Do Institutional Incentives Distort Asset Prices?

ANTON LINES*

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ABSTRACT

The incentive contracts of delegated investment managers may have unintended negative consequences for asset prices. I show that managers who are compensated for relative performance optimally shift their portfolio weights towards those of the benchmark when volatility rises, putting downward price pressure on overweight stocks and upward pressure on underweight stocks. In quarters when volatility rises most (top quintile), a portfolio of aggregate-underweight minus aggregate-overweight stocks returns 3% to 8% per quarter depending on the risk adjustment. Prices rebound in the following quarter by similar amounts, suggesting that the changes are temporary distortions. Consistent with the growing influence of asset management in the US equity market, the distortions are stronger in the second half of the sample, while placebo tests on institutions without direct benchmarking incentives show no effect. My findings cannot be explained by fund flows and thus constitute a new channel for the price effects of institutional demand. The effects come into play precisely when market-wide uncertainty is rising and distortions are less tolerable, with implications for the real economy. Additionally, the paper offers novel evidence on a prominent class of models for which empirical investigations have been relatively scarce.

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1. Introduction

Financial institutions account for a large and growing fraction of US equity holdings—up from roughly a third in 1980 to roughly two thirds in 2014—with the vast majority of this increase coming from the investment advisory sector (see table 1). Investment advisors are delegated asset management companies hired by institutional clients such as mutual funds, and thus are particularly prone to agency conflicts.[1] In the face of such conflicts, the optimal contract involves evaluating investment performance relative to a benchmark index (e.g. Binsbergen, Brandt, and Koijen (2008); Maug and Naik (2011); Buffa, Vayanos, and Woolley (2014)). Indeed, benchmark-based compensation is ubiquitous in practice, whether explicitly in the form of direct performance fees or implicitly as a result of capital flows into the best performing funds.[2] Given the large size of the advisory sector (almost 30% of the market in 2014), it is crucial to understand the incentives of these institutions and the consequences of their behaviour for equilibrium outcomes.

This paper investigates how asset prices might be distorted as a result of the incentives generated by benchmarking. I show that risk-averse preferences over relative returns induce a penalty for tracking error variance. When aggregate volatility rises, in order to maintain an optimal portfolio allocation, investment advisors should seek to reduce the absolute deviation of their portfolio weights from those of the benchmark, buying underweight stocks and selling overweight stocks.[3] If these shifts in demand are not offset by other market participants, assets that are collectively underweight by the advisory sector should see their equilibrium prices rise relative to those that are collectively overweight. The opposite should occur when volatility falls. I document these effects for actively-managed investment advisors using form-13F institutional holdings data. On average, active fund managers deviate less from the benchmark for stocks with higher individual volatilities, and track the benchmark more closely following time-series increases in volatility. I also show that this behaviour has significant price effects: a portfolio of underweight minus overweight stocks generates large alphas when volatility rises. Placebo tests using other types of institutions that either invest passively or are not typically compensated for relative performance (index funds, banks, insurance companies, and

[1] Investment advisors should not be confused with financial advisors, who offer arms-length recommendations to clients but do not manage money directly. See section 3 for a full description of the institutional setting.

[2] There is some debate over the shape of the flow-performance relationship. Chevalier and Ellison (1997) and Sirri and Tufano (1998) find a convex relationship, while more recently Spiegel and Zhang (2013) argue that the apparent convexity is due to empirical misspecification, and that the relationship is in fact linear. A linear relationship fits the assumptions of my model most closely.

[3] While the unconstrained relationship between absolute distance from the benchmark ("active share") and tracking error variance is many-to-one, it is uniquely pinned down in the context of an optimization problem.

conventional pension funds) rule out many alternative explanations. The price distortions I observe occur when aggregate uncertainty is on the rise and informative prices would be particularly beneficial—for example, as firms decide whether to delay investment or abandon planned M&A activity.[4]

While the contribution of the paper is primarily empirical, I start by laying out a simple model to illustrate formally the above intuition. Based on Brennan's (1993) seminal paper, the model features a one-period economy populated by two CARA-utility agents: a household and an institution. The household solves the standard mean-variance optimization problem, while the institution maximizes expected utility over an end-of-period management fee that is proportional to its portfolio return in excess of an exogenous benchmark. Both agents have access to N risky stocks and a riskless bond with an exogenous interest rate. The stocks pay liquidating dividends that are distributed independently but with an aggregate component to volatility. The model delivers closed-form expressions for equilibrium allocations and prices, and the effects of varying aggregate volatility are derived via comparative statics.

To test the model's predictions, I use the Thomson Reuters S34 institutional holdings dataset (constructed from mandatory Form-13F SEC filings) supplemented with three standard mutual fund datasets: Thomson Reuters S12 (formerly CDA/Spectrum), CRSP and Morningstar. The majority of the analysis is performed using the 13F dataset, which covers the entire institutional sector and is ideal for estimating equilibrium price effects. However, these data are at the institution level rather than the fund level, which means that funds with different benchmarks and investment objectives are lumped together. I therefore use the mutual fund data to verify that the aggregation does not introduce bias. I also use it to identify index funds.

The paper's two main results are summarized in figure 2. Panel A shows 13F investment advisors' average active share (the sum of absolute deviations from benchmark weights) for five quintiles of quarterly S&P 500 index volatility, assuming that the benchmark is the S&P 500 index.[5] The relationship is negative and statistically significant: when volatility rises, active advisors track the index more closely. The magnitude, ~4% reduction in active share from the lowest to the highest volatility quintile, is also economically meaningful. Even small changes in average active share translate into substantial buying and selling pressure due to the

[4] See, for example, Edmans, Goldstein, and Jiang (2012).
[5] I use the S&P 500 index because it is by far the most common among funds where the benchmark is observable, and because weights for any broad value-weighted benchmark will be similar for the largest stocks, which are the focus of my analysis. In section 3 I give a more detailed argument for using the S&P 500 index as a proxy for the "aggregate" benchmark.

large size of the advisory sector (USD 9 trillion, or 28% of the market, in 2014).[6] Moreover, the effect is amplified because institutional portfolios tend to be highly concentrated.

Panel B shows the corresponding price effects. The horizontal axis indicates volatility-change quintiles, while the vertical axis shows the average quarterly return on a long-short "underweight minus overweight" (UMO) portfolio, formed by ranking stocks on investment advisors' AUM-weighted average deviations from benchmark. When volatility rises most (top quintile), underweight stocks outperform overweight stocks by about 8% per quarter. When volatility falls most (bottom quintile), overweight stocks outperform instead, by about 5%.

The remainder of the paper is dedicated to showing that these results are robust and cannot be explained by alternative mechanisms. To rule out any biases resulting from advisors who are benchmarked to indices other than the S&P 500, I replicate the first main result (that managers reduce active share when volatility rises) among the subset of mutual funds for which Morningstar reports the S&P 500 as their primary prospectus benchmark. The result is robust to the inclusion of control variables for manager characteristics and the use of different volatility forecasts.[7]

Returning to the broader 13F dataset, I examine the cross-sectional determinants of the advisory sector's aggregate deviations from the benchmark weights—both signed and in absolute value. In addition to the time-series effects discussed above, a further implication of the model is that absolute deviations from the benchmark should vary in the cross-section. Consistent with the model, I show that absolute deviations are smaller for stocks with higher individual stock volatility. I also examine the effect of fund flows. Using a measure of aggregate percentage flows to/from investment advisors holding a particular stock, I provide some evidence that inflows are associated with larger subsequent deviations and outflows with smaller subsequent deviations. However, controlling for flows does not change the effect of volatility.

For signed deviations, I find that advisors tend to be more overweight in smaller, high-beta stocks with high past returns. It is therefore important to control for these characteristics when examining price distortions, which involve the interplay between aggregate deviations, volatility, and returns.

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[6] The change is also fairly large relative to normal time-series variation in active share: the median fund's time-series standard deviation is 2.1%.

[7] What matters for the institution's behaviour in my model is expected volatility rather than realized volatility. While historical volatility is arguably the most robust out-of-sample forecast for future volatility (Figlewski (1997)), changes in a GARCH(1,1) forecast of volatility give similar results.

I use two methods to estimate price distortions: a stock-level regression approach and a portfolio approach. For the former, I regress quarterly stock returns on the interaction between quarterly volatility changes and aggregate deviation from the benchmark at the start of the quarter. The negative and significant coefficient on this interaction term indicates that the returns on overweight stocks are lower than the returns on underweight stocks when volatility rises, and higher when volatility falls. This approach also accounts directly for the influence of stock characteristics. While I find that advisors being overweight in small, high-beta stocks explains some of the observed differences in returns, controlling for these and other characteristics does not drive out the main effect. I also control for stock-level aggregated fund flows. Inflows push up the prices of overweight stocks and push down the prices of underweight stocks; this effect is also unrelated to the main effect of volatility.

The second approach to estimating price distortions involves forming quintile portfolios by ranking stocks on aggregate deviation from benchmark (among investment advisors), and rebalancing each quarter. I then divide the 1980-2014 sample into five volatility-change quintiles. In quarters with the greatest increase in volatility, the most underweight stocks (bottom deviation quintile) outperform the most overweight stocks (top deviation quintile) by between 3% and 7%. The former number is risk-adjusted using a five-factor model (market, size, value, momentum, and liquidity), and the latter is the raw return. The results are robust to subsampling, and in fact are larger (4-8%) in the second half of the sample (1997-2014), consistent with the increasing influence of institutional investors. Returns one quarter ahead show a reversal of about the same magnitude: overweight stocks now outperform underweight stocks by 7-8%. This reversal is accompanied by a reversal in volatility, consistent with the equilibrium mechanism proposed in the model.

A useful check on the results is to run placebo tests using different types of institutions. First, I document that the negative relationship between active share and volatility is not observed for S&P 500 index funds. Second, I show that forming underweight-minus-overweight (UMO) portfolios using the aggregate deviations of insurance companies, banks, and defined-benefit pension funds fails to produce the results observed for the investment advisors. These placebo tests render many competing explanations, such as time-varying risk-aversion, unlikely. One would need to explain how differences among these institutions—other than benchmarking incentives—could cause differences in the behaviour of the stocks in which they are overweight versus underweight, and only in specific volatility states.

This paper is related to two strands of the literature—equilibrium asset pricing with institutional investors, empirical research on the price effects of institutional demand.[8] Among asset pricing theory, the most closely related paper is by Brennan (1993), who derives a two-factor extension of the CAPM in an economy with a benchmarked institution, but does not solve for prices in terms of model primitives or consider the effects of varying aggregate volatility. Cuoco and Kaniel (2011), Basak and Pavlova (2013) and Buffa, Vayanos, and Woolley (2014) extend Brennan's (1993) insights to dynamic economies with more realistic preferences.[9] Intermediary asset pricing is a rapidly-developing field with no current agreement on a standard framework. This paper is the first to provide direct empirical evidence consistent with the novel predictions of models where benchmarking plays a prominent role.

It has been understood that institutional buying and selling pressure can affect asset prices since at least Shleifer (1986) and Harris and Gurel (1986), who document price increases for stocks upon being added to the S&P 500 index. Kaniel, Carhart, Musto, and Reed (2002) provide evidence that fund managers push up prices of the stocks they hold at quarter-ends. More recently, Coval and Stafford (2007) and Lou (2012) show that flow-driven trading by mutual funds can have large price effects, and Barberis, Shleifer, and Wurgler (2005), Boyer (2011), Greenwood and Thesmar (2011), and Anton and Polk (2014) examine comovement in returns induced by institutional/concentrated ownership. Koijen and Yogo (2015) estimate an equilibrium asset pricing model based on institutional demand curves, and Chen (2015) studies price pressure created by institutional portfolio rebalancing after extreme returns in particular stocks. My contribution relative to these papers is to link demand-related price distortions to specific institutional incentives studied in the theoretical literature. The price effects I observe are arguably more consequential because of their timing.

The paper proceeds as follows. In section 2 I develop the model and derive its testable implications. In section 3 I describe the institutional setting and the data. In section 4 I examine the relationship between volatility and distance from the benchmark, and in section 5 I study the related price effects. Section 6 reports the results of placebo tests, and section 7 concludes.

2. Model

In the emerging theoretical literature on asset pricing with institutional investors, most models share a set of basic features that distinguish them from the traditional asset pricing

[8] The paper is also related to the literature on mutual fund tournaments (e.g. Brown, Harlow, and Starks (1996)).
[9] Basak, Pavlova, and Shapiro (2007) study institutions' responses to benchmarking incentives in a partial equilibrium setting. Basak and Pavlova (2015) explore benchmarking incentives in the commodities market.

paradigm (e.g. Cuoco and Kaniel (2011), Basak and Pavlova (2013), Buffa, Vayanos, and Woolley (2014)). However, because these models tend to be quite complex, several of their key predictions are difficult to identify and, as such, have not previously been examined. The purpose of this section is to distil the most salient features into an extremely simple one-period model, based on Brennan (1993), with only the minimum elements necessary to establish the main hypotheses.

