Which Investors Matter for Equity Valuations and Expected Returns?*

Ralph S.J. Koijen[†] Robert J. Richmond[‡] Motohiro Yogo[§]

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Abstract

To understand why valuation ratios vary across firms and over time, a large literature in asset pricing decomposes these ratios into expected returns and expected growth rates of firm fundamentals. This literature leaves two fundamental questions unanswered: (i) what information do investors attend to in forming their demand beyond prices and (ii) how important are different investors in the price formation process? We use a demand system approach to answer both questions. We first show that a small set of characteristics explains the majority of variation in a panel of firm-level valuation ratios across countries. We then estimate an asset demand system using investor-level holdings data, allowing for flexible substitution patterns within and across countries. We use this framework to measure the relative importance of investors — differentiated by type, size, and active share — for connecting firm characteristics to prices and long-horizon expected returns.

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[†]University of Chicago, Booth School of Business, Center for Economic and Policy Research, and National Bureau of Economic Research (ralph.koijen@chicagobooth.edu).

[‡]New York University (rrichmon@stern.nyu.edu).

[§]Princeton University and National Bureau of Economic Research (myogo@princeton.edu).

A large part of the asset pricing literature centers around two questions. First, how important are variation in expected returns and expected growth rates of fundamentals for explaining fluctuations in asset prices over time and across assets? Second, what explains variation in average returns over time and across assets? The empirical findings of this literature have been influential in guiding modern asset pricing theories, with an increasingly important role for intermediaries.

The first question is typically answered by forecasting future returns or growth rates of fundamentals using valuation ratios, and potentially other predictor variables. This methodology is motivated by the present-value identity and follows the seminal work by Campbell and Shiller (1988) in the time series and Vuolteenaho (2002) in the cross-section. In this paper, we study what information investors use so that valuation ratios are informative to begin with and quantify how important different investors are for incorporating this information into prices.

By quantifying how important different investors are for incorporating information into prices, we also provide a new perspective on differences in average returns. It is common practice to use factor models, such as the capital asset pricing model (Sharpe 1964), the 3-factor model of Fama and French (1992), and more recently 5-factor models to explain differences in average returns. However, there is disagreement in the literature as to which factors to include and why certain factors matter for expected returns. Rather than using factor models for returns, our approach uses valuation ratios and their relation to characteristics. By measuring how both valuation ratios and future cash flows relate to characteristics, we measure how much a particular characteristic matters for variation in long-horizon expected returns. We then measure how important different investors are for connecting characteristics to long-horizon expected returns by tracing this variation back to demand by different types of investors. Our approach is particularly useful for theories that emphasize heterogeneity across investors in terms of, for instance, beliefs, objectives, or constraints.[1]

Figure 1 illustrates one of our key findings on the importance of different investors in

[1] Recent literature highlights the importance of particular types of intermediaries, such as mutual funds (Basak and Pavlova 2013), broker dealers (Adrian, Etula, and Muir (2014); He, Kelly, and Manela (2017)), or insurance companies (Ellul, Jotikasthira, and Lundblad 2011), both empirically and theoretically, for asset prices.

the price formation process. We group investors by type: investment advisors, hedge funds, long-term investors, private banking, and brokers. Investment advisors are further broken down by size and active share, as this is a large category including mutual funds. Long-term investors include pension funds and insurance companies.[2] The top panel reports the fraction of total assets under management (AUM) by each group (AUM Fraction), our measure of the contribution of each investor group to unconditional variation in prices (Repricing), and the share of active capital in each investor group's portfolio (Active Share).

Repricing is calculated as the absolute value of the changes in all firms' valuations, relative to the value of the market, in a hypothetical scenario in which a particular investor group were to hold the market portfolio. These repricing scenarios are calculated using an asset demand system that allows for rich heterogeneity across investors' demand curves and imposes market clearing, which we detail below.

Repricing is largest for small, active investment advisors. Cumulatively this group is still relatively large (15% of total AUM). Broker dealers, which have received significant attention in the recent literature on intermediary asset pricing, hardly matter for prices given their small size.[3] To understand what drives variation in repricing across investor types beyond differences in size, the active share bars measure the amount of active capital in each groups portfolio. This is calculated as the AUM share multiplied by the active share (multiplied by two). This measure follows our repricing measure quite closely.[4] To control for differences in AUM, we divide the repricing measure by assets under management in the bottom panel. This shows that hedge funds are most influential, per dollar of assets that they manage, while large, passive investment advisors and long-term investors are least influential.

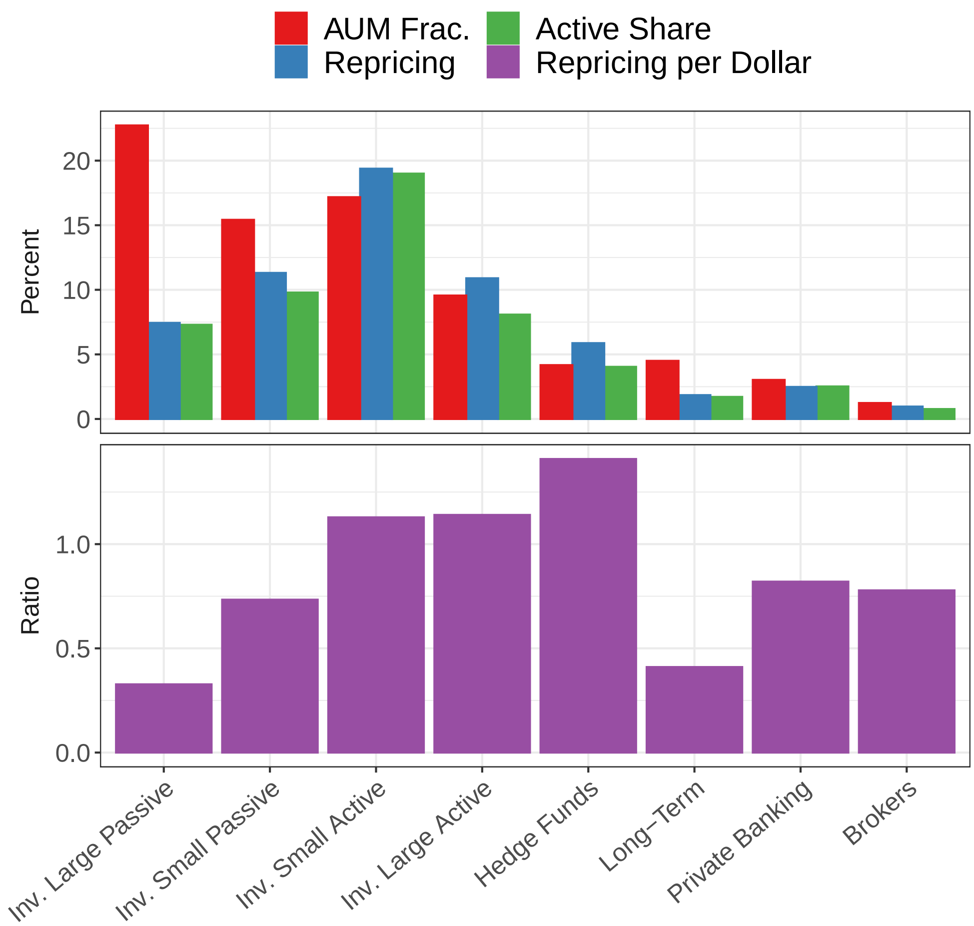
In general, we use our empirical framework to measure how much specific (or groups of) investors matter for valuations – both unconditionally, as illustrated in Figure 1, and conditional on characteristics. To develop intuition for our empirical strategy, we start with a simple model in which investors use a set of characteristics to forecast a firm's future

[2]We discuss the construction of the groups in Section II.

[3]Broker-dealers, and their balance sheet constraints, may matter for asset prices by their ability to extend leverage to other investors such as hedge funds. The traditional stochastic discount factor (SDF) cannot distinguish between the direct impact via their own securities holdings and their indirect impact by providing leverage. We can estimate the importance of the first channel, and find it to be small.

[4]Specifically, this measure is equal to our repricing measure under the assumption that the stock level demand elasticity is one, a typical order of magnitude found in the literature.

Figure 1
Total Repricing By Institution Type (US)



The top panel reports the fraction of ownership, the total repricing, and the share of active capital by investor type. The bottom panel reports the change in market cap normalized by the fraction of ownership by each group. Firm-level fundamentals and equity holdings data are from FactSet from 2006 until 2016.

profitability and to assess its riskiness. Investors form their asset demands as a function of prices, expected future profits, and stocks' riskiness. Investors may disagree on which characteristics are relevant and to what extent these characteristics matter for future profits and risk. In equilibrium, prices depend on characteristics, as in hedonic pricing models. The coefficients on the characteristics are a weighted average of the preferences of the investors, where the weights depend on assets under management.

The model guides our empirical analysis. First, we use firm characteristics to explain the cross-sectional variation in valuation ratios. A large literature studies how variation in these valuation ratios relates to expected returns and firm performance (e.g. Fama and French (1995), Daniel and Titman (2006), and Campbell, Polk, and Vuolteenaho (2009)). We show that a small set of six characteristics related to risk, productivity, and profitability explains the majority of variation in a panel of valuation ratios in the United States (US), the Euro area, Japan, and Great Britain (GB). The residual variation that we cannot explain could be due to other factors such as fluctuations in sentiment (Barberis, Shleifer, and Vishny 1998), funding constraints and other institutional frictions (Brunnermeier and Pedersen 2009), or potentially omitted characteristics. We also show that the same characteristics predict about a third of the variation in firm's future profit growth in each of the regions. By the present-value identity, the difference in the coefficients estimated in the valuation models and profit growth models measure how long horizon expected returns vary with characteristics.

Next, we study which investors attend to firms' characteristics so that prices are informative and related to these characteristics. To this end, we estimate an international asset demand system in which investors' demands are modeled as a function of prices, characteristics, and latent demand, which captures unobserved components of demand. By imposing market clearing, we can solve for equilibrium asset prices under various scenarios. Our modeling approach extends Koijen and Yogo (2019) who estimate a demand system for the cross-section of US equities to study returns instead of valuations. We allow for cross-country substitution across assets that can be different from the within-country substitution across assets.

We estimate the model using data in GB and in the US from 2006 to 2016. Throughout the paper, we focus on the largest and most liquid stocks by restricting attention to the largest 90% in each market. A salient fact revealed by our estimates of investors' demand curves is that the portfolios of institutional investors (e.g., hedge funds, mutual funds, broker dealers, ...) deviate significantly from market weights. Figure 1 quantifies how much this heterogeneity matters for the cross-section of valuation ratios.

We also explore the link to investors' size in detail. Investors' active share is inversely related to size, as is well known. When splitting institutions into five groups of equal size by AUM, the repricing measure is inversely related to size — both in absolute terms terms and per dollar of AUM. These effects are larger compared to the differences in active share, which points to differences in the slopes of demand curves across investors. Indeed, we find that small, active investment advisors and hedge funds are the most price elastic institutional investors. This implies that when those institutions switch to holding a market indexing strategy, prices need to move more to change the portfolios of, for instance, large, passive investors.

