Which Investors Matter for Equity Valuations and Expected Returns?*

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Abstract

We develop a new framework to quantitatively connect valuations, expected returns, and characteristics to the demands of institutional investors and households. Using investor-level holdings data, we estimate asset demand as a function of prices and characteristics and quantify how portfolio tilts across investors affects firm's valuation ratios. The characteristics include environmental and governance measures, as well as traditional risk and return characteristics. We then analyze the impact of two key trends in the asset management industry on valuations and investors' welfare. First, if the trend from active to passive management continues, it has a negative impact on the assets of hedge funds and small-active investment advisors and it would strengthen the relation between valuations and characteristics. Second, we use our model to assess climate-related risks and find that increased demand for green firms would benefit long-term investors, banks, and passive investment advisors at the expense of hedge funds and small-active investment advisors.

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A long-standing question in finance is 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 (2009)). Examples include measures of firm fundamentals like profitability and investment, measures of subjective expectations about cash flows and returns, or environmental, social, and governance (ESG) measures.[1] For each of these measures, the literature provides narratives of how these characteristics are priced by certain groups of investors. For example, sentiment-driven retail investors chase glamour stocks with compelling stories (like technology stocks during the dot-com bubble or "meme stocks" during the COVID-19 pandemic). Pension funds and sovereign wealth funds tilt toward green firms because of sustainability mandates. Arbitrageurs and hedge funds take advantage of mispricings or bet on factor returns ("smart beta") along certain characteristics like market beta, value, and quality.

Although portfolio choice varies significantly both within and across investor groups, it is unclear whether these portfolio tilts have a quantitatively important impact on asset prices. Traditional theories imply that assets are highly substitutable and therefore have high cross-sectional demand elasticities. Consequently, the theoretical prediction is that the portfolio tilt of a group of investors toward certain characteristics only has a small impact on asset prices because other investors quickly rebalance to other stocks, mitigating price impact. However, a large empirical literature shows that demand curves for individual stocks slope down (Shleifer 1986; Chang, Hong, and Liskovich 2015). With inelastic demand, active strategies, or portfolio tilts toward certain characteristics, can have a large impact on asset prices. We develop a framework to *quantitatively* assess the importance of individual investors or groups of investors for the pricing of characteristics in the cross section of valuation ratios and expected returns.

To motivate our empirical work, we develop a simple model in which investors use a set of characteristics to assess each firm's expected future profitability and riskiness. Optimal portfolio choice implies that an investor's demand curves are a function of prices and characteristics. We allow investors to have subjective beliefs and they may disagree about which

[1] Prominent examples include La Porta (1996), La Porta et al. (2002), Bordalo et al. (2019), Hong and Kacperczyk (2009), Yermack (1996), Bebchuk, Cohen, and Ferrell (2009), Fillat and Garetto (2015), Giroud and Mueller (2011), and Gompers, Ishii, and Metrick (2003).

characteristics are important for a firm's expected future profitability and riskiness. In equilibrium, asset prices depend on characteristics, just as in cross-sectional valuation regressions in empirical asset pricing. The coefficients on characteristics are a weighted average of the preferences of individual investors, weighted by their assets under management. This means that active investors, who tilt their portfolios away from the market portfolio, can push up valuation ratios along characteristics that they favor. The actual impact on asset prices also depends on the size of the investor and the slope of the aggregate demand curve that they face.

We then take the model to the data. We first estimate a cross-sectional valuation regression and show that eight characteristics related to risk, productivity, profitability, and ESG measures[2] explain over half of the cross-sectional variation in valuation ratios. The remaining variation in valuation ratios that is not related to characteristics is due to latent demand, which is heterogeneity in beliefs due to unobserved (to the econometrician) characteristics.[3]

Having identified characteristics that are important for valuation ratios, we estimate an asset demand system in which investors' demand curves are a function of prices, characteristics, and latent demand. We estimate the model using quarterly US data from 2000 to 2019. 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,[4] as this is a large category of institutional investors that includes mutual funds. Long-term investors include pension funds and insurance companies. The red bars in the top panel of Figure 1 summarize the size distribution across groups as measured by the share of assets under management.

In estimating the model, we allow for rich heterogeneity across investors, also within institutional type. 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

[2] We use the environmental score from Sustainalytics and an entrenchment index from Bebchuk, Cohen, and Ferrell (2009) as our environmental and governance measures.

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

[4] We define the active share as the sum of absolute deviations of an investors portfolio from a market-weighted portfolio, based on the same securities as the ones held by the investor, divided by two.

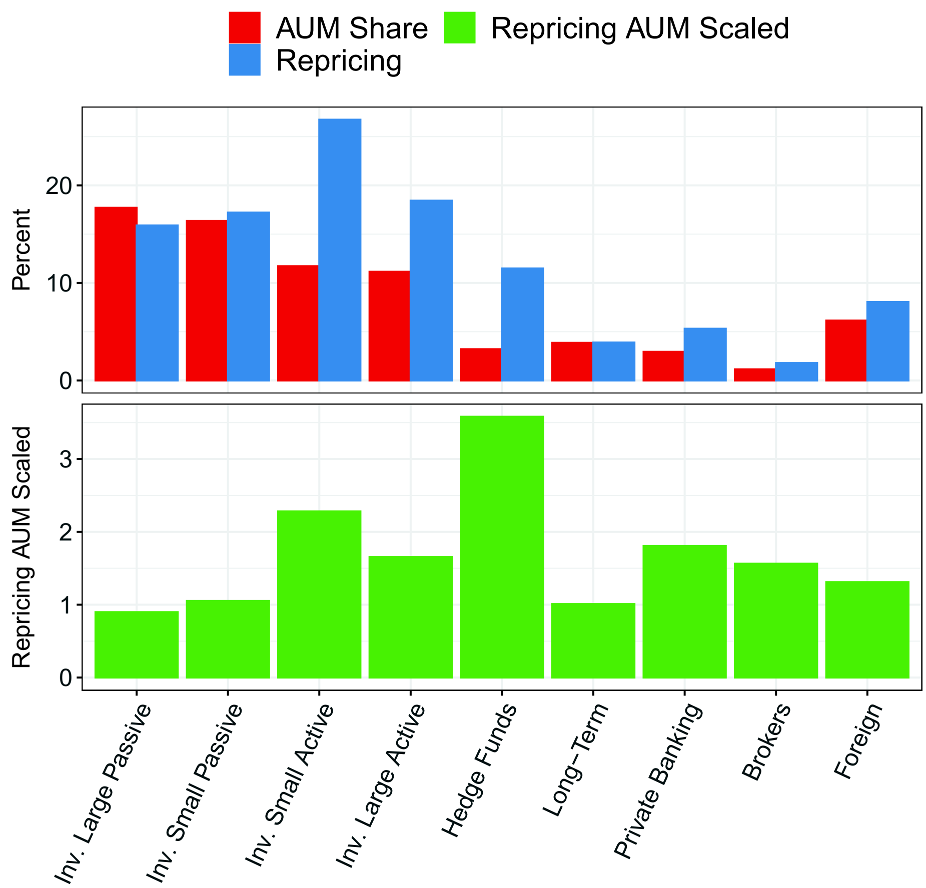

Figure 1
Total Repricing by Institution Type (US)

The top 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. The bottom panel reports the change in market cap normalized by the fraction of ownership. The bottom panel reports the change in market cap normalized by the fraction of ownership. Each bar is the time series average of the quarterly values. Firm-level fundamentals are from CRSP and Compustat. Holdings data are from FactSet. The sample runs from 2000 to 2019.

portfolio.

To measure the importance of groups of investors on valuations, we calculate the impact of an outflow of all assets from one group of investors, which is redistributed to all other institutional investors in proportion to their assets under management. We then recompute the market clearing prices and investors' assets, which are impacted by returns and flows.

Our repricing measure is the absolute changes in market values summed across all stocks, scaled by the initial value of the aggregate stock market. For example, we ask by what percent does the average stock price move if we take BlackRock's assets and redistribute these assets to all other institutional investors. Because BlackRock has certain portfolio tilts, this experiment would lower the stock price along characteristics that BlackRock favors or for stocks for which they have positive latent demand.

The blue bars in Figure 1 summarize the results. Hedge funds and investment advisors are particularly influential, while long-term investors (i.e., pension funds and insurance companies), private banking, and broker dealers have only a small impact. As shown by our theoretical model, the impact of a given investor or group of investors depends on (i) the investor's size, (ii) the elasticity of demand curves of other investors, and (iii) the heterogeneity in demand curves. To adjust for size, we also compute the repricing measure scaled by the total assets managed by a particular group. The results are presented in the bottom panel of Figure 1. Per dollar of assets managed, hedge funds and small-active investment advisors have the largest impact on valuations. At the other end of the spectrum, we find that passive investment advisors (both small and large) and long-term investors have a relatively small impact on valuations.

To understand how much different investors matter the pricing of firm characteristics, we re-estimate the cross-sectional valuation regression using the counterfactual prices and document how the regression coefficients and residuals change. We consider the pricing of the environmental index as an example. The baseline coefficient implies that a one standard deviation increase in the index leads to a 17% increase in valuations. This number would drop to 14% if we reallocate assets from foreign investors, while it would increase to 21% if we reallocate assets from small-active investment advisors to the other institutional investors. Thus, the estimates imply that foreign investors help to lower the cost of capital for green firms in the US, conditional on the other characteristics. This example illustrates how our methodology contributes to the active ESG research agenda by showing which investors matter for the pricing of ESG scores in the cross section of stocks.[5]

Combined with a forecasting model for expected future profitability growth, we also

[5]In addition to governance cited in Footnote 1, a growing literature studies the pricing of environmental and climate-related characteristics, see for instance Hong, Li, and Xu (2019), Bolton and Kacperczyk (2020), Engle et al. (2020), and Ilhan, Sautner, and Vilkov (2020).

measure the importance of each investor type for the pricing of characteristics in long-horizon expected returns, following Campbell and Shiller (1988) and Vuolteenaho (2002). Consistent with our results for valuations, we find that hedge funds are particularly important for pricing characteristics into expected returns, per dollar of assets under management.

We then use our framework to address two broader questions that relate to policy. First, we analyze how firm valuations and investors' welfare are affected by the transition from active to passive management, which is one of the key trends during the last several decades. We start by documenting two stylized facts. First, the aggregate active share across institutional investors drops from 45% in the early 1980s to a little over 25% at the end of our sample in 2019. Second, we use the estimated demand system to understand how investors became more passive. We find that a reduction in latent demand and declining demand elasticities contribute equal amounts to the reduction in the aggregate active share over this period, while portfolio tilts to characteristics in fact increased investors' active share. A possible interpretation of this new fact is the growth in the asset management industry of "smart beta" and factor-based strategies. These strategies typically involve a well diversified portfolio of securities tilted in the direction of characteristics. This corresponds to a lower demand elasticity and smaller latent demand, yet a stronger portfolio tilt to characteristics.

We then explore how valuations and investors' welfare are affected by this trend. We construct a counterfactual in which we scale the three components in 2019 to their values in 2007, essentially "re-activating" institutional investors. We recompute asset prices and investors' AUM. These calculations imply that if the trend from active to passive management continues, hedge funds and small active investment advisors would underperform relative to other institutions. In addition, it would strengthen the relation between valuations and characteristics.

