Model-Free Mispricing Factors

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Abstract

We identify model-free mispricing factors and relate them to global stock prices and investor beliefs. The factors are model-free as they measure variation in the relative prices of assets with the same cash flows. We design three factors to reflect the beliefs and capital flows of important clientele: investors in United States (US), developed, and emerging stock markets; and individuals and institutions. Together the three factors capture most (52%) of the systematic variation in price premiums of individual securities. These factors strongly predict US, developed, and emerging market stock returns. They also explain most (58%) of the variation in US stocks' valuation ratios. Further evidence suggests that stock mispricing is related to investor overreaction to long-term cash flow news and limits to arbitrage.

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1 Introduction

Researchers sharply disagree about the importance of mispricing in global financial markets. Despite an emerging consensus that limits to arbitrage and investor irrationality are prevalent, disagreement persists because empirical evidence is contentious.[1] Conventional measures of mispricing, such as alphas from factor models (e.g., Fama and French (2015) and Stambaugh and Yuan (2017)), suffer from the classic joint hypothesis problem in which mispricing could reflect model misspecification.

This paper contributes to this debate by identifying model-free measures of mispricing and showing that they exhibit strong relationships with global stock prices and investor beliefs. We build on a rich literature documenting relative mispricing in which securities with identical cash flows sell at different prices.[2] We analyze the factor structure of relative mispricing in closed-end funds (CEFs), which often sell at significant discounts or premiums relative to the net asset value of their portfolio holdings.[3] The factor structure of relative mispricing unambiguously reveals systematic discount rate shocks that affect funds and their underlying assets, which include all major securities in global financial markets. Discount rates are the primary drivers of stock valuations (Cochrane (2011)), but their interpretation as mispricing or rational aversion to time-varying risk is disputed.

This study provides new evidence that discount rate factors based on mispricing are highly correlated with discount rate factors in global stock markets. We show that relative mispricing factors are strong predictors of global stock returns (monthly $R^2 \sim 3\%$) in and out of sample. Moreover, these mispricing factors are highly correlated with global stock valuations ($R^2 > 50\%$) in and out of sample. The two key premium factors in our analysis are based on cross-sectional differences in closed-end fund (CEF) premiums in developed and emerging markets and differences in US premiums based on institutional ownership. We also include the general US CEF premium that has received the most attention in prior

[1] Gabaix and Koijen (2021) find that popular and academic beliefs about the elasticity of demand for stocks differ from their empirical estimates by a factor of 500. Although survey evidence on investor rationality abounds, its relevance for asset prices remains unclear because survey participants might not be representative of market participants. In addition, reported expectations differ widely across investors and exhibit weak correlations with investors' own portfolio choices (Giglio, Maggiori, Stroebel, and Utkus (2020)).

[2] Examples of securities exhibiting relative mispricing include closed-end funds (Pontiff (1996)), dual-listed stocks (Froot and Dabora (1999) and De Jong et al. (2009)), equity carve outs (Mitchell, Pulvino, and Stafford (2002) and Lamont and Thaler (2003)), American Depository Receipts (ADRs) (Gagnon and Karolyi (2010)), US Treasuries (Musto, Nini, and Schwarz (2018)), and derivatives, such as options (Ofek, Richardson, and Whitelaw (2004)) and credit default swaps (Duffie (2010)). Pasquariello (2014) finds that the average absolute value of relative mispricing is related to global risk premiums.

[3] Hereafter we refer to CEF discounts as negative premiums.

research, including seminal studies of investor sentiment by Lee, Shleifer, and Thaler (1991) and Baker and Wurgler (2006), but it plays only a minor role in our analysis.

We interpret these mispricing factors through the lens of a theoretical model and empirical evidence on investor beliefs and the CEF market. Our model confirms the intuition that factors based on relative mispricing must reflect differences in investor beliefs or frictions in capital allocation across two markets: those for the CEF and the underlying assets. Thus, CEF premiums reflect belief or flow-driven differences between (US) CEF investors and those who directly hold the CEF's underlying assets. By analyzing the premiums of CEFs that hold stocks with specific clientele, we can observe how beliefs and flows differ across these groups of investors.

We hypothesize that mispricing in global stocks could arise from investors' mistaken beliefs about future global economic growth. We design linear combinations of CEF premiums to measure investor beliefs about global growth—i.e., global sentiment. Our main two measures are differences in premiums of groups of CEFs that we expect to have differential exposure to global sentiment. Motivated by the strong home bias in global equity markets (French and Poterba (1991) and Ferreira and Matos (2008)), we evaluate regional differences in premiums, focusing on the difference in premiums between CEFs that hold non-US developed market stocks and CEFs that hold emerging market stocks—i.e., the DED or developed − emerging difference in premiums. Since each CEF premium reflects differences in the clientele holding the CEF and the underlying assets, the DED factor reflects differences in differences in clientele—e.g., the belief difference between US and developed market investors' relative to the belief difference between US and emerging market investors.

We augment this location-based DED factor with a factor designed to capture differences in the types of US investors who directly hold CEFs. Although individual ownership of CEFs remains common, institutions now own a significant fraction of funds. Differences in premiums across CEFs held by institutions and individuals reflect belief or flow differences across these key groups of investors, who jointly determine the prices of global stocks (Koijen and Yogo (2019)). We construct a premium factor based on relative institutional ownership, which we call the UID (US institutional ownership difference) premium, to capture these investor differences.

The developed − emerging difference (DED) in CEF premiums exhibits a strong positive relationship with US valuations, and it predicts negative expected returns in the US and other stock markets. Similarly, the high minus low institutional ownership difference (UID) in CEF premiums is positively related to US valuations and predicts negative expected returns. The simple US CEF premium used in prior research has insignificant relationships with valuations and returns in univariate tests, though it does exhibit a weak positive relationship with US valuations and a negative relationship with US expected returns when we control for the DED and UID relative premiums.

We propose a simple explanation for these findings based on a bias in US investor reactions to news about future global growth. US investors could overestimate the impact of growth on developed economies, which are familiar to them, but react less to the impact of growth on emerging economies, which are far removed from most US investors' daily experiences. As an example, consider positive news in the late 1990s about how the Internet would transform the US and developed markets. Since the impact of this new technology was highly visible for US investors and easy to retrieve from memory, these investors could mistakenly judge economic transformation in the US and developed economies as overly likely to occur based on the availability and familiarity heuristics (Kahneman and Tverksy (1973) and Arkes, Hackett, and Boehm (1989)). In contrast, these investors could react less to the impact of the Internet on emerging economies, which depends on abstract global supply chain and commodity price links. The increasing difference between developed and emerging market CEF premiums in the late 1990s, followed by a decreasing difference in the early 2000s, is consistent with investor overreaction (less reaction) to the impact of the Internet on developed (emerging) economies.

This explanation is not only consistent with the relationships between the regional CEF premiums and global stock prices, but it also correctly predicts relationships between premiums and investor beliefs about long-run growth. Specifically, we find that the DED and UID premiums are both strongly positively correlated with stock analysts' 10-year forecasts of earnings growth for US firms. The DED finding is consistent with the idea that investors in each region overreact most to the impact of global growth on their region. The UID finding is consistent with the idea that overreaction is greatest for investors in high institutional ownership CEFs. One could interpret these investors as institutions' clients, rather than institutional money managers, assuming that clients' investment flows to institutions drive institutions' trading behavior. Indeed, we find that flows to CEF-holding institutions are related to the premium difference based on institutional ownership.[4] Our evidence is less consistent with the hypothesis that general shocks to arbitrage capital drive variation in val-

[4] Gemill and Thomas (2002) provide intriguing evidence that retail flows are positively associated with CEF premiums in the United Kingdom. This evidence on flows comes from data on retail flows into open-end mutual funds, not CEFs.

uations. Such shocks would primarily affect the US CEF premium, which has only a weak link with valuations, and are less likely to drive variation in the relative CEF premiums, which have stronger relationships with valuations.

Collectively our findings suggest that belief-based mispricing has a pervasive impact on stock valuations around the world. These new empirical links between mispricing and stock prices are somewhat surprising in light of extensive prior research on relative mispricing and closed-end funds (CEFs). Numerous studies of CEFs conclude that systematic time-variation in premiums represents mispricing (Lee, Shleifer, and Thaler (1991), Bodurtha, Kim, and Lee (1995), Pontiff (1996), Hwang (2011)) and is not due to agency costs, illiquidity, or tax effects—even if such effects account for some fund-specific variation in premiums (Berk and Stanton (2007) and Cherkes, Sagi, and Stanton (2009)). However, a common view is that the relative mispricing embodied in CEF premiums comes primarily from mispricing in CEFs rather than their portfolio holdings (Pontiff (1995) and Neal and Wheatley (1998)).[5] Our empirical results are not necessarily at odds with the weak predictability for underlying asset returns in prior studies because we also find that the US CEF premium is a weak predictor when using it in isolation.[6] Our contribution is to show that differences in CEF premiums are the relevant predictors of underlying stock returns and that they exhibit strong correlations with stock valuations.

We consider alternative interpretations of CEF premiums, such as the idea that premiums could arise from CEFs' capitalized after-fee alphas (e.g., Cherkes, Sagi, and Stanton (2009)). Since after-fee alphas could be positive or negative, increases in discount rates could increase or decrease capitalized net alphas and thus CEF premiums. Since we focus on aggregated CEF premiums, discount rate effects for individual CEFs with positive and negative net alphas tend to offset. In fact, we find that the typical CEF has a near-zero net alpha. Furthermore, we focus on the difference between groups of CEF premiums. There would not be material discount rate effects in such differences between premiums unless there are systematic differences in net alphas across CEF groups, which we do not find.

[5] This view comes from empirical studies of CEFs that hold US stocks and even some studies of CEFs that hold foreign stocks, such as Klibanoff, Lamont, and Wizman (1998) who assert that CEF "NAV is an accurate measure of fundamental value ... [that] incorporates fundamental information" (page 674).

[6] This study uses data from 1994 through 2020, which is a much longer and more recent sample than used in prior research.

2 A Model of Mispricing Factors

Although the empirical construction of our mispricing factors does not rely on any model of risk, we use a model to interpret these factors and guide subsequent empirical tests. The model demonstrates how CEF premiums relate to biases in beliefs, which we refer to as sentiment, and arbitrage capital in the market for their underlying assets. The main assumption, which we confirm empirically, is that large groups of CEFs with broad market holdings have effectively the same cash flows as their underlying assets' cash flows. Thus, any discrepancy in prices between CEFs and their asset holdings come from differential investor sentiment or frictions in capital allocation across markets.

2.1 Assets and Cash Flows

As in the data, we consider three markets (the US, non-US developed markets (DM), and emerging markets (EM)). For each region $j \in \{US, DM, EM\}$, there is a market fund with dividends given by:

$$d_t^{(j)} = g_t + f_t^{(j)}, \tag{1}$$

where

$$\begin{aligned} g_t &= \phi g_{t-1} + \varepsilon_{d,t}^{g}, \\ f_t^{(j)} &= \phi f_{t-1}^{(j)} + \varepsilon_{d,t}^{(j)}. \end{aligned} \tag{2}$$

Here g_t refers to a global factor in dividends, $f_t^{(j)}$ is the market-specific component of dividends, and all shocks are independently normally distributed with mean zero and variance σ_d^2. We define all markets dividends as $d_t \equiv [\ d_t^{(US)} \quad d_t^{(DM)} \quad d_t^{(EM)}\ ]^\top$.

To highlight empirically relevant features of the CEF market, we assume there are two closed-end funds investing in the US market, and one closed-end fund each for the other two markets. The dividends for CEFs satisfy:

$$\begin{aligned} d_{c,t} &= \begin{bmatrix} d_{c,t}^{(US),H} & d_{c,t}^{(US),L} & d_{c,t}^{(DM)} & d_{c,t}^{(EM)} \end{bmatrix}^\top \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \times d_t + \varepsilon_{c,t}, \end{aligned} \tag{3}$$

where $\varepsilon_{c,t} \sim N\left(0, \sigma_c^2 I_{4\times 4}\right)$. Thus, the difference in cash flows between the CEFs and their respective underlying market is the i.i.d. shock $\varepsilon_{c,t}$. Consistent with the data, we assume σ_c^2 is small but non-zero, which prevents risk-free arbitrage between the underlying asset and the CEF. The H and L superscripts refer to high and low institutional ownership, which we will relate to investor sentiment. For simplicity, the risky asset has zero net supply. There is also a risk-free asset in infinite supply with gross return $R_f > 1$.

2.2 Agents and Beliefs

We model two representative agents. The first is a rational arbitrageur who maximizes expected utility in each period as follows:

$$\begin{aligned} & \max_{x_{A,t}} E_t\left(e^{-\gamma W_{A,t+1}+\xi_{A,t+1}}\right), \quad s.t. \\ W_{A,t+1} &= W_{A,t} R_f + x_{A,t}\left(P_{t+1} + D_{t+1} - R_f P_t\right), \end{aligned} \tag{4}$$

where

$$D_t = \begin{bmatrix} d_t \\ d_{c,t} \end{bmatrix}, \quad P_t = \begin{bmatrix} p_t \\ p_{c,t} \end{bmatrix}. \tag{5}$$

Here p_t and $p_{c,t}$ refers to the equilibrium prices for the market and CEFs, respectively, γ is the risk-aversion of the arbitrageur, $W_{A,t+1}$ is wealth at $t+1$, and $\xi_{A,t+1} \sim N\left(0, \sigma_{\xi_{A},t}^2\right)$ is a preference shock. We let conditional covariances of asset payoffs with the preference shock vary over time, $C_{A,t} = Cov_t\left(P_{t+1} + D_{t+1}, \xi_{A,t+1}\right)$. This preference shock could represent shocks to leverage constraints or arbitrage capital, in the spirit of Brunnermeier and Pedersen (2009) and Duffie (2010).

Under these assumptions, the arbitrageur's risky asset demand is:

$$x_{A,t} = \frac{1}{\gamma}\Gamma_t^{-1}\left(E_t\left(P_{t+1} + D_{t+1} - R_f P_t\right) + C_{A,t}\right), \tag{6}$$

where Γ_t is the conditional covariance matrix of asset returns, $Var_t\left(P_{t+1} + D_{t+1}\right)$.

There is also a representative sentiment investor, who in each period maximizes:

$$\max_{x_{S,t}} E^S\left[e^{-\gamma W_{S,t+1}+\xi_{S,t+1}}\right], \tag{7}$$

where $E^S\left(\cdot\right)$ denotes this agent's expectation, which can deviate from rational expectations, and $\xi_{S,t+1} \sim N\left(0, \sigma^2_{\xi_S,t}\right)$ is the preference shock with conditional covariances with the asset payoffs given by the column vector $C_{S,t} = Cov_t\left(P_{t+1} + D_{t+1}, \xi_{S,t+1}\right)$. This preference shock causes time-varying demand for the underlying market and the CEFs for reasons other than deviations from rational expectations, such as time-varying hedging demand.

Assuming sentiment investors have rational beliefs about the conditional covariance matrix Γ_t, their demand is:

$$x_{S,t} = \frac{1}{\gamma}\Gamma_t^{-1}\left(E_t^S\left(P_{t+1} + D_{t+1} - R_f P_t\right) + C_{S,t}\right). \tag{8}$$

We allow sentiment investors to hold incorrect beliefs about asset payoffs:

$$E_t^S\left(P_{t+1} + D_{t+1} - R_f P_t\right) = E_t\left(P_{t+1} + D_{t+1} - R_f P_t\right) + S_t, \tag{9}$$

where sentiment S_t captures differences in expected excess returns relative to the rational arbitrageur. Thus, when sentiment for the risky asset is high, these agents have higher beliefs about expected returns than the arbitrageur, and vice versa.

Since the risky assets are in zero net supply, the market clearing condition implies that:

$$P_t = \frac{E_t\left(P_{t+1} + D_{t+1}\right) + \frac{1}{2}\left(S_t + C_{S,t} + C_{A,t}\right)}{R_f}. \tag{10}$$

The direct effect of high (low) S_t, $C_{A,t}$ or $C_{S,t}$ is to increase (decrease) the asset price.

The sentiment agent represents the aggregate demand of sentiment investors across all risky assets. We model sentiment demand as having a hierarchical structure analogous to that of dividends. Sentiment demand for assets $j \in \{US, DM, EM\}$ is:

$$\begin{aligned} s_t^{(j)} &= g_{s,t} + f_{s,t}^{(j)}, \\ f_{s,t}^{(j)} &= \phi f_{s,t-1}^{(j)} + \varepsilon_{s,t}^{(j)}, \\ g_{s,t} &= \phi g_{s,t-1} + \varepsilon_{s,t}^{g}. \end{aligned} \tag{11}$$

That is, $g_{s,t}$ is a common global component in sentiment and $f_{s,t}^{(j)}$ are market-specific sentiments. The global and country-specific shocks, $\varepsilon_{s,t}^{(j)}$ and $\varepsilon_{s,t}^{g}$, have correlation ρ with their dividend counterparts, $\varepsilon_{d,t}^{(j)}$ and $\varepsilon_{d,t}^{g}$. This correlation captures over- or under-reaction to fundamentals as a source of sentiment demand. The variance of all sentiment shocks is σ_s^2.