To compute the importance of investors conditional on characteristics, we estimate valuation regressions in each country using the counterfactual prices and quantify how much the coefficients on the characteristics and the residuals change. Combined with a forecasting model for expected future growth rates, this also measures the importance of each investor type in connecting characteristics to long-horizon expected returns. We show that when we zoom in on prices conditional of characteristics, and hence the connection between long-horizon expected returns and characteristics, we find again that hedge funds appear to be especially important to incorporate information into prices, conditional on their size.

Lastly, we make a methodological contribution in estimating asset demand systems. A standard problem is that a large number of investors hold relatively few stocks. One approach is to pool investors by observable characteristics, but this may mask interesting heterogeneity across investors. We instead propose a shrinkage estimator for the demand curves that we can combine with an instrument for prices, which are endogenous to latent demand, and that an handle zeroes when investors choose not to hold a given stock. The degree of shrinkage depends on the number of stocks held by an investor and vanishes asymptotically. We choose the shrinkage parameters using cross validation to ensure stable demand curve estimates out-of-sample. This approach ensures that we allow for maximum heterogeneity in demand curves across investors.

I. Which investors matter for asset prices? A simple model

We present a simple equilibrium 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 many asset pricing models, and it helps us to outline the empirical strategy that we follow in subsequent sections.

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.

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

$$\max_{Q_i} \mathbb{E}\left[-\exp\left(-\gamma_i A_{1i} + Z_{1i}\right)\right], \tag{1}$$

where Q_i is the vector of asset holdings expressed as the number of shares. Z_{1i} represents other risk factors that impact the investor such as benchmarking, outside income, time-varying investment opportunities, et cetera.

The optimization is subject to the intra-period budget constraint

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

where P denotes the vector of asset prices and Q_i^0 the investment in the outside cash account. The cash account has a price normalized to one and earns a rate of interest that we normalize to zero. We parameterize the cross-sectional distribution of absolute risk aversion coefficients as $\gamma_i = \gamma A_{i0}^{-1}$.[5]

The terminal payoff of the firm is modeled as

$$D_1(n) = B_0(n)\rho_1(n), \tag{3}$$

[5] 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 is similar to Makarov and Schornick (2010).

where $B_0(n)$ denotes book equity and $\rho_1(n)$ is the return on equity (ROE) as firms pay out out all earnings as dividends in the final period.

This implies that we can write

$$\begin{aligned} A_{1i} &= A_{0i} + Q_i'(D_1 - P) && (4) \\ &= A_{0i} + q_i'(\rho_1 - MB), && (5) \end{aligned}$$

where $MB(n) = P(n)/B_0(n)$, a firm's market-to-book ratio, and $q_i(n) = Q_i(n)B_0(n)$. We refer to $\mathbb{E}_i[\rho] - MB = g_i - MB$ as a measure of (long-horizon) expected return, were $\mathbb{E}_i[\cdot]$ corresponds to the expectation of investor i.

Investors may disagree about the expected ROE and its riskiness. We assume a single factor model for ROEs

$$\rho_i = g_i + \beta_i F + \eta, \tag{6}$$

where η and F are independent, normally distributed with mean zero, and we normalize $\mathrm{Var}(F) = 1$.

We assume that investors agree on $\mathrm{Var}(\eta) = \sigma^2 I$, but they may disagree on the systematic exposure of stocks to the factor, β_i. In addition, investors may disagree about the expected growth rate, g_i. We assume that investors agree to disagree and 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, investors rely on public information, "characteristics," and potentially other information, as captured by ν^g and ν^β,

$$\begin{aligned} g_i(n) &= \lambda_i^{g\prime} x(n) + \nu_i^g(n), && (7) \\ \beta_i(n) &= \lambda_i^{\beta\prime} x(n) + \nu_i^\beta(n), && (8) \end{aligned}$$

where ν_i^g and ν_i^β are assumed to be uncorrelated with x.

We refer to the set x as the "basis" of characteristics, which includes a constant. The first characteristic is book equity and captures size effects.

To complete the model, we assume the background risk factor Z_{1i} is normally distributed, $Z_{1i} \sim N(\mu_{Xi}, \sigma^2_{Xi})$, and

$$2\mathrm{Cov}\left(Z_{1i}, \rho_i(n)\right) = z_i(n) = \lambda_i^{Z\prime} x(n) + \nu_i^Z(n). \tag{9}$$

Investors' demand curves The first-order condition for investor i is given by

$$(g_i - MB) - \gamma_i \left(\beta_i \beta_i' + \sigma^2 I\right) q_i + z_i = 0, \tag{10}$$

or equivalently

$$\begin{aligned} q_i &= \frac{1}{\gamma_i}\left(\beta_i\beta_i' + \sigma^2 I\right)^{-1}(g_i - MB + z_i) \\ &= \frac{1}{\gamma_i\sigma^2}\left(I - \frac{\beta_i\beta_i'}{\beta_i'\beta_i + \sigma^2}\right)(g_i - MB + z_i) \\ &= \frac{1}{\gamma_i\sigma^2}(g_i - MB) - \frac{c_i}{\gamma_i\sigma^2}\beta_i + \frac{1}{\gamma_i\sigma^2} z_i, \end{aligned} \tag{11}$$

where $c_i = (\beta_i'\beta_i + \sigma^2)^{-1}\beta_i'(g_i - MB + z_i)$ is a scalar. 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 (7), (8), and (9) we obtain

$$q_i = -\frac{1}{\gamma_i\sigma^2} MB + \frac{1}{\gamma_i\sigma^2}\left(\lambda_i^g - c_i\lambda_i^\beta + \lambda_i^Z\right)' x + \frac{1}{\gamma_i\sigma^2}\left(\nu_i^g - c_i\nu_i^\beta + \nu_i^Z\right). \tag{12}$$

Empirically, we can link portfolio holdings to observable characteristics. However, 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 (12), we cannot tell whether this is due to a particular view on expected growth rates or risk.

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

$$\sum_i q_i = B, \tag{13}$$

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

$$\sum_i -\frac{1}{\gamma_i\sigma^2}MB + \frac{1}{\gamma_i\sigma^2}\left(\lambda_i^g - c_i\lambda_i^\beta + \lambda_i^Z\right)' x + \frac{1}{\gamma_i\sigma^2}\left(\nu_i^g - c_i\nu_i^\beta + \nu_i^Z\right) = B \tag{14}$$

that is

$$MB(n) = \left(\sum_i m_i\lambda_i\right)' x(n) + \sum_i m_i\nu_i, \tag{15}$$

where e_1 denotes the first unit vector,[6] $\lambda_i = \lambda_i^g - c_i\lambda_i^\beta + \lambda_i^Z - \gamma_i\sigma^2 e_1$, $\nu_i = \nu_i^g - c_i\nu_i^\beta + \nu_i^Z$, and

$$m_i = \frac{\gamma_i^{-1}}{\sum_i \gamma_i^{-1}} = \frac{A_i}{\sum A_i}, \tag{16}$$

given our assumption that $\gamma_i = \gamma A_i^{-1}$.

Hence, valuation ratios are connected to characteristics as investors view those characteristics as being relevant to assess risk (via λ_i^β), to forecast future profitability (via λ_i^g), or for hedging purposes (via λ_i^Z). Large investors and investors with more extreme views affect prices more and are therefore more important in the price formation process.

The contribution of investors to price formation In the context of the model, we explain how we quantify the importance of an investor, or group of investors, in the price formation process. We consider a case in which that investor j switches to strict market weights, that is, $Q_j = \theta_j\iota$, where θ_j is chosen to satisfy the budget constraint. Using this

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

demand curve for investor j, the market clearing condition changes to

$$\sum_{i,i\neq j} q_i + \theta_j B = B,$$

that is, $\sum_{i,i\neq j} q_i = (1-\theta_j)B$. The new market-clearing valuation ratio is

$$MB^{CF}(n) = \lambda_{mb}^{-j\prime} x(n) + \nu_{mb}^{-j},$$

where $\lambda_{mb}^{-j} = (1-\theta_j)^{-1}\sum_{i,i\neq j} A_i\lambda_i / \sum_{i,i\neq j} A_i$ and analogously for ν_{mb}^{-j}. Hence, the assets are now priced according to the size-weighted average demand curve of all other investors. Indeed, implementing a passive market indexing strategy is equivalent to assigning investor j the value-weighted demand curve of all other investors.

By comparing λ_{mb}^{-j} to λ_{mb}, we measure the importance of investor j to incorporate information about fundamentals into prices. Likewise, by comparing ν_{mb}^{-j} to ν_{mb}, we measure how important investor j is in explaining the residual in cross-sectional valuation regressions, and hence which investors cause a stock to be a value or growth stock.

Since $g_R(x) - MB$ is a measure of long-horizon expected returns, where g_R is the rational expectations forecast of ρ_i conditional on characteristics x, $g_R(x) \equiv \mathbb{E}[\rho \mid x]$, we can also compute the impact of investors on expected returns by comparing $g(x) - MB$ to $g_R(x) - MB^{CF}$ and how long-horizon expected returns vary with characteristics.

This calculation is accurate under the assumption that $g_R(x)$ does not change in the counterfactual, that is, that there are no real effects of investors switching to passive strategies. To relax this assumption, we would need to augment the model with a production side. While this is an interesting extension to explore in future work, it is beyond the scope of this paper.

II. Data and stylized facts

A. Data

The data on firm fundamentals, stock prices, and portfolio holdings are from FactSet. Details on data construction can be found in Appendix A. While FactSet provides holdings data in many countries, the types of institutions covered varies due to differences in reporting requirements for various institutions. As a result, we only have mutual fund holdings for a large number of countries, which is insufficient for the purposes of this paper.

For the holdings data, we therefore restrict attention to GB and the US. The US holdings data are sourced from 13-F reports and reports to FactSet by individual funds. The GB holdings data are sourced from the UK Share Register (UKSR) in combination with fund holdings. We follow the FactSet methodology, as detailed in the appendix, to combine various sources. We aggregate the holdings to the institutional level by country.

We check the coverage of the data in Figure 3. We plot the total holdings of US firms by UK investors and vice versa for FactSet. As a point of reference we use the IMF's Coordinated Portfolio Investment Survey (CPIS). As the figure illustrates, the FactSet data are highly representative of aggregate cross-border holdings.

We group investors into eight groups. First, we group investors by type: Investment Advisors, Long-term , 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.[7] 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 further by assets under management and active share.[8]. Our final groupings are given by Households (HH), Investment Advisors Large Passive (IA LP), Investment Advisors — Small Passive (IA SP), Investment Advisors — Small Active (IA SA), Investment Advisors — Large Active (IA LA), Hedge Funds (HF), Long-term (LT), Private Banking (PB), and Brokers (BR).

The household sector is constructed so that total holdings of a company add up to the company's market capitalization. In rare instances, the total holdings exceed total market cap, 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 have

[7]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.

[8]We first split investors into two groups of equal size. Within each size group, we split investors above and below the median active share. To have stable classifications across time, we collapse the classification across time and classify an investor as small (active) if it is assigned to a group more than half the periods.

the long positions (Lewellen 2011).

We construct an annual sample of holdings data that begins in 2006 and ends in 2016. While FactSet has data before 2006, the coverage is incomplete. Firm-level fundamentals are from FactSet for the GB, the US, the Euro Area (EU), and Japan (JP). We construct annual firm fundamentals from 2006 until 2016. While we do not have detailed holdings data in the Euro area and Japan, we use data on valuation ratios and fundamentals in these geographies to show that the fundamentals that we use also explain a large share of the variation in valuation ratios and future profits in these geographies.