Our second application is motivated by the observation that 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), 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.[6] 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 asset prices and investors' AUM (a measure of welfare) and assess how they change in these counterfactuals.

As the environmental characteristic is only weakly correlated with all other characteristics, the impact in the valuation regressions is largely limited to the 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. These calculations show how our framework can be used to develop and implement "climate stress tests."

Our paper is part of a broader literature that uses portfolio holdings data to learn about valuations and expected returns. One approach is to invert investors' demand curves, under assumptions about risk perceptions, to estimate expected returns. This seminal idea due to Sharpe (1974) has been applied and extended in recent contributions by Shumway, Szefler, and Yuan (2011) and Egan, MacKay, and Yang (2020), among others.

Our paper relates more closely to a literature on "demand system asset pricing," which models the investors' demand curves and imposes market clearing. 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. Relative this literature, we make five contributions. First, we develop a new framework to quantify how characteristics are priced in the cross section of valuations and expected returns through the portfolio choice of institutional investors and households. Second, we endogenize investors' assets in the

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

counterfactuals, which has been kept fixed in earlier work, which allows us to analyze welfare implications. Third, we use our methodology to analyze questions with policy relevance, such as the transition from active to passive management and the pricing of climate-related risks. Fourth, 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 the analysis.

I. A simple model of how asset prices reflect heterogeneity across investors

We present a simple model to illustrate how we can measure the importance of various investors in the price formation process. While the model is intentionally stylized, the basic economic insights extend to a broad set of asset pricing models. The model also motivates the empirical strategy that we follow in subsequent sections. We summarize the main assumptions and results, and provide further derivations in Appendix B.

Assumptions about beliefs, preferences, and technology We consider a two-period model with time indexed by $t = 0, 1$. There are N assets indexed by $n = 1, \ldots, N$ and I investors indexed by $i = 1, \ldots, I$. The supply of each asset is normalized to one. Vectors and matrices are denoted in bold. Elements of vectors are indexed with parentheses.

Investors have constant absolute risk aversion (CARA) preferences over wealth at time 1,

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

where $\mathbf{q}_i$ is a vector of asset holdings expressed in terms of the number of shares held. Y_{1i} represents other risk factors that impact the investor such as benchmarking, outside income, and time-varying investment opportunities.

The optimization is subject to the intra-period budget constraint

$$A_{0i} = \boldsymbol{q}_i' \boldsymbol{P}_0 + Q_i^0, \tag{2}$$

where $\boldsymbol{P}_0$ denotes the vector of asset prices and Q_i^0 the dollar investment in a cash account. The cash account has a price normalized to one and earns an interest that we normalize to zero. We parameterize the cross-sectional distribution of absolute risk aversion coefficients as $\gamma_i = (\tau_i A_{i0})^{-1}$.[7]

We could extend the model of investor preferences to directly add a "taste" for characteristics (Fama and French 2007). This model extension can be particularly fitting for characteristics that capture a firm's impact on the environment (Pastor, Stambaugh, and Taylor 2020; Pedersen, Fitzgibbons, and Pomorski 2020). Empirically, however, we cannot tell using holdings data whether investors' demand for such a characteristic is driven by risk and return considerations (for instance, due to uncertainty about the transition to a green economy or due to government policy uncertainty) or by non-financial considerations.[8]

The terminal payoffs of firms are denoted by $\boldsymbol{D}_1$ and their book equity values by $\boldsymbol{B}_0$. We define the return on equity (ROE) for firm n as $d_1(n) = D_1(n)B_0^{-1}(n)$. We assume that all investors agree that ROEs follow a factor model,

$$\mathbf{d}_1 = \boldsymbol{g}_i + \boldsymbol{\rho}_i F_1 + \boldsymbol{\eta}_1, \tag{3}$$

where $\text{Var}(\boldsymbol{\eta}_1) = \sigma^2 \boldsymbol{I}$, $\boldsymbol{\eta}_1$ and F_1 are independent, normally distributed with mean zero, and we normalize $\text{Var}(F_1) = 1$. Investors may disagree on the systematic exposure of stocks to the factor, $\boldsymbol{\rho}_i$. In addition, investors may disagree about the expected growth rate, $\boldsymbol{g}_i$. We assume that investors have full information about other investors' beliefs and agree to disagree. They do not revise their beliefs based on asset prices.

In order to estimate the expected growth rate and the riskiness of the firm's future profits,

[7] For this particular choice, the model's implications mimic those of a more standard constant relative risk aversion (CRRA) utility model, while maintaining the tractability of the CARA-normal model. Our modeling strategy follows Makarov and Schornick (2010).

[8] One promising approach to disentangle financial and non-financial concerns may be using survey data (Bauer, Ruof, and Smeets 2019; Krueger, Sautner, and Starks 2020).

investors rely on public information, "characteristics," $\boldsymbol{x}$, and potentially other information, as captured by ν_i^g and ν_i^ρ,

$$g_i(n) = \boldsymbol{\lambda}_i^{g\prime}\boldsymbol{x}(n) + \nu_i^g(n), \tag{4}$$

$$\rho_i(n) = \boldsymbol{\lambda}_i^{\rho\prime}\boldsymbol{x}(n) + \nu_i^\rho(n), \tag{5}$$

where ν_i^g and ν_i^ρ are assumed to be uncorrelated with $\boldsymbol{x}$. The first element of $\boldsymbol{x}$ equals book equity, to capture size differences across firms, and $\boldsymbol{x}$ also includes a constant.

We formulate the budget constraint as

$$A_{1i} = A_{0i} + \boldsymbol{Q}_i'(\boldsymbol{d}_1 - \boldsymbol{MB}_0),$$

where $MB_0(n) = P_0(n)B_0^{-1}(n)$, a firm's market-to-book ratio, and $Q_i(n) = B_0(n)q_i(n)$. We refer to $\boldsymbol{g}_i - \boldsymbol{MB}_0$ as (long-horizon) expected returns.

To complete the model, we assume that the background risk factor Y_{1i} is normally distributed, $Y_{1i} \sim N(\mu_{Yi}, \sigma_{Yi}^2)$, and

$$2\mathrm{Cov}_i\left(Y_{1i}, d_1(n)\right) = y_i(n) = \boldsymbol{\lambda}_i^{Y\prime}\boldsymbol{x}(n) + \nu_i^Y(n), \tag{6}$$

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

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 can extend the model for characteristics to

$$x_k(n) = h_{0,k} + h_{1,k}MB(n) + \nu_k^x(n), \tag{7}$$

where $h_{1,k}$ captures the feedback from valuation ratios to the characteristic and $\nu_k^x(n)$ is a policy shock. In Appendix II.C, we provide the solution for asset prices in this extended model. The solution highlights an identification challenge, namely that $MB(n)$ depends on

$\nu_k^x(n)$ via market clearing. This implies that we cannot estimate (16) using ordinary least squares. We solve this problem in Section V.D and estimate (16) using an instrumental variables estimator.

Model solution We solve the model in Appendix B and summarize the main results here. Investor i's optimal demand is given by

$$\boldsymbol{Q}_i(n) = -\underbrace{\frac{1}{\gamma_i\sigma^2}}_{\beta_{0i}} MB_0(n) + \frac{1}{\gamma_i\sigma^2}\underbrace{\left(\boldsymbol{\lambda}_i^g - c_i\boldsymbol{\lambda}_i^\rho + \boldsymbol{\lambda}_i^Y\right)'}_{\boldsymbol{\beta}_{1i}}\boldsymbol{x}(n) + \frac{1}{\gamma_i\sigma^2}\underbrace{\left(\nu_i^g(n) - c_i\nu_i^\beta(n) + \nu_i^Y(n)\right)}_{\epsilon_i(n)}, \quad (8)$$

where c_i is a scalar that does not vary across securities. Empirically, we can link portfolio holdings to observable characteristics. That said, this expression shows that we cannot tell whether investors attend to a particular characteristic because they view this information as being relevant in forecasting future profits, to assess or hedge risk, or both. Likewise, if an investor deviates from her demand curve conditional on characteristics, which is the last term in (8), we cannot tell whether this is due to a particular view on expected growth rates, risk or hedging benefits.

By imposing market clearing, $\sum_i \boldsymbol{Q}_i = \boldsymbol{B}$, we can solve for equilibrium market-to-book ratios,

$$MB_0(n) \;=\; \overline{\boldsymbol{\beta}}'_{mb}\boldsymbol{x}(n) + \overline{\epsilon}_{mb}(n), \quad (9)$$

where $m_i = (\tau_i A_i)\left(\sum_j \tau_j A_j\right)^{-1}$, $\overline{\boldsymbol{\beta}}_{mb} = \sum_i m_i \boldsymbol{\beta}_{1i} - \frac{\sigma^2}{\sum_i \tau_i A_i}\boldsymbol{e}_1$, with $\boldsymbol{e}_1$ the first unit vector,[9] and $\overline{\epsilon}_{mb}(n) = \sum_i m_i \epsilon_i(n)$.

Hence, valuation ratios are connected to characteristics since investors view those characteristics as being relevant to assess risk (via $\boldsymbol{\lambda}_i^\rho$), to forecast future profitability (via $\boldsymbol{\lambda}_i^g$), or for hedging purposes (via $\boldsymbol{\lambda}_i^Y$). Large investors and investors with more extreme views affect prices more and are therefore more important in the price formation process.

The first element of $\overline{\boldsymbol{\beta}}_{mb}$ has two terms, $\sum_i m_i \boldsymbol{\beta}_{1i}(1) - \frac{\sigma^2}{\sum_i \tau_i A_i}$. The first term, like for all other characteristics, captures how investors use log book equity to forecast a firm's

[9] Recall that we ordered the characteristics in such a way that book equity is the first characteristic.

future growth and to assess its riskiness. The second term reflects the fact that larger firms expose investors to more idiosyncratic risk, which, all else equal, leads to lower valuation ratios. Depending on the slope of the demand curve for individual stocks, we expect log book equity to enter cross-sectional valuation regressions with a negative sign and this effect is larger if stock-level demand is more inelastic.

The contribution of investors to the price formation process We explain how we quantify the importance of an investor, or group of investors, in the price formation process. To this end, we consider the following experiment. An investor k receives an outflow equal to its assets. Investor k's assets then flow to other investors in proportion to each investor's assets. Formally, $A_i^{-k} = \left(1 + \upsilon^{-k}\right) A_i$, with $\upsilon^{-k} = A_k \left(\sum_{i,i\neq k} A_i\right)^{-1} > 0$, and $A_k^{-k} = 0$.

The new prices are given by (9) with modified weights, $m_i^{-k} = \left(\tau_i A_i^{-k}\right)\left(\sum_j \tau_j A_j^{-k}\right)^{-1}$ and analogously for $\overline{\boldsymbol{\beta}}_{mb}$. The change in valuation ratios is then given by

$$MB_0^{-k}(n) - MB_0(n) = \sum_i \Delta m_i^{-k} \boldsymbol{\beta}'_{1i}\boldsymbol{x}(n) + \sum_i \left(\frac{\sigma^2}{\sum_i \tau_i A_i} - \frac{\sigma^2}{\sum_i \tau_i A_i^{-k}}\right) B_0(n) + \sum_i \Delta m_i^{-k} \epsilon_i(n),$$

where $\Delta m_i^{-k} = m_i^{-k} - m_i$.