Sentiment demand for CEF $k \in \{US\_H, US\_L, DM, EM\}$ is

$$s_{c,t}^{(k)} = \beta_{c,s}^{(k)} s_t^{(k \to j)}, \tag{12}$$

where $\beta_{c,s}^{(k)}$ captures possible under- or over-reaction relative to the underlying market's sentiment and the superscript $(k \to j)$ refers to the market j associated with CEF k.

The impact of preference shocks on asset demand follows an autoregressive process:

$$C_t = \begin{bmatrix} C_{A,t} \\ C_{S,t} \end{bmatrix} = \phi C_{t-1} + \varepsilon_{C,t}, \tag{13}$$

where the shocks could be correlated within this vector and with the other shocks above. For parsimony, we assume the autocorrelation scalar ϕ is the same for all persistent processes.

2.3 Underlying Market Valuations and Expected Returns

Under the above assumptions, equilibrium asset prices are linear in cash flow, sentiment, and preference shocks (see Appendix A) with intuitive coefficients. Prices in the underlying markets are:

$$p_t^{(j)} = \frac{\phi}{R_f - \phi}(g_t + f_t^{(j)}) + \frac{0.5}{R_f - \phi}(g_{s,t} + f_{s,t}^{(j)}) + \frac{0.5}{R_f - \phi} C_t^{(j)}. \tag{14}$$

where $j \in \{US, DM, EM\}$. In addition to the usual effect of expected dividends on prices, increased (decreased) sentiment and hedging demand both push prices up (down). The risk premium is:

$$E_t\left(p_{t+1}^{(j)} + d_{t+1}^{(j)}\right) - p_t^{(j)} R_f = -0.5\left(g_{s,t} + f_{s,t}^{(j)} + C_t^{(j)}\right). \tag{15}$$

Thus, higher sentiment and hedging demand reduce the risk premium as they increase current asset prices without affecting future fundamentals.

2.4 The CEF Premium

We now demonstrate that the CEF premium is exposed to underlying asset sentiment if CEF investors have different susceptibility to this sentiment than investors in the underlying asset. The CEF premium also depends on differences in asset demand from preference shocks in the CEF relative to the underlying. Thus, any given CEF premium is a combination of these belief- and flow-based factors.

The CEF premium for CEF $k \in \{US\_H, US\_L, DM, EM\}$ is defined as:

$$
\begin{aligned}
CEF_{k,t} &= p_{c,t}^{(k)} - p_t^{(k\to j)} \\
&= \frac{0.5}{R_f - \phi}(\beta_{c,s}^{(k)} - 1)(g_{s,t} + f_{s,t}^{(k\to j)}) + \frac{0.5}{R_f - \phi}(C_t^{(k)} - C_t^{(k\to j)}).
\end{aligned}
\tag{16}
$$

where $k \to j$ refers to the underlying market j that corresponds to CEF k. Since the fundamental dividend exposures of the CEF and underlying are the same, the CEF premium is not a function of these fundamentals. However, if $\beta_{c,s}^{(k)} \neq 1$, the CEF is more or less sensitive to sentiment-driven demand than the underlying market. For example, the emerging market CEF premium is negatively exposed to global sentiment if $\beta_{c,s}^{(EM)} < 1$, meaning US CEF investors are less apt than local investors to apply global sentiment to emerging markets. Similarly, the US institutional CEF premium is exposed to global and market-specific sentiment if $\beta_{c,s}^{(US\_H)} \neq 1$ — that is, if investors in institutionally held US CEFs are more or less subject to sentiment than investors directly investing in US stocks.

Differences in demand due to the preference shock, which we think of as other sources of capital flows (e.g., increased marketing of CEF funds, or increased CEF-fund arbitrage from institutional investors) makes the CEF premium a noisy proxy for global and market-specific sentiment.

2.5 Model Implications

From Equation (16), CEF premiums reflect a combination of underlying market sentiment and other sources of capital flows, assuming the exposure of the CEF to these factors differs from that of the underlying. As we show empirically, CEF premiums aggregated to the market level are quite persistent and volatile, which implies that exposures must differ for sentiment, capital flows, or both. The high co-movement in CEF premiums across markets that we document must be due to a global sentiment factor or a global capital flow factor.

From Equation (15), the global sentiment and capital flow factors predict returns in all markets with exposure to them, which plausibly includes markets for CEFs and their underlying assets. The existence of CEF-market specific flow factors means all CEF premiums are noisy proxies for the elements that drive underlying market valuation ratios and conditional expected returns (Equations (14) and (15)). Using multiple CEF premiums across different markets in regressions relating CEF premiums to valuations and expected returns can help to reduce this noise.

Disentangling sentiment from flow-based sources of price and risk premium fluctuations requires either direct data on investor expectations and fund flows or identifying funds that have no exposure to one of these two factors. In the empirical section, we address these issues using the model to guide the analysis.

3 Data

3.1 Facts about Closed-End Funds

Although they are ideal assets for studying mispricing, closed-end funds are not popular investment vehicles in recent years. Whereas open-end mutual funds and exchange-traded funds (ETFs) in the US have amassed trillions (T) of dollars in assets under management ($15T in equities and $24T overall), closed-end funds managed just $277 billion (B) overall ($106B in equities) in 2020 according to the Investment Company Institute (ICI (2021)).

Within the estimated 3 million US households owning CEFs, 90% also owned stocks directly (75%) or through mutual funds (86%) (ICI (2020)). Households owning mutual funds or individual stocks tend to have more assets, income, and education relative to the general US household; and households owning closed-end funds have even more assets (+29%), income (+18%), and education (+16%) than those owning stocks (ICI (2020)).

Institutional ownership (IO) is increasingly common in closed-end funds. We provide evidence of this trend for three types of CEFs that hold stocks, those focusing on United States, developed markets (Dev), and emerging markets (Emg), as well as CEFs that hold mostly non-stocks. Aggregating Thomson data for each fund type, we find that the share of equity CEFs owned by institutions increases dramatically from 1994 to 2020, as shown in Figure B.1 in Appendix B. For US stock CEFs, IO rises from 5.7% in 1994 to 15.6% in 2020; for Dev, it rises from 7.4% to 54.3%; and for Emg, IO increases from 13.8% to 52.9%. For non-stock CEFs, IO rises from 1.2% to 20.2% in our sample period.[7] These increases echo increases in institutions' holdings of equities outside CEFs. We document the rise of IO in US stocks, ADRs, and ETFs in Figure B.2, which shows more modest increases for these securities as IO starts from a higher base.

[7]In a related phenomenon, shareholder activism in CEFs has increased sharply with filings for proxy contests tripling in frequency from 1995 to 2020 (ICI (2020)).

In the 1990s, the vast majority of household CEF holdings were directly held, whereas today owning CEFs through institutional intermediaries is more common. We use disaggregated Thomson data to provide evidence on which institutions and types of institutions hold CEFs during our sample. Table B.1 in Appendix B reports institutional holdings of the institutions with the largest holdings of equity CEFs in our sample. The table shows the names of institutions that hold more than 1% of shares in at least three equity CEFs in at least one quarter in our sample, which we define as a holding event. Table B.1 ranks institutions by the number of 1% holding events and lists the top 25 institutions. The columns labeled Quarters, Big Hldgs, and Big Value show the number of quarters with 1% holdings, average number of 1% holdings per quarter, and average value of 1% holdings per quarter, respectively, for each institution.

The top CEF holders listed in Table B.1 include five institutions that specialize in CEF arbitrage, including City of London Investments, 1607 Capital, and Karpus in the top 10. Table B.1 also features large endowment funds of universities, such as Harvard and Ohio State, and hedge funds, such as Renaissance Technologies, with highly sophisticated managers. The last notable category of institution is banks with full-service brokerages and private wealth management groups, such as Citigroup and Morgan Stanley, who often hold assets as custodians for wealthy individuals.

The last two columns in Table B.1 show that the top 10 institutions hold 10 to 20 CEFs with total values ranging from \$100M to \$500M per quarter. Given that our main sample includes an average of 61 CEFs, each of the top 10 institutions holds large (1% or higher) stakes in approximately one quarter of these CEFs when the institution is active in this market. The high granularity of institutional holdings in CEFs is consistent with general patterns in US stocks (Ben-David et al. (2021)). This concentration of ownership motivates our UID premium designed to capture the influence of institutions on CEF prices.

3.2 Data Methods

We combine several data sources to analyze closed-end funds (CEFs) and global equity markets. We now provide an overview of our methods for collecting and processing data and direct the reader to Appendix B for further details.

We begin our main analysis in 1994 based on the availability of high-quality data on fund net asset values and the proliferation of CEFs with foreign holdings in the early 1990s. Compustat provides comprehensive data on net funds' asset values (NAVs) starting in December of 1993, and Bloomberg coverage also improves in the 1990s. We focus on monthly data to minimize problems caused by illiquidity and sparse data coverage at higher frequencies.

Because we are interested in general measures of mispricing that affect a wide range of global equities, our analysis of CEFs focuses on those with broad mandates to invest in all stocks in a global region, rather than those specializing in a particular industry or investment style within or across regions. We further restrict the sample to funds with clear regional focuses to facilitate benchmarking and interpretation. The three regions that we consider are the United States (US), non-US developed markets (Dev), and emerging markets (Emg), motivated by the popular Morgan Stanley Capital International (MSCI) classification of regions and countries. We define the Dev and Emg CEFs in our sample based on country and regional focuses as follows:

- Dev: Australia, Austria, France, Germany, Ireland, Israel, Japan, Portugal, Singapore, Spain, and Switzerland; and general European or developed markets; and
- Emg: Brazil, Chile, China, India, Indonesia, Korea, Mexico, Malaysia, Philippines, Russia, South Africa, Thailand, Turkey, and Taiwan; and general Asia, Asia excluding Japan, Latin America, and emerging markets.

We exclude global funds with unclear regional focuses, specifically those with world, international, or Pacific mandates that cross US, Dev, and Emg boundaries.

Our main sample of CEFs comes from Bloomberg, Compustat, and the Center for Research on Security Prices (CRSP). We identify US CEFs available to US investors using Bloomberg's fund screener with filters for fund type, country of availability, country of domicile, and currency, along with CRSP's share code designation for US CEFs. We classify CEF mandates using Bloomberg information on funds' geographic, asset class, and industry focus and their objective and strategies. We manually inspect individual funds by name to correct classification errors and changes in fund strategies over time, which are infrequent. We obtain annual data on fund expenses using the Capital IQ fields for selling, general, and administrative expenses (SGA) and total equity.

We obtain monthly data on United States closed-end fund prices, returns, dividends, shares outstanding, and trading volume from CRSP. We obtain quarterly data on institutional investment managers' Form 13-F reports of CEF holdings to the Securities and Exchange Commission (SEC) from Thomson and Bloomberg. These institutional ownership sources are complementary and help us correct errors and gaps in data coverage, as described in Appendix B.

We use funds' country and geography classifications to match them to appropriate ETF benchmarks with the same country or regional focus. We also match all US funds with value- and size-based style focuses to US ETFs with the same focus. We collect data on ETFs that track country indexes by searching ETF names for countries of CEFs and manually searching the major ETF sponsors—mainly BlackRock, State Street, and Vanguard, but also Global X and VanEck. We select the ETF representing each country based on the largest ETF indexed to a benchmark for the country in a given year.

To ensure that measures of mispricing are based on liquid securities available to investors, we restrict our analyses to CEFs that meet the following minimum liquidity and size criteria:

- positive trading volume, stock price data, and shares outstanding in each of the last six months and the current month;
- non-missing NAV data in five of the last six months and in the current month;
- non-zero returns in at least three of the last six months;
- price times shares outstanding (size) of at least $10 million; and
- an age of at least six months since their initial public offerings (IPOs).

Although we relax the six-month history requirement in the first six months of our sample (January to June of 1994), we maintain the age criterion to avoid introducing idiosyncratic variation in fund performance immediately following CEF IPOs, as shown in Weiss (1989) and Shao and Ritter (2018).

We use a combination of automatic filters and manual inspection to correct significant errors in monthly NAV and price data in Compustat, CRSP, and Bloomberg. Errors in CEF price data are rare, but we find approximately 100 mistakes in Compustat and Bloomberg NAV data, about half of which apply to equity CEFs, which are our primary focus. We manual check for errors when fund NAV changes by 50% or more relative to fund price in a single month. When such changes are temporary, inconsistent with price, NAV, and shares outstanding data in other sources, or clearly reflect typographic mistakes, we consider them to be errors and correct them based on available data.

We compute and define key variables for CEFs and other assets as follows:

- Ret = monthly percentage change in split- and dividend-adjusted price
- NAV Ret = monthly percentage change in split- and dividend-adjusted NAV

- ExRet = monthly return in US dollars minus US risk-free rate
- lnPrem = log fund price minus log fund NAV
- Size = monthly price times shares outstanding
- Inst Own (IO) = quarterly shares owned by institutions divided by shares outstanding
- Exp Ratio = annual SG&A divided by annual total equity
- Track Err = monthly difference in fund NAV and benchmark returns

When data frequency is ambiguous, we denote monthly and annual variables with suffixes Mo and Ann, respectively. We denote changes in variables such as lnPrem with Δ—for example, ΔlnPrem = monthly change in lnPrem and ΔlnPrem Ann = annual change in lnPrem.

Table 1 summarizes key statistics for the closed-end funds that qualify for our sample. The values represent time-series averages of the monthly cross-sectional distribution of statistics. The columns show means (Mean), standard deviations (Std Dev), percentiles (P5, P25, P50, P75, P95), and the number of qualifying CEFs (Funds). There are 61 funds on average in our 324 sample months from 1994 to 2020.

[Insert Table 1 here]

The rows in Table 1 show key attributes of CEFs. The first two rows show that funds' excess returns (CEF ExRet Ann) average 7.9% per year and their NAV excess returns (NAV ExRet) average 7.5%. This slight discrepancy makes sense given the average discount (lnPrem) of −9.4% shown in row three. The average discount is small, however, compared to the average cross-sectional standard deviation of 10.0% shown in column two. The percentiles P5 and P95 indicate that 5% of funds sell at premiums of 9.5% or higher and 5% sell at discounts of more than 20% in an average month. Annual changes in premiums (Δlnprem Ann) also vary widely with P5 and P95 values of −12.5% and 11.7%, respectively, meaning that 10% changes in premiums are not uncommon.

Row five in Table 1 shows that average fund size is $356 million (M) with a wide range from $45M at the 5th percentile to $1.25B at the 95th percentile. Institutional ownership averages 22.3% and also ranges widely from just 3.3% at P5 to 50.4% at P95. Fund expense ratios average 1.50% (150 basis points or bps) and vary from 60 bps to 260 bps. In summary, funds exhibit large cross-sectional differences in returns, premiums, institutional ownership (IO), size, and expenses. We exploit the variation in IO in future analyses of fund premiums.

4 The Factor Structure of Mispricing

Here we lay the groundwork for our main empirical tests in Section 5 by investigating the factor structure of CEF premiums—i.e., relative mispricing. First, we analyze the risk for an arbitrageur aiming to profit from nonzero CEF premiums and show that this risk satisfies the key properties assumed in our model in Section 2. Second, we construct our main measures of relative mispricing based on groups of CEF premiums. Third, we investigate the factor structure of CEF premiums.

4.1 Arbitrage Risk: ETF Benchmarks for CEFs

Consider an arbitrageur who buys an equity CEF at a discount and shorts a portfolio of similar stocks to profit from relative mispricing. This trader faces two key risks: the discount rate risk that the fund premium fluctuates over time, which is the relative mispricing of interest; and cash flow risk from the trader's inability to design and maintain a replicating portfolio with a value that exactly matches the NAV of the CEF's stock holdings. We refer to this error in replicating NAV as tracking error. It arises because traders can observe CEF's real-time actively managed holdings only at infrequent horizons such as quarterly.

Our first set of tests investigates the properties of tracking error based on replicating CEFs using ETFs with similar holdings. This simple benchmark produces an upper bound on the tracking error for a sophisticated investor who uses more granular CEF holdings information. Using even the basic ETF benchmark, we will show that tracking error is small, especially when aggregating across CEFs. Tests in the next subsection will demonstrate that tracking error is not highly correlated with relative mispricing, as assumed in the model in Section 2.

We attempt to identify an ETF with similar holdings to serve as a benchmark for each CEF. ETF selection is usually straightforward given the CEF's geographic investment mandate. For example, the ETF benchmark for the Swiss Helvetia CEF (ticker SWZ), which holds only Swiss stocks, is the iShares Swiss ETF (ticker EWL). In this case, the number and type of fund holdings are quite similar for the CEF and ETF benchmark. We match all non-US CEFs that are country funds to ETFs that track a broad index in the same country. We match regional non-US CEFs to ETFs that track broad indexes in the same or similar region using the following iShares (BlackRock) ETFs: Europe, MSCI Europe Australasia Far East (EAFE), Asia 50, Asia ex Japan, Latin America 40, and MSCI Emerging.

We match general US CEFs to the largest S&P 500 ETF (initially ticker SPY; later VOO); and we match US CEFs with size (small or big) or value (growth or value) focuses to the corresponding style-focused US ETF, such as the large value US ETF (ticker IWD). We can compare CEFs to their matching ETFs only for the periods in which these ETFs exist. Although this limitation does not apply to the S&P 500 ETF, several style-focused ETF and country-specific ETFs did not launch until the early 2000s, shortening the period of comparison.