B. *Firm granularity*

Table 1 documents firm characteristics along the firm size distribution, as measured by market capitalization. The top two panels are for the US in 2006 and 2016. In 2016, the top 90% of firms of market capitalization is accounted for by only 761 firms. The largest 82 firms already account for 50% of the aggregate market capitalization.

The largest 50% of firms account for only 38% of sales, 33% of investment and employment, yet 63% of net income. This implies that profits are highly concentrated among the largest firms. By comparing the distribution to 2006, we see that these statistics have been fairly stable over time.

In the bottom two panels, we compute similar statistics for the Euro area, Japan, and GB in 2006 and 2016. The patterns are similar, though less extreme, in other countries. In 2016, the top 50% of firms is made up by 44, 85, and 22 firms in the Euro area, Japan, and GB, respectively. At the 90th percentile, these numbers change to 274, 682, and 182. To illustrate the concentration at the top, we list the largest 10 firms in each geography in Table 2.

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 in terms of employment, investment, and profitability.

C. Distribution of institutional types

Figure 2 reports the ownership shares by institutional type, which have been fairly stable during the last decade. Table 3 lists the largest investor by type 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). To illustrate this in our sample, we list the assets under management in 2016 of the largest 10 investors in the US and GB in Table 4. Part of this concentration is driven by the increased popularity of passive indexing strategies and has resulted in questions regarding the broader impact on market efficiency (Garleanu and Pedersen 2019). In this paper, we provide a framework to empirically assess how the price formation process is affected if a particular investor or group of investors were to follow a passive indexing strategy instead.

III. Cross-sectional valuation regressions: Global evidence

We show that a small set of characteristics explains the majority of the cross-sectional variation in valuation ratios in the US, GB, the Euro area, and in Japan.

A. Selection of characteristics

We consider six characteristics. The first characteristic is log book equity (LNbe), which captures size effects. To forecast 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 more productive firms enter the export market. 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. Lastly, we include a stock's market beta, measured relative to the local market return, as the canonical measure of stock market risk. We cross-sectionally standardize all characteristics by region and year.

B. Explaining valuation ratios using characteristics

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

$$mb_t(n) = a_t + \lambda'_{mb} x_t(n) + \epsilon_t(n), \tag{17}$$

where a_t are time fixed effects. The characteristics are standardized to have mean zero and unit standard deviation. The results are reported for each of the four regions in Table 5.

First, we find that the coefficient on log book equity is negative, while the productivity and markup variables all enter positively. A potential interpretation of the negative coefficient on book equity is that investors' demand curves slope down. Second, the point estimates are quite comparable across regions. The region that deviates somewhat more from the others is Japan. Third, and importantly from our perspective, we can account for a large fraction of the cross-sectional variation in prices. The within year R-squared ranges from 37% (in Japan) to 68% (in GB). In the US, we explain 52% of the variation in the panel of valuation ratios.

Table 5 shows that the same characteristics explain a substantial fraction of the cross-sectional variation in future profitability,[9] often with similar coefficients in terms of sign and magnitude as in the valuation regressions.[10] We do note that our global sample is quite 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.

[9]Following Campbell, Polk, and Vuolteenaho (2009), we use the accounting identity $B_t = B_{t-1} + X_t - NF_t - D_t$, where NF_t are net issuances, D_t cash dividends, B_t denotes book equity, and X_t the implied earnings. 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 $\rho = 0.95$.

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

IV. A tractable empirical model of the international asset demand system

In this section, we introduce an empirically-tractable asset demand system, which allows for rich heterogeneity in demand curves across investors. The model extends the asset demand system in Koijen and Yogo (2019) by allowing for substitution across countries.

A. *Notation*

There are N_c assets, indexed by $n = 1, \ldots, N_c$, in country c. Lowercase letters denote the logarithm of the corresponding uppercase variables. We denote the characteristics of asset n in period t as $x_t(n)$. The financial assets are held by I investors, indexed by $i = 1, \ldots, I$. One of the investors in each country is a household sector, which holds whatever assets are not held by institutional investors in that country.

B. *The universe of assets and asset demand*

Motivated by the evidence in Section II, we use the top 90% of stocks by market capitalization in each country as the universe of assets. This ensures that our model focuses on pricing the largest firms that capture almost all economic activity among listed firms and that our estimates are not driven by a large number of small and micro-cap firms.

Each investor allocates assets A_{it} in period t across assets in its choice sets $\mathcal{N}_{i,c,t} \subseteq \{1, \ldots, N\}$. An investor's choice set is a subset of assets that the investor considers or is allowed to hold. Restrictions in the choice set may be driven by investment mandates, benchmarking or information frictions that limit an investor's ability to analyze a large universe of stocks (Merton 1987). We refer to stocks within an investor's choice set as inside assets. There is an outside asset in each country. We define the outside asset in a given country as all stocks that are not part of the top 90% and it is indexed by 0 in each country.

An investor's universe is the set of stocks that the investor holds at some point in our sample from 2006 to 2016, that is $\mathcal{N}_{i,c} = \cup_{t=1}^{T} \mathcal{N}_{i,c,t}$. We denote the number of assets in the investment universe of country c as $|\mathcal{N}_{i,c}|$.

Investors may invest in GB and the US, and can substitute across countries. The portfolio weight of investor i in stock n and country c is

$$w_{i,t}(n,c) = w_{i,t}(n|c)w_{i,t}(c). \tag{18}$$

The first term on the right side, $w_{i,t}(n|c)$, is the portfolio weight across stocks in a given country. The second term, $w_{i,t}(c)$, is the portfolio weight across countries. We next discuss the models of $w_{i,t}(n|c)$ and $w_{i,t}(c)$, which are guided by the idea that demand elasticities within and across countries may be different.

The portfolio weight on stock n within country c is

$$w_{i,t}(n|c) = \frac{\delta_{i,t}(n|c)}{1 + \sum_{m \in \mathcal{N}_{i,c}} \delta_{i,t}(m|c)}, \tag{19}$$

where

$$\delta_{i,t}(n|c) = \exp\left\{b_{0,i,c,t} + \beta_{0,i,c} mb_t(n) + \beta_{1,i,c}' x_t(n)\right\} \epsilon_{i,c,t}(n), \tag{20}$$

and $b_{0,i,c,t}$ are investor-country-time fixed effects. An investor's demand depends on the log market-to-book ratio, firm characteristics, and latent demand, $\epsilon_{i,c,t}(n)$. Latent demand captures investor i's demand beyond characteristics. Zero holdings, within an investor's choice set, correspond to $\epsilon_{i,c,t}(n) = 0$.

This demand curve is motivated by the simple model in Section I, but is empirically more realistic as portfolio holdings are log-normally distributed. We normalize the mean of latent demand $\epsilon_{i,c,t}(n)$ to one so that the intercept $b_{0,i,c,t}$ in equation (20) is identified. This implies that the error terms averages to one for a given investor across stocks in each year, but the error terms do not necessarily 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 (15).

To specify the allocation across countries, $w_{i,t}(c)$, we define $\zeta_{i,t}(c) = 1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m|c)$, which is the inverse of the fraction invested in the outside asset, $\zeta_{i,t}(c) = \frac{1}{w_{i,t}(0|c)}$. Intuitively, when $\zeta_{i,t}(c)$ is large, inside assets are relatively attractive to investor i, compared to the outside asset, in country c. This happens when an investor considers the prices to be low relative to fundamentals and latent demand. In this case, the investor may also want to reallocate assets from the foreign country to country c.

Following this intuition, we model the portfolio weight of country c as

$$w_{i,t}(c) = \frac{\zeta_{i,t}(c)^{\psi_{1,i}}\delta_{i,t}(c)}{\zeta_{i,t}(US)^{\psi_{1,i}}\delta_{i,t}(US) + \zeta_{i,t}(UK)^{\psi_{1,i}}}, \tag{21}$$

where

$$\ln \delta_{i,t}(US) = \psi_{0,i} + \epsilon^{\psi}_{i,t}, \tag{22}$$

and $\delta_{i,t}(UK) = 1$, which is a normalization. The model in (21) implies that the country weight is increasing in $\zeta_{i,t}(c)$, that is, the relative attractiveness of inside assets in country c. Our model of portfolio weights is a nested logit model.

It is useful to consider two special cases to gain intuition. When $\psi_{1,i} = 1$, the model collapses to a standard logit model

$$w_{i,t}(n,c) = \frac{\delta_{i,t}(n|c)\delta_{i,t}(c)}{\sum_{k=1}^{2}\sum_{m=0}^{N}\delta_{i,t}(m|k)\delta_{i,t}(k)}, \tag{23}$$

and the elasticity of substitution within and across countries is identical. This implies that the equity markets in GB and the US are perfectly integrated.

When $\psi_{1,i} = 0$,

$$w_{i,t}(n,c) = \frac{\delta_{i,t}(n|c)}{\sum_{m=0}^{N}\delta_{i,t}(m|c)}\frac{\delta_{i,t}(c)}{\sum_{k=1}^{2}\delta_{i,t}(k)}, \tag{24}$$

the allocation across asset classes depends only on $\psi_{0,i} + \epsilon^{\psi}_{i,t}$. In this case, the equity markets in both countries are segmented and the relative allocation does not respond to prices, characteristics or latent demand in either country. Empirically, we expect the willingness of investors to substitute within a country to be higher than across countries, and we therefore expect $\psi_{1,i} \in (0,1)$.[11]

[11] Theoretically, there is no upper-bound on ψ_{1i} and values above one would imply that investors are more willing to substitute across countries compared to within countries.

C. Market clearing

We complete the model with the market clearing condition for each asset n in country c

$$ME_t(n, c) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n, c), \tag{25}$$

that is, 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 the following assumption is a sufficient condition for both individual and aggregate demand to be downward sloping.

Assumption 1. The coefficient on log market equity satisfies $\beta_{0,i,c} < 1$ for all investors and in each country.

We impose this condition in estimating the demand system, which we discuss in the next section. Readers may choose to skip this section the first time reading the paper and directly go to Section VI for the empirical results.

V. Estimating the asset demand system

We discuss in this section how we estimate the international asset demand system as summarized by equations (19)-(20) and (21)-(22). We first discuss an estimator of the demand system within each country that accounts for the fact that some investors hold concentrated portfolios. We then discuss the instrument that we use for prices, and we conclude by developing a new shrinkage estimator of asset demand systems that is designed to handle investors that hold relatively few stocks.

A. A ridge instrumental variables estimator of the within-country demand curves

Our goal in this section is to estimate the demand model for investor i in a given country, which can be written as

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left\{b_{0,i,t} + \beta_{0,i} mb_t(n) + \beta_{1,i}' x_t^\star(n)\right\} \epsilon_{i,t}(n), \tag{26}$$

where we omit country subscripts to simplify the notation as we focus on the within-country demand system. We standardize all the characteristics cross-sectionally, denoted by $x_t^\star(n)$, and order them such that the first characteristic is log book equity, $be_t(n)$.

We assume throughout this section that characteristics are exogenous to latent demand,

$$\mathbb{E}_t\left[\epsilon_{i,t}(n) \mid x_t(n)\right] = 1, \tag{27}$$

where the expectation is taken across stocks in a given period as we include time fixed effects.

