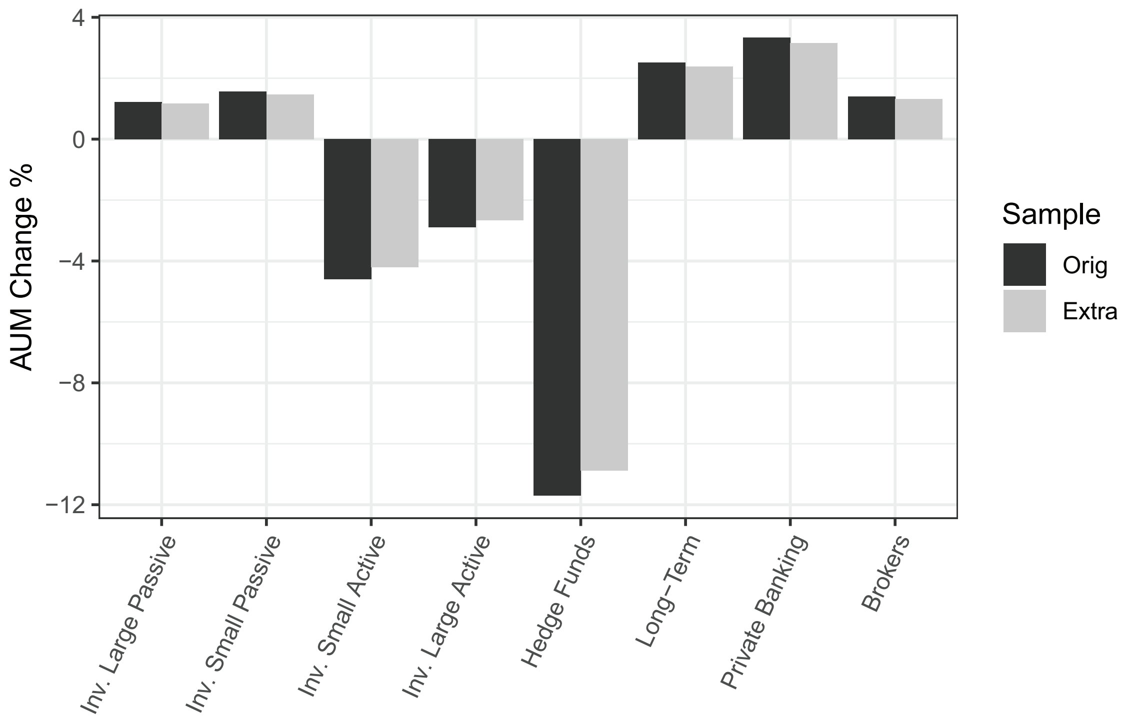

Figure F.7

AUM change in ESG counterfactual (robustness to including extra characteristics)

Comparison of AUM change by investor type in ESG counterfactuals as in Figure 6 described in Section 6. Baseline is the repricing in the baseline demand specification. Extra includes three additional characteristics in investor demand curves: investment, net repurchases, and earnings surprises.

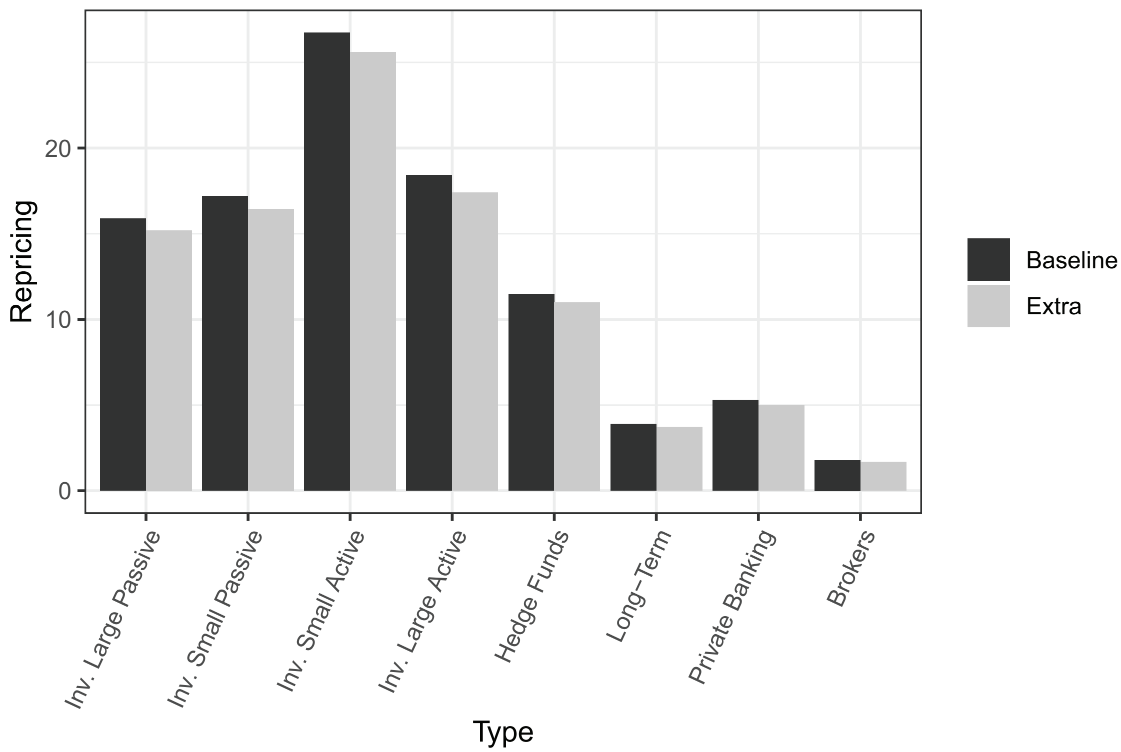

Figure F.8
Repricing by institutional type in flow counterfactuals (robustness to including extra characteristics)

Comparison of total repricing in flow counterfactuals as in Figure 7 described in Section 7.1. Extra includes three additional characteristics in investor demand curves: investment, net repurchases, and earnings surprises.