To estimate the error in tracking CEF NAV, we regress each CEF's excess NAV return on the matching excess ETF return.[8] Table 2, Panel A summarizes the estimates from 82 regressions for the 82 CEFs for which we have at least 24 months of matching ETF data. The first two columns show the annualized regression intercept (Alpha Ann) and slope coefficient (Beta ETF). The average fund alpha is 0.04% per year, which is extremely close to zero. This finding suggests that these ETFs and CEFs have extremely similar average risk-adjusted returns. The interquartile range of alphas is −1.75% to 1.33% per year, indicating a small range of values for most funds. However, alphas that deviate from zero by more than 4% exist for individual CEFs in the extremes of the distribution.

[Insert Table 2 here]

The ETF betas in column two of Table 2A show that the median (and mean) fund has a beta slightly less than 1.0. The median value of 0.935 means that a trader trying to replicate the typical CEF would put a 93.5% weight on the ETF and a 6.5% weight in the risk-free asset (US Treasury bills). Column three shows that the median adjusted R^2 value of these 82 ETF regressions is 85.6%, indicating a close match between CEFs and ETFs. For example, the Singapore ETF (ticker EWS) tracks the Singapore CEF with an adjusted R^2 value of 85.3%, meaning that hedging with the ETF reduces the CEF's annualized NAV volatility from 24.5% to 9.4%. An actual trader hedging the CEF could reduce tracking error further by selecting stocks that the CEF is likely to be holding based on its most recent quarterly disclosure, rather than using a similar ETF. Thus, these results represent a lower bound on how well a sophisticated trader could replicate CEF NAVs.

In reality, CEF arbitrage entails buying and selling groups of CEFs and constructing an aggregate replicating portfolio for these groups. Analogously, we aggregate NAV replicating portfolios based on ETFs across all CEFs in each of the three regions: US, Dev, and Emg. For

[8] We account for stale prices in reported NAV in 30 of our 82 CEFs by adding up to two monthly lags of ETF ExRet as regressors along with the contemporaneous month's ETF ExRet. We include one monthly lag of ETF ExRet for 22 CEFs and two monthly lags for 8 CEFs. For these 30 funds, we report the sum of all ETF ExRet coefficients as the funds' ETF betas; and we compute CEF tracking error relative to the predicted CEF NAV that accounts for all lags of ETF ExRet. We determine the number of lags in the ETF benchmark based on lagged beta thresholds of 0.05.

example, if the Swiss and Singapore CEFs were the only two Dev CEFs, we would aggregate the regression-weighted ETFs matching the Swiss and Singapore CEFs to replicate the Dev CEF. We then compute aggregate R^2 statistics for each region based on the fraction of variance in aggregated CEF NAV ExRet explained by the aggregated ETF benchmarks. We weight all CEFs and ETFs by the lagged size of the CEFs when aggregating benchmark and NAV returns.

Table 2, Panel B shows that the aggregate R^2 statistics for the US, Dev, and Emg regions are 96%, 90%, and 95%, respectively. Aggregated benchmarks track aggregated CEFs more closely than individual benchmarks track individual CEFs because much of the individual tracking error is idiosyncratic. The second row emphasizes that the remaining unexplained variance (Agg Track Err $R^2 = 1 - R^2$) is quite small. For example, the US Agg Track Err R^2 of 4% reflects US CEFs' aggregated tracking error volatility of 2.99% per year as compared to aggregated US NAV ExRet volatility of 14.79% per year ($4\% = \frac{2.99^2}{14.79^2}$).

Since there is still nontrivial aggregate tracking error for each region, we test whether this tracking error is systematically related to stock market returns in each region, as measured by the Fama and French (2017) market factor for the US, Dev, and Emg markets. The fourth row in Table 2, Panel B shows that market returns in each region explain at most 4% of the variation in tracking error. Even for developed markets (Dev), which have the largest tracking error and the biggest correlation with the market, the projection of tracking error on market returns has a volatility of just 1.15% per year.

Since arbitrageurs would likely hold CEFs in all three regions, we evaluate whether tracking error is correlated across markets. Table 2, Panel C shows that there are very weak positive correlations between tracking error in US and developed markets (0.126) and in US and emerging markets (0.061). There is a moderate positive correlation of 0.245 between developed and emerging market tracking error. Although this correlation is statistically significant, it is economically small from the standpoint of an arbitrageur diversifying across markets. We conclude from these analyses that arbitrageurs who hedge CEF NAV using ETFs would face small and primarily idiosyncratic cash flow risk. The next subsection evaluates the discount rate risk in CEF arbitrage by constructing and examining aggregate CEF premiums.

4.2 Aggregate Fund Premiums

Here we analyze deviations between CEF prices and NAVs as measured by log CEF premiums (lnPrem). These deviations represent relative mispricing of the CEF and its underlying assets, which reflects differences in the discount rate (DR) components in the value of the CEF and its underlying assets. We examine the systematic part of these DR components by classifying CEFs into similar groups and measuring the premiums of these groups.

We use two approaches to classify CEFs into similar groups. Our main approach is to group CEFs by their similarity in observable characteristics. We compare this approach to a secondary data-driven approach in which we use principal components analysis (PCA) to detect the factor structure in CEF premiums. We refer to aggregated premiums from the primary approach as predefined factors and those from the secondary approach as PCA factors.

Motivated by the model in Section 2, we construct predefined premium factors based on CEF characteristics that reflect differences in investor clienteles between CEFs and their underlying assets. The primary location of CEF holdings (US, Dev, or Emg) is strongly related to investor location because of pronounced home bias, which applies to individuals and institutions (French and Poterba (1991) and Ferreira and Matos (2008)). Whereas US CEFs are primarily held by US investors, their underlying stocks are primarily held by investors in the stock's home country, which differs for US, Dev, and Emg CEFs.

Our other characteristic of interest is the fraction of CEF shares owned by institutions (IO), which is a direct measure of the CEF's clientele. As shown in Figure B.1 in the Appendix, average IO for US CEFs in our sample ranges from 10% to 20%, which is significant. Moreover, the cross-sectional dispersion IO across US CEFs is 2% at the 5th percentile to 34% at the 95th percentile. These differences in IO across CEFs capture differences in whether individuals hold CEFs directly or indirectly through institutions. We use these differences as the basis for forming groups of CEFs with similar clientele.

We compute predefined factors as value-weighted averages of log CEF premiums (lnPrem) in each month based on the characteristics above: US, Dev, Emg, and IO. For each location characteristic (US, Dev, Emg), the premium factor is a simple value-weighted average of log premiums of individual CEFs in that location.[9,10] We include the US premium factor since

[9] We use one-month lagged size as the value weights for log premiums. Lagged size weights have two advantages relative to current size weights: 1) they facilitate comparisons between aggregated premiums and aggregate returns, which are also based on lagged weights; and 2) they do not introduce mechanical correlations between weights and returns.

[10] We compute log premiums before averaging to reduce the influence of outliers.

it has been used in prior literature. But we focus on the difference in the Dev and Emg factors (DED) to measure differences in US and local investor beliefs about developed and emerging markets.

We also define a UID factor based on the difference in fund premiums according to IO. We use regressions to estimate this factor as the difference between log premiums between US CEFs with high IO and those with low IO. In each month, we regress US CEF log premiums on IO converted into percentile rank for that month.[11] The factor is the difference between the predicted values of log premiums at the 75th and 25th percentiles (i.e., interquartile range) of IO. We refer to this difference in log premiums as UID (US IO Difference). This regression-based factor construction is similar to the traditional portfolio sort method but is less sensitive to outliers and portfolio rebalancing, two significant advantages in the small sample of US CEFs.

Table 3, Panel A reports the monthly distribution of five predefined log premium factors (US, Dev, Emg, DED, and UID), as well as the distribution of monthly and annual changes in these factors. The means of all five CEF premiums are negative, which is consistent with the longstanding finding that CEFs sell at discounts on average. The mean and median discounts for the US, Dev, and Emg CEFs are approximately 10%. The variation in these premiums is quite large, ranging from roughly −20% to 0% in the extreme deciles. The UID premium is negative even at the 75th percentile, meaning that US CEFs with high values of IO usually sell at lower premiums (i.e., higher discounts) than those with low values of IO, consistent with the idea that institutions seek cheap CEFs.

[Insert Table 3 here]

The CEF premium factors exhibit markedly different volatility. The well-known US aggregate premium exhibits the lowest volatility of the five premiums at just 3.3% per year. The premium factor based on cross-sectional differences in US premiums sorted by IO (UID) actually has higher volatility at 4.6% than the aggregate US premium. The Dev and Emg premiums are quite volatile at 4.7% and 6.7%, respectively. Their difference, DED, is also volatile at 4.8%, though much less volatile than it would be if the Dev and Emg premiums were independent. The yearly and monthly changes in premiums shown in the bottom ten rows of Table 3, Panel A confirm these patterns. Again, the volatility of the Dev and Emg CEF factors exceeds that of the US-based CEF factors. As expected, the means of changes in CEF premiums are close to zero.

[11] These regressions use lagged size as observation weights to mimic value weights.

We plot the time series of the three simple regional premium factors in Figure 1, Panel A. This graph illustrates the patterns noted above and provides two new insights about systematic variation in premiums. First, there is strong comovement in the US, Dev, and Emg premium factors, especially for the volatile Dev and Emg premium factors. Second, these three factors exhibit significant volatility during volatile periods for global and regional equity markets. For example, the Emg premium spikes up during the 1997 Asian financial crisis and down in the 1998 crisis in which Russia and Long-term Capital Management (LTCM) defaulted. These three premiums plummet and rebound during the dot-com boom and bust circa 2000 with the Emg premium being most sensitive to these events. The US and Dev premiums drop during the global financial crisis circa 2008, whereas the Emg premium actually rises slightly. Lastly, these three premiums drop significantly when COVID-19 begins spreading in the US in March 2020; and they rebound by the end of 2020 as promising vaccine news arrives.

[Insert Figure 1 here]

Next we plot the time series of the two premium factors based on cross-sectional differences between Dev and Emg (DED) and between US CEFs with high and low IO (UID) in Figure 1, Panel B. The most striking regularity is that the DED factor exhibits the same peaks and troughs as US stock valuations, e.g., as measured by price-dividend ratios. Much like stock valuations, DED rises into the dot-com boom of 2000 and falls thereafter; then it rises prior to the global financial crisis circa 2008, before falling sharply in the crisis and rebounding sharply thereafter. Interestingly, the UID premium also falls and rebounds around the time of the 2008 crisis. The patterns in Figure 1 strongly suggest that common discount rate variation affects CEF premiums and global stock markets, an intriguing possibility that we will test thoroughly.

Since premiums measure relative mispricing, the force of arbitrage should cause reversion in premiums toward zero, which is evident in both panels of Figure 1. We formally test for stationarity of the five predefined premium factors using the classic Lo and MacKinlay (1988) variance ratio test, as shown in Table 3, Panel B.[12] The variance ratio at the m-month horizon is the variance of m-month changes in log premiums divided by m times the variance of one-month changes in log premiums. This ratio is less than one if there is mean reversion in log premiums at the m-month horizon. The columns in Table 3B show the variance ratios (VR),

[12] Using related variance statistics, Pontiff (1997) finds that individual US CEFs exhibit excessive volatility relative to their underlying assets from 1965 to 1985.

standardized ratios (Rs), and p-values from the variance ratio test based on three-month (quarterly), 12-month (yearly), and 36-month (3-year) changes in log premiums.

The main finding in Table 3B is that the variance ratios of all five premiums are considerably less than one at all horizons—one quarter, one year, and three years—suggesting that these premiums are stationary. In addition, the Rs values are less than -1 at all horizons. At the 36-month horizon, the variance ratios of four of the five premiums are less than 0.5 (and the fifth is 0.547), indicating substantial long-run mean reversion. Although several VR test statistics are statistically significant at the 5% and 10% levels, these are not powerful tests for detecting mean reversion. Even though one cannot reject a unit root based on the variance ratios of the UID premium, one can detect mean reversion using the autocorrelation of monthly changes in the UID premium. A regression of Δlnprem Mo UID on its one-month lagged value has a coefficient of -0.182 (standard error of 0.063), which is significantly different from zero at the 1% level. Based on these results, the remainder of our analysis proceeds under the assumption of stationarity for all predefined premium factors.

4.3 Factor Structure of Premiums

Here we investigate the factor structure of relative mispricing and thus discount rates. As shown in the model in Section 2, premium factors represent relative discount rate shocks, whereas NAV tracking error represents cash flow shocks to arbitrageurs exploiting relative mispricing. We first analyze the correlation structure of premiums to understand discount rates and then relate these shocks to tracking error. Table 4, Panel A shows correlations between the log premium factors measured in levels; and Table 4, Panel B shows correlations between monthly changes in the log premium factors.

[Insert Table 4 here]

Two correlations in relative mispricing (discount rate shocks) are consistently strong in Panels A and B of Table 4.[13] First and foremost, there is a strong positive correlation between the premiums of CEFs that hold developed (Dev) and those that hold emerging (Emg) market stocks: 0.69 in levels (Panel A) and 0.58 in changes (Panel B). This relationship could arise because common shocks to arbitrage capital devoted to exploiting premiums in non-US equity CEFs drive both premiums. Such common shocks, however, would not affect the DED premium representing the difference between the Dev and Emg premiums.

[13]We do not emphasize strong correlations in premium levels that do not also appear in premium changes in Panel B, such as the one between US and UID, because coincidental slow-moving trends could drive these findings.

The second notable fact in Panels A and B in Table 4 is the positive correlation between the US and Dev CEF premiums: 0.45 in levels and 0.31 in changes. This correlation could arise because of differences in beliefs between investors who hold US and Dev CEFs, primarily individuals, and investors who hold the underlying stocks in global equity markets, primarily institutions.

Panel C of Table 4 reports correlations between monthly changes in the premium factors and tracking error in NAV for the five groups of CEFs. These relationships are direct tests of our modeling assumptions in Section 2. Changes in premium factors measure systematic discount rate (DR) shocks, whereas tracking error in NAV measures cash flow (CF) shocks to arbitrageur portfolios. Our model assumes that these DR and CF shocks are uncorrelated. Consistent with this assumption, Panel C of Table 4 shows that none of the 25 possible pairwise correlations between the five CF and DR shocks is economically significant. The only correlation that exceeds 0.2 in absolute value is the -0.229 correlation between tracking error and premium changes in emerging markets. This negative correlation would reduce, not increase, the risk of premium arbitrage in the Emg CEF, and it could be due to chance.

In all subsequent analyses, we use only the US, DED, and UID factors to facilitate interpretation of the results. Whereas the simple premiums such as US, Dev, and Emg could all be driven by common shocks to arbitrage capital, differences in premiums between similar CEFs, such as DED and UID, are less likely to be subject to these shocks. Instead these premium differences or spreads are more likely to be driven by investors' different beliefs about CEFs' underlying stocks, a hypothesis that we will formally test.[14]

We first examine whether these three aggregate premium factors—US, DED, and UID—are systematic in that they can explain variation in many individual CEFs' premiums. We also investigate whether individual CEF premiums exhibit stable relationships (i.e., betas) with respect to these three factors. We estimate factor models for individual CEFs using monthly changes in log premiums (ΔlnPrem Mo), not levels of log premiums, to focus on the factor structure of innovations in premiums.

We estimate individual CEF betas by regressing ΔlnPrem Mo for each CEF on ΔlnPrem Mo for the three predefined factors as described in Equation (17):

$$\Delta lnPremMo_{i,t} = \text{constant}_i + \sum_k \beta^K_{k=1} \Delta lnPremMo_{k,t} + \epsilon_{i,t}, \tag{17}$$

[14]In an early version of this paper, we estimated unrestricted regressions in which Dev and Emg enter separately and found that the Dev and Emg premiums have roughly equal and opposite coefficients in these regressions, consistent with the simpler specification here with just the DED premium.

where $k \in 1, 2, 3$ represents each factor (US = 1, DED, = 2, UID = 3) used as a regressor, i is the individual CEF, and $t = 1, ..., T$ is the monthly period. We require $T \geq 24$ months of available data for each CEF in these regressions. We estimate models with $K = 1$, 2, or 3 regressors in which we include the {US}, {US, DED}, or {US, DED, UID} factors, respectively.

Table 5, Panel A reports factor betas and t-statistics for the $K = 3$ model with all three predefined factors. For the typical CEF, the US factor explains more variation in log premium changes than the two spread factors. The positive mean of the US beta in column one reflects the on-average positive exposures of CEFs with primary holdings in this market as well as those with global stock holdings. In contrast, CEF betas on the two spread factors, DED and UID, range from negative loadings to positive ones—e.g., Dev (Emg) funds tend to have positive (negative) betas on DED, and high (low) IO US funds tend to have positive (negative) betas on UID. Even so, the US factor beta exhibits the largest dispersion across CEFs, as shown in the StdDev column. The $t\beta_{US}$ row shows that the median fund's US factor beta has a significant t-statistic. The last two rows show that significant fractions of funds have significant betas on the DED and UID factors. By chance, one would expect to observe a spread of 3.3 for a 90% confidence interval in a t distribution. The actual dispersion of the t-stats is significantly higher for the DED (7.8) and UID (4.7) factor betas. The weak relationship of UID with most CEFs arises because this factor is based on differences within CEFs that hold US stocks, whereas many of the CEFs in our sample mainly hold developing and emerging market stocks.