To clarify the economic intuition, we first consider the case in which $\tau_i = \tau$. Under this assumption, the change in valuation ratios simplifies to

$$MB_0^{-k}(n) - MB_0(n) = \sum_i \Delta w_i^{-k} \boldsymbol{\beta}'_{1i}\boldsymbol{x}(n) + \sum_i \Delta w_i^{-k} \epsilon_i(n),$$

where $\Delta w_i^{-k} = \left(1 + \nu^{-k}\right) m_i$ for $i \neq k$ and $\Delta w_k^{-k} = -m_k$. The price effects now only differ due heterogeneity in preferences for characteristics and in latent demand. The additional price effects are due to heterogeneity in τ_i, which reflect differences in risk aversion or, more broadly, heterogeneity in demand elasticities. In all cases, the strength of these effects depends on an investor's size.

Put together, the valuation impact of an investor depends on its size, heterogeneity in demand elasticities, and differences in the investor's demand for characteristics and latent demand.

Lastly, we define $\boldsymbol{g}_R(\boldsymbol{x}) - \boldsymbol{MB}_0$ as our measure of long-horizon expected returns, where $\boldsymbol{g}_R$ is the rational expectations forecast of $\boldsymbol{d}_1$ conditional on characteristics $\boldsymbol{x}$, $\boldsymbol{g}_R(\boldsymbol{x}) \equiv \mathbb{E}[\boldsymbol{d}_1 \mid \boldsymbol{x}]$. We can therefore also compute the impact of investor k on expected returns by comparing $\boldsymbol{g}_R(\boldsymbol{x}) - \boldsymbol{MB}_0$ to $\boldsymbol{g}_R(\boldsymbol{x}) - \boldsymbol{MB}_0^{-k}$. In addition, we can measure how much investor k matters for the relation between long-horizon expected returns and characteristics, $\boldsymbol{x}$.[10]

II. 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).

II.A. 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 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.

II.B. The universe of assets and asset demand

Financial markets are highly concentrated, as we show in Section III. 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 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 $n = 0$.

[10]This calculation is accurate under the assumption that $\boldsymbol{g}_R(\boldsymbol{x})$ does not change in the counterfactual, that is, that there are no real effects in response to the counterfactual investor flow. To relax this assumption, we would need to allow for corporate decisions regarding capital structure, investment, and payout policy. While this is an interesting extension to explore in future work, it is beyond the scope of this paper.

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

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

where

$$\delta_{i,t}(n) = \exp\left\{b_{0,i,t} + \beta_{0,i} mb_t(n) + \boldsymbol{\beta}'_{1,i} \boldsymbol{x}_t(n)\right\} \epsilon_{i,t}(n), \tag{11}$$

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, $\epsilon_{i,t}(n)$. 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 I 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 (11) 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 (9).

II.C. Market clearing

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

$$ME_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n). \tag{12}$$

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.

III. Data and stylized facts

III.A. Data

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

We classify investors into eight groups. First, we group investors by type: Investment Advisors, Long-Term Investors, Hedge Funds, Private Banking, Brokers, and Households. The category Long-Term includes primarily insurance companies and pension funds, and the category Investment Advisors includes investment advisors and mutual funds.[11] We use FactSet's classification of investor types to assign institutions to institutional groups. Second, as the group of investment advisors is large, we further split this group of investors 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 so that the total holdings of a company add up to the company's market capitalization. In rare instances, the total holdings exceed the market

[11] 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.

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 we only measure the long positions (Lewellen 2011).[12]

In addition to characteristics constructed using data from firms' income statements and balance sheets, we use 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.

Our methodology can naturally be applied to other characteristics or to different environmental and governance scores as the literature evolves. 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.

III.B. Firm granularity

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

[12] 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.

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.

For the remainder of the paper, 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 shows that the economic impact of these firms is small among all listed firms.

III.C. Distribution of institutional types

Figure 2 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 (see for instance Azar, Schmalz, and Tecu (2018)), and this concentration has increased over time (Itzhak et al. 2018). Part of this concentration is driven by the increased popularity of passive indexing strategies, which we explore in more detail in Section VII.

IV. Cross-sectional valuation regressions

In this section, we 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.

IV.A. 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-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 Guitierrez 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. Lastly, we include the environmental scores and governance scores. We cross-sectionally standardize all characteristics, by quarter, by removing the mean and dividing by the standard deviation.

IV.B. Explaining valuation ratios using characteristics

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

$$mb_t(n) = a_t + \boldsymbol{\lambda}'_{mb}\boldsymbol{x}_t(n) + \epsilon_t(n), \tag{13}$$

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 (9) and points to downward-sloping demand curves for individual stocks, as discussed in the theory in Section I. 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.

Table 3 shows that the same characteristics also explain a substantial fraction of the cross-sectional variation in future profitability,[13] often with similar coefficients in terms of sign and magnitude as in the valuation regressions.[14] 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 (2009). 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 VI.

V. Estimating the asset demand system

In this section, we discuss how we estimate the asset demand system as summarized by equations (10) and (11).

V.A. *The estimating equation*

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

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left\{b_{0,i,t} + \beta_{0,i} mb_t(n) + \boldsymbol{\beta}'_{1,i}\boldsymbol{x}_t(n)\right\}\epsilon_{i,t}(n), \tag{14}$$

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,

$$\mathbb{E}_t\left[\epsilon_{i,t}(n) \mid \boldsymbol{x}_t(n)\right] = 1. \tag{15}$$

[13]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 $\rho = 0.95$.

[14]Kacperczyk, Sundaresan, and Wang (2019) show that price informativeness is increasing in the fraction of equity held by foreign investors, in particular in developed economies (see also Bena et al. (2017)).

In Section V.D, 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 V.B. 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 V.C to estimate the demand curves for each investor separately.

V.B. 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 as latent demand is correlated across investors or as 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 V.D.[15]

V.C. 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 (15) 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 C. To estimate the model, we use quarterly data.

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.[16] We therefore need to choose a shrinkage target and how much shrinkage to apply. To

[15] 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.

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

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 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 $\xi = 0.7$.

V.D. Robustness and potential threats to identification

We make two important identifying assumptions in estimating the asset demand system. First, we assume 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 assume that latent demand is exogenous to the characteristics, which rules out that characteristics depend on prices. We now explore the robustness of our demand elasticity estimates to those assumptions and discuss potential threats to identification.

While investment mandates and restrictions are ubiquitous, measuring investment mandates is challenging. 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 3, 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 demand elasticity, $\beta_{i,0}$, by institutional type in 2010, which is in the middle of our sample, in Figure 3. While there is some variation, the demand elasticity estimates are robust to varying the window to estimate the investment mandate.

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. In the top panel of Figure 4, we show a scatter plot of $\beta_{0,i}$ of our benchmark estimates and estimates using our instrument with the only difference that we exclude hedge funds in its construction. We find that the two sets of estimates are highly correlated.

The second assumption is that the characteristics, $\boldsymbol{x}_t(n)$, are exogenous to latent demand. We now extend our model to relax this assumption. 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

$$x_{k,1,t}(n) = h_{0,k} + h_{1,k} mb_t(n) + \boldsymbol{h}'_{2,k} \boldsymbol{x}_{2,t}(n) + \nu^x_{k,t}(n), \tag{16}$$

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 $\mathbb{E}[\epsilon_{i,t}(n) \mid \boldsymbol{x}_t(n)] = 0$,

$$\begin{aligned} \mathbb{E}[\boldsymbol{\nu}^x_t(n) \mid z_{i,t}(n), \boldsymbol{x}_{2,t}(n)] &= 0, & (17) \\ \mathbb{E}[\epsilon_{i,t}(n) \mid z_{i,t}(n), \boldsymbol{\nu}^x_t(n), \boldsymbol{x}_{2,t}(n)] &= 0. & (18) \end{aligned}$$

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 panel of Figure 4, 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 are highly correlated, which illustrates the robustness of our results 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.

VI. Demand estimation and implications for asset prices

In this section, we present the demand estimation results and we compute how much different investors matter for asset prices, both unconditionally and conditional on characteristics. We also show how different investors affect the relationship between expected returns across firms and characteristics.

VI.A. Demand estimation results

We present the asset demand estimation results in Figure 5, Figure 6, and Table 4. To summarize each investor's demand curve, we compute the time-series average of coefficients. In Figure 5, 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.[17]

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 to 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 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

[17]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.

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 index, 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 6, 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 comes 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.

VI.B. Measuring the importance of investors for asset prices

We use the demand system estimates to measure the impact of different investors on valuations. We closely follow the experiment we discussed in Section I. In particular, for a specific investor, or group of investors, we consider an outflow equal to their assets.

For expositional simplicity, we consider a single investor k. We refer to counterfactual values with a superscript "CF". We set $A_{kt} = 0$ and add a flow to the assets of all other institutional investors

$$A_{i,t}^{CF} = A_{i,t} R_{i,t}^{P} + F_{i,t}, \tag{19}$$

where $F_{i,t} = A_{k,t} A_{i,t} \left(\sum_{j, j \neq k, HH} A_{j,t} \right)^{-1}$ and HH indexes households. 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 flows occur. An important extension relative to the literature is that we endogenize the distribution of assets.[18] This allows us to explore the impact on investors' assets and thus a measure of welfare.

We then solve for prices so that markets clear, as in (12),

$$ME_t^{CF}(n) = \sum_{i=1}^{I} A_{i,t}^{CF} w_{i,t}^{CF}(n), \tag{20}$$

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 (19).

To measure the impact of different investors on asset prices, we compute the average change in valuations

$$\theta = \frac{1}{T} \sum_t \left(\frac{\sum_{n=1}^{N} \mid ME_t^{CF}(n) - ME_t(n) \mid}{\sum_{n=1}^{N} ME_t(n)} \right), \tag{21}$$

which measures the total repricing if capital flows from one investor, or a group of investors,

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

to all other investors.

VI.C. How much do different investors matter for asset prices?

We report the results in Table 5. In the first column, we report the 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 the previous section. 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, brokers only move 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. It may be the case that brokers have a larger impact on asset prices, for instance, by extending leverage to other investors, including hedge funds. We think that understanding such linkages is an interesting topic for future research.

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 mispricing 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.

VI.D. Investor size and repricing

In Figure 7, we explore the link between investor size and repricing in more detail. In the top panel, we plot the AUM share (red bars) and the repricing impact (blue bars). We sort institutions into five quintiles so that the total AUM per group is identical (up to discreteness). As we focus on institutions, the AUM shares add up to less than 100% and the remainder is held by the household sector. In the bottom panel, we plot the repricing relative to the AUM shares, which therefore closely mimic the blue bars in the top panel.

We find that small investors (quintile 5), as a group, have an outsized effect on prices compared to large investors (quintile 1). This is the result of two reinforcing effects. First, small investors have larger active shares[19] and smaller choice sets. This implies that reallocating their assets leads to a larger demand shock. Second, as we show in Table 4, larger and more passive investors have more inelastic demand. As a result, the residual demand curve is steeper when small investors experience demand shocks as opposed to when large investors experience demand shocks. Both effects combined result in more repricing for small investors compared to large investors.