There are two challenges in estimating the demand curve. First, as some investors hold concentrated portfolios, we may not be able to estimate all coefficients precisely. We propose a shrinkage estimator of the coefficients, which avoids pooling across investors as in Koijen and Yogo (2019). Second, prices are endogenous to latent demand. In the next section, we present details of an instrument, $z_{i,t}(n)$. We assume in this section that this instrument is relevant, $\mathbb{E}_t[z_{i,t}(n) mb_t(n) \mid x_t(n)] \neq 0$, and exogenous, $\mathbb{E}_t[\epsilon_{i,t}(n) \mid x_t(n), z_{i,t}(n)] = 1$.

In this section, we discuss how we modify the standard GMM moment conditions to impose the shrinkage penalty and how we choose the shrinkage target. We start from the moment conditions based on (27),

$$\mathbb{E}_t\left[\left(\frac{w_{i,t}(n)}{w_{i,t}(0)} \exp\left\{-\beta_i' X_t(n)\right\} - 1\right) Z_t(n)\right] = 0, \tag{28}$$

where $X_t(n) = (mb_t(n), x_t^{\star\prime}(n), d_t')'$, $\beta_i = (\beta_{0,i}, \beta_{1,i}', \beta_{2,i}')'$, $Z_t(n) = (\widehat{z}_t, x_t^{\star\prime}(n), d_t')'$, and d_t a vector of time fixed effects. In forming the moment conditions, we use the projection of $mb_t(n)$ on $(z_{i,t}(n), x_t^\star(n), d_t)$ as in case of linear two-stage least squares.

We implement the shrinkage estimator by adding a ridge penalty (Hoerl and Kennard

1970) to the moment conditions:

$$\mathbb{E}_t\left[\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\exp\left\{-\beta_i' X_t(n)\right\}-1\right)Z_t(n)\right]-D(\Lambda_i)\left(\beta_i-\beta^T\right)=0. \tag{29}$$

The term $D(\Lambda_i)\left(\beta_i-\beta^T\right)$ is the ridge penalty, where $D(x)$ denotes a diagonal matrix with the elements of the vector x on the diagonal.

The shrinkage target, β^T, equals $\beta^T = \left(\beta^T_{0,i}, \beta^T_{1,i1\times K}, 0_{1\times T}\right)'$, implying that we do not shrink the time fixed effects. For investors with more than 1,500 observations, across stocks and years, we can estimate $(\beta_{0,i}, \beta_{1,i}')'$ without any shrinkage. We use the average of these estimates across investors with great than 1,500 observations as the shrinkage etarget.

We set the shrinkage penalty to $\lambda N_i^{-\xi}$, with $\xi > 0$. This implies that the penalty becomes less important as investors hold more stocks. ξ controls the speed at which the penalty vanishes asymptotically. If the implied estimates result in an estimate of $\beta_{i,0}$ that exceeds 1, then we increase the first element of Λ_i to to ∞ to impose $\beta_{0,i} = 1$. Even though the moment conditions in (29) are non-linear, we develop a simple numerical algorithm to solve them efficiently as we discuss in Appendix B .

To complete the estimation procedure, we need to determine (λ, ξ). As is common practice in the machine learning literature, we choose both parameters 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 $(\lambda, \xi) = (2.3, 0.1)$.

B. Construction of the instrument

As discussed before, we cannot simply estimate investors' demand curves using ordinary least squares, as latent demand is likely correlated with 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 assumption is that the set of stocks that an investor holds over time is exogenous. Investors may drop certain stocks in a particular year as a result of variation in latent demand, that is, that is, $\epsilon_{i,t}(n)$ and $\mathcal{N}_{i,t}$ are correlated, but the boundaries of the investment universe, $\mathcal{N}_i = \cup_{t=1}^{T} \mathcal{N}_{i,t}$, are assumed to be exogenous. The boundaries of an investor's investment universe in case of institutional investors is typically determined by investment mandates.

Within the universe of mandates, the actual portfolio holdings are endogenous. As instruments, we compute the counterfactual prices as if investors hold a $1/(1+|\mathcal{N}_j|)$ portfolio, excluding the investor's own assets and the assets of the household sector

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

C. Estimating the cross-country demand curves

To complete the model estimation, we estimate $\psi_{0,i}$ and $\psi_{1,i}$ in (21)-(22) that determine the cross-country demand curves. The model implies

$$\begin{aligned}\ln\left(\frac{w_{i,t}(US)}{w_{i,t}(GB)}\right) &= \psi_{0,i} + \psi_{1,i}\ln\left(\frac{\zeta_{i,t}(US)}{\zeta_{i,t}(GB)}\right) + \epsilon_{i,t}^{\psi} \\ &= \psi_{0,i} - \psi_{1,i}\ln\left(\frac{w_{i,t}(0|US)}{w_{i,t}(0|GB)}\right) + \epsilon_{i,t}^{\psi} \qquad (30)\end{aligned}$$

where we use $\zeta_{i,t}(c) = \frac{1}{w_{i,t}(0|c)}$. Equation (30) highlights that $\psi_{0,i}$ controls the average allocation to GB relative to the US. $-\psi_{i,1}$ is the elasticity of the total GB-US share with respect to the GB-US share in the respective outside assets. Intuitively, ψ_{1i} measures how much an investor would shift assets from GB to the US when, within GB, the investor shifts from inside assets to the outside asset.

We estimate (30) using a pooled regression by investor type with investor fixed effects. The investor fixed effects provide an estimate of $\psi_{i,0}$ and that we use within-investor variation in the GB-US share over time to identify ψ_1.

VI. Empirical results

We report the estimation results in Section A. In Section B, we define the counterfactual to determine how much different investors matter for asset prices. In Section C, we compute the counterfactual using the earlier estimates. In Section D, we explore the link between investors' size and repricing in more detail. Lastly, we show how different investors impact the link between characteristics and either valuations or expected returns in Section E.

A. Estimation results

Table 6 summarizes the estimation results for the US (top panel) and GB (middle panel). In the bottom panel, we report the estimates of the cross-country allocation model, that is, $\psi_{1,i}$. The columns correspond to different institutional types and we report the AUM-weighted average of the coefficients in the table. In Figure 4, we summarize the results graphically for the US.

In the top and middle panel, the coefficient on the log market-to-book ratio, $\beta_{0,i,c}$, captures the demand elasticity with respect to price. Lower values correspond to demand curves that are more sensitive to prices. We find that hedge funds are the most elastic institutional investors, while long-term investors (pension funds and insurance companies) and large, passive investment advisors are the least elastic investors in both countries. Moreover, active investment advisors are more price elastic, conditional on size, compared to passive investment advisors.

The remaining coefficients reflect the response of demand to characteristics. The estimates imply that investors disagree in particular about the valuation of dividend-to-book equity, log book equity, and foreign sales in both countries. For large, passive investment advisors, all coefficients are close to zero and the coefficient on log book equity is close to one, consistent with these investors holding a market portfolio.

In the bottom panel of Table 6, we report the estimates of $\psi_{1,i}$ in equation (21). Recall that ψ_1 equal to one corresponds to the same substitution patterns across and within countries, while ψ_1 equal to zero implies that the cross-country shares are insensitive to relative prices and characteristics. The estimates are relatively close to zero, suggesting limited substitutability across countries.

B. Measuring the importance of investors for asset prices

To measure the relative contribution of different investors to asset prices, we compute prices under the assumption that one group of institutional investors switches to holding the market portfolio. As explained in Section I, this implicitly implies that we assign the size-weighted demand curve of all other investors to this group.

The impact on asset prices of switching one particular group of institutional investors to market weights is determined by: (i) their relative size, (ii) how different their demand curve is from the other investors, and (iii) how price sensitive the other investors are, that is, how much do prices need to move for other investors to absorb the demand, as so far as it deviated from the market portfolio.

To compute the counterfactual using the estimated demand system, we set $\beta_{0,i} = 1$, $\beta_{1,i} = e_1 \sigma_b$, and $\epsilon_i(n) = 0$, for all n. We do not adjust the extensive margin. We then compute asset prices using this demand system by ensuring that asset markets clear. Appendix C provides the computational details. We can then explore how much asset prices change on average, but we can also re-run the valuation regressions as in Section III to explore how much different investors matter to incorporate information about fundamentals into prices.

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

To measure the average change in valuations, we compute the following statistic

$$\theta = \frac{1}{T} \sum_t \left(\frac{\sum_{n=1}^{N} \mid ME_t^{CF}(n) - ME_t(n) \mid}{\sum_{n=1}^{N} ME_t(n)} \right), \tag{31}$$

which measures the total repricing if we change a group's demand to holding the market portfolio. We report the results in Table 7, in which the top panel reports the results for asset prices in the US and the bottom panel for asset prices in GB. In computing the counterfactual, we switch, for instance, hedge funds both in the US and GB to the market portfolio and solve for asset prices. In doing so, we allow investors also to rebalance across countries according to equation (21) and (22).

We report the active share in the first column, the repricing measure in the second column, the share of AUM in the third column, and the repricing per dollar AUM in the fourth column.

In both countries, there is a strong relation between the size of the sector and the impact on prices, which is to some extent mechanical. We summarize this graphically in the top panel of Figure 1 for the US. The first (red) bar for each sector is the fraction of total assets managed and the second (blue) bar is the change in valuations.

However, the impact is far from proportional. The bottom panel of Figure 1 displays the ratio of repricing to the ownership share for each institutional type. The ratio is 0.33 for large, passive investment advisors, 0.41 for long-term investors, 0.78 for broker dealers,[12] and over 1.41 for hedge funds. This points to the relative importance of hedge funds in determining asset prices, while large, passive investment advisors and long-term investors follow market indexing strategies. These numbers are also relevant in the context of the debate regarding the shift from active to passive investing (see for instance Garleanu and Pedersen (2019)).

Across countries, we find that switching investors to the market portfolio has a larger impact in the US compared to GB. The effects in GB are smaller for two reasons: (i) the household sector is larger and (ii) our estimates imply that the household sector in GB is more price elastic than the household sector in the US. Any shock to demand curves of institutions therefore has a smaller impact on asset prices.

In Table 8, we summarize the most influential investors by type. This calculation reveals some striking differences. For instance, the repricing measure for The Vanguard Group, a large, passive investor, is 3.35%, although they manage almost $1.6 trillion in 2016. Capital Research & Management, a large, active investment advisor, has almost the same repricing impact with 2.56%, but managing a sixth of Vanguard's assets at $250 billion. Similarly, AQR Capital Management, the hedge fund with the highest repricing measure, has a repricing measure of 0.62% while investing $62 billion in assets. Per dollar of AUM, Capital Research and AQR have approximately the same impact on prices, and substantially more than Vanguard.

D. Investor size and repricing

In Figure 5, we explore the link between investor size and repricing in more detail. Investors' active share is inversely related to size, as is well known. When splitting institutions into

[12] We only measure the direct impact of changing the holdings of the broker-dealer sector. It may well be the case, however, that by restricting leverage, broker-dealers have an outsized effect on other investors, which has a larger overall impact on prices.

five groups of equal size by AUM, the repricing measure is inversely related to size, both in absolute terms terms and per dollar of AUM. These effects are larger compared to the differences in active share, which points to differences in the slopes of demand curves. Indeed, we find that small, active investment advisors and hedge funds are the most price elastic institutional investors. This implies that when those institutions switch to holding a market indexing strategy, prices need to move more to change the portfolios of, for instance, large, passive investors.