[Insert Table 5 here]

To assess the stability of the relationship between individual CEF premiums and the premium factors, we estimate the factor model in Equation (17) separately in two non-overlapping halves of our sample: 1994 to 2006 and 2007 to 2020. Table 5, Panel B shows correlations between CEFs' factor betas across these two subperiods. The three rows in this panel refer to estimations of models with different numbers of factors: $K = 1$ (1F), $K = 2$, (2F), and $K = 3$ (3F).

Even though 13 years separate the midpoints of the two halves of our sample, the subperiod correlations in individual CEF betas are all statistically and economically significant for all three models. The betas on the two location-based factors (US and DED) are more stable than the UID betas because a fund's regional mandate is more persistent than its institutional ownership. Overall, this analysis indicates that individual CEFs' factor loadings are quite persistent, implying that the factor structure of CEF mispricing is reasonably stable even at the level of individual CEFs.

As a benchmark for the three predefined factors (US, DED, and UID), we construct three data-driven factors from a PCA of all 41 individual CEFs that have non-missing and qualifying data for our entire 324-month sample. By construction, PCA identifies the factors that explain the most variance in individual CEF premiums. That is, PCA factors attain the maximum average R^2 values in the factor model regressions in Equation (17) for each value of $K = 1$, 2, or 3, making them challenging benchmarks.

Figure 2 compares the ability of value-weighted (VW) predefined factors and PCA factors to explain variation in the 41 CEFs' premiums, based on funds' average R^2 values in Equation (17). The leftmost set of two bars compares average R^2 values with a single factor ($K = 1$) in Equation (17). In the predefined factor models, the first factor is the VW log premium of all qualifying US CEFs. In PCA, the first factor represents the linear combination of log CEF premium changes that explains the most variance, which in practice is similar to an average across all 41 CEFs' log premium changes. Beyond the fact that PCA maximizes variance explained, the predefined US factor has two disadvantages in this comparison of average R^2 values: 1) many CEFs do not hold US stocks and are thus not represented in the US factor; and 2) the US factor includes many CEFs that are not included in this analysis because they do not exist for our entire sample.

[Insert Figure 2 here]

Despite these disadvantages, the predefined US premium factor (1F) explains most (68%) of the variance that the first principal component (PC) explains: average $R^2 = 11.8\%$ for VW US vs. 17.3% for PCA. The middle set of two bars compares average R^2 values for the factor model with two predefined factors (US and DED) versus the PCA model with the first two PCs. With two factors (2F), the predefined factor model again captures most (57%) of the variance explained by PCs: 14.9% for VW 2F versus 26.2% for two PCs. The three-factor model comparison in the rightmost set of bars shows that the third PC captures somewhat more variation than the third characteristic-based predefined factor (UID). However, the overall variance explained by the three-factor model still accounts for most of the variance (52%) explained by the first three PCs.

We conclude that the simplicity and interpretability advantages of the predefined factors outweigh the slight improvement in explanatory power from the PCA factors, especially since this latter effect could arise from overfitting.

5 Fund Mispricing and Stock Prices

Here we conduct our main empirical tests of whether CEF premium factors predict global stock returns and exhibit strong and stable correlations with stock valuations. We focus on the US stock market because the design of the three CEF premium factors is well-suited for detecting mispricing in US stocks. However, we also conduct tests for developed and emerging markets to help us interpret the findings for the US.

We design our key tests with guidance from the model in Section 2 in which common shocks to sentiment and flows drive comovement in expected stock returns, stock valuations, and CEF premiums. We test the expected return part of this hypothesis by regressing the monthly excess return of each regional market on the one-month lagged CEF premium factors. We estimate these regressions using three predictive models that include different numbers of factors: one (US), two (US and DED), and all three (US, DED, and UID).

The third column in Table 6, Panel A shows that models with three factors have substantial predictive power for US stock market returns at the one-month horizon. The two most powerful predictors of stock returns are the DED and UID mispricing factors, which exhibit statistically significant and economically large negative coefficients across all three models that span the full sample (columns one to three). The US premium coefficient is marginally statistically significant and negative only in the column three specification that includes all factors. It is not significant in the first two specifications, which do not include the UID premium.

[Insert Table 6 here]

One can interpret the negative predictability coefficients on the DED and UID premiums within the model in Section 2. These premiums could arise from differential sensitivity to global sentiment (or flows) for CEF investors and those in the underlying assets. We propose that sentiment-driven US investors, especially those holding CEFs, overreact to the impact of global economic growth news on developed markets but not the impact on emerging markets, or at least not to the same extent. Since US investors are quite familiar (unfamiliar) with developed (emerging) markets, the impact of global growth news on these markets is likely to be highly (less) available to them. As a result, increases in global growth prospects, such as the dot-com boom before 2000, will cause US investors to bid up the prices of Dev CEFs relative to Emg CEFs—i.e., the DED premium—along with the prices of US stocks in general.[15] An implication is that the DED (Dev − Emg) CEF premium would predict negative risk-adjusted returns on US stocks, consistent with anecdotal evidence from the post-2000 Internet bust and the formal tests in Table 6A.

The same overreaction to global growth by US investors could drive the negative coefficient on UID, which is based on the high minus low IO premium in US CEFs, shown in Table 6A. This investor sentiment could have a disproportionate effect on high IO CEFs if flows to institutions holding CEFs predominantly come from sentiment-driven retail investors and these flows affect CEF prices. Later we use data on US investor beliefs to explore this hypothesis further.

An alternative hypothesis is that return predictability from CEF premium factors arises because of the bias in predictive regressions studied by Stambaugh (1999). However, using the formula in Stambaugh (1999), we find that this bias can explain only 1.2%, 0.4%, and 2.8% of the magnitude of the multivariate coefficients on the US, DED, and UID premiums, respectively. The main reason is that unexpected returns exhibit only weak positive correlations with innovations in CEF premium factors. We conclude that the Stambaugh bias is negligible in our return predictability regressions.

We now examine the predictive ability of CEF premium factors in subperiods with the caveat that stock returns are highly volatile and difficult to forecast in short samples. In columns four and five in Table 6A, we separately estimate the regression of US excess returns on lagged premiums in the 1994 to 2006 and 2007 to 2020 subperiods. The R^2_{adj} in both columns exceeds 2.6%, indicating substantial predictive power for premiums in both periods. However, the magnitudes and even signs of key predictive coefficients vary considerably, suggesting some instability in the predictive relationship.

Motivated by this instability and the cautionary findings of Goyal and Welch (2008), we examine whether CEF premium factors can predict US stock returns out of sample. Using the coefficient estimates from 1994 to 2006 (column four in Table 6A), we predict excess returns from 2007 to 2020—i.e., a 14-year span that lies outside of the initial estimation period. Figure 3 displays this out-of-sample (OOS) prediction along with the in-sample prediction of US stock returns from column five in Table 6A.

[Insert Figure 3 here]

This figure illustrates that the OOS return predictions from the first half of the sample are remarkably similar to the full-sample predictions. Still, there are differences between the

[15] This idea of global economic trends could inspire sentiment contagion that has differential effects on region-specific beliefs is much like the idea in Baker, Wurgler, and Yuan (2012).

OOS prediction and that based on the second-half regression estimated in column five of Table 6A. Whereas the in-sample R^2 for the column five model is 0.063, the R^2 for the OOS prediction is “only” 0.031, as reported in Figure 3.

The OOS R^2 of 3.1% is very high by the standards of the return predictability literature, as Goyal and Welch (2008) find that most models do not have any OOS predictive ability. Figure 3 shows that the OOS monthly expected US equity premium based on CEF premiums varies from -1% just before the global financial crisis of 2008 to nearly $+4\%$ immediately afterward. The equity premium experiences two more negative episodes in the 2010s, and it has a ephemeral peak of 2% per month in the aftermath of the 2020 stock market crash that coincided with negative COVID-19 news.

The OOS R^2 of 3.1% is also very high in economic terms. Following Campbell and Thompson (2008), we compute the increase in the expected return of an investor who uses premiums to time the stock market. The proportional increase in expected return is $\frac{R^2}{1-R^2}\frac{1+S^2}{S^2}$, where S^2 is the market's squared Sharpe ratio, which is 0.0117 per month in Campbell and Thompson's (2008) historical US sample dating back to 1871. Substituting the OOS R^2 value, we find a proportional increase in expected return of 2.77. The absolute increase in expected return, which is $\gamma^{-1}\frac{R^2}{1-R^2}\left(1+S^2\right)$, would be 12.9% per year (38.8% per year) for an investor with relative risk aversion of $\gamma = 3$ ($\gamma = 1$).

In Panels B and C of Table 6, we test whether the ability of US CEF premiums to predict stock returns generalizes to developed and emerging markets. These two panels report coefficient estimates from the same models used to predict US markets in Panel A. The main finding is that the mispricing premiums forecast returns in developed and emerging markets as well as they predict returns in US markets. The negative signs and statistical significance of the two key predictive coefficients (DED and UID) are the same in the main model for all three markets—see full-sample model with all premiums included shown in column three in the Panels A, B, and C. Based on the R^2 values, return predictability from premiums in developed markets (Panel B) is the same as that in US markets (Panel A), but predictability is stronger in emerging markets (Panel C) than in US markets.

Having established strong short-term stock return predictability from CEF premiums, we now investigate the long-run relationship between mispricing and stock prices. Our strategy is to project the level of stock valuations, as measured by log price-dividend ratios (pd) of the US market, on to the contemporaneous level of CEF mispricing factors. Long-horizon tests are informative about the magnitude of mispricing, but they are also subject to concerns about persistent regressors and structural breaks. Hence we view these tests as complementary to the short-horizon return predictability regressions. Table 7 shows the relationship between US *pd* and CEF premiums for the same models used to predict US stock returns. The only difference is that we use contemporaneous, not lagged, values of the three log premiums in Table 7 to measure the common component in mispricing and valuations.

[Insert Table 7 here]

Table 7 shows that there is a very strong positive relationship between US valuations (*pd*) and the DED log premium.[16] There is also a notable positive relationship for UID premium. The R^2_{adj} values in columns one, two, and three for the one-, two-, and three-factor models are 0.7%, 47.7%, and 58.1%, respectively. The signs and statistical significance of the coefficients on the DED and UID factors are consistent in columns three in Tables 6A and 7. That is, these two CEF premiums exhibit opposite signs when predicting US returns and relating to US *pd* ratios. This pattern indicates that these two mispricing premiums have qualitatively similar short- and long-run relationships with stock prices. Quantitatively, the relatively large coefficient for DED (UID) in Table 7 (6A) indicates that it is somewhat more predictive of long-run (short-run) returns.

We address concerns about structural breaks and non-stationarity in three ways. First, we separately estimate the relationship between US valuations (*pd*) and CEF premiums in both halves of our sample, as shown in the last two columns in Table 7. The R^2 from premiums is very high at 69.8% and 60.6% in both periods. Second, to assess the stability of the relationship, we predict US *pd* ratios in 2007 to 2020 using the coefficient estimates from the 1994 to 2006 period, shown in column four of Table 7. We plot the resulting out-of-sample predictions of US *pd* together with full-sample predictions and actual *pd* values in Figure 4.

[Insert Figure 4 here]

The green line in Figure 4 representing the out-of-sample prediction of *pd* closely resembles the red line depicting the full-sample *pd* prediction based on CEF premiums. Furthermore, both lines are strongly correlated with actual US valuation (*pd*) ratios. The out-of-sample squared correlation of 55.0% is quite large in statistical and economic terms

[16]We use Newey-West (1987) standard errors to account for persistence in the residuals. As recommended by Lazarus et al. (2018), we use a truncation bandwidth of $S = 1.3T^{0.5}$ lags, where T is the sample length, and perform hypothesis tests based on critical values from the fixed-b distribution in Kiefer and Vogelsang (2005), where $b = S/T$.

and almost as high as the in-sample R^2 of 60.6% in column five of Table 7.[17] Most importantly, the out-of-sample predicted pd ratio matches the sharp drop and rebound of US stock valuations around the global financial crisis circa 2008.

Third, we re-estimate the relationship between US valuations and CEF premiums using year-over-year differences. We obtain an adjusted R^2 value of 41.6% and find that the coefficient estimates on the DED and UID premiums remain positive and highly statistically significant.

6 Mispricing and Beliefs

Here we investigate whether mispricing is highly correlated with stock valuations because both are driven by investors' mistaken beliefs. We examine belief correlations and do not claim causality, recognizing the possibility of alternative explanations. However, to the extent that correlations between mispricing and beliefs are high, causality becomes more likely as alternative explanations would need to coincide closely with errors in beliefs.

These tests face the empirical challenge that there is little uniformity in data on beliefs about stock returns and cash flow growth. Survey questions, respondents, time horizons, data frequency, and sample periods differ across sources. We gather investor belief data from numerous sources and jointly analyze the properties of myriad correlations to reduce the likelihood that sampling error obscures an underlying relationship between mispricing and beliefs.

The belief data vary along three dimensions: surveys of professionals (e.g., analysts or institutional investor) versus individuals; expectations of returns versus cash flow (e.g., dividend or earnings) growth; and short (e.g., one-year) versus long (e.g., 10-year) forecast horizons. To the extent possible, we examine each dimension by holding the others constant. We compare professional and institutional investors' beliefs by gathering a wide variety of one-year expectations of US stock returns. We compare return and cash flow growth forecasts for sell-side analysts, who make both predictions. We explore the impact of forecast horizon by comparing analysts' short- and long-term cash flow (earnings) growth forecasts.

We adopt methods from prior research to reduce superficial differences across sources. Many sources on the beliefs of individual investors ask them whether they are optimistic

[17] Because pd ratios are highly persistent, we focus on out-of-sample squared correlations rather than out-of-sample R^2 statistics since the latter depend heavily on the difference in the average pd ratio across subperiods.

(i.e., bullish) or pessimistic (i.e., bearish) about one-year US stock returns, whereas other sources directly ask for expected stock returns in percent per year. As in Greenwood and Shleifer (2014), we use the close relationship between these two questions in Gallup surveys to convert net optimism into one-year stock return expectations. We also convert all nominal expectations of returns and growth rates into real terms by subtracting one-year expected inflation from the Survey of Professional Forecasters (SPF), following De La O and Myers (2021).

We collect the following three types of expectation measures:

- Three measures of individual investors' net optimism about one-year US stock returns from Conference Board (CnfBrd), Gallup, and the American Association of Individual Investors (AAII); and a fourth net optimism measure from the Investors' Intelligence Advisor Newsletters (IIAN), which is not easily classifiable as a professional or individual source. We convert all four net optimism measures into one-year real stock return expectations as described above.

- Two direct measures of one-year US expected stock returns based on the SPF and sell-side stock analysts (SSA). The analyst measure is based on aggregated price targets for individual stocks as in Wang (2021).

- Three expected growth measures from sell-side analysts based on their one-year dividend growth (DivG), one-year earnings growth (ErnG), and 10-year earnings growth (ErnG10) forecasts as computed in De La O and Myers (2021).

We compute pairwise correlations between the nine standardized real return and growth forecasts and report these in Table 8, Panel A.[18] We use all available monthly data for each pair in these computations, some of which span all 324 months in our 1994 to 2020 sample period. Other correlations rely on shorter and less frequent samples because survey data are unavailable in some months.

[Insert Table 8 here]

A key finding in Table 8, Panel A is that survey measures of individuals' expectations of one-year (real) stock returns are highly positively correlated with each other. The CnfBrd and Gallup measures, which are available for the majority of our sample, exhibit a 0.88 correlation. These two measures also exhibit correlations exceeding 0.5 with one-year return

[18]We use 10-year, not one-year, expected inflation from the SPF to convert the 10-year earnings growth forecast into real terms.

expectations from AAII and IIAN, which is consistent with Greenwood and Shleifer (2014). Interestingly, individuals' expectations of stock returns are strongly negatively correlated with professionals' expectations of returns, as measured by SSA and SPF. This divergence between Wall Street and Main Street expectations confirms a key finding in Wang (2021).

Table 8, Panel A reveals a more complex relationship between return and cash flow growth expectations. Individuals' one-year expectations of returns (e.g., Gallup) are positively correlated with one-year dividend growth (DivG) and ten-year earnings growth (ErnG10) forecasts of sell-side analysts. In contrast, professionals' returns forecasts, even those of sell-side analysts, are not positively correlated with either of these cash flow growth expectations that reflect long-horizon thinking. These two sets of correlations have opposite signs for short-horizon (one-year) earnings growth. The long-horizon forecasts are more relevant for stock valuation.

We relate these measures of investor beliefs to CEF premium factors in Table 8, Panel B. To facilitate interpretation, we form two linear combinations of the three premium factors based on their relationships with stock prices and returns. Specifically, we use the predicted values of the US equity premium (ER Prem) and log price-dividend ratio (pd Prem) shown in Figures 3 and 4, respectively. These forecasts come from the regression models in column three in Tables 6A (ER Prem) and 7 (pd Prem).