VI.E. Which investors matter for the link between characteristics and valuation ratios?

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 (13). In the first column of Table 6, 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%.

[19] This is consistent with Cremers and Petajisto (2009).

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.

VI.F. The impact of investors on long-horizon expected returns

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 (2009). We write the log market-to-book ratio of firm n, $mb_t(n)$, as

$$mb_t(n) = \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t \left[e_{t+s}(n) \right] - \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t \left[r_{t+s}(n) \right], \tag{22}$$

where

$$e_t(n) = \ln \left(1 + \frac{\Delta BE_t(n) + D_t(n)}{BE_{t-1}(n)} \right), \tag{23}$$

$$r_t(n) = \ln \left(1 + \frac{\Delta ME_t(n) + D_t(n)}{ME_{t-1}(n)} \right), \tag{24}$$

and $BE_t(n)$ a firm's book equity, $ME_t(n)$ its market equity, and $D_t(n)$ its dividend.[20]

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 re-

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

turns, 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.[21]

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).

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

We now use the estimated asset demand system to analyze the impact of two key developments in the asset management industry on the cross-section of valuations and the welfare of investors. In particular, in this section we study the transition from active to passive management and, in the next section, we study the growing concern about the pricing of climate-related risks by investors.

VII.A. Understanding the trend towards passive management

We first summarize the basic fact that institutional investors have become more passive over time, as measured by the active share. We then use the estimated asset demand system to understand *how* investors became more passive due to changes in components of their strategies. Finally, we study how this trend impacted different firms and investors.

Let $w_{it}^m(n)$ be the market portfolio based on the stocks held by investor i. We define an aggregate measure of active risk taking by institutions as

$$AS_t = \sum_{i, i \neq HH} S_{it} AS_{it},$$

where $S_{it} = A_{it}/(\sum_{j, j \neq HH} A_{jt})$, $AS_{it} = \frac{1}{2}\sum_n \mid w_{it}^{\star}(n) - w_{it}^m(n) \mid$, and $w_{it}^{\star}(n) = \frac{\delta_{it}(n)}{\sum_m \delta_{it(m)}}$.

[21] 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 $(1-0.932 \times 0.969)^{-1} \simeq 10$.

In the right panel of Figure 8, we plot AS_t for our sample. There is a strong decline during our sample. In the left panel, we plot the same trend but now using a sample starting in 1980 based on the data used in Koijen and Yogo (2019). This illustrates the broader trend during the last 40 years. We next turn to understanding *how* investors changed their strategies over time.

We write $\delta_{it}(n)$ as

$$\delta_{it}(n) \quad = \quad \exp(me_t(n)) \times \exp((\beta_{0i} - 1)me_t(n)) \times \exp(\hat{\boldsymbol{\beta}}_{1i}^{\prime}\boldsymbol{x}_t(n)) \times \epsilon_{it}(n),$$

where $\hat{\boldsymbol{\beta}}_{1i} = \boldsymbol{\beta}_{1i} - \sigma_b\beta_{0i}\boldsymbol{e}_1$ and σ_b is the cross-sectional standard deviation of log book equity that we use to standardize the characteristic.

This decomposition shows that an investor's portfolio deviates from the market portfolio due to elastic demand, $\beta_{0i} - 1 < 0$, a preference for characteristics, $\hat{\boldsymbol{\beta}}_{1i}$, and latent demand, $\epsilon_{it}(n)$. We decompose the decline in the active share into these three components for the period from 2007 to 2019, which captures the long term trend better than the period from 2000 to 2019, see Figure 8.

We compute portfolio weights using $\delta_{it}(n)$ for a given combination of $(\beta_{0i}, \hat{\boldsymbol{\beta}}_{1i}, \epsilon_{it}(n))$, $w_{it}^{\star}(n; \beta_{0i}, \hat{\boldsymbol{\beta}}_{1i}, \epsilon_{it}(n))$. We then decompose the active share of a given investor in a given quarter as

$$\begin{aligned} AS_{it} \quad &= \quad \frac{1}{2}\sum_n \mid w_{it}^{\star}(n; \beta_{0i}, \hat{\boldsymbol{\beta}}_{1i}, \epsilon_{it}(n)) - w_{it}^m(n) \mid - \frac{1}{2}\sum_n \mid w_{it}^{\star}(n; \beta_{0i}, \hat{\boldsymbol{\beta}}_{1i}, 1) - w_{it}^m(n) \mid \\ &+ \quad \frac{1}{2}\sum_n \mid w_{it}^{\star}(n; \beta_{0i}, \hat{\boldsymbol{\beta}}_{1i}, 1) - w_{it}^m(n) \mid - \frac{1}{2}\sum_n \mid w_{it}^{\star}(n; \beta_{0i}, 0, 1) - w_{it}^m(n) \mid \\ &+ \quad \frac{1}{2}\sum_n \mid w_{it}^{\star}(n; \beta_{0i}, 0, 1) - w_{it}^m(n) \mid . \end{aligned}$$

The first line measures the contribution of latent demand, the second line of portfolio tilts to characteristics, and the third line captures the contribution due to elastic demand.

We plot the change in the three components from 2007 to 2019 in Figure 9. Latent demand and demand elasticities contribute equal amounts to the reduction in the active share, while portfolio tilts to characteristics in fact increased the investors' active share.

A possible interpretation of this finding is the growth in the asset management industry of "smart beta" and factor-based strategies. Those strategies typically involve a well diversified portfolio of securities tilted in the direction of characteristics. This corresponds to a lower demand elasticity and smaller latent demand, yet a stronger portfolio tilt to characteristics. This is a paradox of modern passive asset management in which the active share declines, yet characteristics are priced more strongly.

VII.B. The impact on firm valuations and investors

We are interested in the impact of the trend in the active share on firm valuations and investors' welfare if investors in 2019 would be as active as in 2007. This requires us to specify how we "re-activate" investors, for which we use the decomposition in the previous section.

Specifically, we adjust the coefficients of the demand system to match the components of the active share in 2007. We select three scalars, (c_1, c_2, c_3), to adjust demand elasticities, $1 - \tilde{\beta}_{0,i} = c_1(1 - \beta_{0,i})$, the sensitivity to characteristics, $\tilde{\boldsymbol{\beta}}_{1,i} = c_1\hat{\boldsymbol{\beta}}_{1,i}$, and latent demand, $\tilde{\epsilon}_{i,t}(n) = c_2\epsilon_{i,t}(n)$. In our specification, the demand elasticity is (proportional to) $1 - \beta_{0,i}$, which explains our choice for the scaling factor of $\beta_{0,i}$. We adjust the constant of the demand curve so the fraction invested in the outside asset does not change. We choose the scaling factors so that the active share contributions of each of the three components, and thus also the overall active share, matches those of 2007.[22] For this counterfactual demand system, we solve for asset prices and assets under management.

Before discussing the results, we provide intuition for how this counterfactual affects firm valuations and investors' welfare. There are three effects. First, if the (size-weighted, across investors holding a given stock) average latent demand across institutional investors is positive, re-activating investors leads to relatively higher valuations and the opposite is true for firms with negative average latent demand. After all, those firms with positive latent demand receive an additional demand shock relative to the firms with negative latent demand, which boosts their valuations. Second, and analogously, if $\overline{\boldsymbol{\beta}}_1' \boldsymbol{x}_t(n) > 0$, re-activating institutional investors leads to relatively higher valuations compared to the case when $\overline{\boldsymbol{\beta}}_1' \boldsymbol{x}_t(n) < 0$. The

[22] The solution is given by $(c_1, c_2, c_3) = (1.93, 0.88, 1.34)$.

final effect is due to changes in investors' demand elasticity. As demand becomes more elastic, investors allocate more capital to stocks with low market capitalization relative to stocks with a high market capitalization, all else equal.

The change in valuations then affects investors' assets. For instance, if an investor has positive latent demand for a stock, but the stock's size-weighted average latent demand is negative, the investor will experience a lower return on that position relative to an investor who has positive latent demand for the same stock.

In Table 7, we report the impact on firm valuations by regressing $mb_t(n)$, in the first column, and the change, $mb_t^{CF}(n) - mb_t(n)$, in the second column, on firm characteristics in the last quarter of 2019. We find that re-activating investors shifts the coefficients on both the environmental and governance characteristics closer to zero. While a one-standard deviation change in the environmental index increases valuation ratios by 23% in 2019, this would reduce by 14% if investors are as active as in 2007. For the entrenchment index, the response would reduce toward zero from -14% to -5=-14%+9% per one standard deviation increase in the entrenchment index. Taken together, these results imply that if the trend from active to passive management continues, characteristics play an increasingly important role in explaining valuation ratios.

In Figure 10, we plot the changes in assets under management if institutional investors are as active in 2019 as they were in 2007. If we re-activate investors, the largest beneficiaries are small-active investment advisors, who experience a 6.9% increase, and hedge funds, who experience a 14.1% increase. We find that the assets under management of all other institutional investors decline.

This implies that if the trend of the last four decades continues, and the activeness of institutional investors declines even further, hedge funds and small-active investment advisors would underperform relative to the other investors. Intuitively, hedge funds have high latent demand for stocks with positive latent demand among institutions. This implies that as other institutions reduce latent demand in their transition to passive management, hedge funds underperform.

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

VIII.A. 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 we discuss in more detail in Section VIII.C. 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 5). 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.

VIII.B. Empirical results

In Table 8, 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.[23] 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 11 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.

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

VIII.C. Potential extensions

We have thus far focused on a particular form of regulatory risk and on stakeholder risk. While those are two important dimensions, as indicated by the survey of Stroebel and Wurgler (2021), we conclude by briefly discussing how our framework can be extended to cover other climate-related risks.

One interesting extension is to model the impact of a carbon tax on firm valuations and investors. As detailed data on carbon emissions are available for a large number of firms, we can adjust profits for a given carbon tax policy. In the presence of a carbon tax, the regulatory framework of banks and insurance companies may also be adjusted to align with the tax incentives. This would would amplify the impact of a carbon tax.

Another extension could be to model the expected impact of physical damages and the uncertainty surrounding it. While modeling such damages is challenging, it also implies that future cash flows of exposed firms are risky. To the extent that we can use observable characteristics to capture such risks, we can construct counterfactuals in which investors' perception of risk changes.

By simultaneously adjusting characteristics and asset demand, we can develop a comprehensive framework to conduct "climate stress tests" that could be useful for, for instance, bank and insurance supervisors across the world who are currently exploring such questions.

IX. Conclusion

We develop a framework to quantitatively assess how much different investors contribute to incorporating information into prices and long-horizon expected returns. Our framework allows economists to put numbers on narratives that explain patterns in prices and characteristics using different groups of investors such as retail investors, hedge funds, and patient long-term investors.

We show that a small set of characteristics explains more than half of the cross-sectional variation in valuation ratios in a panel of countries. The same characteristics also predict future profitability with comparable coefficients. To measure how investors' demands respond to the characteristics, we estimate an asset demand system. The demand system allows us to quantify the importance of different institutional types (e.g., mutual funds and broker dealers) for price formation.