Of course, the simplicity of my model comes at a cost: its predictions will not be quantitative. Rather the magnitudes of predicted effects will be left as open questions to be answered by data.

2.1 Assets

The economy lasts for one period (two dates). At the beginning of the period (date 0), agents trade N risky stocks at endogenously-determined prices $p \equiv (p_1, \dots, p_N)'$ and a riskless bond with an exogenous gross interest rate of R_f. All stocks are in net supply of 1 share. There is an exogenous benchmark index, defined as a vector of weights for each stock, $b \equiv (b_1, \dots, b_N)$, where $\sum_{i=1}^{N} b_i = 1$. At the end of the period (date 1), risky asset i pays liquidating dividend D_i. The vector of dividends $D \equiv (D_1, \dots, D_N)'$ is jointly normally distributed:

$$D \sim N(\mu, \Sigma), \tag{1}$$

where $\mu \equiv (\mu_1, \dots, \mu_2)'$. For simplicity Σ is assumed to take the form $diag\{(\sigma_1^2, \dots, \sigma_N^2)'\}$; that is, assets' dividends are independent. The individual dividend volatilities σ_i are also assumed to have a particular structure:

$$\sigma_i = \bar{\sigma} + \xi_i, \tag{2}$$

where $\bar{\sigma}$ is an aggregate component and ξ_i is an idiosyncratic component. The parameters μ, $\bar{\sigma}$, and $\xi \equiv (\xi_1, \dots, \xi_2)$ are known by all agents at date 0. The endogenous gross return on asset i is given by $R \equiv (R_1, \dots, R_N)'$ and is distributed as follows:

$$R \sim N(\mu^R, \Sigma^{\mathrm{R}}), \tag{3}$$

with $\mu^R \equiv (\mu_1^R, \dots, \mu_N^R)'$. Since $R_i = D_i/p_i$, the mean return on asset i can be written as $\mu_i^R = \mu_i/p_i$ and the asset return covariance matrix can be written as $\Sigma^{\mathrm{R}} = diag\{(\sigma_1^2/p_1^2, \dots, \sigma_N^2/p_N^2)'\}$.

2.2 Agents

There are two agents, a representative household and a representative institution. Both agents consume only at date 1 and have negative exponential (CARA) utility over terminal consumption C_1:

$$U = -\exp(-\gamma C_1), \tag{4}$$

where γ is the coefficient of absolute risk aversion. The household and the institution differ only in their wealth accumulation. The household invests directly in the $N + 1$ available assets, choosing a portfolio with weights $\theta_H \equiv (\theta_1^H, \dots, \theta_N^H)'$ in the N stocks and a residual weight of $1 - \theta_I{}'\iota$ in the bond (where ι is a vector of ones). Terminal household wealth is therefore given by:

$$W_1^H = W_0^H\big(\theta_H{}'R + (1 - \theta_I'\iota)R_f\big), \tag{5}$$

where W_0^H is the household's starting wealth. The institution, on the other hand, does not accumulate wealth directly but is paid a variable management fee as payment for investing on behalf of a set of unmodelled fund investors. These fund investors can be thought of as additional households who simply invest in the "default" 401(K) plan offered by their employers. They do not make active portfolio or manager-selection choices.

At this point, the primary agency friction enters the model in a reduced-form manner: to prevent the institution from shirking or taking the wrong amount of risk (see Buffa, Vayanos, and Woolley (2014)), the management fee is assumed to be a function of the return generated by the institution *in excess of the benchmark index return*. Further, following Berk and Green (2004), I assume that all surplus generated relative to the benchmark is extracted by the institution. Thus at date 1 the unmodelled fund investors simply receive their starting wealth W_0^I multiplied by the benchmark index return $b'R$, while the institution's terminal wealth is given by:

$$\begin{aligned} W_1^I &= W_0^I\big(\theta_I{}'R + (1 - \theta_I'\iota)R_f\big) - W_0^I b'R \\ &= W_0^I\Big((\theta_I - b)'R + (1 - \theta_I'\iota)R_f\Big), \end{aligned} \tag{6}$$

where $\theta_I \equiv (\theta_1^I, \dots, \theta_N^I)$ is the institution's vector of stock weights and $1 - \theta_I{}'\iota$ is its weight in the bond.

2.3 Household's optimization problem

Since consumption happens only at date 1 and utility is monotonically increasing, all wealth is consumed at the end of the period. The household therefore solves the following problem:

$$\max_{\theta_H} \mathbb{E}_0\{-\exp[-\gamma^H W_0^H(\theta_H{}'R + (1-\theta_I'\iota)R_f)]\}, \tag{7}$$

which has the standard mean-variance portfolio choice solution (all proofs are in the appendix):

$$\theta_i^H = \frac{\mu_i^R - R_f}{\gamma^H W_0^H (\sigma_i^R)^2}, \quad i = 1, \dots, N. \tag{8}$$

Rewriting this expression in terms of prices and the parameters of the dividend distribution gives:

$$\theta_i^H = \frac{\mu_i - p_i R_f}{\gamma^H W_0^H \sigma_i^2} \cdot p_i. \tag{9}$$

2.4 Institutions' optimization problem

The institution's problem is similar to the household's problem, the only difference being that the relative portfolio return $(\theta_I - b)'R$ now replaces the absolute portfolio return $\theta_H{}'R$ in the objective function. Thus the institution solves:

$$\max_{\theta_I} \mathbb{E}_0\{-\exp[-\gamma^I W_0^I((\theta_I - b)'R + (1-\theta_I'\iota)R_f)]\}. \tag{10}$$

The solution is also similar to that of the households, with the benchmark weight in stock i simply appearing as an extra term in the otherwise standard mean-variance formula (rewritten again in terms of prices and dividend parameters):

$$\theta_i^I = \frac{\mu_i - p_i R_f}{\gamma^I W_0^I \sigma_i^2} \cdot p_i + b_i, \quad i = 1, \dots, N. \tag{11}$$

Since the benchmark is exogenously specified, it will not generally be mean-variance efficient. This is the reason why the institution will want to deviate in the first place.

2.5 Equilibrium

The definition of equilibrium is standard:

Definition 1. *A vector of prices p^*, and vectors of household portfolio weights θ_H^* and institutional portfolio weights θ_I^*, together constitute an equilibrium if:*

(i) θ_H^* solves the household's optimization problem (equation 7);

(ii) θ_I^* solves the institution's optimization problem (equation 10);

(iii) Markets clear:

$$W_0^H \theta_i^H + W_0^I \theta_i^I = p_i, \quad i = 1, \dots, N. \tag{12}$$

This setup yields closed-form solutions for all endogenous quantities in the model.

For ease of illustration, I make two further simplifying assumptions:

Assumption 1. The household and the unmodeled investors have the same initial wealth: $W_0^H = W_0^I = W_0$.

Assumption 2. The household and the institution have the same risk aversion: $\gamma^H = \gamma^I = \gamma$.

These assumptions only affect the solution quantitatively and are not crucial for the predictions discussed below. I now proceed to the main proposition of the model.

Proposition 1. *The elements of the equilibrium price vector p^*, household portfolio weight vector θ_H^* and institutional portfolio weight vector θ_I^* are given, respectively, by:*

$$p_i^* = \frac{2\mu_i - \gamma\sigma_i^2 + \sqrt{(2\mu_i - \gamma\sigma_i^2)^2 + 8\gamma\sigma_i^2 W_0 R_f b_i}}{4R_f}, \quad i = 1, \dots, N; \tag{13}$$

$$\theta_i^{H*} = \frac{p_i^*}{2W_0} - \frac{b_i}{2}, \quad i = 1, \dots, N; \tag{14}$$

$$\theta_i^{I*} = \frac{p_i^*}{2W_0} + \frac{b_i}{2}, \quad i = 1, \dots, N. \tag{15}$$

The first noteworthy feature of the solution is that the equilibrium price p_i^* reduces to the standard mean-variance price (i.e., without institutions) if the stock is not part of the benchmark index. This occurs when $b_i = 0$:

$$p_i^* = \frac{1}{R_f}\left(\mu_i - \frac{1}{2}\gamma\sigma_i^2\right), \quad i = 1, \dots, N. \tag{16}$$

The institution exerts no "excess" demand pressure on non-benchmark stocks because it has access to the riskless bond and uses leverage to fund its increased holdings of benchmark stocks rather than shorting non-benchmark stocks. For non-benchmark stocks, the expressions for the household's and the institution's equilibrium portfolio weights also reduce to the standard mean-variance solution. Allowing the institution access to unlimited borrowing and lending at the risk-free rate may seem an unrealistic assumption, since most equity funds are required to remain fully invested and/or are prohibited from using leverage.[10] Indeed, in Brennan's (1993) original paper, the institution cannot invest in the riskless bond. However, the assumption is necessary in order to obtain closed-form solutions for prices, and more importantly it does not qualitatively change the model's predictions for benchmark stocks—which are the focus of the paper.

Second, if a stock is included in the benchmark ($b_i > 0$), its price is inflated relative to an otherwise identical non-benchmark stock. This result is common to all models with benchmarked institutions, and is highlighted in particular by Cuoco and Kaniel (2011) and Basak and Pavlova (2013).

2.6 Comparative statics

The advantage of a simple model is that the effects of changes in underlying parameters can be more easily identified. In this paper I am mostly concerned with the effects of changes in dividend volatility—and, consequentially, return volatility. The intuition for why these changes should matter is that risk-averse, benchmarked institutions incur a penalty for tracking error variance (the variance of the difference between their portfolio return and that of the benchmark index). This penalty can be seen directly from the institution's optimization problem (equation 10), which can be rewritten in mean-variance form using the properties of the normal distribution:

[10] One exception to this rule is 130/30 funds (and other variants such as 150/50 or 120/20), which have been increasing in popularity.

$$\max_{\theta_I} W_0^I\big((\theta_I - b)'\mu^R + (1-\theta_I'\iota)R_f\big) - \frac{1}{2}\gamma(W_0^I)^2 \underbrace{(\theta_I - b)'\Sigma^R(\theta_I - b)}_{\text{Tracking error variance}}. \tag{17}$$

Unlike the household, which can lower its variance penalty by holding more of the riskless bond, the institution can only lower its variance penalty by adjusting its portfolio weights θ_I towards those of the benchmark b. The institution's incentive to deviate in the first place comes because the benchmark is specified exogenously and therefore not generally mean-variance efficient. However, if volatility rises, the variance penalty increases and the institution is incentivised to reduce its distance from the benchmark in response. Recall that the diagonal elements of Σ are assumed to have an aggregate component and an idiosyncratic component (equation 2). Thus changes in aggregate volatility $\bar{\sigma}$ will drive changes in the institution's portfolio weights.

Adjustments in the institution's portfolio holdings that are not offset by opposite adjustments in the household's portfolio holdings must have price effects. Because these price effects are the product of institutional incentives, they can be regarded as distortions relative to the frictionless case where institutions simply act in the best interests of their investors without the need for agency-mitigating contracts.

Proposition 2. *The responses of equilibrium institutional portfolio weights θ_i^{I*} and equilibrium prices p_i^* to the aggregate component of dividend volatility $\bar{\sigma}$ are given, respectively, by:*

$$\frac{\partial \theta_i^{I*}}{\partial \bar{\sigma}} = \frac{\gamma\bar{\sigma}}{4W_0R_f}\chi_i, \quad i = 1, \ldots, N; \tag{18}$$

$$\frac{\partial p_i^*}{\partial \bar{\sigma}} = \frac{\gamma\bar{\sigma}}{2}\chi_i, \quad i = 1, \ldots, N; \tag{19}$$

$$\text{where } \chi_i = \frac{\gamma\bar{\sigma}^2 - 2\mu_i + 4W_0R_fb_i}{\sqrt{(\gamma\bar{\sigma}^2 - 2\mu_i)^2 + 8\gamma\bar{\sigma}^2W_0R_fb_i}} - 1. \tag{20}$$

When will these partial derivatives be positive (negative)? From equation 20 it can be seen that both derivatives will be zero when the first term of χ_i is equal to 1, or, equivalently, when:

$$\gamma\bar{\sigma}^2 - 2\mu_i + 4W_0R_fb_i = \sqrt{(\gamma\bar{\sigma}^2 - 2\mu_i)^2 + 8\gamma\bar{\sigma}^2W_0R_fb_i}. \tag{21}$$

The two solutions to equation 21 are:

$$b_i = \left\{0,\ \frac{\mu_i}{R_fW_0}\right\}. \tag{22}$$

Substituting the nonzero solution into equation 15, I obtain $\theta_i^{I*} = b_i$.[11] In words, the partial derivatives of prices and institutional holdings with respect to dividend volatility will be zero when the institution's weight is equal to the benchmark weight. It is then straightforward to show (see appendix) that both derivatives will be positive when $b_i > \frac{\mu_i}{R_fW_0}$, or equivalently, $\theta_i^{I*} < b_i$. So underweight (overweight) stocks will see an increase (decrease) both in institutional portfolio weight and the equilibrium price when aggregate volatility rises.