E. *Linking characteristics to valuation ratios and long-horizon expected returns*

It is common practice in empirical asset pricing to uncover characteristics that are linked to either valuations or expected returns. Often, the relevance of specific characteristics are motivated by narratives or formal models based on investor types, such as retail investors, smart money (e.g., hedge funds), or long-term investors such as pension funds and insurance companies. Our framework can be used to understand how important different groups are to connect characteristics to prices and expected returns.

To this end, we re-run the valuation regressions by regressing the counterfactual log market-to-book ratios on characteristics in a panel with time fixed effects, as in (17). We compute the change in loadings on characteristics (multiplied by 100).

The results are presented in Table 9 for the US (top panel) and GB (bottom panel). The columns correspond to different counterfactuals. To interpret the coefficients, the estimate of 8.28 on dividend-to-book equity for small, active investment advisors in the US means that the valuation difference of firms with a one standard deviation difference in dividend-to-book equity would increase by 8.28% if investment advisors switch to strict market weights. We also report the change in the R-squared value in the bottom line of each panel.

We find the largest change in the coefficients for small, active investment advisors, which is driven in part by their size, as discussed before. However, hedge funds still play an important role in incorporating information about firm fundamentals into asset prices, which is particularly remarkable given the smaller amount of assets that they manage compared to investment advisors.

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

$$mb_t(n) = \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t \left[e_{t+s}(n) \right] - \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t \left[r_{t+s}(n) \right], \tag{32}$$

where

$$e_t(n) = \ln \left(1 + \frac{\Delta BE_t(n) + D_t(n)}{BE_{t-1}(n)} \right), \tag{33}$$

$$r_t(n) = \ln \left(1 + \frac{\Delta ME_t(n) + D_t(n)}{ME_{t-1}(n)} \right), \tag{34}$$

and $BE_t(n)$ a firm's book equity, $ME_t(n)$ its market equity, and $D_t(n)$ its dividend.[13]

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, then the change in valuation ratios links one-to-one to changes in expected returns, with a scaling coefficient of $(1-\rho)^{-1}$. Using a typical value of $\rho = 0.95$, we obtain that the scaling factor is 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.[14]

Hence, using the estimate of 8.28 as before, the relation between dividend-to-book equity and expected returns would change by 41bp per year for a one standard deviation change in dividend to book equity. If expected returns are less (more) persistent, for instance because

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

[14] 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 $(1 - 0.932 \times 0.969)^{-1} \simeq 10$.

characteristics are less (more) persistent, then these effects would be larger (smaller).

VII. Conclusion

It is common practice to decompose levels and variation in prices into expected returns and expected fundamentals. However, it is unclear what information investors use for prices to be informative and how important different investors are for incorporating information into prices.

We show that a small set of characteristics explains the majority of the variation in a panel of firm-level valuation ratios across countries. The same characteristics also predict future profitability with comparable coefficients. To measure how investors' demands respond to the characteristics, we estimate a demand system in Great Britain and in the United States. The demand system allows us to quantify the importance of different institutional types (e.g., mutual funds, broker dealers, ...) for price formation by computing counterfactual prices if a particular type were to follow a passive investment strategy. By combining these estimates with our forecasts of future profitability, we measure the contribution of each institutional type to cross-sectional variation in long-term expected returns.

Our framework can be used whenever one is interested in understanding why certain characteristics affect the cross-section of valuation ratios or long-term expected returns. For instance, our approach may be useful in understanding which investors matter most in connecting asset prices to corporate governance, or ESG factors model broadly (Baker et al. 2018), how risk is priced (Pflueger, Siriwardane, and Sunderam 2018), et cetera.

By focusing on groups of intermediaries, which may differ in terms of regulations, their funding structure, and investment horizon, our approach may inform the growing theoretical literature on intermediary asset pricing to develop micro-foundations for the demand curves that we estimate for different intermediaries.

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Table 1
Firm-Level Fundamentals Granularity

Region	Mkt Pct	Size Rank	Sales Frac	NI. Frac	Inv. Frac	Emp. Frac
			US (2016)			
	10	5	6.4	14.8	7.9	2.0
	20	14	13.1	26.7	15.3	6.9
	30	26	22.2	40.3	22.2	18.0
	40	47	29.4	52.6	25.4	26.2
	50	82	38.1	63.4	32.5	33.0
	60	138	50.2	75.4	45.9	42.1
	70	231	63.7	84.1	60.0	52.5
	80	396	72.8	91.4	71.8	61.8
	90	761	84.6	99.3	84.3	77.3
	100	3622	100.0	100.0	100.0	100.0
			US (2006)			
	10	6	7.7	14.7	7.4	3.2
	20	14	15.9	24.7	13.7	12.1
	30	27	24.3	36.4	23.8	16.8
	40	49	31.2	46.0	29.1	22.3
	50	84	41.2	57.7	36.7	31.3
	60	146	52.1	67.1	45.7	40.2
	70	242	63.7	76.7	58.7	51.6
	80	423	74.5	86.0	69.4	62.8
	90	872	86.5	94.6	83.0	78.3
	100	4673	100.0	100.0	100.0	100.0
			2016			
EA	50	44	40.4	53.0	48.4	33.3
EA	90	274	87.2	90.3	89.5	81.0
JP	50	85	37.9	54.3	50.1	34.0
JP	90	682	83.3	89.9	90.4	79.7
GB	50	22	40.2	40.2	46.6	27.5
GB	90	181	87.0	90.6	86.3	79.3
			2006			
EA	50	51	48.5	58.6	51.9	35.3
EA	90	304	87.2	92.4	88.5	80.0
JP	50	70	38.1	54.4	47.8	34.6
JP	90	657	81.5	91.5	84.4	79.6
GB	50	17	45.5	46.2	47.9	28.0
GB	90	155	89.0	92.3	88.6	80.8

Each row represents the number of firms as well as the fraction of sales, net income, investment, and employment represented by the top deciles of market cap. Firm-level fundamentals are annual from FactSet from 2006 to 2016.

Table 2
Top firms in 2016

Name	ME
US (2016)	
Apple Inc	609
Alphabet Inc	548
Microsoft Corp	480
Berkshire Hathaway Inc	402
Exxon Mobil Corp	374
Amazoncom Inc	358
Facebook Inc	333
Johnson Johnson	312
JPMorgan Chase Co	307
Wells Fargo Co	276

Name	ME
GB (2016)	
HSBC Holdings Plc	161
BP Plc	122
British American Tobacco plc	106
GlaxoSmithKline Plc	94
AstraZeneca Plc	69
Vodafone Group Plc	66
Diageo Plc	66
Reckitt Benckiser Group Plc	60
Lloyds Banking Group Plc	55
Prudential Plc	52

Name	ME
EA (2016)	
Royal Dutch Shell Plc	237
AnheuserBusch InBev SA/NV	205
Total SA	124
Unilever NV	117
Industria de Diseo Textil SA	107
Siemens AG	105
SAP SE	105
L'Oral SA	102
Sanofi	102
Medtronic Plc	98

Name	ME
JP (2016)	
Toyota Motor Corp	176
Nippon Telegraph Telephone Corp	86
NTT DoCoMo Inc	85
Mitsubishi UFJ Financial Group Inc	83
SoftBank Group Corp	73
KDDI Corp	62
Japan Tobacco Inc	59
Honda Motor Co Ltd	53
Sumitomo Mitsui Financial Group Inc	52
Mizuho Financial Group Inc	46

Top 10 firms by market cap within each region in 2016. Market cap is in billions of USD. Price data is from FactSet.

Table 3
Top Investors by Type

Type	Name	AUM
Households		6588
Inv. Large Passive	The Vanguard Group, Inc.	1598
Inv. Large Active	T. Rowe Price Associates, Inc.	423
Long-Term	Norges Bank Investment Management	199
Private Banking	Goldman Sachs & Co. LLC (Private Banking)	99
Inv. Small Passive	Managed Account Advisors LLC	94
Inv. Small Active	PRIMECAP Management Co.	84
Hedge Funds	AQR Capital Management LLC	62
Brokers	Credit Suisse Securities (USA) LLC (Broker)	60

Largest investors in the US by assets under management for each type in 2016. Investor types are: Households (HH), Investment Advisors Large Passive (IA LP), Investment Advisors — Small Passive (IA SP), Investment Advisors — Small Active (IA SA), Investment Advisors — Large Active (IA LA), Hedge Funds (HF), Long-term (LT), Private Banking (PB), and Brokers (BR).

Table 4
Top Investors.

Name	Type	AUM
US (2016)		
The Vanguard Group, Inc.	Inv. Large Passive	1598
BlackRock Fund Advisors	Inv. Large Passive	1069
SSgA Funds Management, Inc.	Inv. Large Passive	954
Fidelity Management & Research Co.	Inv. Large Passive	554
T. Rowe Price Associates, Inc.	Inv. Large Active	423
Capital Research & Management Co. (World Investors)	Inv. Large Passive	328
Wellington Management Co. LLP	Inv. Large Active	324
Northern Trust Investments, Inc.	Inv. Large Passive	276
Capital Research & Management Co. (Global Investors)	Inv. Large Active	250
Norges Bank Investment Management	Long-Term	199
Total		**5974**
GB (2016)		
The Vanguard Group, Inc.	Inv. Large Passive	61
Legal & General Investment Management Ltd.	Inv. Small Passive	47
Norges Bank Investment Management	Long-Term	45
BlackRock Investment Management (UK) Ltd.	Inv. Large Passive	43
BlackRock Advisors (UK) Ltd.	Inv. Small Passive	28
Invesco Asset Management Ltd.	Inv. Large Active	28
Capital Research & Management Co. (World Investors)	Inv. Large Passive	28
Capital Research & Management Co. (Global Investors)	Inv. Large Active	27
SSgA Funds Management, Inc.	Inv. Large Passive	27
BlackRock Fund Advisors	Inv. Large Passive	27
Total		**359**

Top 10 institutional investors by assets under management in the US and GB in 2016. Investor types are: Households (HH), Investment Advisors Large Passive (IA LP), Investment Advisors — Small Passive (IA SP), Investment Advisors — Small Active (IA SA), Investment Advisors — Large Active (IA LA), Hedge Funds (HF), Long-term (LT), Private Banking (PB), and Brokers (BR). Equity holdings data are from FactSet.