We find that hedge funds, per dollar of assets that they manage, have the largest impact on prices. For the pricing of characteristics, we focus on how investors price environmental and governance characteristics. We find that foreign investors are particularly important for the valuation of green firms, while small-active investment advisors for the valuation of well-governed firms. Our methodology can easily be adopted to other characteristics, and can be applied to individual institutional investors as well as groups of institutions.

We use the estimated asset demand system to analyze the impact of two key trends in the asset management industry on firm valuations and investors' welfare. First, we study the transition from active to passive management. Second, we analyze how climate-related risks, either due to changes in regulation or changes stakeholders' preferences, affect asset prices and investors' welfare. We discuss how the second application can be used to develop "climate-risk stress tests" for a broader set of climate-related risks.

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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 represents 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 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. 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 oefficients are multiplied by 100 except for $LNmebe$. 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
Total Repricing by Investor Type

	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

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

	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. 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. Holdings data are from FactSet. Firm-level fundamentals are from CRSP and Compustat.

Table 7
Change in Valuation Regression Coefficients Active Share Counterfactuals (2019)

	Original	Change
Environment	0.23	−0.14
	(4.61)	(−4.43)
Governance	−0.14	0.09
	(−1.97)	(1.86)
Log Book Equity	−0.74	−0.21
	(−19.91)	(−8.76)
Foreign Sales	0.11	−0.02
	(3.49)	(−0.89)
Lerner	0.11	−0.04
	(3.45)	(−2.13)
Sales to Book	0.22	−0.09
	(6.18)	(−3.91)
Dividend to Book	0.16	−0.03
	(4.47)	(−1.54)
Market Beta	−0.04	0.02
	(−1.27)	(1.12)
Adj. R^2	0.65	0.29
Num. obs.	540	540

The first column is a regression of log market-to-book ratios on characteristics. The second column is a regression of changes in log market-to-book ratios on characteristics. The new market-to-book ratios are calculated in a scenario where institutional demand curves in 2019 re-activated so that components of active share are the same as in 2007. 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. Holdings data are from FactSet. Firm-level fundamentals are from CRSP and Compustat. Data is end of year for 2019.

Table 8
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. 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. Holdings data are from FactSet. Firm-level fundamentals are from CRSP and Compustat. Data is end of year for 2019.

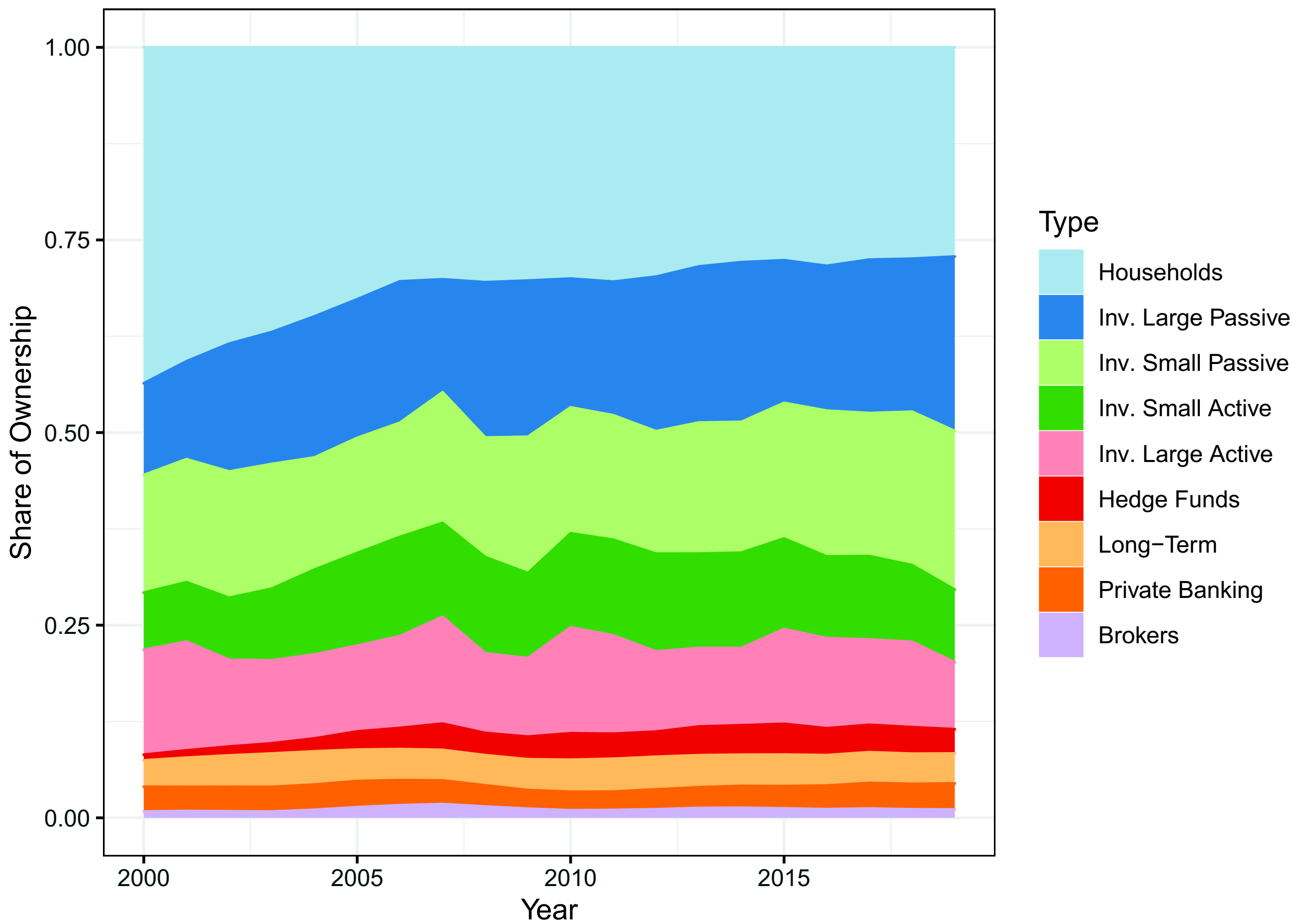

Figure 2
Time Series of Ownership by Institutional Type

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.

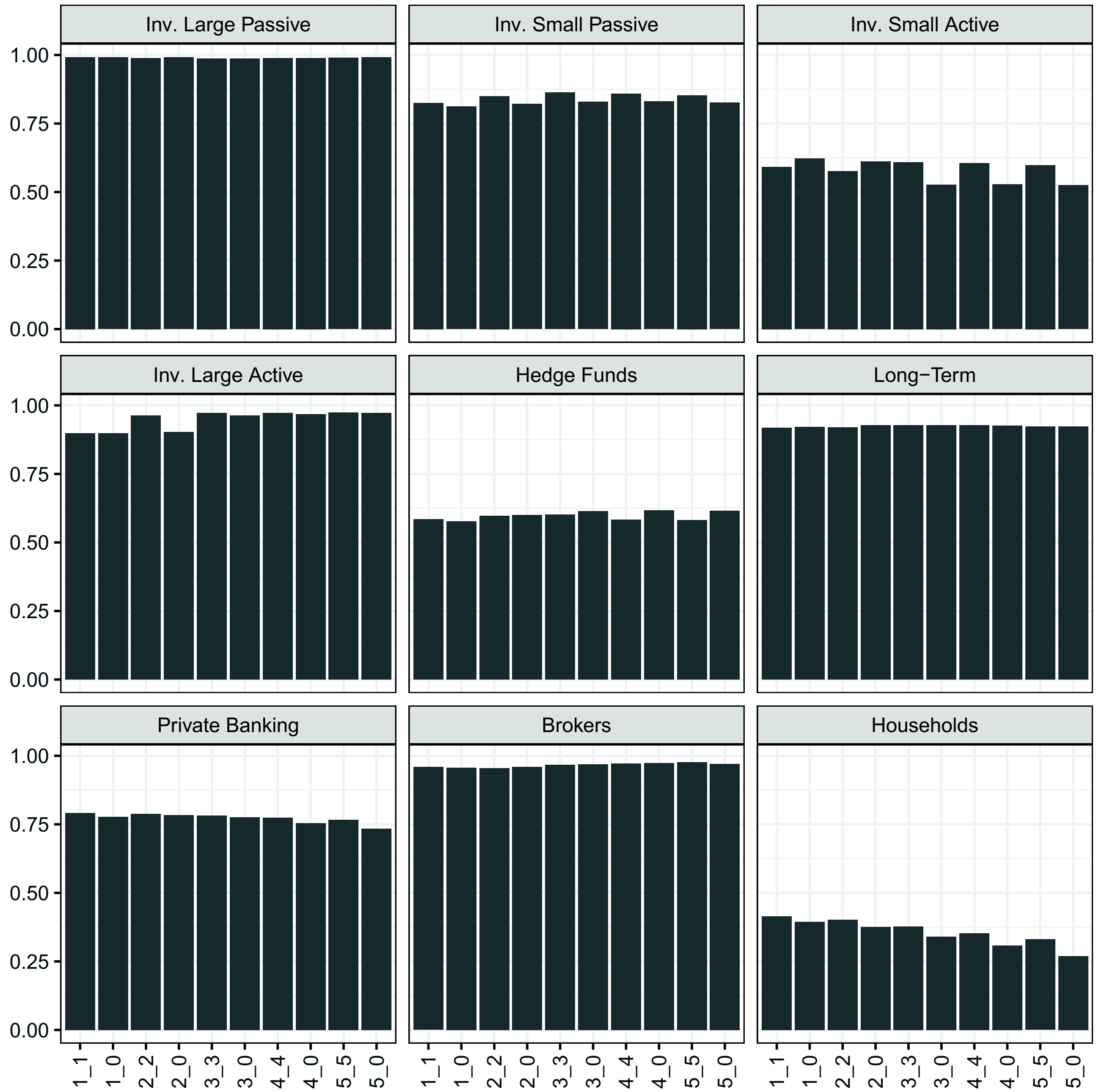

Figure 3
Expanding Window Demand Coefficients

Figure presents estimates of 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 are 3 years back and 0 years forward.