The central finding in Table 8B is that predicted valuations from CEF mispricing are strongly positively correlated with analysts' long-run cash flow growth expectations: correlations of 0.40 with DivG and 0.46 with ErnG10.[19] In addition, the predicted equity premium (ER Prem) exhibits negative correlations with analysts' long-run cash flow growth expectations: correlations of -0.48 with DivG and -0.25 with ErnG10. The similarity in these results is consistent with the similarity in the predictive coefficients in Tables 6A and 7. None of the correlations between mispricing premiums and individuals' beliefs exceeds 0.28, which is reminiscent of the evidence in Qiu and Welch (2006).

The strong relationship between expected long-run cash flow growth and mispricing is consistent with the hypothesis that investors overreact to news about long-run growth, which causes overpricing in the stock market. An alternative possibility is that past stock returns drive variation in long-run growth expectations and predicted valuations from CEF premiums.

[19] We treat one-year expectations of dividend growth as long-horizon forecasts because most corporations only adjust dividend policy when their perceptions of long-run prospects change.

We test this alternative by regressing the two long-run growth expectations measures (DivG and ErnG10) on all three CEF premiums and past US stock returns. Our past return measures are log returns that span the most recent five years: last 6 months, months 6 to 12, years 1 to 3, and years 3 to 5. Table 9 reports the coefficient estimates from three regression models for each of the two growth measures. The three specifications used to predict growth beliefs differ in the set of regressors: three premiums only (columns one and four), four returns only (columns two and five), or premiums and returns (columns three and six).

[Insert Table 9 here]

The regressions show that CEF premiums explain a significant fraction of variance in long-run growth expectations ($R^2_{adj} = 39.1\%$ for ErnG10 and 33.2% for DivG), whereas past returns explain less (10.6% for ErnG10 and 27.8%). Furthermore, by comparing R^2_{adj} values in columns one to three (and four to six), one sees that the incremental explanatory power of past returns is just 4.0% for ErnG10 and 10.5% for DivG after controlling for CEF premiums.

We conduct analogous comparisons of R^2_{adj} values for the other seven belief measures and present them alongside the R^2_{adj} values for long-run cash flow growth expectations in Figure 5. Long-run cash flow growth beliefs are unique among belief measures in that CEF premiums account for over 33% of their variation and past returns have little incremental explanatory power. These results are consistent with the overreaction theory proposed above, though they are not conclusive.

[Insert Figure 5 here]

The coefficients from the regressions of long-run growth beliefs on CEF premiums in Table 9 deliver additional insights into the theory that investors overreact to long-run growth. This evidence guides our interpretation of the DED and UID premiums and their relationships with expected returns and valuations in Tables 6 and 7. Table 9 shows that the DED and UID premiums are strongly positively related to expected long-run earnings growth, which is consistent with their strong positive relationships with valuations in Table 7. This evidence supports the earlier belief-based interpretation for the DED and UID premiums, consistent with the idea that both are proxies for overreaction to global growth news.

We note that clients' investment flows to institutions could be proxies for overreaction to growth even if the institutions themselves act as sophisticated arbitrageurs with their available capital. In this story, time-varying sentiment determines how much capital is devoted to arbitrage, which drives variation in discount rates in CEF and stock markets. Indeed, we find evidence in Table B.1 that some highly sophisticated institutions have large CEF holdings.

Although we do not directly observe the beliefs of institutions' clients, we can examine time-variation in their investment flows. We find that flows do exhibit a strong positive correlation of 0.56 with investors' long-run growth beliefs and that this correlation can explain much of the observed relationship between the UID premium and beliefs. We measure equity flows (Eq Flow) to all institutions in the Refinitiv Global Institutional Ownership (GIO) database and weight these by institutions' total dollar holdings in equity CEFs (CW).[20] We cannot reliably measure flows to institutions' CEF holdings since their CEF allocations depend heavily on how much sophisticated institutions decide to invest in CEFs, rather than how much capital is available to institutions which is driven by client decisions. We sum percentage equity flows over the current quarter and the last three quarters to obtain a one-year flow measure: CW Eq Flow 1-Yr.

Table 10 shows that equity flows weighted by institutions' equity CEF holdings (CW Eq Flow 1-Yr) are strongly related to long-run growth beliefs, as measured by analysts' 10-year earnings growth forecasts (ErnG10), as shown in column two.[21] By comparing columns one and three, we see how the correlation between growth beliefs and the UID premium changes when we hold equity flows constant. The coefficient on UID declines from 0.86 to 0.44, though it does remain statistically significant. By comparing columns two and three, we see that the incremental R^2 of UID is only 4.0% after controlling for flows, as compared to the univariate R^2_{adj} of 24.6% for UID. This result demonstrates that clients' flows to institutions could explain most of the relationship between the UID premium and beliefs. We speculate that client optimism about long-term global growth increases flows to institutions, which in turn increases US stock prices and the prices of CEFs disproportionately held by institutions; and client pessimism forces selling by institutions, which reduces the prices of US stocks and these institutionally-held CEFs.

7 Conclusion

This paper provides novel evidence that mispricing in a small corner of US asset markets, namely CEFs, reflects broader mispricing in global equity markets. Relationships with beliefs suggest that mispricing arises primarily from US investor overreaction to long-run growth

[20] As in Gabaix and Koijen (2021), we define quarterly equity flows as the difference between the current value of equity holdings and last quarter's value grown at this quarter's return, divided by the average of these two values.

[21] We estimate these regressions using quarterly data from 1998 to 2020 because the GIO data become available in 1997.

prospects. Relationships with institutional ownership suggest that commonality in mispricing also partly stems from sentiment-driven variation in capital flows to arbitrageurs. This paper is one of the fist systematic analyses of the factor structure of mispricing. This research area is fertile ground for further investigation.

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Table 1: Summary Statistics

Time-series average of monthly cross-sectional distribution of statistics on closed-end funds. The columns show averages of cross-sectional means, standard deviations (Std Dev), percentiles (P5, P25, P50, P75, P95), and the number of qualifying closed-end funds (CEFs). Funds are eligible for the sample if they are US-based funds with broad mandates to invest in securities in either the US, developed markets, or emerging markets. Funds also must satisfy minimum liquidity and size criteria. The rows show key attributes of CEFs, including funds' annual returns in excess of the risk-free rate (CEF ExRet Ann) and annual percentage changes in net asset value in excess of the risk-free rate (NAV ExRet Ann). Row three shows funds' log premiums (lnPrem), defined as the log difference in price and NAV. Row four shows the annual change in lnPrem (ΔlnPrem Ann). Rows five and six show funds' market capitalization (Size) and institutional ownership as a fraction of shares outstanding (Inst Own), respectively. The last row shows funds' annualized expense ratios (Exp Ratio), which are missing for some funds in early years. The sample consists of 324 months from 1994 through 2020.

	Mean	Std Dev	P5	P25	P50	P75	P95	Funds
CEF ExRet Ann	0.079	0.191	-0.198	-0.052	0.063	0.193	0.398	61.3
NAV ExRet Ann	0.075	0.179	-0.184	-0.043	0.063	0.177	0.371	61.3
lnPrem	-0.094	0.100	-0.205	-0.159	-0.117	-0.053	0.095	61.8
ΔlnPrem Ann	-0.004	0.079	-0.125	-0.042	-0.003	0.035	0.117	61.0
Size	0.356	0.423	0.045	0.097	0.189	0.441	1.247	61.8
Inst Own	0.223	0.173	0.033	0.088	0.178	0.337	0.504	61.2
Exp Ratio	0.015	0.006	0.006	0.011	0.014	0.018	0.026	50.5

Table 2: Comparing Closed-End Funds to Exchange-Traded Funds

Panel A: Cross-sectional distribution of time-series regressions of closed-end funds on ETF benchmarks. This panel shows the cross-sectional distribution of estimates from 82 time-series regressions of individual closed-end funds on ETF benchmarks. These 82 funds have broad mandates and matching ETFs for at least 24 months in the sample period from 1994 to 2020. Funds must also meet liquidity and size criteria in these months. The first row reports average (Mean) estimates from these 82 regressions; and the later rows show standard deviations (Std Dev) and percentiles (P5, P25, P50, P75, P95) of regression estimates. The first two columns show annualized alphas (Alpha Ann) and betas (Beta ETF) of funds against their ETF benchmarks; the third column shows the adjusted R^2 of the ETF benchmark; and the last column shows the average number of observations.

	Alpha Ann	Beta ETF	R^2_{adj}	Months
Mean	0.0004	0.944	0.786	176.5
Std Dev	0.0359	0.214	0.185	81.4
P5	-0.0474	0.588	0.447	57.0
P25	-0.0175	0.840	0.695	104.0
P50	0.0020	0.935	0.856	180.0
P75	0.0133	1.014	0.915	246.0
P95	0.0402	1.274	0.951	297.0

Table 2 (cont.): Comparing Closed-End Funds to Exchange-Traded Funds

Panel B: Time-series data on aggregations of broad closed-end funds with matching benchmarks. Each fund's net asset value (NAV) benchmark comes from the fund's regression in Panel A and is the matching ETF's excess return multiplied by the beta of the fund's NAV on the ETF. Individual fund tracking error is the fund's NAV return minus its NAV benchmark. This table aggregates funds' NAV returns and benchmarks across three groups based on the location of funds' primary holdings: US, Developed, and Emerging funds, as shown in columns. The first row (Agg R^2) shows the fraction of variance in value-weighted NAV returns explained by value-weighted NAV benchmarks for each group. The second row (Agg Track Err R^2) is the fraction of unexplained variance. Aggregate tracking error is the unexplained part of the aggregate NAV return. The last two rows show the beta (Track Err Mkt Beta) and fraction of variance (Track Err Mkt R^2) in aggregate tracking error explained by the market return in each of the three regions. The sample is monthly from 1994 to 2020.

	US	Developed	Emerging
Agg R^2	0.96	0.90	0.95
Agg Track Err R^2	0.04	0.10	0.05
Track Err Mkt Beta	0.01	0.07	0.04
Track Err Mkt R^2	0.00	0.04	0.03

Panel C: Time-series correlations between aggregated tracking error of broad closed-end funds with matching benchmarks. Aggregate tracking error is the unexplained part of funds' aggregated NAV returns for CEFs in each of three regions: US, developed (Dev), and emerging (Emg) markets. The first row reports the three pairwise correlations between aggregated tracking errors in these regions. The second row reports standard errors. The sample consists of 324 months from 1994 to 2020.

	US-Dev	US-Emg	Dev-Emg
Correlation	0.126	0.061	0.245
Std Err	0.058	0.058	0.056

Table 3: Factors in Closed-End Premiums

Panel A: Time-series distributions of log premiums (lnPrem) and annual and monthly changes in log premiums (ΔlnPrem Ann and ΔlnPrem Mo) in groups of closed-end funds. The first three groups or factors are based on the primary location of funds' holdings—United States (US), developed markets (Dev), and emerging markets (Emg). The fourth is the Dev − Emg difference (DED) between fund groups. The fifth factor is the difference between US funds with high and low institutional ownership (UID). The sample consists of 324 months from 1994 to 2020.

	Mean	Std Dev	P5	P25	P50	P75	P95
lnPrem US	-0.094	0.033	-0.141	-0.118	-0.096	-0.071	-0.041
lnPrem Dev	-0.116	0.047	-0.192	-0.148	-0.112	-0.089	-0.032
lnPrem Emg	-0.106	0.067	-0.228	-0.137	-0.106	-0.072	0.003
lnPrem DED	-0.009	0.048	-0.108	-0.026	-0.002	0.016	0.060
lnPrem UID	-0.047	0.046	-0.111	-0.075	-0.056	-0.015	0.040
ΔlnPrem Ann US	-0.001	0.034	-0.050	-0.024	-0.003	0.016	0.058
ΔlnPrem Ann Dev	-0.004	0.041	-0.075	-0.030	-0.007	0.025	0.068
ΔlnPrem Ann Emg	-0.004	0.056	-0.107	-0.035	-0.004	0.026	0.092
ΔlnPrem Ann DED	0.000	0.045	-0.073	-0.027	0.003	0.024	0.076
ΔlnPrem Ann UID	0.004	0.035	-0.058	-0.015	0.006	0.028	0.062
ΔlnPrem Mo US	-0.000	0.014	-0.022	-0.008	-0.000	0.008	0.021
ΔlnPrem Mo Dev	-0.001	0.019	-0.030	-0.010	-0.000	0.010	0.025
ΔlnPrem Mo Emg	-0.001	0.023	-0.038	-0.012	-0.001	0.010	0.039
ΔlnPrem Mo DED	-0.000	0.019	-0.029	-0.011	-0.001	0.011	0.032
ΔlnPrem Mo UID	0.000	0.012	-0.018	-0.007	0.000	0.008	0.020

Panel B: Variance ratios based on changes in premiums for groups of closed-end funds from 1994 to 2020. The first three columns show the variance ratios (VR), standardized ratios (Rs), and p-values from the Lo and MacKinlay (1988) variance ratio test based on three-month (quarterly) changes in log premiums. The next two sets of three columns show these values for 12-month (yearly) and 36-month (3-year) changes in premiums. The standardized ratios (Rs) and p-values are based on heteroskedasticity robust standard errors.

	VR 3	Rs 3	p-val 3	VR 12	Rs 12	p-val 12	VR 36	Rs 36	p-val 36
lnPrem US	0.657	-2.35	0.019	0.537	-1.46	0.144	0.452	-1.17	0.240
lnPrem Dev	0.796	-1.56	0.118	0.461	-2.04	0.042	0.462	-1.25	0.211
lnPrem Emg	0.809	-1.68	0.093	0.559	-1.63	0.103	0.547	-1.00	0.320
lnPrem DED	0.685	-3.16	0.002	0.460	-2.22	0.027	0.389	-1.44	0.150
lnPrem UID	0.876	-1.14	0.254	0.681	-1.26	0.207	0.350	-1.50	0.135

Table 4: Correlations in Premium Factors and Tracking Error

Panel A: Time-series correlations between value-weighted premiums of groups of closed-end funds in 324 months from 1994 to 2020.

	lnPrem US	lnPrem Dev	lnPrem Emg	lnPrem DED
lnPrem US	1.000	0.446	0.193	0.173
lnPrem Dev	0.446	1.000	0.691	0.030
lnPrem Emg	0.193	0.691	1.000	-0.702
lnPrem DED	0.173	0.030	-0.702	1.000
lnPrem UID	-0.502	-0.359	-0.055	-0.278

Panel B: Time-series correlations between value-weighted monthly changes in premiums for groups of closed-end funds from 1994 to 2020.

	ΔlnPrem Mo US	ΔlnPrem Mo Dev	ΔlnPrem Mo Emg	ΔlnPrem Mo DED
ΔlnPrem Mo US	1.000	0.313	0.143	0.136
ΔlnPrem Mo Dev	0.313	1.000	0.583	0.283
ΔlnPrem Mo Emg	0.143	0.583	1.000	-0.614
ΔlnPrem Mo DED	0.136	0.283	-0.614	1.000
ΔlnPrem Mo UID	0.005	0.058	0.037	0.013

Panel C: Time-series correlations between value-weighted monthly changes in premiums for groups of closed-end funds' and the value-weighted tracking errors of these groups from 1994 to 2020.

	Trk Err US	Trk Err Dev	Trk Err Emg	Trk Err DED	Trk Err UID
ΔlnPrem Mo US	0.063	0.065	0.079	-0.005	-0.127
ΔlnPrem Mo Dev	0.088	-0.036	-0.085	0.035	-0.002
ΔlnPrem Mo Emg	0.085	-0.008	-0.229	0.168	0.044
ΔlnPrem Mo DED	-0.015	-0.026	0.188	-0.166	-0.056
ΔlnPrem Mo UID	0.097	0.085	0.116	-0.015	-0.091

Table 5: Sensitivity of Individual Funds to Premium Factors

Panel A: Cross-sectional statistics on individual closed-end fund betas from 1994 to 2020. Fund betas are coefficients from time-series regressions of log changes in premiums ($\Delta lnPrem$) of individual funds on three factors based on $\Delta lnPrem$ for groups of funds. The first two factors are based on the primary location of funds' holdings: United States (US), developed markets (Dev), and emerging markets (Emg). The first factor is the US $\Delta lnPrem$ and the second is the Dev $-$ Emg difference (DED) in $\Delta lnPrem$. The third factor represents the difference in $\Delta lnPrem$ between US funds with high and low institutional ownership (UID). This table shows betas for funds with at least 24 months of qualifying data as described in the data section.

	Mean	StdDev	P5	P25	P50	P75	P95
β_{US}	0.79	0.52	0.09	0.40	0.69	1.14	1.66
β_{DED}	-0.13	0.44	-0.98	-0.47	-0.03	0.16	0.49
β_{UID}	0.02	0.39	-0.52	-0.15	0.01	0.21	0.48
$t\ \beta_{US}$	4.57	3.71	0.30	1.76	3.53	6.32	12.40
$t\ \beta_{DED}$	-0.74	2.42	-5.24	-2.65	-0.25	1.33	2.58
$t\ \beta_{UID}$	0.19	1.69	-1.81	-0.67	0.08	1.02	2.89

Panel B: Correlations between fund betas in sample subperiods: 1994 to 2006 and 2007 to 2020. Each row represents one of the three factor models that have one (1F), two (2F), or three (3F) factors. The first two factors are based on the primary location of funds' holdings: United States (US), developed markets (Dev), and emerging markets (Emg). The first factor is the US $\Delta lnPrem$ and the second is the Dev $-$ Emg difference (DED) in $\Delta lnPrem$. The third factor represents the difference in $\Delta lnPrem$ between US funds with high and low institutional ownership. The first column shows the factor model used, while the three column labels show the factor used to construct the three betas: US, DED, and UID. Correlations are based on the 62 CEFs with at least 24 months of data in both subperiods.