2.7 Testable hypotheses

The model's predictions serve as the basis of my empirical tests. If the model is an adequate description of reality, the relationship between institutional portfolio holdings, prices and aggregate volatility should resemble that shown in figure 3. Because return volatility is easier to measure than dividend volatility, the figure uses the former, computed as follows:

$$\bar{\sigma}^R = \frac{\bar{\sigma}}{|p_i|} = \frac{4R_f\bar{\sigma}}{2\mu_i - \gamma\bar{\sigma}^2 + \sqrt{(2\mu_i - \gamma\bar{\sigma}^2)^2 + 8\gamma\bar{\sigma}^2W_0R_fb_i}}. \tag{23}$$

The left panel of figure 3 plots the institutions' deviation from the benchmark weight $\theta_i^{I*} - b_i$ (for stock i) against aggregate return volatility $\bar{\sigma}^R$ for several values of the benchmark weight b_i, holding the other model parameters fixed. In particular, the mean dividend μ_i is set to 10, the risk-aversion parameter γ is set to 4, the gross risk-free rate R_f is set to 1, and initial wealth is set to 100. Thus, $b_i < \frac{\mu_i}{W_0} = 0.1$ indicates that the stock is overweighted by the institution, and $b_i > 0.1$ indicates that it is underweighted. The resulting plots are typical. As $\bar{\sigma}^R$ increases, overweight stocks become less overweight, and underweight stocks become less underweight. In other words, absolute deviation from the benchmark decreases.

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[11] The solution with nonzero b_i is used because I am concerned with the behaviour of benchmark stocks.

The right panel of figure 3 plots the equilibrium price p_i^* as a function of the aggregate return volatility $\bar{\sigma}^R$, again for various values of b_i, which determine whether the stock is overweight or underweight. The other parameters are as described above, and the plots are typical. The right panel shows that the prices of overweight stocks fall relative to the prices of underweight stocks. The model is extreme in this regard—it predicts that the prices of overweight stocks will actually rise as volatility increases. Given that the model is not designed to be quantitative, I focus instead on the difference between overweight and underweight stocks.

The two main empirical hypotheses can be summarized as follows:

Hypothesis 1. Fund managers' total distance from their benchmarks should decrease when expected volatility rises, and increase when expected volatility falls.

Hypothesis 2. Prices of underweight stocks should rise relative to prices of overweight stocks when expected volatility rises, and vice versa when expected volatility falls.

3. Institutional setting and data sources

Delegated asset management in the United States has a particular institutional and legal structure, established by the 1940 Investment Company Act. Mutual funds do not manage the assets of their shareholders directly—rather, the fund's board of directors hires an investment advisory firm, which supplies portfolio management services in exchange for an advisory fee. The investment advisor then hires the portfolio manager(s), investment analysts, and support staff required to operate the fund. The advisor may either be external or owned by the mutual fund family itself, but is a separate legal entity with a separate compensation arrangement. In addition to mutual funds, investment advisors manage money on behalf of other institutions such as pension sponsors or endowments.

The compensation structure of investment advisors is tightly regulated. In a 1970 amendment to the Investment Company Act, the US congress mandated that any advisory fees with a performance-based component must be symmetric with respect to the performance benchmark—that is, underperforming the benchmark should incur a penalty of the same size as the bonus earned from outperforming the benchmark by the same amount. Advisory contracts must also be disclosed on form N-SAR. Perhaps as a result of the symmetric fee restriction, Elton, Gruber, and Blake (2003) report that many advisory contracts do not make use of performance fees, instead paying the advisor a fixed percentage of assets under management (AUM). In these cases, incentives are generated implicitly through fund flows, especially in the case of open-ended mutual funds where capital moves continuously into and out of the fund. Even in cases where month-to-month flows are largely unrelated to performance (e.g. pension sponsors), similar incentives nonetheless operate because the advisor is able to win new business as a result of superior performance or lose existing business as a result of inferior performance. The shape of the flow-performance relationship is disputed. Chevalier and Ellison (1997) and Sirri and Tufano (1998) find a convex relationship, while Spiegel and Zhang (2013) argue that the apparent convexity is the result of empirical misspecification and the true relationship is linear. A linear relationship fits my model most closely.

A second layer of agency exists between the investment advisor and the portfolio manager. In 2005, the Securities and Exchange Commission (SEC) adopted Rule S7-12-04, requiring advisors to disclose the details of the portfolio managers' compensation contracts. Using these disclosures, Ma, Tang, and Gómez (2016) document that portfolio manager bonuses are typically based on multiple factors, with 77% involving investment performance, 52% involving the profitability of the advisor, and 19% involving AUM. Whether explicitly or implicitly, portfolio managers thus face similar incentives personally to those faced by the advisory firm as a whole.

All institutions in the United States with at least USD 100 million under management must file form 13F with the SEC, as stipulated by the Securities Exchange Act of 1934. Through this form institutions must disclose their stock holdings once per calendar quarter. With minor exceptions, such as small holdings (under USD 200,000) and limited confidentiality restrictions (see sections 13(f)(4) and (5)), the 13F data provide a complete picture of institutional common stock ownership in the US.

The 13F data are compiled by Thomson Reuters in the "S34 file", and include the number of shares of each stock held, as well as some limited information about the filing institution. Thomson Reuters classifies institutions into types according to the following scheme: (1) banks; (2) insurance companies; (3) investment companies; (4) investment advisors; (5) "other" (mostly pensions and endowments).[12] In addition, I construct two additional institution type codes: (6) hedge funds, using the methodology of as Agarwal, Jiang, Tang, and Yang (2013);

[12] There are significant errors in the raw typecodes reported in the Thomson Reuters S34 file after 1999, which I correct as per Kacperczyk, Nosal, and Stevens (2014).

and (7) index funds, identified using fund-level data, which I describe below. The remainder of total market capitalization is attributed to the household sector.

Figure 1 displays the share of US equity held by the seven classes of institutions, plus households, from 1980-2014. In particular, the share held by investment advisors increases from 5% to 28% over the sample period, ultimately displacing households as the largest single investor group. It is important to note that assets owned by non-advisor institutions but managed by investment advisors are classified as type 4 in the S34 file. The proportion of stocks held by banks, pensions and insurance companies declines over the sample, while the proportion held by index funds and hedge funds increases.

In addition to the institution-level 13F dataset, I also make use of a combined dataset of open-ended mutual funds, which is better suited to examining fund manager behaviour since the individual benchmarks can be identified and there are no aggregation issues. The mutual fund dataset (which is at the fund level rather than the fund family level) is formed by merging the three most commonly-used data sources: Thomson Reuters S12 (formerly CDA/Spectrum), which contains quarterly stock holdings; CRSP, which contains index fund flags and can be linked to the Morningstar database; and Morningstar Direct, which contains its own index fund flags as well as benchmarks obtained directly from the fund prospectuses.

These datasets are merged using three separate procedures. First, Morningstar Direct is merged with CRSP using the method of Pástor, Stambaugh, and Taylor (2015). The combined Morningstar/CRSP dataset is then merged (via CRSP) with Thomson Reuters S12 using MFLINKS (see Wermers (2000)). Finally, the combined Morningstar/CRSP/S12 dataset is partially matched to the 13F institution-level data using the Thomson Reuters "S12Type5" linking file.

I classify an individual fund in the Morningstar/CRSP/S12 dataset as an index fund if the CRSP variable *Index_fund_flag* has a value of 'D' or 'E', if either of the Morningstar variables *Index* and *Enhanced Index* have a value of 'Yes', or any of the following words appear in the CRSP or Morningstar *fundname*: 'Index', 'Ind', 'Idx', 'Indx', 'Mkt', 'Market', 'Composite', 'S&P', 'SP', 'Russell', 'Nasdaq', 'DJ', 'Dow', 'Jones', 'Wilshire', 'NYSE', 'iShares', 'SPDR', 'HOLDRs', 'ETF', 'Exchange-Traded Fund', 'PowerShares', 'StreetTRACKS', '100', '400', '500', '600', '1000', '1500', '2000', '3000', '5000' (following Ma, Tang, and Gómez (2016)). After identifying index funds at the fund level, I designate any S34 (13F) institution with more than half of its assets in index fund products as an overall index fund.

I use the S&P 500 index as the "aggregate" benchmark for 13F investment advisors. Although different funds in the same family may have different benchmarks, the 13F data are at the institution level, meaning a single choice of benchmark must be made. I choose the S&P 500 index for three reasons. First, it is by far the most common benchmark among the subset of funds for which Morningstar reports benchmark information, accounting for almost 60% of domestic US equity funds by assets under management. Second, the largest 500 stocks have very similar weights in broader value-weighted benchmarks such as the Russell 1000, Russell 3000, and Wilshire 5000, because the S&P 500 is a substantial fraction of the total market. Third, when aggregating across opposite investment styles, such as value and growth, benchmarks should net to something close to the S&P 500 for the largest 500 stocks. What matters for equilibrium pricing is *aggregate* deviations from the benchmark across the entire sector.

At the stock level, security prices, returns, shares outstanding, and trading volume come from CRSP, while book values come from Compustat.

4. Volatility and deviations from the benchmark

In this section I investigate *Hypothesis 1* from the model (see section 2.7): namely, that investment advisors' absolute distance from the S&P 500 index should decrease when volatility rises. I start by examining time-series movement towards the benchmark at the fund level when aggregate volatility rises, before considering how stock-level deviations are related to individual stock volatility in the cross section. I then investigate the role played by fund flows, asking whether outflows in uncertain times can account for the observed effects.

4.1 Fund-level deviations from benchmark

As a summary fund-level measure of distance from the benchmark, I use Cremers and Petajisto's (2009) active share. Active share is defined as the sum of absolute differences between portfolio weights and benchmark weights (divided by two, since for each overweight there will be a corresponding underweight). In more concrete terms, active share is a number between zero and one that measures the fraction of portfolio holdings that are different from those of the benchmark. Although it is possible for investment opportunities (i.e., expected future dividends) to change at the same time as volatility increases, prompting managers to increase deviation in some stocks, the portfolio as a whole should still move closer to the benchmark. Active share captures this overall effect.

It should be noted that the relationship between active share and tracking error variance is not identified in a general sense—many different levels of active share can give rise to the same tracking error. However, if fund managers are optimizing, in theory all but one of these different possible configurations will be ruled out due to having lower expected returns. Thus, when volatility rises, the optimal response is to scale down overweights and underweights proportionally (see the model in section 2).

Active share is formally defined as follows:

$$AS_{i,t} \equiv \frac{1}{2}\sum_{n=1}^{N}\left|\frac{Shares_{i,n,t} \times Price_{n,t}}{\sum_{m=1}^{N}\left(Shares_{i,m,t} \times Price_{m,t}\right)} - \frac{MCap_{n,t}}{\sum_{m=1}^{N} MCap_{m,t}}\right|, \qquad (24)$$

where the first term inside the absolute value is the portfolio weight in stock n and the second term is the benchmark weight in stock n. The outer sum is over N, which denotes all stocks in the S&P 500 index. $Shares_{i,n,t}$ is the number of shares of stock n held by fund i at quarter-end t; $Price_{n,t}$ is the price of stock n at quarter-end t; and $MCap_{n,t}$ is the market capitalization (price multiplied by shares outstanding) of stock n at quarter-end t. Thus $AS_{i,t}$ is computed within the universe of S&P 500 stocks—each fund's holdings are reweighted using only the stocks that appear in the index.[13] This reweighting is done in order to isolate changes in active share that are driven by changes in benchmark stock weights, since these stocks are where the model's predictions regarding price distortions are most salient.

Figure 2, panel B, shows that active share decreases by 4.1% from the first to the fifth quintile of S&P 500 volatility (significant at the 5% level). However, this number is computed using the institution-level 13F dataset (Thomson Reuters S34), and may be affected by the assumption that all investment advisors are benchmarked against the S&P 500 index. Another potentially problematic assumption is that the institution-level holdings can be meaningfully aggregated across different funds within the same fund family, some of which may have very different investment styles and thus different benchmarks (e.g. value and growth).

To verify that these assumptions do not introduce bias, I replicate this result at the fund level. Using the combined Morningstar/CRSP/S12 mutual fund sample (see section 3), I identify active US equity mutual funds by first removing index funds and any fund with less than 50% of its assets in common equity.[14] I identify funds benchmarked to the S&P 500 using the *Primary Prospectus Benchmark* variable in the Morningstar Direct database.