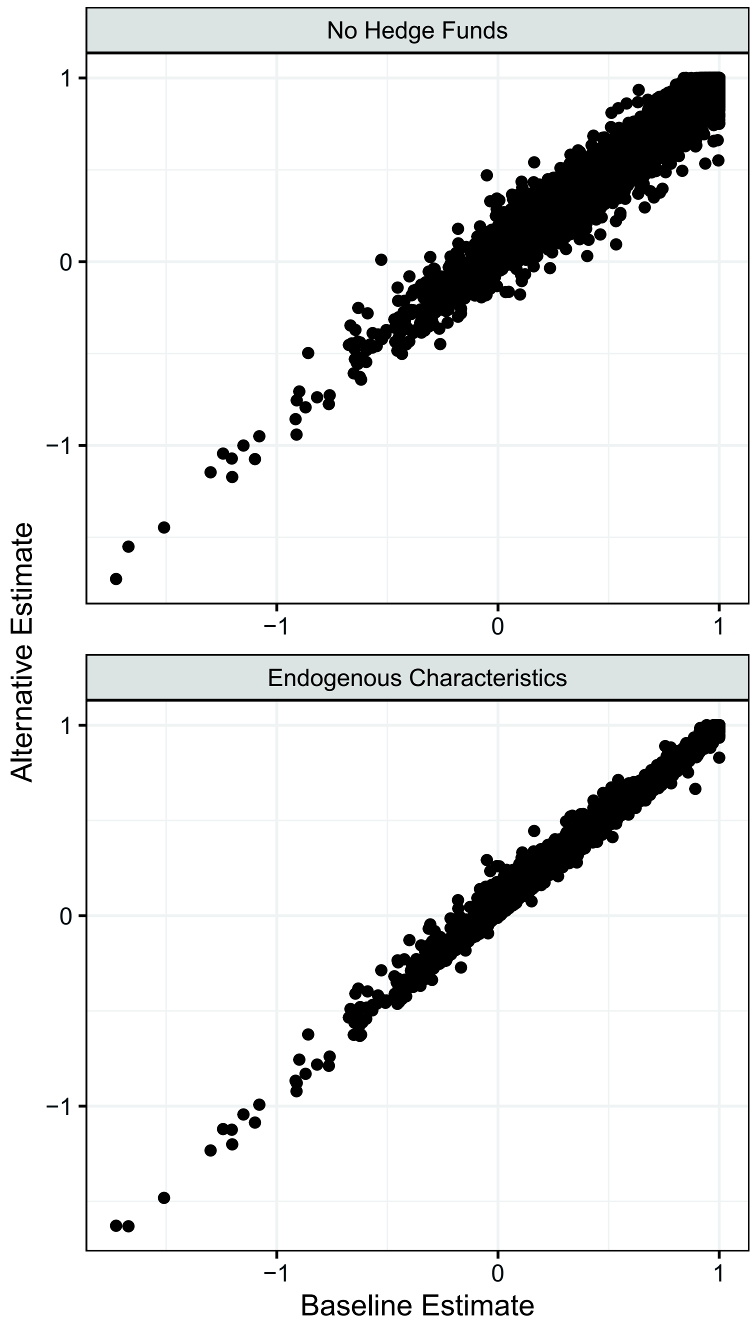

Figure 4

Comparison of Baseline Estimates with Alternative Estimates

Figure displays the coefficient on log market-to-book for two alternative estimates versus the baseline estimates. In the top panel the alternative estimates are from a model that allows for endogenous dividend-to-book. In the bottom panel the instrument for market equity is constructed omitting hedge funds. Firm-level fundamentals are from CRSP and Compustat. Holdings data are from FactSet. The sample runs from 2000 to 2019.

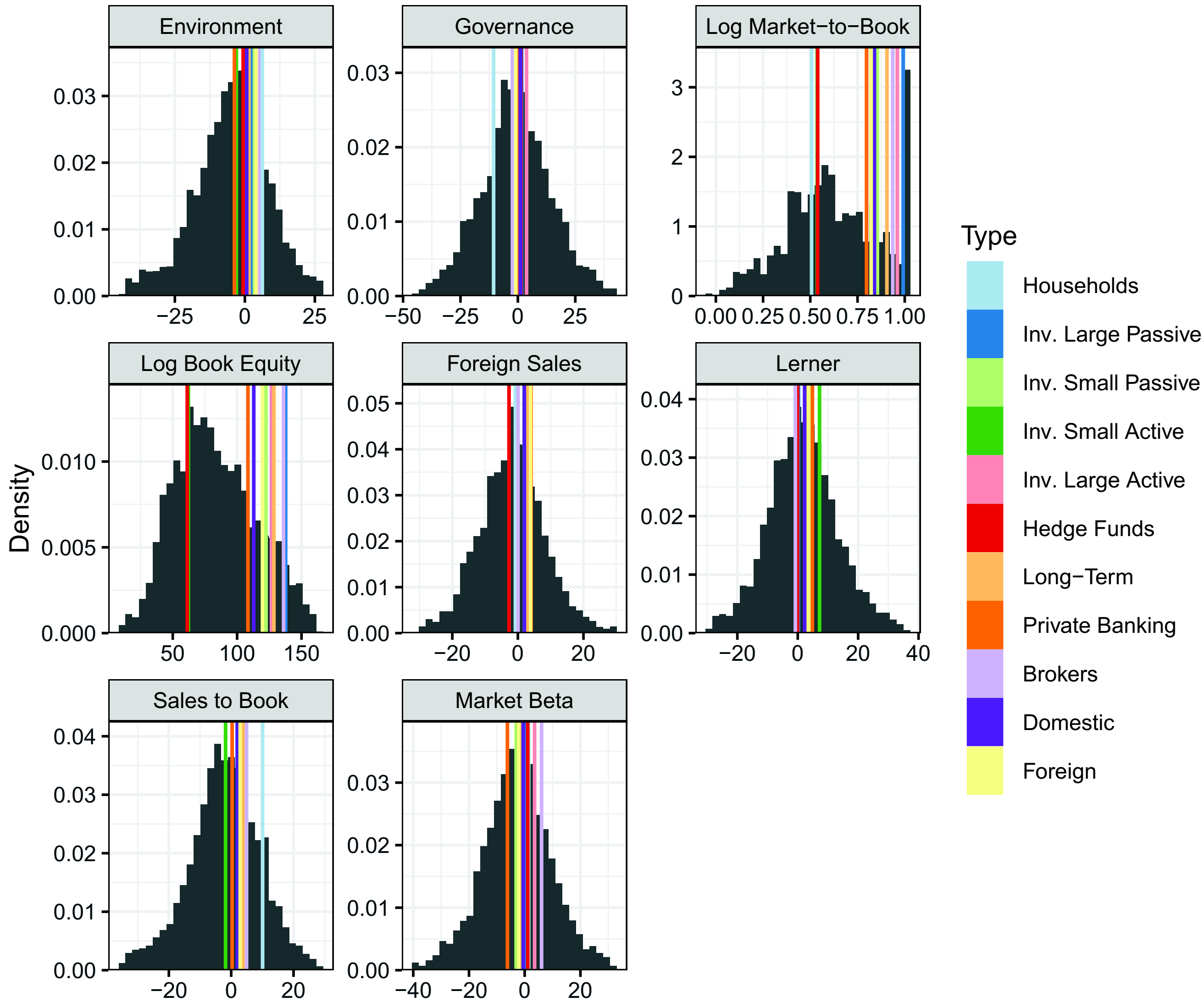

Figure 5

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 institutions 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.

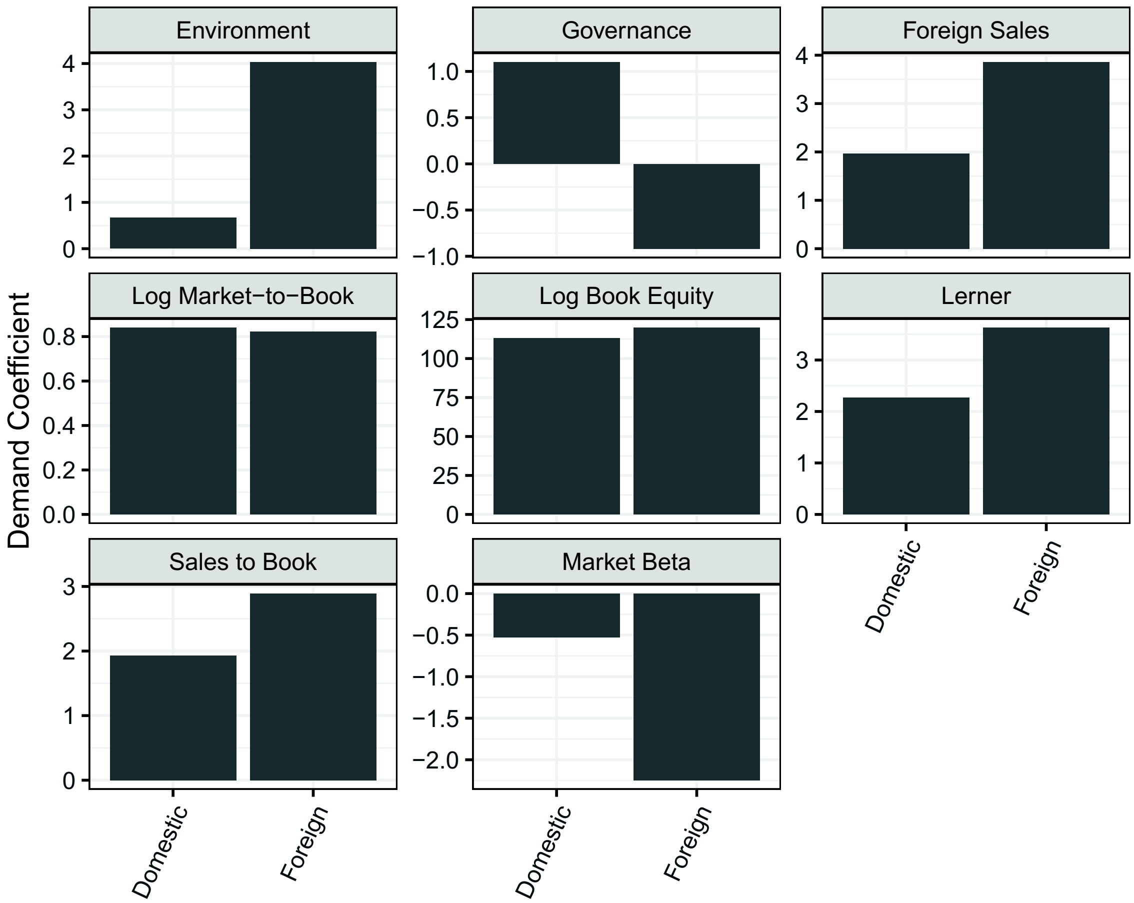

Figure 6

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.