Table 5
Valuation and Earnings Regressions (4 Regions)

	mb (US)	e^5 (US)	mb (EA)	e^5 (EA)	mb (JP)	e^5 (JP)	mb (GB)	e^5 (GB)
Foreign Sales	0.16	0.07	0.12	0.02	0.10	0.00	0.12	0.08
	(21.60)	(5.52)	(7.74)	(2.68)	(7.73)	(0.34)	(5.83)	(1.82)
Lerner	0.06	0.13	0.11	0.08	0.13	0.10	0.06	0.15
	(5.27)	(9.74)	(6.21)	(8.55)	(11.91)	(6.80)	(2.74)	(3.41)
Sales to Book	0.19	0.19	0.14	0.06	0.15	0.09	0.21	0.16
	(30.50)	(18.46)	(16.64)	(4.28)	(17.53)	(20.19)	(5.80)	(2.02)
Dividend to Book	0.16	0.10	0.20	0.17	0.19	0.03	0.32	0.19
	(16.27)	(7.09)	(14.36)	(6.51)	(17.07)	(1.88)	(11.58)	(3.80)
Market Beta	−0.06	−0.02	−0.04	−0.02	−0.01	0.03	−0.04	0.04
	(−3.19)	(−1.03)	(−2.63)	(−1.12)	(−0.31)	(2.08)	(−1.73)	(1.57)
LNbe	−0.46	−0.18	−0.43	−0.20	−0.23	−0.09	−0.45	−0.23
	(−36.10)	(−8.38)	(−47.88)	(−16.25)	(−12.24)	(−9.52)	(−12.78)	(−6.51)
Adj. R^2	0.54	0.33	0.61	0.38	0.42	0.28	0.70	0.52
Within Adj. R^2	0.52	0.32	0.56	0.32	0.37	0.21	0.68	0.50
Num. obs.	8537	3090	3027	1124	7100	2800	1638	539

Regressions of valuation ratios on firm-level characteristics for 4 regions: United States (US), Euro Area (EA), Japan (JP), and Great Britain (GB). All regressions include year fixed effects. mb is the log market-to-book ratio at time t. e^5 is cumulative return on equity from time t to $t+5$ adjusted for repurchases. Characteristics are measured at time t. Foreign sales is the fraction of sales from abroad, and Lerner is operating income after depreciation divided by sales, market beta is 60-month rolling market beta where the market is the local MSCI index, and $LNbe$ is log book equity. Firm-level fundamentals are from FactSet from 2006 until 2016.

Table 6
Demand Estimation Summary

	Households	Inv. Large Passive	Inv. Small Passive	Inv. Small Active	Inv. Large Active	Hedge Funds	Long-Term	Private Banking	Brokers
US									
LNmebe	-0.022	0.957	0.805	0.597	0.771	0.644	0.851	0.750	0.744
Foreign Sales	0.133	0.014	0.035	0.036	0.030	-0.006	0.006	0.065	0.011
Lerner	-0.017	-0.003	0.021	0.035	0.000	-0.020	0.022	0.042	-0.025
Sales to Book	0.189	0.026	0.050	0.015	0.041	0.046	0.029	0.070	0.067
Dividend to Book	0.294	-0.004	0.014	-0.065	-0.076	-0.079	0.005	0.045	0.079
Market Beta	-0.073	0.003	-0.019	-0.030	0.008	0.013	0.007	-0.057	0.055
LNbe	0.899	1.270	1.123	0.705	1.090	0.724	1.191	1.008	1.206
GB									
LNmebe	-0.457	0.676	0.805	0.733	0.754	0.755	0.730	0.726	0.715
Foreign Sales	0.130	0.069	0.010	0.047	0.039	0.004	0.022	-0.016	-0.015
Lerner	0.171	-0.001	-0.017	-0.013	-0.060	0.025	0.024	-0.008	0.001
Sales to Book	0.527	0.129	0.024	0.060	0.079	0.071	0.070	0.073	0.069
Dividend to Book	0.327	0.085	0.049	0.019	0.060	0.001	0.028	0.055	0.042
Market Beta	0.127	-0.021	-0.034	-0.034	-0.067	-0.053	-0.049	-0.035	-0.021
LNbe	0.642	1.236	1.211	1.106	1.140	1.040	1.256	1.180	1.184
Combined									
Cross-Country		0.191	0.334	0.264	0.474	0.126	0.267	0.214	0.104

Summary statistics of coefficient estimates from investor level demand system estimation in the United States (US) and Great Britain (GB). AUM is the time series average of the total AUM for each investor group. All other cells are the time series average of the within year assets under management weighted average coefficients. *LNmebe* is the coefficient on log market-to-book ratio. The remaining coefficients are the deviations from the market valuation regression coefficients. Investor types are: Households (HH), Investment Advisors Large Passive (IA LP), Investment Advisors — Small Passive (IA SP), Investment Advisors — Small Active (IA SA), Investment Advisors — Large Active (IA LA), Hedge Funds (HF), Long-term (LT), Private Banking (PB), and Brokers (BR). The household sector is constructed so that total holdings of a company add up to the company's market capitalization. Equity holdings data are from FactSet from 2006 until 2016.

Table 7
Total repricing by investor type.

	Active	Repricing	Share AUM	Repricing per $
US				
Inv. Large Passive	7.3	7.4	22.7	0.33
Inv. Small Passive	9.8	11.3	15.4	0.73
Inv. Small Active	19.0	19.4	17.2	1.13
Inv. Large Active	8.1	10.9	9.6	1.14
Hedge Funds	4.0	5.9	4.2	1.41
Long-Term	1.7	1.8	4.5	0.41
Private Banking	2.5	2.5	3.0	0.82
Brokers	0.8	1.0	1.2	0.78
GB				
Inv. Large Passive	9.7	5.7	16.5	0.34
Inv. Small Passive	13.0	5.9	18.3	0.32
Inv. Small Active	11.3	7.4	10.5	0.71
Inv. Large Active	7.1	5.5	7.7	0.72
Hedge Funds	0.8	0.8	0.8	1.00
Long-Term	2.7	1.6	6.1	0.26
Private Banking	1.8	1.4	2.3	0.58
Brokers	2.2	1.5	2.8	0.55

Each change is the time series average of the total absolute change in firm's market caps divided by the total original market cap. frac Inst is the time series average of the fraction of institutional ownership by that type and frac Tot is the fraction of total ownership. The repricing is calculated under the assumption that each investor type follows strict market weights. Investor types are: Households (HH), Investment Advisors Large Passive (IA LP), Investment Advisors — Small Passive (IA SP), Investment Advisors — Small Active (IA SA), Investment Advisors — Large Active (IA LA), Hedge Funds (HF), Long-term (LT), Private Banking (PB), and Brokers (BR). Firm-level fundamentals and equity holdings data are from FactSet from 2006 until 2016.

Table 8
Largest Repricing by Individual Investors (US 2016)

Type	Name	AUM (bn)	Active Share	Repricing (%)
Inv. Large Active	T. Rowe Price Associates, Inc.	423	0.45	4.19
	Wellington Management Co. LLP	324	0.41	2.91
	Capital Research & Management Co. (Global Investors)	250	0.44	2.56
	JPMorgan Investment Management, Inc.	194	0.39	1.78
Inv. Large Passive	Fidelity Management & Research Co.	554	0.33	3.99
	The Vanguard Group, Inc.	1,598	0.09	3.35
	Capital Research & Management Co. (World Investors)	328	0.37	2.92
	SSgA Funds Management, Inc.	954	0.11	2.12
Inv. Small Active	PRIMECAP Management Co.	84	0.56	1.11
	Jennison Associates LLC	77	0.57	0.99
	ClearBridge Investments LLC	75	0.50	0.92
	Janus Capital Management LLC	68	0.59	0.91
Inv. Small Passive	American Century Investment Management, Inc.	80	0.35	0.68
	State Farm Investment Management Corp.	67	0.44	0.67
	Managed Account Advisors LLC	94	0.31	0.63
	BlackRock Advisors LLC	76	0.35	0.63
Hedge Funds	AQR Capital Management LLC	62	0.45	0.62
	Renaissance Technologies LLC	46	0.44	0.41
	Millennium Management LLC	38	0.51	0.39
	Citadel Advisors LLC	30	0.57	0.37
Private Banking	Goldman Sachs & Co. LLC (Private Banking)	99	0.28	0.61
	Wells Fargo Clearing Services LLC	69	0.34	0.52
	Morgan Stanley Smith Barney LLC (Private Banking)	86	0.26	0.50
	Bank of America, NA (Private Banking)	68	0.27	0.39
Long-Term	Norges Bank Investment Management	199	0.12	0.55
	APG Asset Management NV	48	0.24	0.29
	Loews Corp. (Investment Portfolio)	14	0.98	0.27
	The Caisse de d1/4p1/4t et placement du Qu1/4bec	20	0.51	0.24
Brokers	Morgan Stanley & Co. LLC	50	0.34	0.34
	Credit Suisse Securities (USA) LLC (Broker)	60	0.21	0.28
	Citigroup Global Markets, Inc. (Broker)	21	0.39	0.16
	Susquehanna Financial Group LLLP	13	0.45	0.13

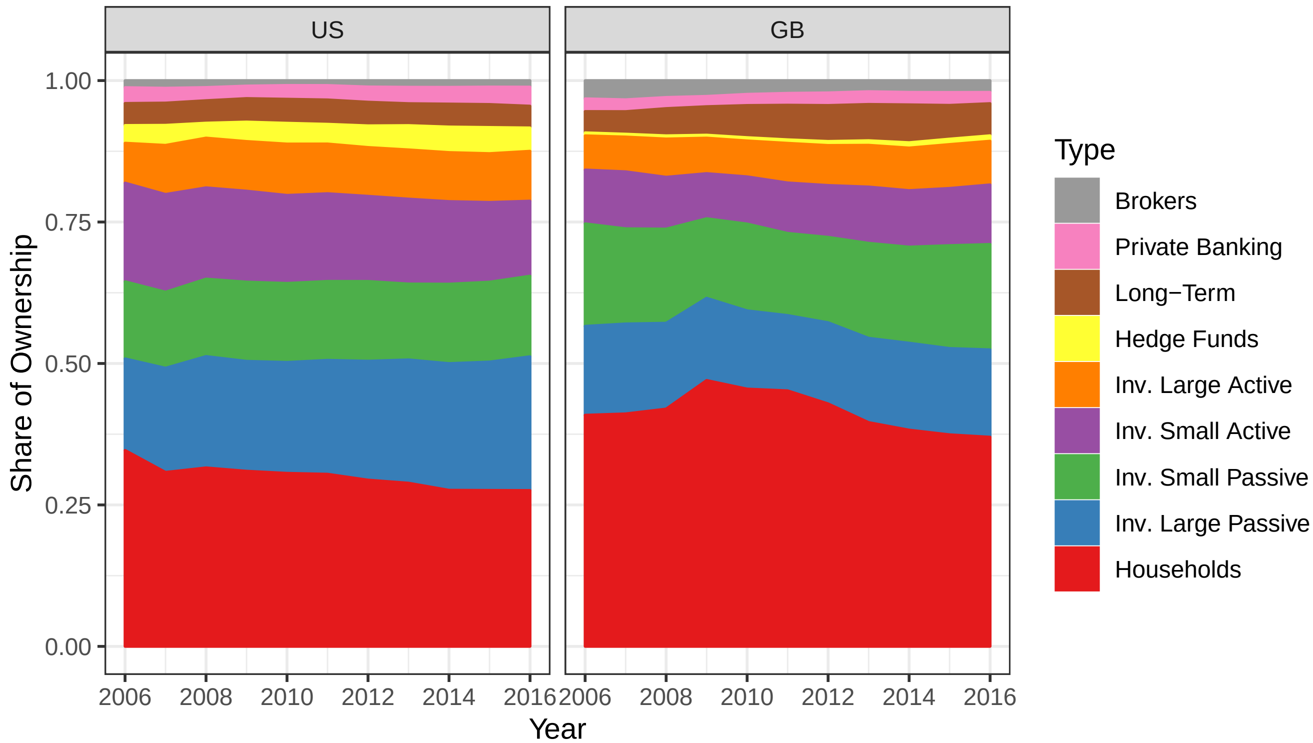
Top 3 investors within each type in terms of repricing. Repricing is calculated as percent change in market cap if that individual investor changes to market weights within their investment universe. Investor types are: Households (HH), Investment Advisors Large Passive (IA LP), Investment Advisors — Small Passive (IA SP), Investment Advisors — Small Active (IA SA), Investment Advisors — Large Active (IA LA), Hedge Funds (HF), Long-term (LT), Private Banking (PB), and Brokers (BR). Firm-level fundamentals and equity holdings data are from FactSet from 2006 until 2016.