Table 1 shows a breakdown of the number of funds with the most common benchmarks, and the fraction of total AUM accounted for by these funds. While Morningstar does not report benchmarks for 45% of the US equity funds in its database, these funds tend to be very small,

[13] The reweighting does not qualitatively affect the results.
[14] The results are insensitive to the exact cut-off in this percentage.

constituting only about a tenth of a percent of the total universe by AUM. Among those funds for which Morningstar does report benchmark information, the S&P 500 is by far the most common, being used by 57% of funds by AUM (23% by number).

What matters for the institution in the model is expected volatility rather than realized volatility. Assuming rational expectations, I construct forecasts of future realized S&P 500 index volatility based on information available prior to quarter-end t (I use S&P 500 index volatility as a proxy for aggregate market volatility). Two different forecast methods are used to ensure robustness: (1) historical volatility, computed as the annualized standard deviation of daily returns within quarter t (prior to quarter-end); and (2) quarterly forecasts from a GARCH(1,1) model estimated on past daily returns over a five-year rolling window (Engel (2001); Figlewski (1997)):

$$v_{d+1}^2 = \omega + \beta(r_d - \bar{r})^2 + \gamma v_d^2, \tag{25}$$

where v_d^2 is the variance on day d, and r_d is the S&P 500 index return from day $d-1$ to day d. The model parameters ω, β and γ, are estimated by maximum likelihood, using daily data from the five years (or five times 252 trading days) prior to quarter-end t. This procedure yields time-varying estimates $\hat{\omega}(t)$, $\hat{\beta}(t)$, and $\hat{\gamma}(t)$. Following Figlewski (1997), I impose a mean daily return $\bar{r}$ equal to zero, which gives more stable estimates by eliminating sampling variation from estimating the mean while introducing negligible bias. I compute 63 daily variance forecasts, starting from quarter-end t:

$$\begin{aligned} \hat{v}_{t,+1}^2 &= \hat{\omega}(t) + \hat{\beta}(t)(r_t - \bar{r})^2 + \hat{\gamma}(t)\hat{v}_t^2, \\ \hat{v}_{t,+d}^2 &= \left(\hat{\beta}(t) + \hat{\gamma}(t)\right)^{d-1} \hat{v}_{t,+1}^2, \qquad d = 2, \dots, 63, \end{aligned} \tag{26}$$

where $v_{t,+d}^2$ is the variance d days after quarter-end t, and the mean daily return $\bar{r}$ is again assumed to be zero. I then compute the average of the daily variance forecasts over the next quarter, annualize, and convert to volatilities:

$$\hat{\sigma}_t^{S\&P} = \sqrt{\frac{1}{63}\sum_{d=1}^{63} \hat{v}_{t,+d}^2 \times 252}. \tag{27}$$

Figlewski's (1997) out-of-sample forecasting exercise indicates that realized volatility is the most robust predictor of future volatility for broad stock indices, but GARCH(1,1) performs almost as well.[15]

For the universe of active mutual funds that are benchmarked to the S&P 500, I estimate variants of the following regression:

$$AS_{i,t} = \delta_i + \kappa \hat{\sigma}_t^{S\&P} + \psi AS_{i,t-1} + \gamma aum_{i,t-1} + \varepsilon_{i,t}, \tag{28}$$

where $AS_{i,t}$ is the active share at the end of quarter t; δ_i is a fund-specific intercept (fixed effect) included to absorb base levels of activeness that may vary across funds; $\hat{\sigma}_t^{S\&P}$ is a quarter-end-t forecast for quarter $t+1$ S&P 500 index volatility; and $aum_{i,t-1}$ is the natural logarithm of fund i's assets under management in quarter $t-1$. Lagged active share $AS_{i,t-1}$ is included in the regression as active share is highly persistent. Standard errors are clustered by quarter to account for potential commonality in manager behaviour and the fact that $\hat{\sigma}_t^{S\&P}$ is the same for all funds at a point in time.[16]

Table 2 reports the estimated coefficients from equation 28. Columns 1 and 2 show specifications using historical quarterly S&P 500 index volatility as a proxy for expected volatility, while columns 3 and 4 show specifications using the GARCH(1,1) volatility forecast. Columns 1 and 3 show specifications without control variables, and columns 2 and 3 show specifications with controls.

A two-standard-deviation increase in volatility leads to a highly significant 1-3% decline in active share, depending on how the regression is specified. This effect is of the same magnitude as the 4.1% decline in active share observed at the institution level (moving from the first to the fifth volatility quintile is a 2.3 standard deviation increase). The decline in active share is economically significant as well as statistically significant. Because the investment advisory sector is so large (about USD 9 trillion, or 28% of the market, in 2014), even small shifts in active share can have large impacts on trading volume. Note that the raw change in active share is only half of the full effect—to reduce active share, every purchase must be matched with an equivalent sale. The change is also fairly large relative to normal time-series variation in active share, with the median fund's time-series standard deviation of active share being 2.1%.

[15] I do not use option implied volatility as there is some debate (see Canina and Figlewski (1993)) over its suitability as a forecast of future realized volatility.
[16] This turns out to be the most stringent method of clustering.

Finally, since the average fund only holds about a hundred stocks, the impact of the portfolio adjustment on individual stocks will be proportionately even larger.

Adding control variables—especially the past active share—increases the adjusted R-square of the regression from <1% to 92%. The full regression specification thus appears to be a good fit for the evolution of active share over time, with most of the explanatory power coming from the persistence of the dependent variable. The high persistence can be seen from the coefficient on lagged active share (~0.70). Assets under management also play a role, with a one-standard deviation change in log assets translating into a decline in active share of 0.015. Funds tend to become somewhat less active as they grow.

The evidence is consistent with investment advisors reducing their distance from the benchmark when aggregate volatility rises, as predicted by the model. It is also robust, showing up in both the institution-level data and the fund-level data.

4.2 Stock-level deviations from benchmark

For the stock-level regressions, I compute each stock's aggregate deviation from benchmark across the entire investment advisory sector (13F dataset). I use the institution-level data as it is the sector-wide deviations that matter most for the asset pricing implications.

Departing slightly from the idealized setting of the model, I compute the *log* aggregate deviation instead of the arithmetic aggregate deviation. Log deviations are approximately equal to percentage deviations. This methodological adjustment is due to the large differences in market capitalization—and therefore large differences in benchmark weights—among S&P 500 index stocks. For example, a 1% overweight position in Apple (roughly 3% of the index in 2016) is much less consequential than a 1% overweight position in Advance Auto Parts (roughly 0.07% of the index). If the entire investment advisory sector were overweight by 1% in Advance Auto Parts, an attempt to rebalance towards the benchmark would have a much larger price effect because its market capitalization and trading volume are much lower than Apple's. Percentage/log deviations account for this effect.

Formally, the aggregate deviation variable $Dev_{n,t}$ is defined as follows:

$$Dev_{n,t} \equiv \log\left(\frac{\sum_{i=1}^{I} AUM_{i,t} \times \theta_{i,n,t}^{I}}{\sum_{i=1}^{I} AUM_{i,t}}\right) - \log(b_{n,t}), \tag{29}$$

where $AUM_{i,t}$ is the value of assets under management of advisor i as of quarter-end t; $\theta_{i,n,t}^{I}$ is advisor i's portfolio weight in stock n at quarter-end t; and $b_{n,t}$ is stock n's weight in the benchmark (the S&P 500 index) at quarter-end t. As with active share, I compute $Dev_{n,t}$ only for stocks that are part of the S&P 500 index at time t. The reason for this is threefold. First, non-index stocks are not as widely held by institutions. Second, in analysing only large, heavily-traded stocks, I can be confident that the effects I report are consequential for the real economy and are not driven by microstructure noise or small-stock return anomalies. Third, and most importantly, the novel predictions of my model concern the relative behaviour of stocks *within* the index.

In addition to investment advisors' time-series response to aggregate volatility, the model also predicts that the same pattern should hold in the cross-section of stocks (see figure 3). The more volatile a particular stock is individually, the lower should be its absolute deviation from the benchmark—*holding expected returns constant.*

Controlling for expected returns is less important at the fund level, since changes in expected returns average out when calculating active share across the whole portfolio.[17] However, it is essential in the cross-section of stocks. This is because especially high (or low) expected returns can offset high volatility and result in a larger absolute deviation from the benchmark. Therefore I use a variety of methods to capture expected returns, which can be summarized in the following regression framework:

$$\left|Dev_{n,t}\right| = \lambda + \kappa\hat{\sigma}_{n,t}^2 + \delta_n + \delta_y + \gamma' Characteristics_{n,t-1} + \varepsilon_{n,t}; \tag{30}$$

$$\left|Dev_{n,t}\right| = \lambda + \kappa\hat{\sigma}_{n,t}^2 + \delta_{n,y} + \gamma' Characteristics_{n,t-1} + \varepsilon_{n,t}. \tag{31}$$

where λ is a regression intercept, $\hat{\sigma}_{n,t}^2$ is the stock's volatility estimated using daily returns from quarter-end $t-1$ up to (but not including) quarter-end t, δ_n is a stock dummy, δ_y is a year dummy, and $\delta_{n,y}$ is a combined stock-year dummy. $Characteristics_{n,t}$ is a vector of stock characteristics measured as of the previous quarter-end ($t-1$): single-factor market beta, the log of market capitalization, the log of book-to-market ratio, annual dividend yield, quarterly turnover (trading volume divided by shares outstanding), past returns for the prior four quarters, and the long-run past return from three years to one year prior. These characteristics have been shown to correlate highly with future expected returns (Brennan, Chordia, and Subrahmanyam (1998)).

[17] At least, the part of the portfolio invested in S&P 500 stocks.

The estimated coefficients from variants of equations 30 and 31 are reported in table 3. The terms of each equation are added cumulatively to control for expected returns in an increasingly strong form. First, the regression in equation 30 is estimated with just the intercept and volatility, along with stock-level fixed effects to control for time-invariant determinants of expected returns across different stocks; e.g. industry effects (column 1). The effect of volatility is thus estimated using only time-series variation in volatility within each stock. Although the coefficient on volatility (-0.039) is negative, it is not significant. However, as I control more stringently for expected returns, the coefficient becomes larger in magnitude (i.e., more negative) and more significant. Simply adding year fixed effects to the previous specification (column 2), and thus controlling for common variation in expected returns through time, is sufficient to produce a significant (at the 1% level) and more negative (-0.068) estimate. Adding time-varying stock characteristics (column 3) further increases the economic significance (-0.139) and statistical significance of the result. The more accurately one controls for expected returns, the less it appears that investment advisors deviate from the benchmark (in either direction) in stocks whose volatility is higher. A one-standard-deviation change in stock volatility leads to a decrease in absolute deviation of between 1.7% and 6.0%, confirming the cross-sectional predictions of the model.

Columns 4 and 5 of table 3 show the estimated coefficients from two variants of equation 31. Here the combination of stock and year fixed effects is replaced by combined stock-year fixed effects. This specification controls for expected returns that can vary from year to year in different ways for each stock; the estimation of the main effect thus comes from variation in volatility within each stock within a given year. This approach leaves few degrees of freedom but theoretically allows for a more comprehensive accounting for differences in expected returns. The estimated coefficient is nonetheless similar: -0.039 (column 4) without stock characteristics in the regression and -0.047 (column 5) with stock characteristics. Both estimates are significant at the 5% level.

4.3 Effect of fund flows

Much of the literature on the price effects of institutional demand has focused on the role of fund flows. Coval and Stafford (2007) study flow-induced buying and selling pressure when a group of mutual funds holding similar stocks collectively underperforms or outperforms. Lou (2012) shows how fund flows can generate stock return momentum and persistence in mutual fund performance. Vayanos and Woolley (2013) model this phenomenon theoretically.

It is therefore important to ask whether fund flows could be responsible for the effects studied in this paper. If flows are negatively correlated with changes in volatility—possibly because investors flee risky assets in times of rising uncertainty—then outflows could prompt a decrease in active risk taking and therefore a narrowing of the distance between funds and their benchmarks. If this effect of flows drives out the effect of volatility, it would suggest a different channel than the one proposed in my model.

I first compute capital flows at the institution level:

$$Flow_{i,t} \equiv \frac{Assets_{i,t} - Assets_{i,t-1}\left(1 + R_{i,t}\right)}{Assets_{i,t-1}\left(1 + R_{i,t}\right)}, \tag{32}$$

where $Assets_{i,t}$ is the total assets of advisor i at quarter-end t, and $R_{i,t}$ is the total return on the stocks held by advisor i at quarter-end t. I then compute aggregate fund flows at the stock level as follows:

$$Aggflow_{n,t} \equiv \frac{\sum_{i=1}^{I} Shares_{i,n,t} \times Flow_{i,t}}{\sum_{i=1}^{I} Shares_{i,n,t}}, \tag{33}$$

where $Shares_{i,n,t}$ is the number of shares of stock n held by advisor i at quarter-end t.