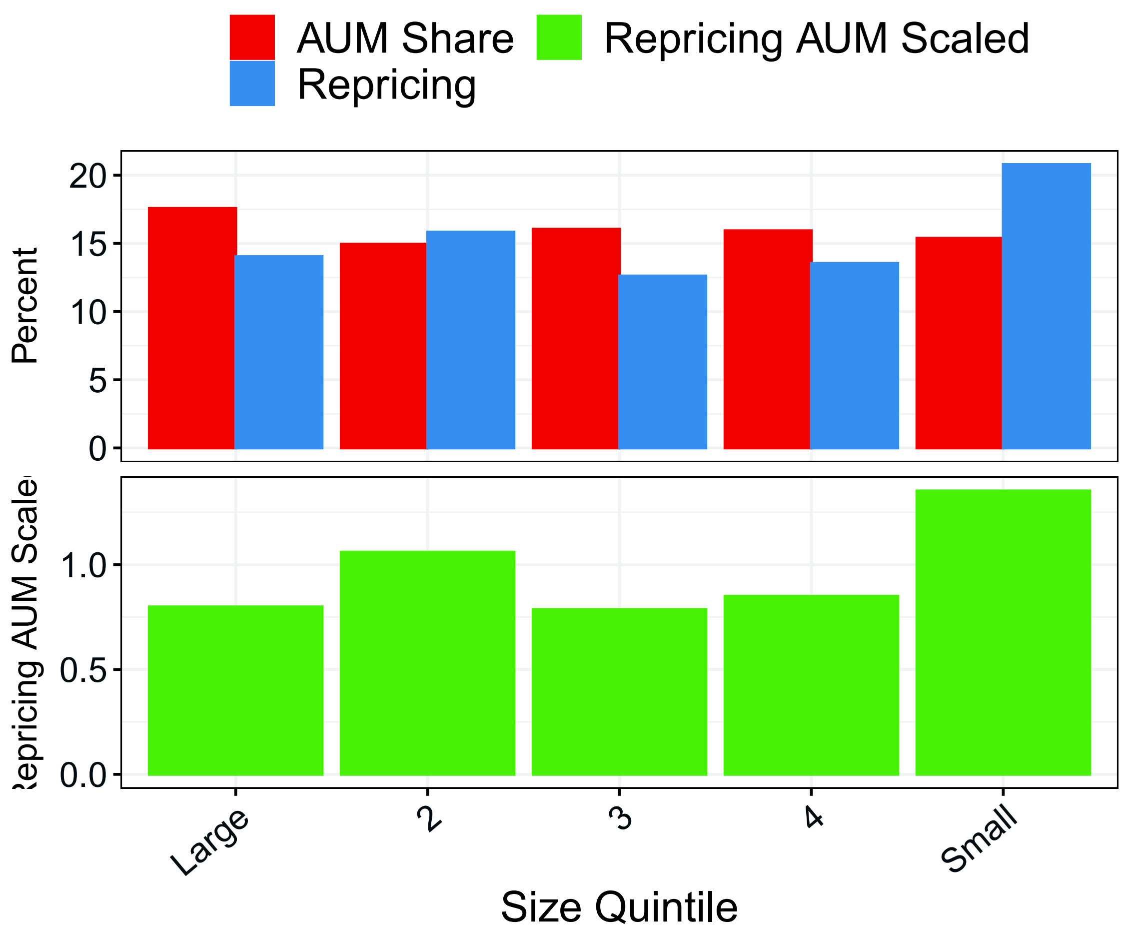

Figure 7
Total Repricing by Size

The top panel reports the fraction of assets under management and repricing. Repricing is the percent change in market cap if the assets of an investor size quintile are reallocated as flows to all other institutional investors in proportion to their assets. The bottom panel reports the change in market cap normalized by the fraction of ownership. The bottom panel reports the change in market cap normalized by the fraction of ownership. Each bar is the time series average of the quarterly values. Firm-level fundamentals are from CRSP and Compustat. Holdings data are from FactSet. The sample runs from 2000 to 2019.

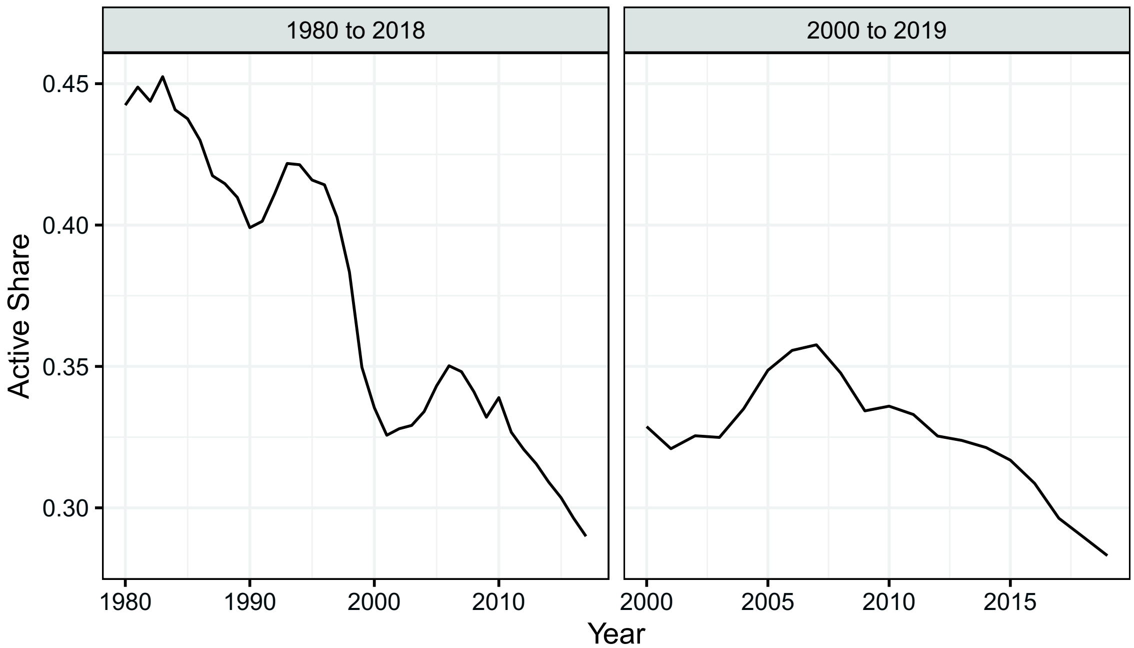

Figure 8
Aggregate Active Share Over Time

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.

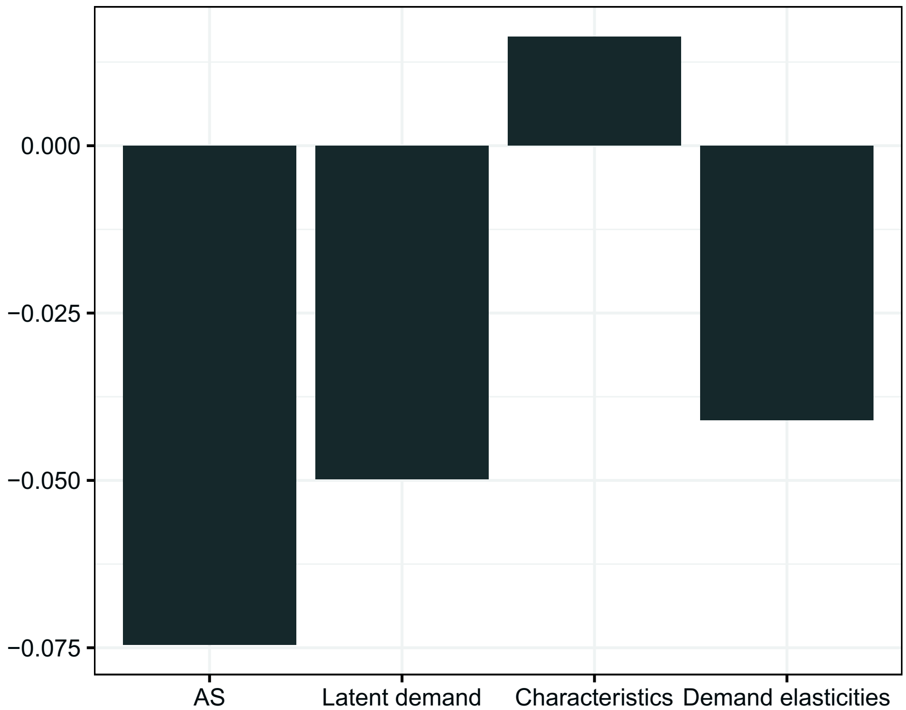

Figure 9
Decomposition of Change in the Active Share

Decomposition of change in the aggregate active share from 2007 to 2019. 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. The first bar measures the total change in the active share. The remaining three bars decompose the total change. The second bar measures the change that can be attributed to changes in latent demand, the third due to changes in characteristics demand, and the fourth due to changes in demand elasticities. Holdings data are from FactSet. Firm-level fundamentals are from CRSP and Compustat.

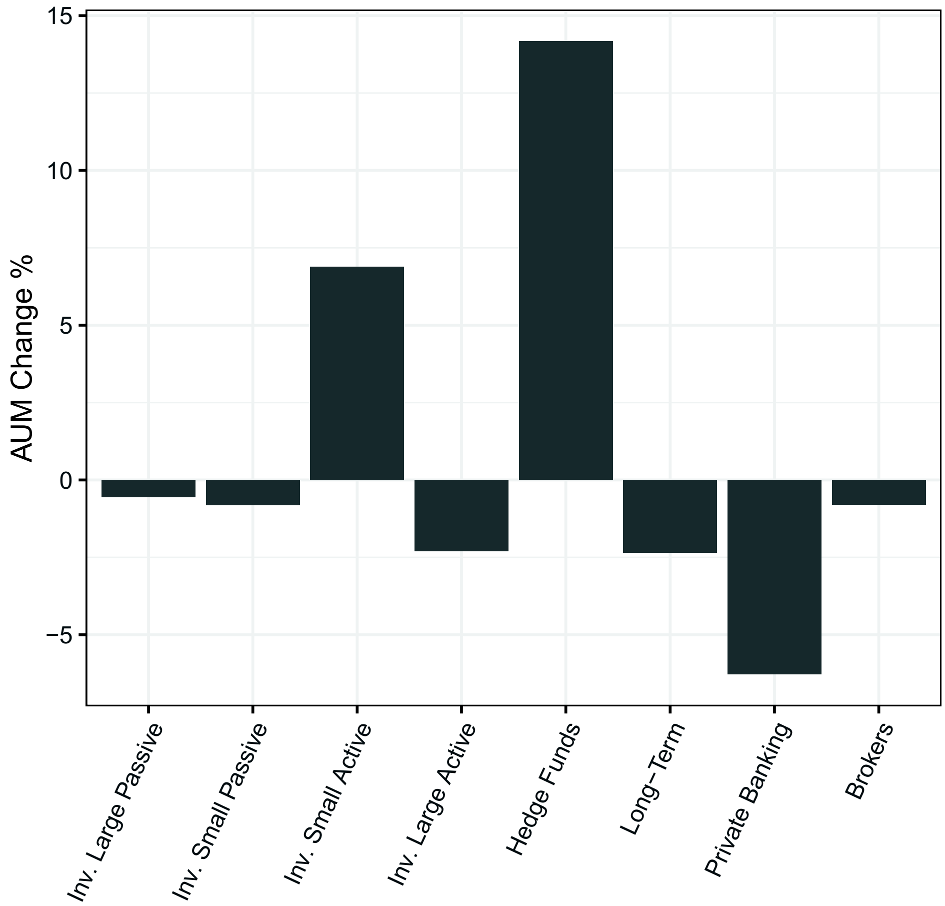

Figure 10
AUM Change in Active Share Counterfactuals

Figure presents the percent change in AUM for each institution type in a scenario where institutional demand curves in 2019 re-activated so that components of active share are the same as in 2007. 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.