Table 9
Change in Valuation Regression Coefficients.

	IA LP	IA SP	IA SA	IA LA	HF	LT	PB	BR
US								
Foreign Sales	0.04	-0.48	-1.67	-0.71	1.17	0.27	-0.20	0.09
Lerner	1.16	0.23	-1.24	0.64	0.82	-0.30	-0.38	0.08
Sales to Book	0.14	0.48	2.21	0.49	-1.14	0.22	-0.18	-0.02
Dividend to Book	0.10	1.21	8.28	2.05	3.38	-0.12	0.19	-0.11
Market Beta	-0.18	0.02	0.13	-0.60	-1.89	-0.42	0.16	-0.22
LNbe	0.58	3.38	18.04	1.57	4.44	0.03	1.18	-0.05
R-squared	-1.43	-5.96	-15.79	-2.38	-5.15	-2.09	-1.24	-0.19
GB								
Foreign Sales	-0.53	0.42	-0.58	0.03	0.04	0.54	0.41	0.44
Lerner	0.57	0.46	0.75	0.92	-0.15	-0.80	0.04	0.02
Sales to Book	-0.59	0.56	1.48	-0.21	-0.12	-0.26	-0.08	0.15
Dividend to Book	0.50	0.56	2.06	0.15	0.27	0.97	0.17	0.10
Market Beta	-0.05	0.47	0.58	1.56	0.24	0.43	0.02	-0.11
LNbe	0.96	3.58	5.12	3.05	0.52	0.31	0.47	0.59
R-squared	-1.48	-2.94	-2.89	-2.75	-0.33	-0.52	-0.40	-0.48

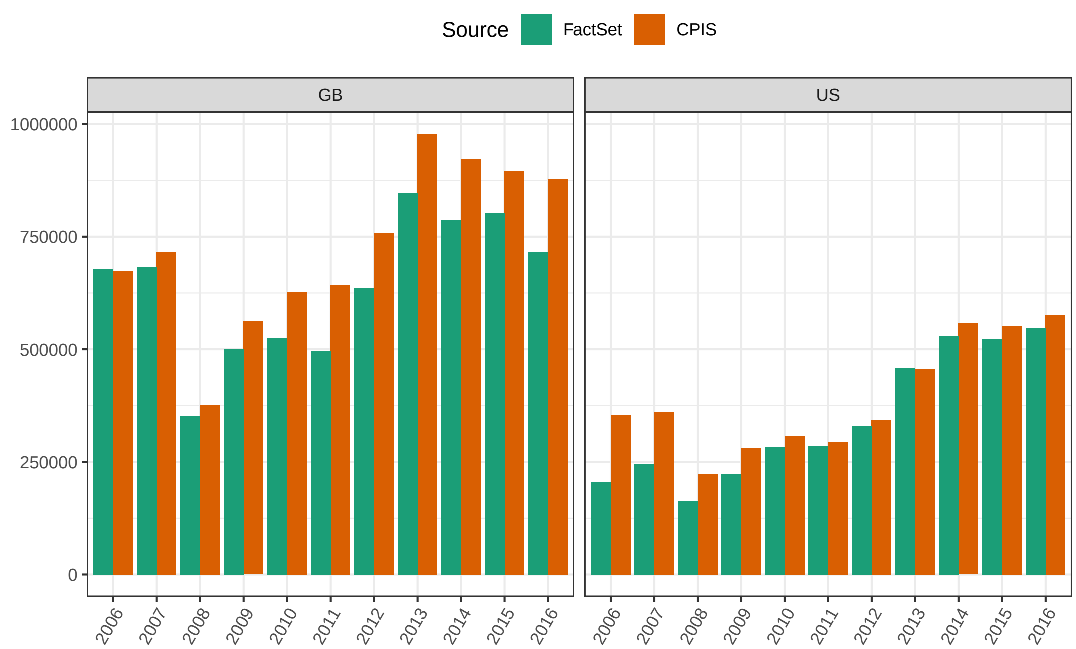
Change in regressions of valuation ratios on firm-level characteristics under each repricing scenario. Each column is the change in the coefficient from the actual valuation regression multiplied by 100. The new market-to-book ratios are calculated under the assumption that each investor type follows strict market weights. All regressions include year fixed effects. mb is the log market-to-book ration at time t. Characteristics are measured at time t. Foreign sales is the fraction of sales from abroad, and 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, and $LNbe$ is log book equity. Investor types are: Households (HH), Investment Advisors Large Passive (IA LP), Investment Advisors — Small Passive (IA SP), Investment Advisors — Small Active (IA SA), Investment Advisors — Large Active (IA LA), Hedge Funds (HF), Long-term (LT), Private Banking (PB), and Brokers (BR). Firm-level fundamentals and equity holdings data are from FactSet from 2006 until 2016.

Figure 2
Time series of ownership by institutional type.



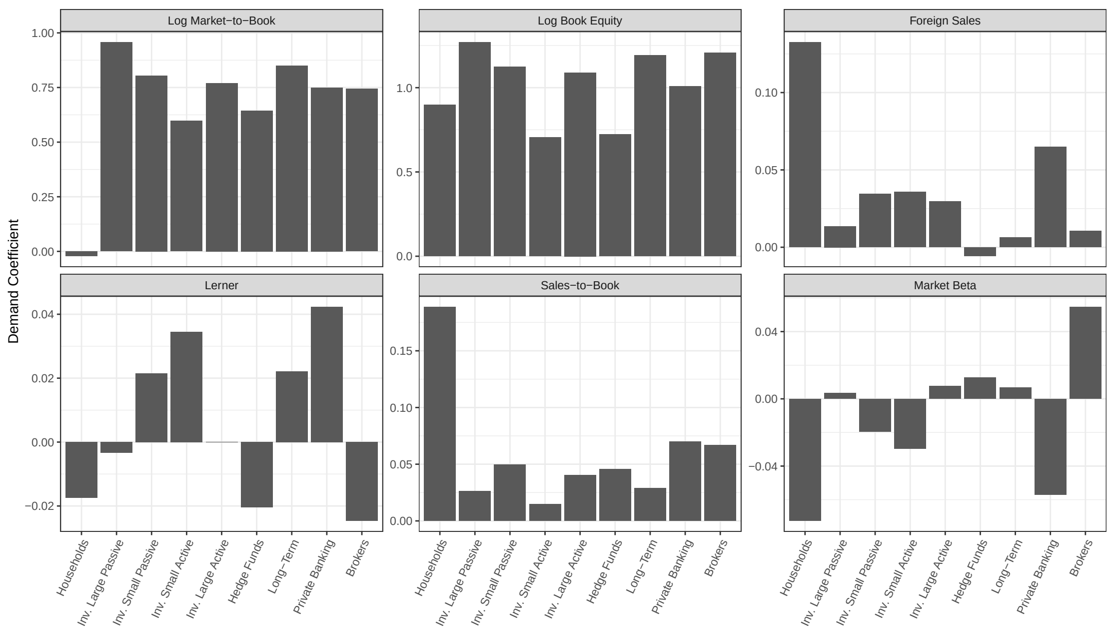
Summary statistics of coefficient estimates from investor level demand system estimation in the United States (US) and Great Britain (GB). AUM is the time series average of the total AUM for each investor group. All other cells are the time series average of the within year assets under management weighted average coefficients. $LNmebe$ is the coefficient on log market-to-book ratio. The remaining coefficients are the deviations from the market valuation regression coefficients. Investor types are: Investment Advisors (IA), Mutual Funds (MF), Long-term (LT), Private Banking (PB), Brokers (BR), and Households (HH). The household sector is constructed so that total holdings of a company add up to the company's market capitalization. Equity holdings data are from FactSet from 2006 until 2016.

Figure 3
Comparison with IMF CPIS.



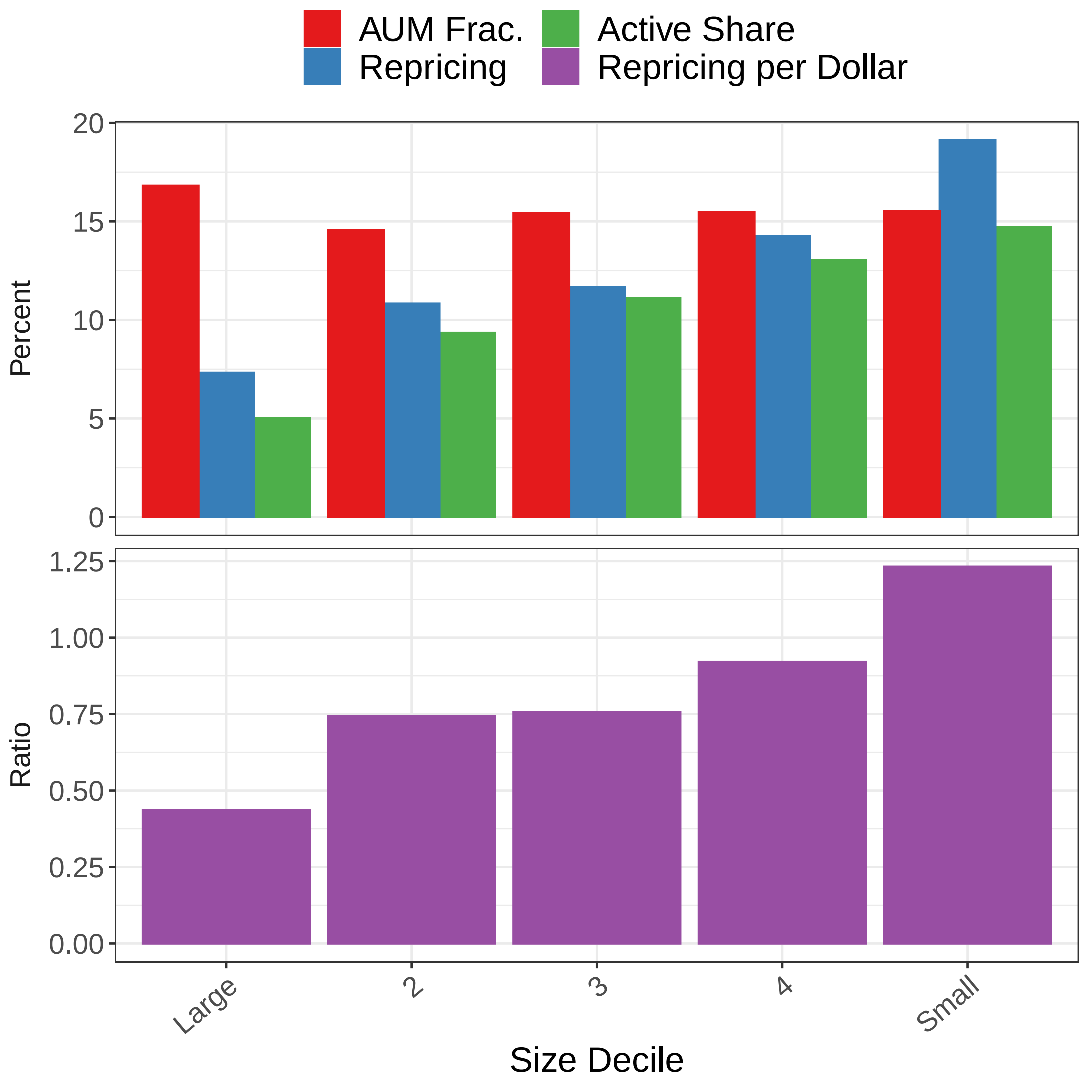
Total cross-border holdings of US and UK equities by US and UK investors. Equity holdings are from the IMF Coordinated Portfolio Investment Survey and FactSet from 2006 until 2016.