I re-run the regressions described in equations 30 and 31, adding the aggregate fund flow variable on the left-hand side:

$$\left|Dev_{n,t}\right| = \lambda + \kappa\hat{\sigma}_{n,t}^2 + \varphi Aggflow_{n,t} + \delta_n + \delta_y + \gamma' Characteristics_{n,t-1} + \varepsilon_{n,t}; \tag{34}$$

$$\left|Dev_{n,t}\right| = \lambda + \kappa\hat{\sigma}_{n,t}^2 + \varphi Aggflow_{n,t} + \delta_{n,y} + \gamma' Characteristics_{n,t-1} + \varepsilon_{n,t}. \tag{35}$$

Table 4 reports the estimated coefficients. The most important feature is that there is virtually no difference between the estimated coefficients on volatility in this table and those reported in table 3. Both in terms of magnitudes and in terms of statistical significance, the addition of the aggregate flow variable does not change the effect of volatility. This result rules out a purely flow-driven explanation and is consistent with the predictions of my model.

Secondly, there is evidence that flows do play an independent role in determining absolute aggregate deviation from the benchmark, though this evidence is mixed. While the sign of the estimated coefficient is always positive—inflows to the funds holding a particular stock tend to result in an increased aggregate distance from the benchmark in that stock—the magnitudes and statistical significance vary considerably depending on the regression specification and the choice of standard error clustering. Panel A and B of table 4 report the results using different clustering methods: panel A uses quarter-level clustering, and panel B uses stock-level clustering. The magnitudes range from 0.05 to 0.24—in other words, a one-standard-deviation increase in aggregate flows is associated with an increase in distance from the benchmark of between 0.5% and 2%. This finding is consistent with the predictions of Basak and Pavlova (2013), where increased wealth leads to greater deviation from the benchmark through decreased absolute risk aversion.

5. Price distortions

This section investigates whether the changes in demand observed in the previous section are associated with the type of price distortions predicted by the model. Specifically, do stocks that are underweighted in aggregate by the investment advisory sector outperform stocks that are overweighted when S&P 500 index volatility rises? And vice versa when volatility falls?

I use two approaches to estimate the price effects, each with its own set of advantages and disadvantages. The first approach is to estimate a stock-level regression of individual realized returns on the *interaction* between aggregate deviation and changes in aggregate volatility. A negative coefficient on this interaction term would indicate that low-deviation (underweight) stocks have more positive/less negative price changes (higher returns) than high-deviation (overweight) stocks when aggregate volatility rises. Stock characteristics can also be included as explanatory variables in the regression, as well as the interaction between these characteristics and changes in volatility. The regression approach thus controls in a multivariate setting for a variety of factors known to affect future returns (e.g. Brennan, Chordia, and Subrahmanyam (1998)). Moreover, it allows me to control for the influence of fund flows, which could be correlated with the state of volatility. Disadvantages of this approach are, firstly, that magnitudes of interaction terms are cumbersome to interpret, and, secondly, that the model constrains the estimated effect to be linear.

The second approach overcomes these difficulties by forming quintile portfolios of stocks ranked on aggregate deviation from the benchmark, and examining their (risk-adjusted) returns in different volatility states. The magnitudes of portfolio returns are straightforward to interpret, and nonlinearity can be observed across both the aggregate deviation and volatility dimensions. The portfolio approach, however, has drawbacks of its own. The sample size is much smaller, and statistical power that much weaker, than for the regression approach. The portfolio approach also does not lend itself to controlling for stock characteristics in a multivariate setting.

In order to accurately estimate equilibrium price effects, deviations must be aggregated over all investment advisors in the economy. Using only a subset of funds, as would be the case for the mutual fund data used in section 4.1, would not account for netting of overweight and underweight positions within fund families, or across funds with complementary investment styles (such as value and growth). I therefore carry out the analysis in this section using the institution-level data in the Thomson Reuters S34 file (13F), which contains the common stock holdings of all investment advisors in the US with equity investments of $100 million or more.

5.1 What determines aggregate overweight/underweight?

Before estimating price distortions, I first ask what drives investment advisors as a group to be overweight or underweight in particular stocks. Are there particular characteristics that could provide an alternative reason for why underweight stocks might outperform overweight stocks when volatility rises?

Using the (signed) aggregate deviation variable defined in equation 29 as the dependent variable, I estimate variants of the following regression:

$$Dev_{n,t} = \delta + \gamma' Characteristics_{n,t-1} + \varepsilon_{n,t}, \tag{36}$$

where $Characteristics_{n,t-1}$ is a vector of stock characteristics recorded in the prior quarter. I use the same characteristics as in the previous section: single-factor market beta, the log of market capitalization, the log of book-to-market ratio, annual dividend yield, quarterly turnover (trading volume divided by shares outstanding), past returns for the prior four quarters, and the long-run past return from three years to one year prior.

The results are presented in table 5. When the stock characteristics are included as univariate regressors, only market beta, log size and log book-to-market show up as significant. When including all characteristics in the same regression, the coefficient on book-to-market flips sign and the coefficients on dividend yield, turnover, and past return become significant.

The relationship of signed deviation with beta and size is robustly positive: the portfolios of investment advisors tend to be overweight in small, high-beta stocks. Looking at the full specification (column 7), value stocks and high dividend-yield stocks tend to be more underweight, while stocks with high trade turnover and high past returns tend to be more overweight.

These relationships are potentially important. Market beta, in particular, could be a driving factor in the return pattern observed in figure 2. The well-known negative relationship between returns and volatility could mean that high-beta (and thus overweight) stocks mechanically have lower returns than low-beta (i.e., underweight) stocks when volatility rises. It is therefore of particular importance to account for beta when testing for price effects. The fact that advisors tend to be overweight in small stocks and in momentum stocks could also play a role. Momentum has been linked to institutional price effects in many other studies (e.g. Lou (2012)). As such, I ensure that these characteristics are controlled for when studying price effects.

5.2 Regression-based estimates of price distortions

The regression approach to testing for price distortions involves estimating variants of the following equation:

$$\begin{aligned} Ret_{n,t} = \delta + \lambda \Delta\sigma_t^{S\&P} + \kappa Dev_{n,t} + \gamma' Characteristics_{n,t-1} \\ + \left[\psi Dev_{n,t} + \varphi' Characteristics_{n,t-1}\right] \times \Delta\sigma_t^{S\&P} + \varepsilon_{n,t}, \end{aligned} \tag{37}$$

where $\Delta\sigma_t^{S\&P}$ is the change in S&P 500 index volatility from quarter $t-1$ to quarter t; $Dev_{n,t}$ is the aggregate deviation from benchmark in stock n at quarter-end t; and $Characteristics_{n,t-1}$ is the same vector of stock characteristics as in equation 36: single-factor market beta, the log of market capitalization, the log of book-to-market ratio, annual dividend yield, quarterly turnover, and past returns over various horizons. All right-hand-side variables are also interacted with the change in S&P 500 index volatility. In particular, the interaction between volatility change and market beta controls for the mechanical effect of beta on returns when volatility rises or falls. Standard errors are clustered by quarter to account for common factors in returns, but are robust to clustering at any level.

The coefficient of primary interest in this regression is ψ, which measures the extent to which overweight stocks' realized returns rise relative to those of underweight stocks when volatility rises. A direct test of the model's prediction for asset prices is therefore whether ψ is negative.

The estimated coefficients are reported in table 6. The measure of volatility used to obtain the reported results is the historical quarterly standard deviation. For robustness, I run the same regressions using changes in a GARCH(1,1) forecast and obtain similar results (see appendix).

Columns 1-3 of table 6 show the estimates for the full sample (1980-2014), and columns 4-6 show the estimates for the second half of the sample (1997-2014). The subsample analysis serves two functions: to check robustness to the sample construction and to examine the hypothesis that price effects will get stronger over time as the size of the investment advisory sector grows.

For the full sample, the specification in column 1 includes just the interaction between aggregate deviations and volatility changes, and results in a highly significant negative coefficient estimate ($\hat{\psi} =$ -75.31). Adding deviations and volatility separately (column 2) reduces the magnitude of the coefficient to -19.90 but maintains its 1% level of significance. Finally, the specification in column 3 also includes the stock characteristics and their interactions with volatility changes. In this case, the magnitude of the estimate $\hat{\psi}$ rises again, to -34.38. To put these numbers into economic terms (using the specification with the full set of controls): if the volatility change moves from the 10^{th} to the 90^{th} percentile of its empirical distribution, the effect of a two-standard-deviation increase in deviation from benchmark on quarterly stock return shifts from +1.46% to -4.30%. These results strongly confirm the predictions of the model.

Running the same specifications for the second half of the sample yields coefficient estimates of -108.71, -40.22, and -39.80 (all significant at the 1% level), which are larger than for the full sample. Thus, the degree to which underweight stocks outperform overweight stocks when volatility rises is greater in the second half of the sample, when investment advisors have more wealth relative to the rest of the market.

Adjusted R-squares are quite high for regressions that have returns on the left-hand side, indicating that the price effects stemming from the interaction of volatility account for around 5% of the variance of quarterly stock returns in the full sample, and 8% of the variance in the second half of the sample. The goodness of fit statistics thus provide further evidence that the effect increases in importance over time.

The coefficients on stock characteristics are left unreported for the sake of brevity. Only two of the characteristics' interactions with volatility changes turn out to be significant. The first is indeed the market beta of the stock. As expected, there is a mechanical relationship between the fact that advisors' portfolios tend to be overweight in high-beta stocks and outperformance of underweight stocks when volatility rises. This can be seen from the negative coefficient on the interaction between beta and volatility changes, which indicates that high-beta stocks tend to underperform low-beta stocks when volatility rises. The coefficient on the interaction between size and volatility changes has the same interpretation: small stocks tend to outperform when volatility rises. However, neither of these characteristic-drive effects drive out the independent effect of being overweight or underweight, again consistent with price effects as predicted by the model.

5.3 Effect of fund flows

As with fund manager behaviour examined in section 4.3, one plausible alternative mechanism that could account for the above price effects is the influence of fund flows. Flows may be negatively correlated with changes in volatility—i.e., investors may withdraw their money from equity funds when aggregate uncertainty rises, and reallocate towards lower risk assets. This reallocation would leave investment advisors with less wealth. Advisors might then scale back their overweights and underweights, not due to volatility changes directly, but because their absolute risk-aversion increases. According to this story, the relationship with volatility is only incidental.

I control for fund flows by re-estimating equation 37 but adding stock-level aggregate fund flows (see definition 33) and the interaction of flows with aggregate deviations (see definition 29) on the right-hand side:

$$\begin{aligned} Ret_{n,t} = \delta + \kappa Dev_{n,t} + \lambda \Delta\sigma_t^{S\&P} + \varphi Aggflow_{n,t} + \gamma' Characteristics_{n,t-1} \\ + \left[\psi Dev_{n,t} + \varphi' Characteristics_{n,t-1}\right] \times \Delta\sigma_t^{S\&P} \\ + \pi\left(Aggflow_{n,t} \times Dev_{n,t}\right) + \varepsilon_{n,t}, \end{aligned} \tag{38}$$

where $\Delta\sigma_t^{S\&P}$ is the change in S&P 500 index volatility from quarter $t-1$ to quarter t; $Dev_{n,t}$ is the aggregate deviation from benchmark in stock n at quarter-end t; $Aggflow_{n,t}$ is the holdings-weighted average fund flow from quarter $t-1$ to quarter t among the investment advisors who hold stock n, and $Characteristics_{n,t-1}$ is the same vector of stock characteristics as in equations 36 and 37.

The coefficient on the interaction between aggregate deviation and aggregate flow, π, measures the degree to which stock returns are higher/lower for overweight or underweight stocks when there are inflows to or outflows from funds holding the stock. If the return differentials observed in the previous subsection are due to flows, the estimate for π should be negative and the estimate for ψ should be driven to zero.

Table 7 shows, however, that while $\hat{\pi}$ is negative and significant across all specifications in the full sample (1980-2014, columns 1-3), and most specifications in the second half of the sample (1997-2014, columns 4-6), the estimates $\hat{\psi}$ are little changed from those in table 6. This indicates that fund flows affect returns in the expected way, but there is still an independent effect from incentive-driven responses to volatility changes, consistent with the predictions of the model.

5.4 Portfolios sorted on aggregate deviation from benchmark

At the beginning of each quarter (i.e., at the end of quarter $t-1$), I sort stocks cross-sectionally from lowest aggregate deviation (most underweight) to highest aggregate deviation (most overweight), forming five quintile portfolios of approximately 100 stocks each. To capture the potential price effect in a single number, I form a zero-net-investment portfolio that is long the stocks in the lowest deviation portfolio (first quintile) and short the stocks in the highest deviation portfolio (fifth quintile).[18] I refer to this as the underweight-minus-overweight (UMO) portfolio. All portfolios are value-weighted, but the results are robust to using equal weights.