	US	DED	UID
1F	0.46		
2F	0.41	0.68	
3F	0.35	0.66	0.33

Table 6: Predicting Stock Market Returns with Premium Factors

Panel A: Time-series regressions of monthly excess returns of the US stock market on one-month lags of three premium factors from 1994 to 2020. The factors are logs of premiums for different groups of closed-end funds. The first two factors are based on the primary location of funds' holdings: United States (US), developed markets (Dev), and emerging markets (Emg). The first factor is the US log premium and the second is the Dev − Emg difference (DED) in log premiums. The third factor represents the difference in log premiums between US funds with high and low institutional ownership (UID). The first three columns report regression models that include different numbers of factors and span the entire sample. The last two columns show regression models based on two subperiods: 1994 to 2006 (column four) and 2007 to 2020 (last column).

	(1) US Mkt	(2) US Mkt	(3) US Mkt	(4) US Mkt	(5) US Mkt
Lag US log Prem	-0.099	-0.073	-0.169*	-0.170	-0.295*
	(0.086)	(0.085)	(0.098)	(0.126)	(0.170)
Lag DED log Prem		-0.109**	-0.140**	-0.145**	0.164
		(0.052)	(0.057)	(0.066)	(0.204)
Lag UID log Prem			-0.152**	-0.108	-0.650***
			(0.067)	(0.093)	(0.180)
Constant	-0.002	-0.001	-0.017	-0.015	-0.062***
	(0.008)	(0.008)	(0.011)	(0.015)	(0.023)
Observations	324	324	324	156	168
R^2_{adj}	0.002	0.013	0.027	0.026	0.063

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 (cont.): Predicting Developed Market Returns with Premium Factors

Panel B: Time-series regressions of monthly excess returns of developed stock markets on one-month lags of three premium factors, US, DED, and UID, from 1994 to 2020. See Panel A for details.

	(1) Dev Mkt	(2) Dev Mkt	(3) Dev Mkt	(4) Dev Mkt	(5) Dev Mkt
Lag US log Prem	0.016	0.037	-0.091	-0.022	-0.378**
	(0.087)	(0.084)	(0.107)	(0.132)	(0.186)
Lag DED log Prem		-0.087	-0.128**	-0.101*	0.226
		(0.054)	(0.058)	(0.058)	(0.228)
Lag UID log Prem			-0.202***	-0.120	-0.874***
			(0.077)	(0.102)	(0.191)
Constant	0.006	0.007	-0.015	-0.002	-0.088***
	(0.008)	(0.008)	(0.013)	(0.016)	(0.025)
Observations	324	324	324	156	168
R^2_{adj}	-0.003	0.002	0.028	0.008	0.101

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 (cont.): Predicting Emerging Market Returns with Premium Factors

Panel C: Time-series regressions of monthly excess returns of emerging stock markets on one-month lags of three premium factors, US, DED, and UID, from 1994 to 2020. See Panel A for details.

	(1) Emg Mkt	(2) Emg Mkt	(3) Emg Mkt	(4) Emg Mkt	(5) Emg Mkt
Lag US log Prem	0.099	0.121	-0.120	-0.141	-0.348
	(0.114)	(0.112)	(0.134)	(0.158)	(0.222)
Lag DED log Prem		-0.091	-0.168**	-0.164**	0.179
		(0.076)	(0.078)	(0.078)	(0.302)
Lag UID log Prem			-0.379***	-0.379***	-0.998***
			(0.094)	(0.116)	(0.246)
Constant	0.014	0.016	-0.026	-0.022	-0.091***
	(0.011)	(0.011)	(0.016)	(0.018)	(0.031)
Observations	324	324	324	156	168
R^2_{adj}	-0.000	0.002	0.056	0.052	0.093

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Relating Stock Valuations to Premium Factors

Time-series regressions of monthly log price-dividend ratios of the US stock market (US pd) on the contemporaneous three premium factors from 1994 to 2020. The factors are logs of premiums for different groups of closed-end funds. The first two factors are based on the primary location of funds' holdings: United States (US), developed markets (Dev), and emerging markets (Emg). The first factor is the US log premium and the second is the Dev − Emg difference (DED) in log premiums. The third factor represents the difference in log premiums between US funds with high and low institutional ownership (UID). The first three columns report regression models that include different numbers of factors and span the entire sample. The last two columns show regression models based on two subperiods: 1994 to 2006 (column five) and 2007 to 2020 (last column).

	(1) US pd	(2) US pd	(3) US pd	(4) US pd	(5) US pd
US log Prem	0.58	-0.14	0.93	-0.22	1.37***
	(1.30)	(0.79)	(0.73)	(0.54)	(0.30)
DED log Prem		2.83***	3.14***	3.27***	2.45***
		(0.59)	(0.46)	(0.36)	(0.75)
UID log Prem			1.64***	0.56	1.14
			(0.52)	(0.51)	(0.62)
Constant	4.08***	4.04***	4.22***	4.15***	4.17***
	(0.10)	(0.07)	(0.08)	(0.07)	(0.07)
T in months	324	324	324	156	168
NW Lags	23	23	23	16	17
R^2_{adj}	0.00651	0.477	0.581	0.698	0.606

Newey-West (NW) standard errors with $1.3T^{0.5}$ lags
*** p<0.01, ** p<0.05, * p<0.10 from fixed-b distribution

Table 8: Relating Beliefs to Premium Factors

Panel A: Time-series correlations between subjective expectations of real US stock returns and cash flow growth from 1994 to 2020. Three measures of subjective expected returns are from surveys of individual investors by The Conference Board (CnfBrd), Gallup, and the American Association of Individual Investors (AAII); and a fourth is based on Investors' Intelligence Advisor Newsletters (IIAN). These measures reflect net optimism about the US stock market, defined as percentage of bullish minus bearish respondents. We convert these four net optimism measures into one-year stock return expectations as in Greenwood and Shleifer (2014). Two measures of subjective one-year US expected returns are based on the Survey of Professional Forecasters (SPF) and sell-side stock analysts (SSA). The analyst measure is based on aggregated price targets for individual stocks as in Wang (2021). The subjective expected growth measures are sell-side analysts' one-year dividend growth (DivG), one-year earnings growth (ErnG), and 10-year earnings growth (ErnG10) from De La O and Myers (2021). We convert nominal return and growth expectations into real terms by subtracting one-year expected inflation from the SPF. Pairwise correlations are based on non-missing data for both series.

	CnfBd	Gallup	AAII	IIAN	SSA	SPF	DivG	ErnG	ErnG10
CnfBd	1.00								
Gallup	0.88	1.00							
AAII	0.58	0.56	1.00						
IIAN	0.53	0.57	0.43	1.00					
SSA	-0.57	-0.70	-0.30	-0.74	1.00				
SPF	-0.33	-0.64	0.12	0.11	0.73	1.00			
DivG	0.37	0.58	0.51	0.30	-0.19	-0.09	1.00		
ErnG	-0.26	-0.44	-0.14	-0.13	0.39	0.55	-0.58	1.00	
ErnG10	0.18	0.35	0.12	0.14	-0.12	-0.15	0.27	-0.37	1.00

Table 8 (cont.): Relating Beliefs to Premium Factors

Panel B: Time-series correlations between investor beliefs and fund premium factors from 1994 to 2020. We report correlations between the nine measures of return and growth beliefs from Panel A and the predictions of US valuations and excess returns based on closed-end fund premiums. The prediction of US valuations (log price-dividend ratio) is the predicted value from the regression in column three in Table 7 (pd Prem). The prediction of the US stock market excess return is the predicted value from the regression in column three in Table 6, Panel A (ER Prem). Each predicted value is a linear combination of the three fund premium factors: US, DED, and UID. Pairwise correlations are based on non-missing monthly data for both series.

	CnfBd	Gallup	AAII	IIAN	SSA	SPF	DivG	ErnG	ErnG10
pd Prem	0.13	0.28	0.16	0.28	-0.28	-0.16	0.40	-0.36	0.46
E(r) Prem	-0.09	-0.19	-0.12	-0.10	0.18	0.26	-0.48	0.35	-0.25

Table 9: Regressing Growth Beliefs on Premium Factors

Time-series regressions of investor beliefs about cash flow growth on fund premium factors. The dependent variables are the two subjective expected growth measures are sell-side analysts' one-year real dividend growth (DivG) and their 10-year earnings growth (ErnG10) from De La O and Myers (2021). We multiply annualized ErnG10 by 10 to facilitate interpretation. The three fund premium factors are the US, DED, and UID measures described in Table 3 and the main text. The other four regressors are log returns of US stocks for the past 6 months, months 6 to 12, year 1 to 3, and year 3 to 5. The three specifications used to predict each growth belief differ in the set of regressors: three premiums only (columns 1 and 4), four returns only (columns 2 and 5), or premiums and returns (columns 3 and 6). These regressions use quarterly data from 1994 to 2020.

	(1) ErnG10	(2) ErnG10	(3) ErnG10	(4) DivG	(5) DivG	(6) DivG
log Ret 6-Mo		0.04	0.00		0.16***	0.02
		(0.06)	(0.06)		(0.05)	(0.07)
log Ret 6,12-Mo		0.15**	0.01		0.19	0.07
		(0.06)	(0.05)		(0.14)	(0.11)
log Ret 1,3-Yr		0.05	-0.08*		-0.05	-0.05
		(0.05)	(0.04)		(0.09)	(0.08)
log Ret 3,5-Yr		0.04	-0.01		-0.09**	-0.10**
		(0.04)	(0.03)		(0.03)	(0.03)
US log Prem	-0.70*		-0.93**	1.64**		1.28*
	(0.35)		(0.32)	(0.64)		(0.59)
DED log Prem	0.61***		0.73***	0.13		0.27
	(0.12)		(0.08)	(0.29)		(0.26)
UID log Prem	0.31**		0.48**	0.81*		0.61**
	(0.10)		(0.15)	(0.41)		(0.22)
Constant	0.00	0.03*	0.00	0.27***	0.07*	0.24***
	(0.03)	(0.01)	(0.03)	(0.07)	(0.03)	(0.07)
T in quarters	94	94	94	66	66	66
NW Lags	13	13	13	11	11	11
R^2_{adj}	0.391	0.106	0.431	0.332	0.278	0.437

Newey-West (NW) standard errors with $1.3T^{0.5}$ lags

*** p<0.01, ** p<0.05, * p<0.10 from fixed-b distribution

Table 10: Regressing Growth Beliefs on Flows and the UID Premium

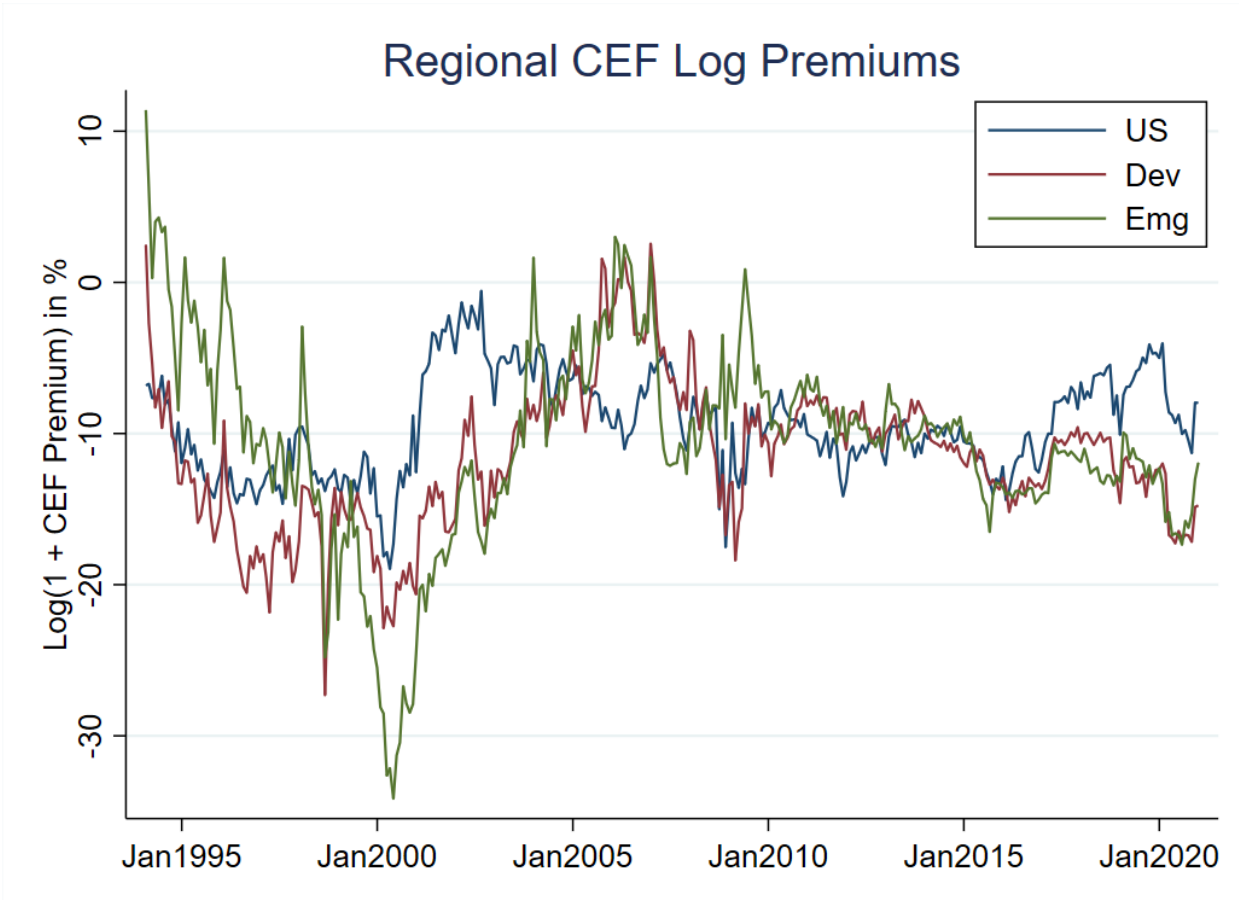
Time-series regressions of investor beliefs about cash flow growth on the UID premium factor and investor flows to institutions. The dependent variable is sell-side analysts' 10-year earnings growth forecast (ErnG10) from De La O and Myers (2021). We multiply annualized ErnG10 by 10 to facilitate interpretation. The premium factor is the UID measure equal to the difference between premiums of CEFs with high and low institutional ownership, as described in Table 3 and the main text. The other regressor is one-year equity flows to institutions weighted by the values of their CEF holdings (CW Eq Flow 1-Yr). These regressions use quarterly data from 1998 to 2020.