Figure 4
Demand Curve Summary by Investor Type (US)



Summary of demand curves by investor type. Each bar represents the time series average of the AUM weighted demand curve coefficients within each investor-type and year. Investor types are: Households (HH), Investment Advisors Large Passive (IA LP), Investment Advisors — Small Passive (IA SP), Investment Advisors — Small Active (IA SA), Investment Advisors — Large Active (IA LA), Hedge Funds (HF), Long-term (LT), Private Banking (PB), and Brokers (BR). Firm-level fundamentals and equity holdings data are from FactSet from 2006 until 2016.

Figure 5
Total Repricing By Size (US)



Change is percent change in market cap switching each investor size group to a pure indexing strategy. The top panel reports the fraction of ownership, the total repricing, and the share of active capital by investor type. The bottom panel reports the change in market cap normalized by the fraction of ownership by each group. Investors are grouped into 5 quintiles by AUM, excluding the household sector. Firm-level fundamentals and equity holdings data are from FactSet from 2006 until 2016.

A. Data construction

All FactSet data are from WRDS. We use FactSet fundamentals annual version 3 and FactSet ownership version 5. MSCI return indices are from DataStream. Interest rate data are from Global Financial Data.

We combine data from these sources to build an annual end-of-year panel of firm-level fundamentals and investor-level equity holdings from 2006 until 2016. Our fundamentals data covers 4 regions: United States (US), Euro Area (EA), Great Britain (GB), and Japan (JP). Our holdings data covers 2 regions: United States (US) and Great Britain (GB). EA consists of companies in Austria, Belgium, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal, and Spain.

Market capitalization We combine monthly security prices and company-level shares outstanding from monthly_prices_final_usc and monthly_prices_final_int with point-in-time exchange rates from fx_rates_usd. We calculate company-level USD market cap using shares outstanding (ff_shs_out) times price (price_m) and convert to USD. Shares outstanding is the common shares outstanding at the company level. If a company has more than one share class, shares outstanding is adjusted for the relative par values of all share classes. Both prices and shares outstanding are adjusted for splits.

Some companies have many listed securities. To merge market caps with fundamentals, we select a unique primary security fsym_id for each company (factset_entity_id). We start from the set of securities which we can calculate a USD market cap for and merge on security and firm identifying information from sym_coverage and ff_sec_coverage. We sequentially select the first security for each company which is uniquely identified by the following criteria: one security for the company, ff_iscomp is 1 for the security, the security is identified as primary by fsym_primary_equity_id. If this procedure does not uniquely identify a primary security, we do not include the company in our sample. This occurs in a very small number of cases.

For each firm-year we use the market cap reported at the end of December.

Fundamentals Fundamentals are in 4 files for each of 3 regions: ff_FILE_REGION where FILE is one of basic_af, basic_der_af, advanced_af, advanced_der and REGION is one of ap, eu, am. We merge these 12 files together with point-in-time exchange rates from fx_rates_usd and convert monetary values to USD. For fundamentals in December of each year we use the most recently available fundamentals as of the end of June of that year.

- Book equity is total shareholders equity (ff_shldrs_eq) plus deferred taxes and investment tax credits (ff_dfd_tax_itc) minus preferred stock (ff_pfd_stk). We set preferred stock to zero if it does not exist and drop negative book equity values.
- Market equity is total value of common equity as detailed in the market capitalization section above.
- Foreign sales share is international sales (ff_sales_intl) divided by total sales (ff_sales).

- Lerner is operating income before depreciation (ff_oper_inc_bef_dep) minus depreciation and amortization (ff_dep_amort_exp) if available or operating income (ff_oper_inc) divided by sales (ff_sales).
- Sales to book is sales (ff_sales) divded by book equity
- Dividends to book are dividends (ff_div_cf) divided by book equity.
- Betas are from 60-month rolling regressions on MSCI local equity market index returns. Excess returns are calculated using 3-month rates from Global Financial data.
- Net repurchases are ff_stk_purch_cf minus ff_stk_sale_cf and are set to 0 if missing.

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 region-year. We set values of Lerner that are less than -1 to -1.

Portfolio Holdings We build a panel of end-of-year equity holdings of US and GB companies for institutional and non-institutional investors. FactSet collects data for global companies and institutions, but the coverage outside of the US and GB is not sufficient for our purposes of estimating a demand system. To remain consistent with FactSet's methodology we construct holdings data for all countries and then select holdings of only US and GB companies. We also limit our sample to 2006 until 2016 due to lower coverage in GB prior to 2006.

FactSet holdings data are from 4 broad sources:

- 13F holdings (13F). 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.
- Sum of fund-level reports (SOF). Fund-level data are from SEC mandated reports in the US and are collected directly from funds managers by FactSet in other countries. Data is in own_fund_detail_eq. Fund-level reports are aggregated to the institution level using the mapping from fund ids to intitution ids in own_ent_funds.
- Institutional Stakes (INST). Institutional stakes data for GB and are sourced from share registers (UKSR) and regulatory news service filings (RNS). FactSet analyzes share registers at minimum annually, though for companies larger than fledgling the frequency is quarterly. Institutional stakes data for the US are sourced from regulatory filings such as 10K, 13D, 13G, and proxies. For other countries FactSet collects data from various regulatory filings. Data is in own_inst_stakes_detail_eq.
- Non-institutional stakes (NISTK). Non-institutional stakes are from regulatory filings and primarily represent holdings by firm insiders or by other companies. Data is in own_stakes_detail_eq.

We combine data from the 4 sources. Securities are identified as either 13F US (fds_13f_flag=1), 13F Canada (fds_13f_ca_flag=1), or UKSR (fds_uksr_flag=1) in own_sec_coverage. Holder's are identified as 13F institutions (fds_13f_flag=1) in own_ent_institutions. We use the following rules to combine institutional holdings as is done by FactSet:

- For UKSR securities, select UKSR or RNS positions (types W and Q) if the as_of_date is within 18 months of December of each year. If there are no intitutional stakes based filings for a given institution use SOF if the report is within 18 months of December of each year.
- For 13F institutions and 13F US securities, use the 13F position if it is within 18 months of December of each year unless there is a more recent INST position.
- For 13F institutions and 13F CA securities, use the 13F position if it is within 18 months of December of each year unless there is a more recent INST position. If there is are no 13F or INST positions, use SOF if it is within 18 months of December of each year.
- For non-13F institutions and/or non-13F US/CA securities, use the INST position if it is within 18 months of December of each year for US securities and 21 month for non-US securities. If there is no INST position, use SOF if it is within 18 months of December of each year.
- Use NISTK positions if tphey are within 18 months of December of each year.

We merge on prices from own_sec_prices_eq and calculate dollar values of holdings for holdings of each security. We limit holdings to common equity and ADRs:

(fref_security_type=SHARE,ADR,DR,GDR,NVDR and issue_type=EQ in sym_coverage)

We aggregate dollar values of security-level holdings to company-level holdings using the mapping in own_sec_entity_eq.

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; Long-term=FO,SV,IN; Mutual Fund = MF.

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 insitutions are great than the market cap, in which case we proportionally scale back all institutions holdings.

We classify the outside asset as any firm which is outside of the top 90% of market cap within each region. Any instituion which has less that \$1mm in holdings in the outside asset, is classified as a non-institutional stakes holder, or has less than 20 holdings across all years is moved into the household sector.

B. Numerical algorithm to compute the ridge estimator

We start from

$$\mathbb{E}_t\left[\left(\delta_{i,t}(n)\exp\left\{-\beta_i' X_t(n)\right\}-1\right)Z_t(n)\right]-D(\Lambda_i)\left(\beta_i-\beta^T\right)=0. \tag{35}$$

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

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

implying

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

We iterate on this procedure until convergence. Note that the numerator of the adjustment term are the moment conditions in (35), implying that upon convergence, the moment conditions are satisfied.

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

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

implying

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

C. Computing counterfactual asset prices

To compute the counterfactual asset prices in this case, we start from

$$
\begin{aligned}
y_{it}(n) \quad & = \quad \ln\left(\frac{w_{it}(n)}{w_{it}(0)}\right)-\gamma' x_{it}^{\star}(n)-b_t(n) \\
& = \quad c_{0it}+\beta_{0i}u_t(n)+c_{1i}'x_t^{\star}(n)+\epsilon_{it}(n),
\end{aligned}
$$

where $u_t(n)=mb_t(n)-c_{mb,t}-\gamma' x_t^{\star}(n)$. Combining these identities implies

$$
\begin{aligned}
\ln\left(\frac{w_{it}(n)}{w_{it}(0)}\right) \quad & = \quad c_{0it}-c_{mb,t}\beta_{0i}+\beta_{0i}mb_t(n)+(c_{1i}+\gamma(1-\beta_{0i})+e_1\sigma_b)'x_t^{\star}(n)+\epsilon_{it}(n) \\
& = \quad c_{wi,t}(\beta_{0i})+\beta_{0i}mb_t(n)+\beta_{1i}'x_t^{\star}(n)+\epsilon_{it}(n),
\end{aligned}
$$

where $c_{wi,t}(\beta_{0i})=c_{0i,t}-c_{mb,t}\beta_{0i}$ and $\beta_{1i}=c_{1i}+\gamma(1-\beta_{0i})+e_1\sigma_b$.

We use this last equation as the demand curve and change the coefficients and latent demand for one investor type. In particular, under the counterfactual, we assume

$$\ln\left(\frac{w_{it}(n)}{w_{it}(0)}\right) = c_{wi,t}(1) + me_t(n) = c_{0it} - c_{mb,t} + me_t(n),$$

for one type of investors. The demand curve of all other investors remains unchanged. We then solve for asset prices using the market clearing equation

$$ME_t^{CF}(n) = \sum_i w_{it}^{CF}(n, ME_t^{CF}(n))A_{it}, \tag{36}$$

where w^{CF} are the counterfactual portfolio weights. We use the algorithm in Koijen and Yogo (2019) to compute counterfactual market capitalizations, which iterates on (36) until convergence.

D. Variance decompositions using characteristics

We show how our valuation regressions and earnings predictability regressions connect to traditional variance decompositions. Starting from (32) without expectations, it holds

$$mb_t(n) = c + \sum_{s=1}^{\infty} \rho^{s-1} e_{t+s}(n) - \sum_{s=1}^{\infty} \rho^{s-1} r_{t+s}(n). \tag{37}$$

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

$$a_{mb,t} = a_{e,t} - a_{r,t}, \tag{38}$$

$$\lambda_{mb} = \lambda_e - \lambda_r. \tag{39}$$

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 $\Sigma_x = \text{Var}(\Sigma_x)$. As characteristics are cross-sectionally standardized, if the characteristics are also uncorrelated, then 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.