From quarter $t-1$ to quarter t, I record the returns on each quintile portfolio and the UMO portfolio, as well as the change in S&P 500 index volatility.[19] I then perform a time-series sort by the volatility change, and subdivide the five portfolio's returns into five volatility-change quintiles. The first quintile consists of quarters where volatility decreases most compared to the previous quarter, and the fifth quintile is where volatility shows the largest increase. The volatility measure is the annualized daily standard deviation.[20] Standard errors on the portfolio returns are adjusted for clustering by quarter to account for error dependencies introduced by common variation in the cross-section of returns.

According to the predictions of the model, the UMO portfolio should have positive returns in high volatility-change states and negative returns in low volatility-change states. The model is not designed to be quantitative, though it does predict a symmetric response to positive and negative changes in volatility. There are reasons that reality might deviate from the model in this regard, however. If fund managers face asymmetric penalties for high tracking error, such

[18] As the focus of this paper is price distortions rather than trading strategies, I do not account specifically for transaction costs involved in short-selling or turning over the portfolio.

[19] I use contemporaneous measures of price and volatility changes because the low frequency data do not allow me to measure the precise moment within the quarter when the market's expectation of future volatility changes.

[20] In untabulated results, I obtain qualitatively similar portfolio returns using changes in a GARCH(1,1) volatility forecast.

as the threat of litigation,[21] rising volatility may prompt a more rapid response and therefore larger price effects than falling volatility.

Table 8 shows the results of these portfolio sorts for two different samples: the full sample, running from 1980 to 2014 (panel A), and the second half of the sample, running from 1997 to 2014 (panel B). The reason for subsampling is to test the adjunct hypothesis that incentive-driven price distortions become stronger over time, as institutions come to represent a greater share of stock ownership.

In panel A, for quarters in the full sample with the largest decreases in volatility (quintile 1), the UMO portfolio has an average return of -2.5%. This indicates that overweight stocks outperform underweight stocks by 2.5%, which is significantly different from zero at the 5% level. Most of the effect comes via lower returns from the lowest aggregate deviation portfolio (underweight stocks). As we move towards higher volatility-change quarters the UMO portfolio return increases nearly monotonically, to 2.4% (significant at the 10% level) in the fourth volatility-change quintile, and to 7.1% (significant at the 5% level) in the fifth, highest, volatility-change quintile. In these quarters where volatility increases most, the effect is also monotonic in the cross-section: the first aggregate deviation quintile portfolio outperforms the second, which outperforms the third, and so on. There does indeed appear to be an asymmetry between the strength of the effect in the top and bottom volatility-change quintiles, suggesting that fund managers are penalized more heavily when volatility rises than they benefit when volatility falls.

The overall magnitudes are large: 7.1% is a quarterly return. While annualization is inappropriate due to the fact that these returns occur on average only every five quarters, 7% over a single quarter is a significant price change differential that is likely to affect the decision-making of affected firms. The timing of the price change also makes the effect more consequential. For example, firms with an option to defer investment will see the value of their option rise when aggregate uncertainty rises, bringing many of them closer to the margin of whether or not to invest. At the margin, a temporarily high or low stock price can make the difference.

The picture grows even more stark in the second half of the sample, as seen in panel B. In the lowest volatility-change quarters (quintile 1), the UMO portfolio has an average return of -5% (significant at the 1% level), indicating that overweight stocks outperform underweight stocks. Moving towards the higher volatility states, the return on the UMO portfolio increases

[21] See, for example, Unilever Superannuation Fund vs. Merrill Lynch, Harvard Business School Case Study (2002)

monotonically, reaching 8.5% (significant at the 5% level) for the highest volatility-change quarters (quintile 5). The monotonicity is also apparent in the cross-section for both the lowest and the highest volatility-change states. The fact that the effect both strengthens and becomes more regular in the latter period is what we should expect to see in a world where institutional investors (and investment advisors in particular) are increasing in importance. In further unreported subsamples, the UMO portfolio returns remain highly robust.

These portfolio returns alone do not, of course, indicate that the price changes are distortionary. The first step I take in judging whether this is the case is to examine returns in the *subsequent* quarter. If the price changes during quarter t are due to information about the future cash flows of the company, or variation in stock characteristics or fund managers' demand for those characteristics, we would expect the changes to be permanent. However, if the changes are distortionary, we would expect them to revert to their previous levels in quarters after t. I perform exactly the same sorting exercise as the one described above, but this time I record returns in quarter $t + 1$ instead of quarter t.

The $t + 1$ portfolio returns are reported in table 9 for the same quintiles of aggregate deviation (underweight/overweight) and changes in S&P 500 index volatility as in table 8. The most readily apparent feature of the table is that for quarters with the greatest increase in volatility during quarter t (quintile 5), the UMO portfolio's average return over the subsequent quarter ($t + 1$) is highly significant, of similar magnitude to the return over quarter t, but with the opposite sign. This is the case for both the full sample (1980-2014, panel A), where the average UMO return is -7.8%, and the second half of the sample (1997-2014, panel B), where the return is -7.0%. That is, overweight stocks outperform underweight stocks, whereas the quarter before it had been underweight stocks outperforming overweight stocks. A rebound in prices also appears to occur in quarters following the largest decreases in volatility (quintile 1), but the test is not powerful enough to confidently state that the UMO portfolio returns are greater than zero in these states. The magnitudes (2.3% in the full sample, and 3.8% in the second half of the sample) are smaller than for the fifth quintile volatility change states, which is consistent with the asymmetry observed in quarter t returns. Another noteworthy feature of table 9 is that most of the rebound after high-volatility quarters seems to come from the fifth aggregate deviation quintile portfolio (i.e., the most overweight stocks).

The $t + 1$ return patterns indicate a reversion in prices, suggesting that the effects in quarter t were merely temporary. This result lends support to an interpretation of these price changes as distortions. The consistent asymmetry between high and low volatility-change states is consistent with portfolio managers being more heavily penalized for high tracking error than they are rewarded for low tracking error, perhaps due to the threat of costly litigation.

At this stage, two explanations for the $t + 1$ reversion in prices seem plausible. First, due to information asymmetries, the market may be misinterpreting incentive-driven buying pressure for underweight stocks and selling pressure for overweight stocks as private information, in the sense of Kyle (1985). Once it becomes clear that the trades by investment advisors were not informed, prices would then revert to their previous level. The second explanation follows from the equilibrium described in the model in section 2: the reversion in prices may be driven by negative serial correlation in volatility changes. I shed some light on this question of asymmetric information versus equilibrium explanations by examining volatility changes in the subsequent quarter. For each of the five volatility quintiles, I compute the average change in volatility over the subsequent quarter (t to $t + 1$).

Table 10 displays the results. Consistent with the equilibrium view, initially large increases in volatility (quintile 5) are followed by significantly negative changes in volatility in the subsequent quarter. According to the model, these volatility reversions would incentivize fund managers to return to larger deviations from the benchmark after volatility peaks. In the full sample (1980-2014), average $t + 1$ volatility falls by 3.2% (significant at the 1% level) following the fifth quintile of volatility changes in quarter t. In the second half of the sample (1997-2014), the fall in volatility is slightly greater, at 3.8%. The is no consistent significant reversion for the lowest volatility-change quintile (or any other quintile except the fifth). While the magnitudes of the fifth quintile reversions are not particularly large, leaving room for the asymmetric information explanation to still account for some of the rebound in $t + 1$ returns, the asymmetry in $t + 1$ volatility changes (significant reversion in volatility only after quarters with the highest increase) closely matches the asymmetry observed in the $t + 1$ returns. This is again consistent with the equilibrium explanation.

Given the correlation shown between market beta and aggregate deviation from the S&P 500 index (table 5), it seems important to consider to what extent differences in beta are driving the UMO portfolio returns. Investment advisors tend to be overweight high-beta stocks, and because of the negative relationship between volatility and returns, stocks with higher betas could mechanically have lower returns than stocks with low betas when volatility rises. Therefore, I estimate time-varying factor loadings $\hat{\beta}_t^f$ for four standard empirical asset pricing factor models, using monthly returns over a five-year rolling window.

Armed with these estimated loadings, I compute portfolio alphas from the raw returns (R_t) as follows:

$$\hat{\alpha}_t^{\mathcal{F}} = R_t - \left(R_{f,t} + \hat{\beta}_t^1 F_t^1 + \cdots + \hat{\beta}_t^{\mathcal{F}} F_t^{\mathcal{F}}\right), \tag{39}$$

where F_t^1 is the return on a replicating portfolio for the first risk factor, and so on up to the $\mathcal{F}$th risk factor, $F_t^{\mathcal{F}}$. The set of factors is taken from the risk models most commonly used in the empirical asset pricing literature: the Fama-French three-factor model (market risk premium, size, and book-to-market); the Fama-French-Carhart four-factor model (market risk premium, size, book-to-market, and momentum); the Fama-French model plus the Pástor-Stambaugh liquidity factor; and the Fama-French-Carhart model plus the Pástor-Stambaugh liquidity factor.[22]

Table 11 reports the average alphas on the UMO portfolio for each of the five volatility-change quintiles—largest decrease (quintile 1) to largest increase (quintile 5). Alphas computed using each of the aforementioned factor models are shown alongside the raw average returns for comparison (see the last column of table 8). As in previous tables, panel A reports alphas computed over the full sample (1980-2014) and panel B reports alphas computed over the second half of the sample (1997-2014).

Starting with the full-sample alphas, it is evident that the linear, almost-monotonic relationship between the raw UMO portfolio return and changes in volatility disappears once risk factor exposures are accounted for. Instead, the relationship starts to look binary. Only in quarters with the largest increases in volatility (quintile 5) do we see a positive and consistently significant alpha on the UMO portfolio. Simply adjusting for exposure to the market risk premium is sufficient to reveal this binary effect, which seems to indicate that the linear relationship is induced simply by variations in beta across the underweight and overweight portfolios. However, the large and reliably significant UMO alphas (from 3.0% using the Fama-Frency-Carhart plus liquidity model, to 4.0% using just the Fama-French three-factor model) continue to support an interpretation of the evidence as incentive-driven price distortions. This evidence is consistent with an asymmetric penalty for tracking error variance, where fund managers are hurt more when volatility rises than they gain when volatility falls.

[22] Fama and French (1993); Carhart (1997); Pastor and Stambaugh (2003). The market, size, book-to-market, and momentum factors are taken from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The liquidity factor is taken from Ľuboš Pástor's website: http://faculty.chicagobooth.edu/lubos.pastor/research/.

The results for the second half of the sample are again stronger, and once again consistently show a binary relationship between the UMO portfolio return and the change in volatility. In the highest volatility-change quintile, underweight stocks outperform overweight stocks on a risk-adjusted basis by between 3.9% (Fama-French-Carhart plus liquidity factor) and 5.0% (Fama-French three-factor model). Alphas are not consistently significant for lower volatility-change states.

6. Placebo tests

My claim in this paper is that the UMO portfolio returns reported in section 5 are the result of excess demand (buying and selling pressure) by investment advisors, stemming from their benchmarking incentives. This "excess" buying and selling—compared to an economy with no benchmarked institutions—is not offset by opposite behaviour from other market participants, which results in temporary price distortions. To strengthen further the argument that institutional incentives are in fact responsible for the observed price distortions, I conduct placebo tests using passively managed index funds, as well as other institution types for which benchmarking incentives are much weaker.

Index funds' portfolio allocations are determined simply by minimizing tracking error variance; i.e., there is no "mean" in an index fund's "mean-variance" optimization problem. As such, the only incentive these funds have to deviate from the benchmark is in order to control trading costs. Because of this simpler objective function, the relationship between tracking error variance and active share is no longer identified (many different levels of active share will give rise to the same tracking error variance). Therefore we should not expect index funds to reduce their distance from the benchmark when volatility increases, and consequentially we should not observe price distortions based on their holdings.

Moreover, institutions that do not outsource their portfolio management needs should have less acute (or at least different) agency problems, and thus weaker benchmark-driven incentives. Banks, insurance companies and traditional pension funds have objective functions that are quite different from those of investment advisors. Banks hold investment assets to bolster their profitability in absolute terms, and can be thought of as being closer to households in this regard. Insurance companies and defined-benefit pension funds hold assets primarily to match the duration of their liabilities rather than to outperform competitors. Thus, with less incentive to rebalance towards the benchmark when volatility rises, we should not expect observe a significant return on UMO portfolios when they are constructed using the holdings of these institutions.