	(1)	(2)	(3)
	ErnG10	ErnG10	ErnG10
UID log Prem	0.86***		0.44**
	(0.22)		(0.17)
CW Eq Flow 1-Yr		1.27***	0.97***
		(0.35)	(0.26)
Constant	0.11***	0.04***	0.07***
	(0.02)	(0.01)	(0.01)
T in quarters	78	78	78
NW Lags	11	11	11
R^2_{adj}	0.246	0.344	0.384

Newey-West (NW) standard errors with $1.3T^{0.5}$ lags

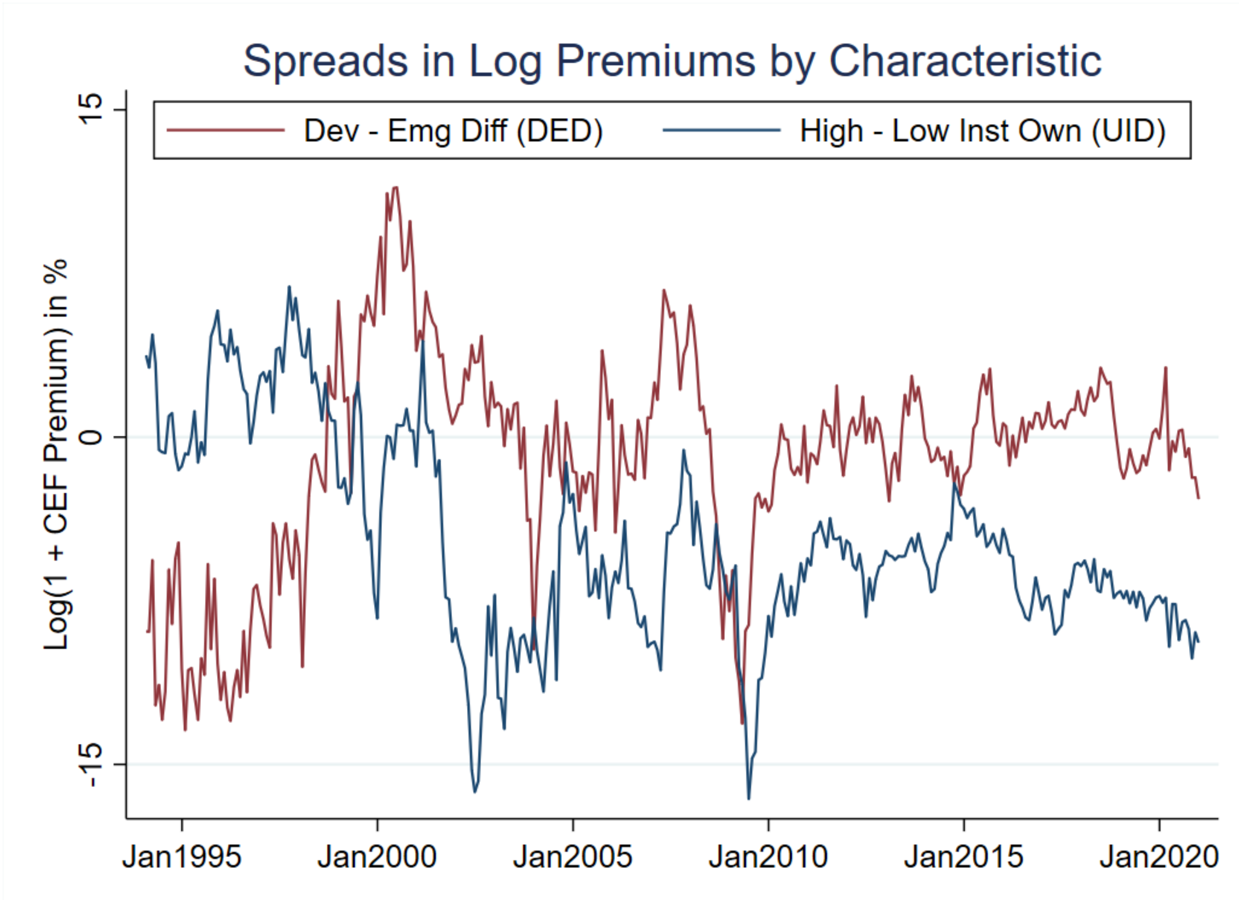
*** p<0.01, ** p<0.05, * p<0.10 from fixed-b distribution

Figure 1: Regional Fund Premiums



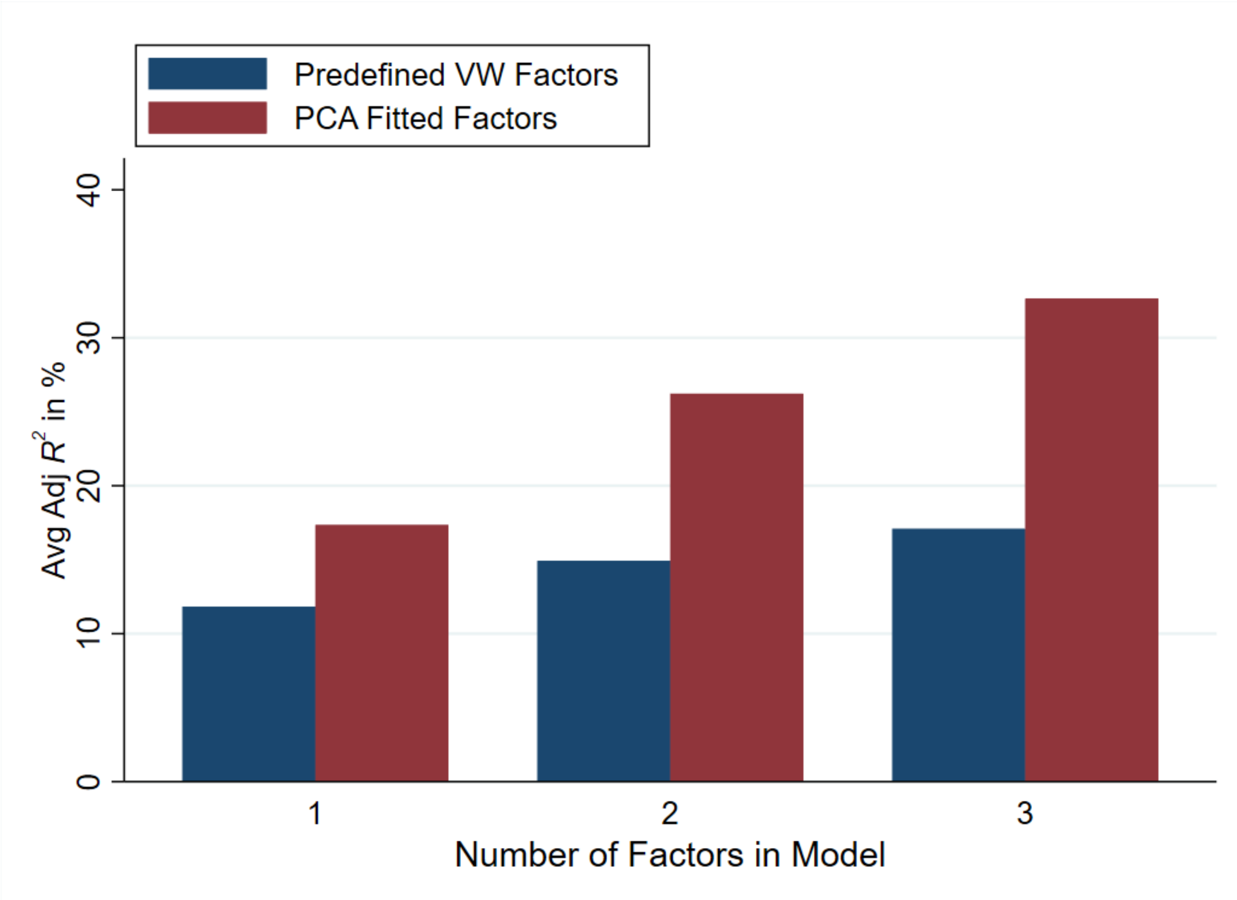
Panel A: This figure shows how average premiums of three groups of closed-end funds (CEFs) vary over time. The three groups are based on the primary location of a funds' holdings: US, developed (Dev), and emerging (Emg) markets. A fund's log premium is defined as the log difference in its per-share price and net asset value. We weight log premiums by funds' dollar values within each of the three regional groups to obtain the aggregated US, Dev, and Emg log premiums. The data on log premiums are monthly from 1994 through 2020.

Figure 1 (cont.): Spreads in Premiums by Fund Characteristic



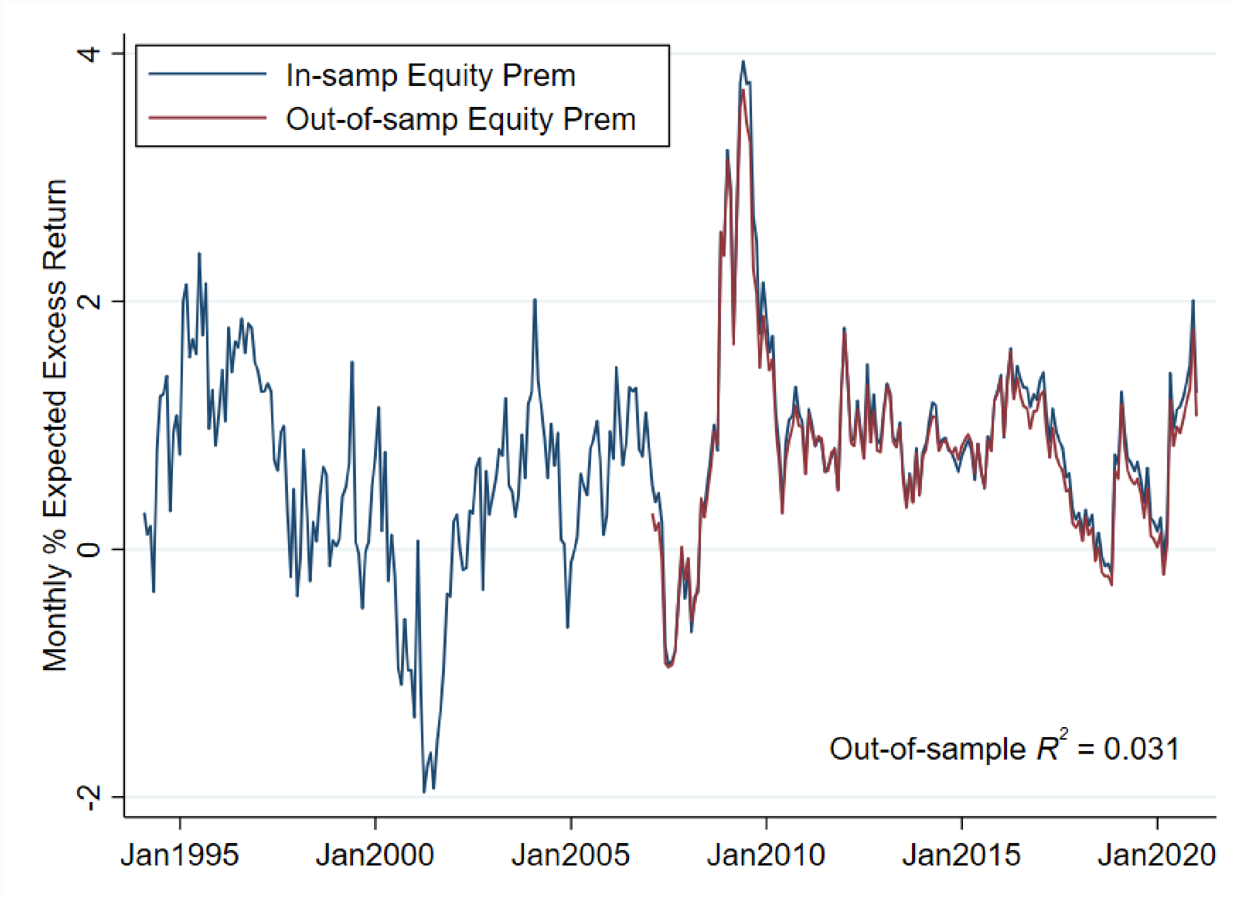
Panel B: This figure shows how two differences or spreads in fund premiums of closed-end funds (CEFs) vary over time. The red line (DED) shows the log premium of (Dev) funds holding developed stocks minus the log premium of (Emg) funds holding emerging market stocks. The blue line (UID) shows the log premium for US funds with high institutional ownership minus the log premium of US funds with low institutional ownership. A fund's log premium is defined as the log difference in its per-share price and net asset value. We aggregate log premiums by funds' dollar values within each of the four groups to obtain the two differences in log premiums. See main text for details. The data on log premiums are monthly from 1994 through 2020.

Figure 2: Explanatory Power of Factor Models



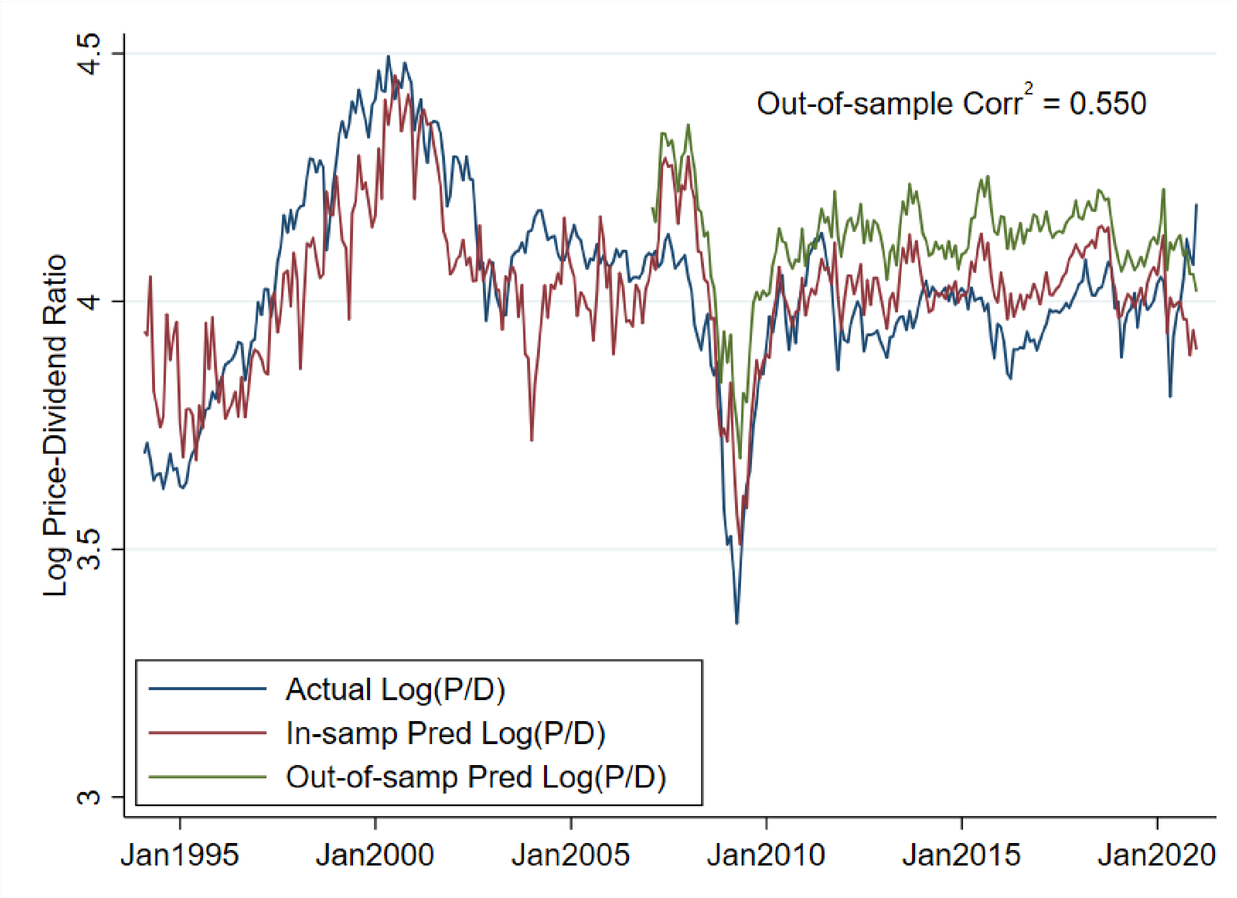
This figure compares the fraction of variance in individual funds' changes in log premiums ($\Delta lnPrem$) explained by various factor models. The adjusted R^2 values are from time-series regressions of monthly $\Delta lnPrem$ of individual funds on up to three factors based on $\Delta lnPrem$ for groups of funds. The factors are based on either predefined fund characteristics, such as location of holdings, or a principal components analysis (PCA) of funds' $\Delta lnPrem$. The first two predefined factors are based on the primary location of the funds' holdings: United States (US), developed markets (Dev), and emerging markets (Emg). The first is US $\Delta lnPrem$ and the second is the Dev $-$ Emg difference (DED) in $\Delta lnPrem$. The third predefined factor (UID) is the difference in $\Delta lnPrem$ between US funds with high and low institutional ownership. Each set of columns represents one of three factor models: only the US factor (1), the US and DED factors (2), and all three factors (3): US, DED, and UID. The blue bar within each set shows the average fund R^2 values in regressions on the predefined factors, which are based on value weighting (VW) CEFs. The red bars show average R^2 values for regressions based on factors from PCA of the individual funds. These statistics and PCA analyses are based on the 41 funds with data for all 324 months from 1994 through 2020.