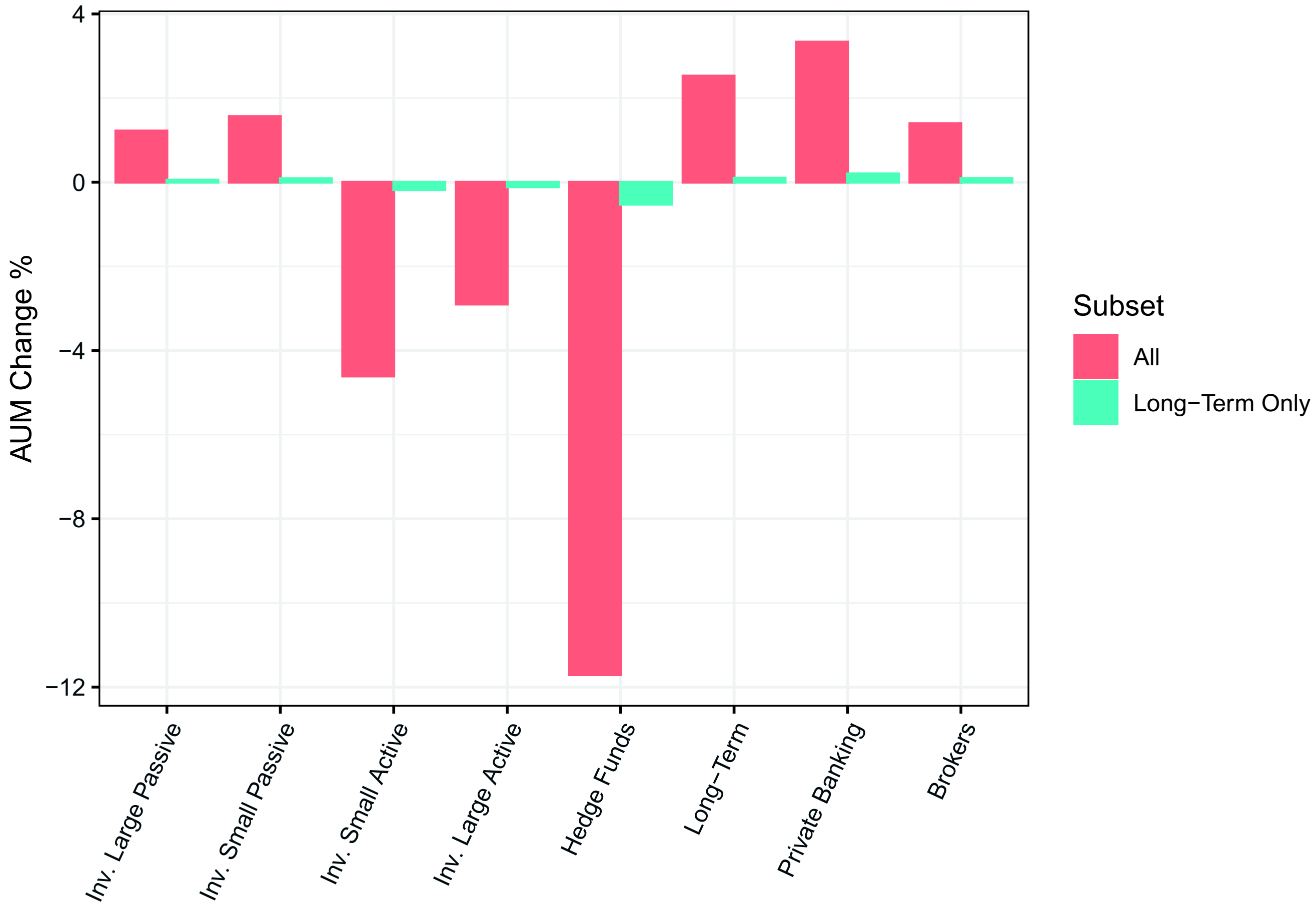

Figure 11
AUM Change in ESG Counterfactuals

Figure presents the percent change in AUM for each institution type in scenarios where institutions care more about environmental scores of companies. 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.

A. Empirical appendix

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 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 firms market cap. On occasion, total holdings of institutions are greater than the market cap, in which case we proportionally scale back all institutions holdings.

We split investment advisors into four groups. We first split investors into two groups of equal size in a given quarter. Within each size group, we split investors into two groups which 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, divided by two to avoid double-counting.

We classify the outside asset as any firm which is outside of the top 90% of market cap. Any institution which has less that $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.

Fundamentals and prices We calculate firm-level market capitalization using FactSet prices and shares outstanding data.

Our construction of firm-level fundamentals largely follows the procedure in Fama and French (2015).

Accounting data are from the Compustat Fundamentals Annual and Quarterly Databases. 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).

- 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.
- 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.

We winsorize beta at the 2.5% and 97.5% level 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 CUSIP.

We merge data from Sustainalytics on CUSIP by taking the most recent observation up to 12 months before.

B. Model derivations

II.A. First-order conditions

The first-order condition of investor i is given by

$$(\boldsymbol{g}_i - \boldsymbol{M}\boldsymbol{B}_0) - \gamma_i \left(\boldsymbol{\rho}_i\boldsymbol{\rho}_i' + \sigma^2\boldsymbol{I}\right)\boldsymbol{Q}_i + y_i = 0, \tag{25}$$

implying

$$\begin{aligned}
\boldsymbol{Q}_i &= \frac{1}{\gamma_i}\left(\boldsymbol{\rho}_i\boldsymbol{\rho}_i' + \sigma^2\boldsymbol{I}\right)^{-1}(\boldsymbol{g}_i - \boldsymbol{M}\boldsymbol{B}_0 + y_i) \\
&= \frac{1}{\gamma_i\sigma^2}\left(\boldsymbol{I} - \frac{\boldsymbol{\rho}_i\boldsymbol{\rho}_i'}{\boldsymbol{\rho}_i'\boldsymbol{\rho}_i + \sigma^2}\right)(\boldsymbol{g}_i - \boldsymbol{M}\boldsymbol{B}_0 + y_i) \\
&= \frac{1}{\gamma_i\sigma^2}(\boldsymbol{g}_i - \boldsymbol{M}\boldsymbol{B}_0 + y_i) - \frac{c_i}{\gamma_i\sigma^2}\boldsymbol{\rho}_i,
\end{aligned} \tag{26}$$

where $c_i = (\boldsymbol{\rho}_i'\boldsymbol{\rho}_i + \sigma^2)^{-1}\boldsymbol{\rho}_i'(\boldsymbol{g}_i - \boldsymbol{M}\boldsymbol{B}_0 + y_i)$ 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 (4), (5), and (6) we obtain

$$\boldsymbol{Q}_i(n) = -\frac{1}{\gamma_i\sigma^2}\boldsymbol{M}\boldsymbol{B}_0(n) + \frac{1}{\gamma_i\sigma^2}\left(\boldsymbol{\lambda}_i^g - c_i\boldsymbol{\lambda}_i^\rho + \boldsymbol{\lambda}_i^Y\right)'\boldsymbol{x}(n) + \frac{1}{\gamma_i\sigma^2}\left(\nu_i^g(n) - c_i\nu_i^\beta(n) + \nu_i^Y(n)\right),$$

which is the expression announced in (8).

II.B. Asset prices with exogenous characteristics

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

$$\sum_i \boldsymbol{Q}_i = \boldsymbol{B}, \tag{27}$$

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

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

that is,

$$MB(n) = \left(\sum_i m_i \boldsymbol{\beta}_{1i}\right)' \boldsymbol{x}(n) + \sum_i m_i\epsilon_i(n) - \sigma^2\left(\frac{B(n)}{\sum_i \tau_i A_i}\right). \tag{28}$$

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

$$m_i = \frac{\gamma_i^{-1}}{\sum_j \gamma_j^{-1}} = \frac{\tau_i A_i}{\sum_j \tau_j A_j}, \tag{29}$$

given our assumption that $\gamma_i = (\tau_i A_i)^{-1}$.

II.C. Asset prices with endogenous characteristics

We now solve the model once more in the extended model as specified in equation (16). In vector notation, we have

$$\boldsymbol{x}(n) = \boldsymbol{h}_0 + \boldsymbol{h}_1 MB(n) + \boldsymbol{\nu}^x(n).$$

We substitute this expression into (28) and solve for the valuation ratio,

$$MB(n) = \Omega\left(\sum_i m_i\boldsymbol{\beta}_{1i}\right)'(\boldsymbol{h}_0 + \boldsymbol{\nu}^x(n)) + \Omega\sum_i m_i\epsilon_i(n) - \Omega\sigma^2\left(\frac{B(n)}{\sum_i \tau_i A_i}\right), \tag{30}$$

where

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

The solution (30) highlights an important identification challenge in estimating equation (16) as valuation ratios depend on $\boldsymbol{\nu}^x(n)$. We therefore cannot estimate (16) and need to use an instrumental variables estimator instead. We implement this instrumental variables approach in Section V.D.

C. A ridge-IV estimator of the demand curve

III.A. 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,

$$mb_t(n) = a_{0i}z_{i,t}(n) + a_{1i}'\boldsymbol{x}_t(n) + a_{2i}\boldsymbol{d}_t + e_t(n), \tag{31}$$

for each investor. We refer to the fitted value as $\widehat{z}_{it}(n)$. We then form the moment conditions based on (15),

$$\mathbb{E}_t\left[\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\exp\left\{-\boldsymbol{\beta}_i'\boldsymbol{X}_t(n)\right\}-1\right)\boldsymbol{Z}_{it}(n)\right]=0, \tag{32}$$

where $\boldsymbol{X}_t(n)=(mb_t(n),\boldsymbol{x}_t'(n),\boldsymbol{d}_t')'$, $\boldsymbol{\beta}_i=(\beta_{0,i},\boldsymbol{\beta}_{1,i}',\boldsymbol{\beta}_{2,i}')'$, $\boldsymbol{Z}_{it}(n)=(\widehat{z}_{it}(n),\boldsymbol{x}_t'(n),\boldsymbol{d}_t')'$.

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

$$\mathbb{E}_t\left[\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\exp\left\{-\boldsymbol{\beta}_i'\boldsymbol{X}_t(n)\right\}-1\right)\boldsymbol{Z}_{it}(n)\right]-D(\boldsymbol{\Lambda}_i)\left(\boldsymbol{\beta}_i-\boldsymbol{\beta}_i^T\right)=0. \tag{33}$$

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 $\left(\beta_{0,i}^T,\boldsymbol{\beta}_{1,i}^T\right)$ and no shrinkage for the time fixed effects.[24]

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 (33) are non-linear, 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.

III.B. Numerical algorithm to compute the ridge estimator

We start from

$$\mathbb{E}_t\left[\left(\delta_{i,t}(n)\exp\left\{-\boldsymbol{\beta}_i'\boldsymbol{X}_t(n)\right\}-1\right)Z_t(n)\right]-D(\boldsymbol{\Lambda}_i)\left(\boldsymbol{\beta}_i-\boldsymbol{\beta}^T\right)=0. \tag{34}$$

[24] 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.

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

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

We iterate on this procedure until convergence. Note that the numerator of the adjustment term are the moment conditions in (34), 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

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

D. Variance decompositions using characteristics

We show how our valuation regressions and earnings predictability regressions connect to traditional variance decompositions. Starting from (22) without expectations, it holds

$$mb_t(n)=c+\sum_{s=1}^{\infty}\rho^{s-1}e_{t+s}(n)-\sum_{s=1}^{\infty}\rho^{s-1}r_{t+s}(n). \tag{35}$$

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

$$a_{mb,t} = a_{e,t}-a_{r,t}, \tag{36}$$

$$\lambda_{mb} = \lambda_e-\lambda_r. \tag{37}$$

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

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

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 $\Sigma_x = \text{Var}\left(\Sigma_x\right)$. 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.