In table 12, I test whether index funds reduce their active share when volatility rises. I re-estimate 28 (table 2) using only funds designated as index funds by CRSP or Morningstar, or whose names indicate that they are passively managed (see section 3 for details). Consistent with the objective function described above, these passive vehicles do not exhibit the same decrease in active share that actively managed funds show when S&P 500 index volatility rises. If anything the relationship appears to be slightly positive, but the coefficients on volatility (first row) are insignificant for most specifications whether I use historical standard deviation or the GARCH(1,1) forecast. Active share remains persistent with a coefficient on its lagged values of around 0.11, but it is much less persistent than for the actively managed funds. The base level of active share is also lower, as shown by an intercept between 0.10 and 0.15, again consistent with the expected behaviour of index funds.

The second set of placebo tests uses the same portfolio sorting approach described in section 5. The difference is that now I compute the aggregate deviation from benchmark for each stock using only the portfolio holdings of index funds, banks, insurance companies, and pension funds (separately), rather than the holdings of investment advisors. I then form underweight-minus-overweight (UMO) portfolios that are long stocks in the lowest deviation quintile (1) and short stocks in the highest deviation quintile (5).

Table 13 reports the returns on these portfolios for five volatility-change quintiles. The returns on the investment-advisor-deviation UMO portfolio (see table 8) are shown in the first column for comparison. I report raw portfolio returns as these are the most likely to show statistically significant results (alphas tend to be closer to zero), and thus make it easier to reject the null hypothesis that the portfolios have zero average returns when volatility rises or falls.

I am unable to consistently reject this hypothesis for any of the placebo institution types. Aside from sporadic cases of statistical significance at the 10% level, which are to be expected due to type I error, returns across volatility-change states are effectively zero for the UMO portfolios based on index funds (column 2), insurance companies (column 3), and pension funds (column 4). In addition, I do not observe the pattern of increasing portfolio returns when moving from a fall in volatility to a rise in volatility, which can be seen for investment advisors (column 1). There is some indication, mostly in the second half of the sample (panel B), that banks (column 5) show the *opposite* pattern: UMO portfolio returns decrease and ultimately become significantly negative as we move from low to high volatility-change states (-5.4%, significant at the 5% level, for the top volatility-change quintile). However, these returns appear to be driven entirely by factor exposures. Column 6 reports the Fama-French-Carhart alphas for banks' UMO portfolio, which are again economically and statistically close to zero across all volatility-change quintiles. In untabulated results, I confirm that banks tend to be overweight in *low-beta* stocks.

The difference between the price effects observed for the advisory sector and for other institution types is striking, and lends further credibility to the proposed incentive-based mechanism.

7. Conclusion

This paper investigates how asset prices are distorted as a result of the incentives generated by benchmarking, a ubiquitous feature of the fund management industry. Intuitively, risk-averse preferences over relative returns induce a penalty for tracking error variance for benchmarked institutions. When aggregate volatility rises, in order to maintain an optimal portfolio allocation, benchmarked institutions seek to reduce the absolute deviation of their portfolio weights from those of the benchmark, buying underweight stocks and selling overweight stocks. Since these shifts in demand are not offset by other market participants (who have different incentives), assets that are collectively underweight by the advisory sector see their equilibrium prices rise relative to those that are collectively overweight. The difference in returns can be substantial: a portfolio of underweight minus overweight stocks (UMO) returns 7% to 8% in quarters where volatility rises most (fifth quintile) and -2.5% to -5% in quarters where volatility falls most (first quintile). Prices rebound the following quarter: the UMO portfolio returns -7% to -8% the quarter after large rises in volatility, and 2% to 4% the quarter after large decreases in volatility. The price reversal coincides with a reversal in volatility, supporting an equilibrium mechanism.

The UMO portfolio returns are robust to risk-adjustment using standard asset pricing factor models and controls for stock characteristics in a stock-level regression framework. All results are also robust to controlling for fund flows. I document these effects only for actively-managed form-13F investment advisors, and not for other types of institutions that either invest passively or do not have strong incentives to care about relative performance. The price distortions I observe occur precisely when aggregate uncertainty is rising and informative prices would be most beneficial. The results therefore have large potential consequences for real outcomes such as firm investment and M&A transactions.

References

Agarwal, V., Jiang, W., Tang, Y., & Yang, B. (2013). Uncovering hedge fund skill from the portfolio holdings they hide. *Journal of Finance*, *68*(2), 739-783.

Anton, M., & Polk, C. (2014). Connected stocks. *Journal of Finance*, *69*(3), 1099-1127.

Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. *Journal of Financial Economics*, *75*(2), 283-317.

Basak, S., & Pavlova, A. (2013). Asset prices and institutional investors. *American Economic Review*, *103*(5), 1728-1758.

Basak, S., & Pavlova, A. (2015). A model of financialization of commodities. *Journal of Finance, forthcoming*.

Basak, S., Pavlova, A., & Shapiro, A. (2007). Optimal asset allocation and risk shifting in money management. *Review of Financial Studies*, *20*(5), 1583-1621.

Berk, J. B., & Green, R. C. (2004). Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy*, *112*(6), 1269-1295.

Binsbergen, V., Jules, H., Brandt, M. W., & Koijen, R. S. (2008). Optimal decentralized investment management. *Journal of Finance*, *63*(4), 1849-1895.

Boyer, B. H. (2011). Style-Related Comovement: Fundamentals or Labels? *Journal of Finance*, *66*(1), 307-332.

Brennan, M. J. (1993). Agency and Asset Pricing. *Unpublished Working Paper.*

Brennan, M. J., Chordia, T., & Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics*, *49*(3), 345-373.

Brown, K. C., Harlow, W. V., & Starks, L. T. (1996). Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. *Journal of Finance*, *51*(1), 85-110.

Buffa, A. M., Vayanos, D., & Woolley, P. (2014). Asset management contracts and equilibrium prices. *Working Paper*.

Canina, L., & Figlewski, S. (1993). The informational content of implied volatility. *Review of Financial studies*, *6*(3), 659-681.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of finance*, *52*(1), 57-82.

Carhart, M. M., Kaniel, R., Musto, D. K., & Reed, A. V. (2002). Leaning for the tape: Evidence of gaming behavior in equity mutual funds. *Journal of Finance*, *57*(2), 661-693.

Chen, H. (2016). Portfolio management pressure. *Working Paper.*

Chevalier, J., & Ellison, G. (1997). Risk Taking by Mutual Funds as a Response to Incentives. *Journal of Political Economy*, *105*(6), 1167-1200.

Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, *86*(2), 479-512.

Cremers, K. M., & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies*, *22*(9), 3329-3365.

Cuoco, D., & Kaniel, R. (2011). Equilibrium prices in the presence of delegated portfolio management. *Journal of Financial Economics*, *101*(2), 264-296.

Edmans, A., Goldstein, I., & Jiang, W. (2012). The real effects of financial markets: The impact of prices on takeovers. *Journal of Finance*, *67*(3), 933-971.

Elton, E. J., Gruber, M. J., & Blake, C. R. (2003). Incentive fees and mutual funds. *Journal of Finance*, *58*(2), 779-804.

Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *Journal of Economic Perspectives*, *15*(4), 157-168.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56.

Figlewski, S. (1997). Forecasting volatility. *Financial Markets, Institutions & Instruments*, *6*(1), 1-88.

Greenwood, R., & Thesmar, D. (2011). Stock price fragility. *Journal of Financial Economics*, *102*(3), 471-490.

Harris, L., & Gurel, E. (1986). Price and volume effects associated with changes in the S&P 500 list: New evidence for the existence of price pressures. *Journal of Finance*, *41*(4), 815-829.

Kacperczyk, M., Nosal, J. B., & Stevens, L. (2014). Investor sophistication and capital income inequality. *Working Paper*.

Koijen, R. S., & Yogo, M. (2015). An equilibrium model of institutional demand and asset prices. *Working Paper*.

Kyle, A. (1985). Continuous Auctions and Insider Trading. *Econometrica*, *53*(6), 1315-35.

Lou, D. (2012). A flow-based explanation for return predictability. *Review of Financial Studies*, *25*(12), 3457-3489.

Ma, L., Tang, Y., & Gómez, J. P. (2016). Portfolio manager compensation in the US mutual fund industry. *Working Paper*.

Maug, E. G., & Naik, N. Y. (2011). Herding and delegated portfolio management: The impact of relative performance evaluation on asset allocation. *Quarterly Journal of Finance*, 01, 265.

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, *111*(3), 642-685.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2015). Scale and skill in active management. *Journal of Financial Economics*, *116*(1), 23-45.

Shleifer, A. (1986). Do demand curves for stocks slope down? *Journal of Finance*, *41*(3), 579-590.

Spiegel, M., & Zhang, H. (2013). Mutual fund risk and market share-adjusted fund flows. *Journal of Financial Economics*, *108*(2), 506-528.

Vayanos, D., & Woolley, P. (2013). An institutional theory of momentum and reversal. *Review of Financial Studies*, *26*(5), 1087-1145.

Appendix

A.1 Model solution

Households solve:

$$\max_{\theta_H} \mathbb{E}_0\{-\exp[-\gamma^H W_0^H(\theta_H{}'R + (1-\theta_I'\iota)R_f)]\}$$
$$= \max_{\theta_H} W_0^H(\theta_H{}'\mu^R + (1-\theta_H{}'\iota)R_f) - \frac{1}{2}\gamma^H (W_0^H)^2 \theta_H{}'\Sigma^R \theta_H \quad (40)$$

by the properties of the normal distribution. Using the fact that Σ^R is diagonal with elements σ_i^2, the FOCs can be written:

$$W_0^H(\mu_i^R - R_f) - \frac{1}{2}\gamma^H (W_0^H)^2 \sigma_i^2 \theta_i^H = 0. \quad (41)$$

Rearranging gives:

$$\theta_i^H = \frac{\mu_i^R - R_f}{\gamma^H W_0^H (\sigma_i^R)^2}. \quad (42)$$

Substituting in for $\mu_i^R = \mu_i/p_i$ and $(\sigma_i^R)^2 = \sigma_i^2/p_i^2$, I obtain:

$$\theta_i^H = \frac{\mu_i - p_i R_f}{\gamma^H W_0^H \sigma_i^2} \cdot p_i. \quad (43)$$

Institutions solve:

$$\max_{\theta_I} \mathbb{E}_0\{-\exp[-\gamma^I W_0^I((\theta_I - b)'R + (1-\theta_I'\iota)R_f)]\}$$
$$= \max_{\theta_I} W_0^I((\theta_I - b)'\mu^R + (1-\theta_I'\iota)R_f) - \frac{1}{2}\gamma (W_0^I)^2 (\theta_I - b)'\Sigma^R(\theta_I - b), \quad (44)$$

by the properties of the normal distribution. Using the fact that Σ^R is diagonal with elements σ_i^2, the FOCs can be written:

$$W_0^I(\mu_i^R - R_f) - \frac{1}{2}\gamma^I (W_0^I)^2 \sigma_i^2 (\theta_i^I - b_i) = 0. \quad (45)$$

Rearranging gives:

$$\theta_i^I = \frac{\mu_i^R - R_f}{\gamma^I W_0^I (\sigma_i^R)^2} + b_i. \tag{46}$$

Substituting in for $\mu_i^R = \mu_i / p_i$ and $(\sigma_i^R)^2 = \sigma_i^2 / p_i^2$, I obtain:

$$\theta_i^I = \frac{\mu_i - p_i R_f}{\gamma^I W_0^I \sigma_i^2} \cdot p_i + b_i. \tag{47}$$

The market clearing condition is as follows:

$$W_0^H \theta_i^H + W_0^I \theta_i^I = p_i^*. \tag{48}$$

Substituting in for θ_i^H and θ_i^I using equations 43 and 47:

$$\frac{\mu_i - p_i^* R_f}{\gamma^H \sigma_i^2} + \frac{\mu_i - p_i^* R_f}{\gamma^I \sigma_i^2} + \frac{W_0^I b_i}{p_i^*} = 1. \tag{49}$$

Setting $W_0^H = W_0^I = W_0$ and $\gamma^H = \gamma^I = \gamma$:

$$\frac{2(\mu_i - p_i^* R_f)}{\gamma \sigma_i^2} + \frac{W_0 b_i}{p_i^*} = 1. \tag{50}$$

Solving for p_i^* gives:

$$p_i^* = \frac{2\mu_i - \gamma\sigma_i^2 \pm \sqrt{(2\mu_i - \gamma\sigma_i^2)^2 + 8\gamma\sigma_i^2 W_0 R_f b_i}}{4R_f}. \tag{51}$$