Figure 3: Expected US Equity Premium



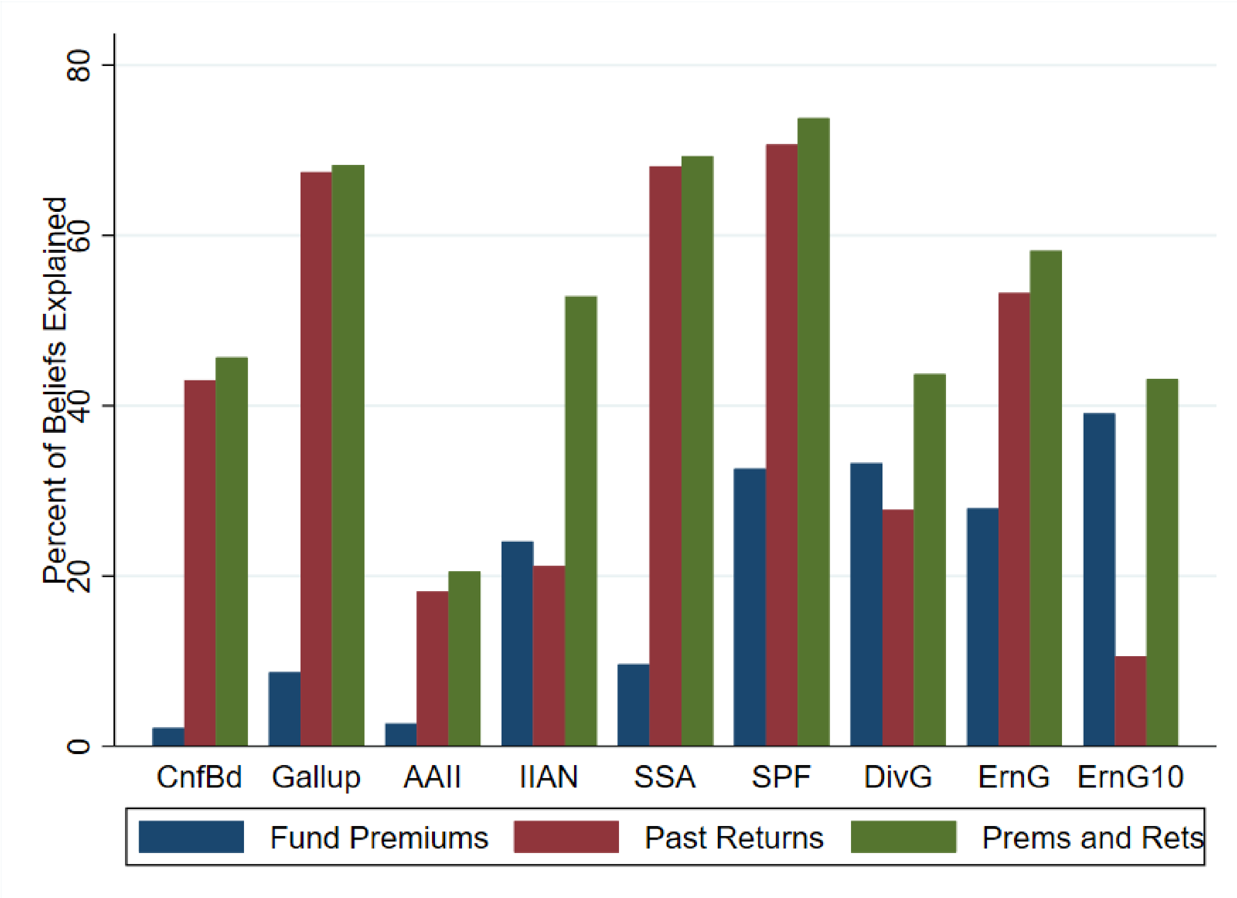
This figure shows predictions of excess returns of the US stock market (i.e., the expected US equity premium) from time-series regressions of monthly excess returns of the US stock market on one-month lags of the three premium factors (US, DED, and UID) described in Table 6, Panel A. The in-sample line depicts the expected US equity premium from the single full-sample regression from 1994 through 2020 shown in column four in Table 6, Panel A. The out-of-sample line shows the expected US equity premium in 2007 to 2020 based on the regression from 1994 to 2006 shown in column five in Table 6, Panel A. The out-of-sample R^2 statistic is one minus the squared difference between actual excess returns on the US stock market and the predicted out-of-sample value divided by the variance of actual excess returns for the 168 months from 2007 through 2020.

Figure 4: Predicted vs. Actual US Stock Valuations



This figure shows predictions of the log price-dividend ratio for the US stock market (Log(P/D)) from time-series regressions of Log(P/D) on contemporaneous values of the three premium factors (US, DED, and UID) described in Table 7. The actual line shows the realized values of Log(P/D) for the US. The in-sample line depicts the predicted Log(P/D) from the single full-sample regression from 1994 through 2020 shown in column four in Table 7. The out-of-sample line shows the prediction of Log(P/D) in 2007 to 2020 based on the regression from 1994 to 2006 shown in column five in Table 7. The out-of-sample statistic is the squared correlation between actual US Log(P/D) and the predicted out-of-sample value for the 168 months from 2007 through 2020.

Figure 5: Investor Beliefs and Fund Premiums



This figure shows percentage R^2 values from time-series regressions of nine investor belief measures on fund premium factors and past returns. The regression models for two belief measures, sell-side analysts' one-year real dividend growth (DivG) and their 10-year earnings growth (ErnG10) from De La O and Myers (2021), appear in Table 9. The other seven belief measures are defined in Table 8, Panel A. The three fund premium factors are the US, DED, and UID measures described in Table 3 and the main text. The other four regressors are log returns of US stocks for the past 6 months, months 6 to 12, year 1 to 3, and year 3 to 5. The three specifications used to predict each investor belief differ in the set of regressors: five premiums only (Fund Premiums bars), four returns only (Past Returns bars), or premiums and returns (Prems and Rets bars). The data are from 1994 through 2020.

Appendix for
“Model-Free Mispricing Factors”

by

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A Equilibrium of the Mispricing Factor Model

Based on the assumptions in Section 2, we consider the linear price equilibrium:

$$P_t = A_F F_t + A_S F_{s,t} + A_C C_t, \tag{18}$$

where A_F, A_S, and A_C are constants determined in equilibrium, and where:

$$F_t = \left[\begin{array}{cccc} g_t & f_t^{(US)} & f_t^{(DM)} & f_t^{(EM)} \end{array} \right]^\top, \tag{19}$$

and

$$F_{s,t} = \left[\begin{array}{cccc} g_{s,t} & f_{s,t}^{(US)} & f_{s,t}^{(DM)} & f_{s,t}^{(EM)} \end{array} \right]^\top. \tag{20}$$

Uppercase subscripts on matrices indicate they are endogenous, while lowercase subscripts indicate exogenously specified matrices.

Note that:

$$E_t\left(F_{t+1}\right) = \phi F_t, \tag{21}$$

$$E_t\left(F_{s,t+1}\right) = \phi F_{s,t}, \tag{22}$$

$$E_t\left(C_{t+1}\right) = \phi C_t, \tag{23}$$

and that:

$$E_t\left(D_{t+1}\right) = A_d \phi F_t, \tag{24}$$

where

$$A_d = \left[\begin{array}{cccc} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{array} \right]. \tag{25}$$

Thus:

$$E_t\left(P_{t+1} + D_{t+1}\right) = A_F \phi F_t + A_S \phi F_{s,t} + A_C \phi C_t + A_d \phi F_t. \tag{26}$$

Next, note that we can write:

$$S_t = A_s F_{s,t}, \tag{27}$$

where

$$A_s = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ \beta_{c,s}^{(US\_H)} & \beta_{c,s}^{(US\_H)} & 0 & 0 \\ \beta_{c,s}^{(US\_L)} & \beta_{c,s}^{(US\_L)} & 0 & 0 \\ \beta_{c,s}^{(DM)} & 0 & \beta_{c,s}^{(DM)} & 0 \\ \beta_{c,s}^{(EM)} & 0 & 0 & \beta_{c,s}^{(EM)} \end{bmatrix}. \tag{28}$$

Market clearing can then be written:

$$\begin{aligned} R_f P_t &= E_t\left(P_{t+1} + D_{t+1}\right) + \frac{1}{2}\left(S_t + C_t\right) \\ &\Updownarrow \\ R_f\left(A_F F_t + A_S F_{s,t} + A_C C_t\right) &= A_F \phi F_t + A_S \phi F_{s,t} + A_C \phi C_t ... \\ &\quad + A_d \phi F_t + \frac{1}{2}\left(A_s F_{s,t} + A_c F_{c,t} + C_t\right). \end{aligned} \tag{29}$$

By the method of undertermined coefficients, we have:

$$A_F = \frac{\phi}{R_f - \phi} A_d, \tag{30}$$

$$A_S = \frac{0.5}{R_f - \phi} A_s, \tag{31}$$

$$A_C = \frac{0.5}{R_f - \phi}. \tag{32}$$

Thus, the effect of sentiment (S) or flows (C) on prices increases with their persistence ϕ.

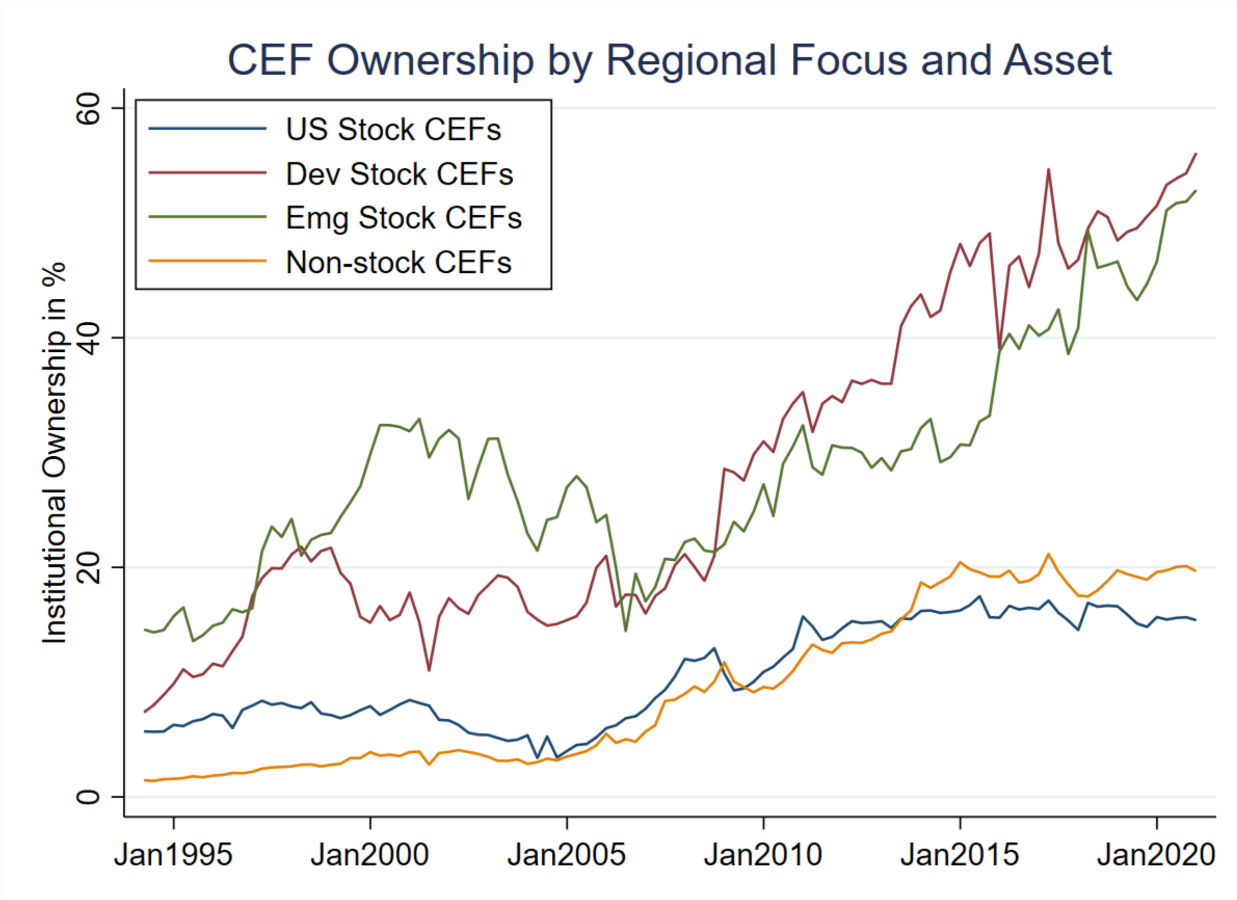
B Closed-End Fund and Institutional Ownership Data

Table B.1: Institutions with Large Closed-End Fund Holdings

This table reports the institutional holdings of the 25 institutions with the largest holdings of equity CEFs. Column one shows the names of institutions that hold more than 1% of shares in at least three equity CEFs in at least one quarter in our sample, which we define as a holding event. The table ranks institutions by the number of 1% holding events. The columns labeled Quarters, Big Hldgs, and Big Value show the number of quarters with 1% holdings, average number of 1% holdings per quarter, and average value of 1% holdings per quarter, respectively, for each institution.

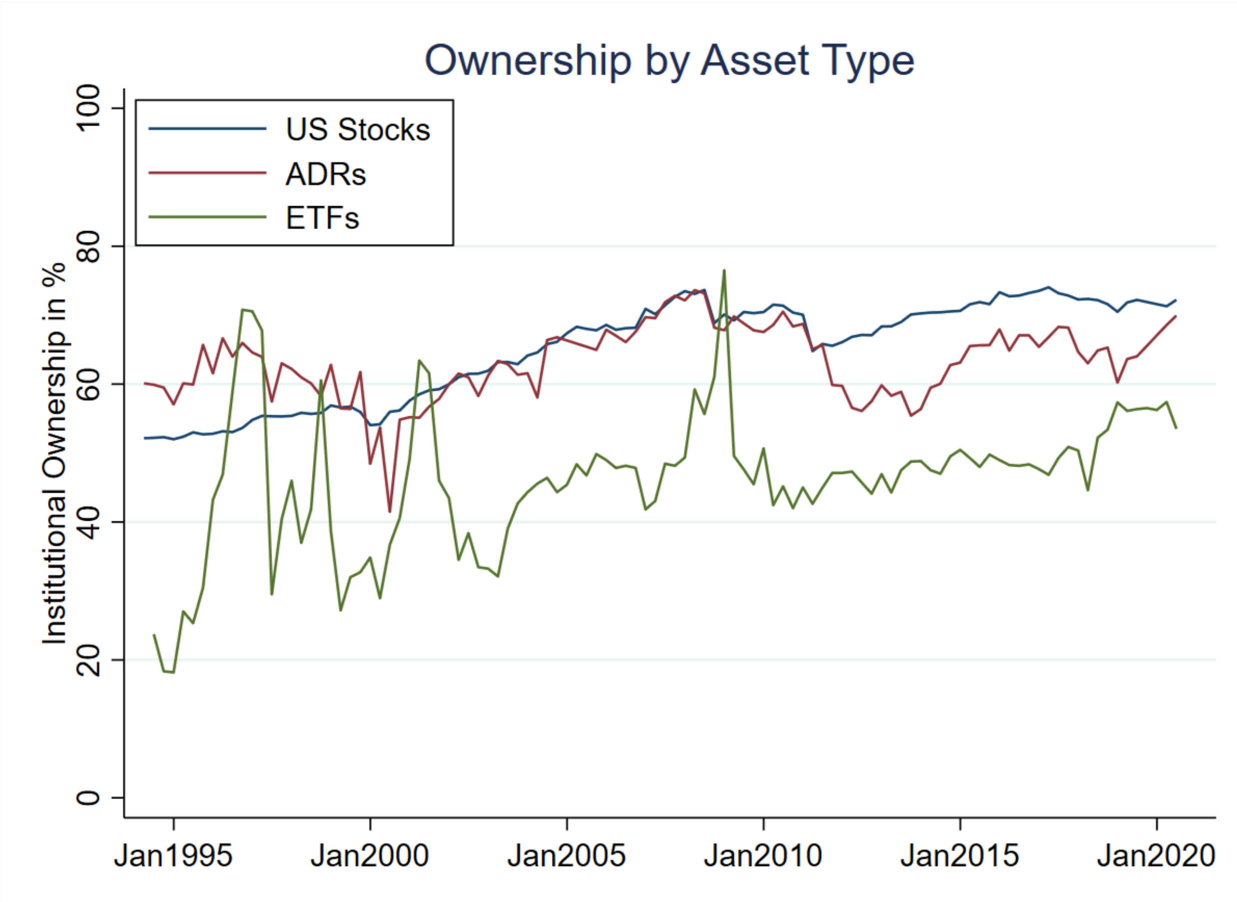
Inst Manager Name	Hldg Events	Quarters	Big Hldgs	Big Value
LAZARD CAPITAL MARKETS LLC	1757	87	20	399
CITY LONDON INV MGMT LTD. (US)	1467	85	17	531
MSDW & COMPANY	951	86	11	180
HARVARD MANAGEMENT CO, INC.	874	43	20	343
1607 CAPITAL PARTNERS, LLC	789	38	21	239
WACHOVIA CORPORATION	742	66	11	96
KARPUS INVESTMENT MANAGEMENT	564	51	11	121
FIDELITY MANAGEMENT & RESEARCH	493	39	13	95
GRAMERCY ADVISORS, L.L.C.	449	35	13	98
WELLS FARGO & (NORWEST CORP)	414	31	13	180
FRANKLIN RESOURCES INC	326	59	6	35
CITIGROUP INC	317	60	5	30
STATE TEACH RETIREMENT SYS OH	266	41	6	56
DEUTSCHE BK AKTIENGESELLSCHAFT	264	33	8	40
MCDONALD & CO SECURITIES	250	28	9	110
RIVERNORTH CAPITAL MGMT LLC	205	35	6	70
BULLDOG INVESTORS, LLC	199	28	7	77
FIXED INCOME SECURITIES	167	32	5	61
RENAISSANCE TECHNOLOGIES CORP.	156	11	14	100
SHUFRO, ROSE & CO., LLC	149	42	4	18
RELATIVE VALUE PTNR GROUP, LLC	145	34	4	85
RAYMOND JAMES & ASSOC, INC.	136	19	7	68
AMVESCAP PLC LONDON	132	27	5	45
NEWGATE CAPITAL MANAGEMENT LLC	132	21	6	57
GUGGENHEIM INVESTMENTS	130	30	4	33

Figure B.1: Institutional Ownership in Closed-End Funds



This figure shows institutions' overall ownership shares of three types of equity closed-end funds (CEFs) and non-equity CEFs have changed from 1994 through 2020. This figure infers missing ownership data on CEFs in Thomson from June 2015 through December 2017 using Bloomberg as an alternative source. In the missing quarters, we apply the growth rate of institutional ownership from Bloomberg to the Thomson data.

Figure B.2: Institutional Ownership in Stocks



This figure shows institutions' overall ownership shares of three types of stocks have changed from 1994 through 2020.