One of these solutions is always positive and the other always negative, since $\{b_i, \gamma, W_0, \sigma_i^2\} \geq 0$. Given that prices must be positive, the valid solution is the one shown in equation 13. Substituting the expression for p_i^* in equation 13 into equations 43 and 47 and simplifying, gives:

$$\theta_i^{H*} = \frac{2\mu_i - \gamma\sigma_i^2 - 4b_iW_0R_f + \sqrt{(2\mu_i - \gamma\sigma_i^2)^2 + 8\gamma\sigma_i^2W_0R_fb_i}}{8W_0R_f}$$

$$= \frac{p_i^*}{2W_0} - \frac{b_i}{2}; \tag{52}$$

$$\theta_i^{I*} = \frac{2\mu_i - \gamma\sigma_i^2 + 4b_iW_0R_f + \sqrt{(2\mu_i - \gamma\sigma_i^2)^2 + 8\gamma\sigma_i^2W_0R_fb_i}}{8W_0R_f}$$

$$= \frac{p_i^*}{2W_0} + \frac{b_i}{2}. \tag{53}$$

To derive the implications of a change in the aggregate component of volatility, substitute $\sigma_i = \bar{\sigma} + \xi_i$ into equations 51 and 53, and compute partial derivatives with respect to $\bar{\sigma}$:

$$\frac{\partial p_i^*}{\partial \bar{\sigma}} = \frac{\gamma\bar{\sigma}}{2}\left(\frac{\gamma\bar{\sigma}^2 - 2\mu_i + 4W_0R_fb_i}{\sqrt{(\gamma\bar{\sigma}^2 - 2\mu_i)^2 + 8\gamma\bar{\sigma}^2W_0R_fb_i}} - 1\right); \tag{54}$$

$$\frac{\partial \theta_i^{I*}}{\partial \bar{\sigma}} = \frac{\gamma\bar{\sigma}}{4W_0R_f}\left(\frac{\gamma\bar{\sigma}^2 - 2\mu_i + 4W_0R_fb_i}{\sqrt{(\gamma\bar{\sigma}^2 - 2\mu_i)^2 + 8\gamma\bar{\sigma}^2W_0R_fb_i}} - 1\right). \tag{55}$$

These derivatives will both be zero when:

$$\gamma\bar{\sigma}^2 - 2\mu_i + 4W_0R_fb_i = \sqrt{(\gamma\bar{\sigma}^2 - 2\mu_i)^2 + 8\gamma\bar{\sigma}^2W_0R_fb_i}. \tag{56}$$

Equation 56 is implicitly quadratic. One solution can be found by squaring both sides:

$$\left(\gamma\bar{\sigma}^2 - 2\mu_i + 4W_0R_fb_i\right)^2 = (\gamma\bar{\sigma}^2 - 2\mu_i)^2 + 8\gamma\bar{\sigma}^2W_0R_fb_i.$$

$$\Rightarrow (\gamma\bar{\sigma}^2 - 2\mu_i)^2 + 8W_0R_fb_i(\gamma\bar{\sigma}^2 - 2\mu_i) + \left(4W_0R_fb_i\right)^2$$
$$= (\gamma\bar{\sigma}^2 - 2\mu_i)^2 + 8\gamma\bar{\sigma}^2W_0R_fb_i$$

$$\Rightarrow 2(\gamma\bar{\sigma}^2 - 2\mu_i) + 4W_0R_fb_i = 2\gamma\bar{\sigma}^2$$

$$\Rightarrow b_i = \frac{\mu_i}{R_f W_0}. \tag{57}$$

The other solution can be found by inspection: setting $b_i = 0$ leaves:

$$\gamma\bar{\sigma}^2 - 2\mu_i = \sqrt{(\gamma\bar{\sigma}^2 - 2\mu_i)^2}, \tag{58}$$

which holds trivially, provided $\gamma\bar{\sigma}^2 - 2\mu_i$ is positive.

The solution $b_i = 0$ implies the stock is not part of the benchmark. Thus I focus on the solution $b_i = \mu_i/(R_f W_0)$. Substituting $b_i = \mu_i/(R_f W_0) + \varepsilon$ (where $\varepsilon > 0$) into the RHS of equation 56 gives:

$$\sqrt{(\gamma\bar{\sigma}^2 - 2\mu_i)^2 + 8\gamma\bar{\sigma}^2\mu_i + 8\gamma\bar{\sigma}^2 W_0 R_f \varepsilon}. \tag{59}$$

Expanding $(\gamma\bar{\sigma}^2 - 2\mu_i)^2$ and simplifying gives:

$$\sqrt{(\gamma\bar{\sigma}^2 + 2\mu_i)^2 + 8\gamma\bar{\sigma}^2 W_0 R_f \varepsilon}. \tag{60}$$

Substituting $b_i = \mu_i/(R_f W_0) + \varepsilon$ (where $\varepsilon > 0$) into the LHS of equation 56 gives:

$$\gamma\bar{\sigma}^2 + 2\mu_i + 4W_0 R_f \varepsilon, \tag{61}$$

which can be rewritten as:

$$\sqrt{\left(\gamma\bar{\sigma}^2 + 2\mu_i + 4W_0 R_f \varepsilon\right)^2}. \tag{62}$$

Expanding the brackets and simplifying gives:

$$\begin{aligned} &\sqrt{(\gamma\bar{\sigma}^2 + 2\mu_i)^2 + 8\gamma\bar{\sigma}^2 W_0 R_f \varepsilon + 16 W_0 R_f \varepsilon(\mu + W_0 R_f \varepsilon)} \\ &> \sqrt{(\gamma\bar{\sigma}^2 + 2\mu_i)^2 + 8\gamma\bar{\sigma}^2 W_0 R_f \varepsilon} = RHS, \end{aligned} \tag{63}$$

where the inequality holds because $\{W_0, R_f, \mu, \varepsilon\} > 0$.

Therefore,

$$b_i > \frac{\mu_i}{R_f W_0} \Rightarrow \frac{\partial p_i^*}{\partial \bar{\sigma}} > 0 \ and \ \frac{\partial \theta_i^{I*}}{\partial \bar{\sigma}} > 0. \tag{64}$$

A.2 Price distortion regression with GARCH forecast of volatility

Table A.1 shows the results of the regression test for price distortions (equation 37) using changes in a GARCH(1,1) forecast of volatility instead of changes in the quarterly standard deviation of S&P 500 index returns. The results are highly similar to those reported in table 6.

Figure 1

This figure plots the share of the US stock market held by various institution types from 1980 to 2014. Stock holdings are taken from form-13F mandatory holdings disclosures. Institution types are identified by Thomson Reuters, except for hedge funds and index funds. Hedge funds are identified as in Agarwal, Jiang, Tang, and Yang (2013). Index funds are identified by fund name and Morningstar/CRSP index fund flags (see section 3). After accounting for the holdings of all institutions, the remainder is assumed to represent the household sector. However this remainder includes some institutions that are too small to be represented in the 13F data.

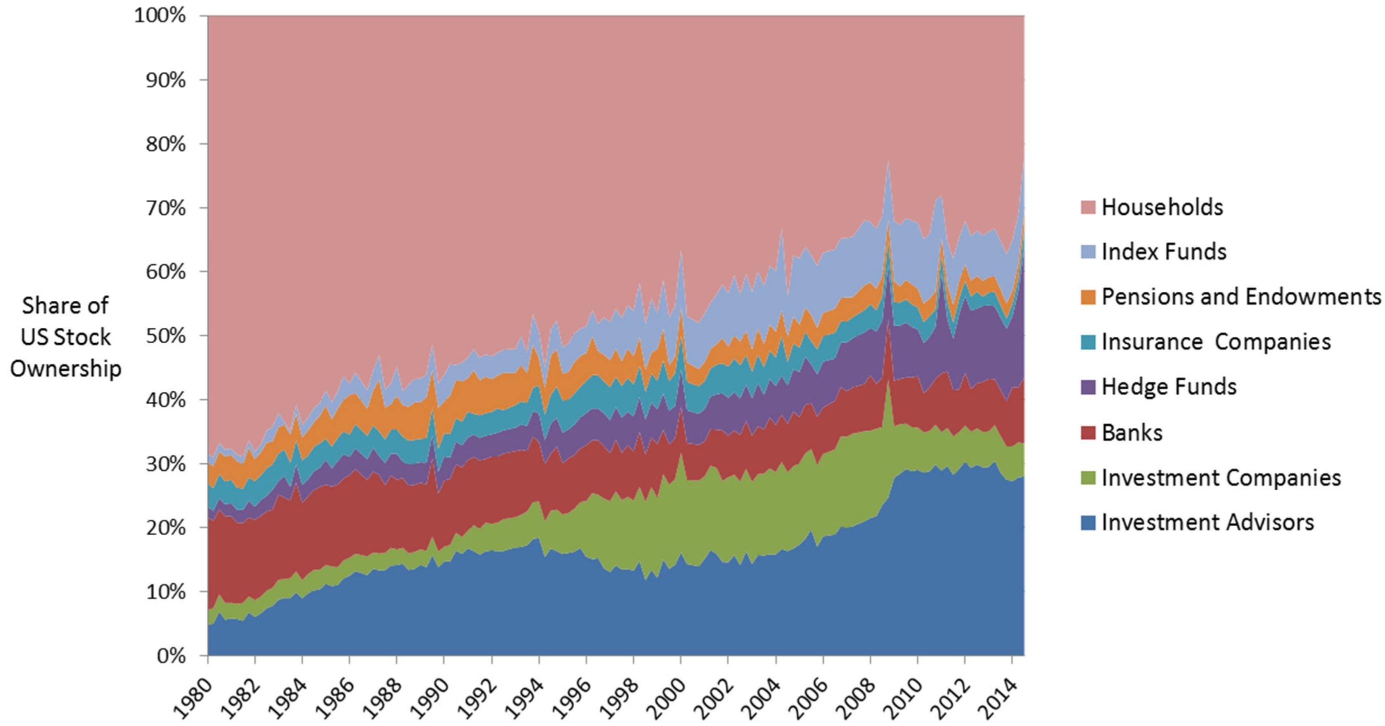
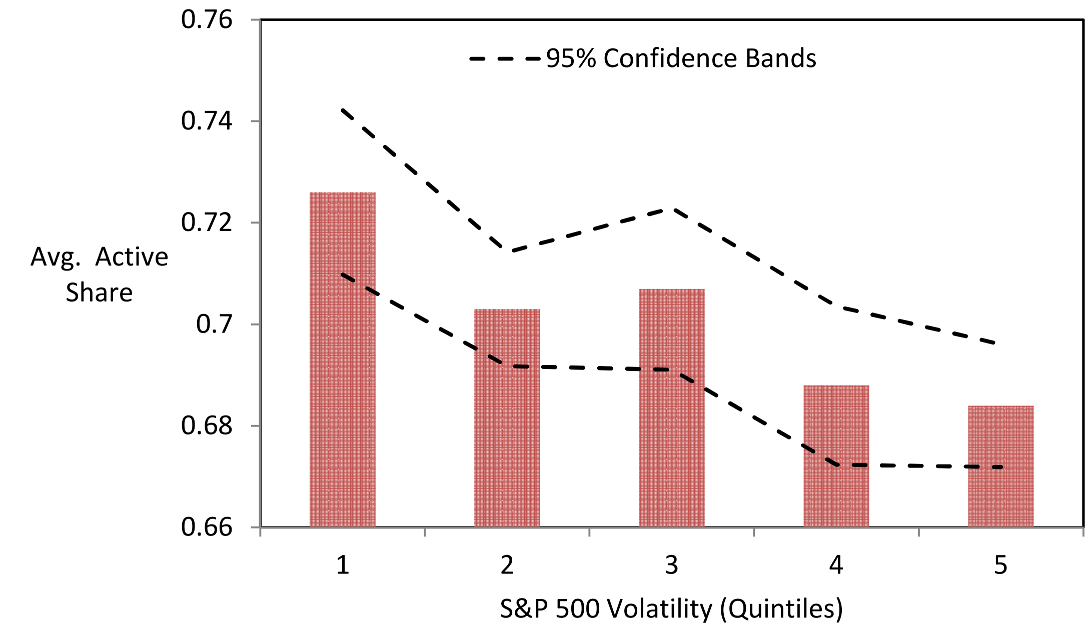


Figure 2

Panel A of this figure plots the quarterly AUM-weighted average active share of the investment advisory sector (type 4 in Thomson Reuters S34 file (13F)) for five quintiles of S&P 500 index volatility. Active share is defined as the sum of absolute deviations of portfolio weights minus benchmark weights (definition 24), with the benchmark being the S&P 500 index. Panel B plots the return on a portfolio of underweight (quintile 1) minus overweight (quintile 5) stocks for five quintiles of changes in S&P 500 volatility. Stocks are classed as underweight or overweight based on log average deviation from benchmark (definition 26) among investment advisors. In both panels, the 95% confidence intervals are derived from standard errors clustered by quarter, and the sample runs from 1997-2014.

Panel A



Panel B

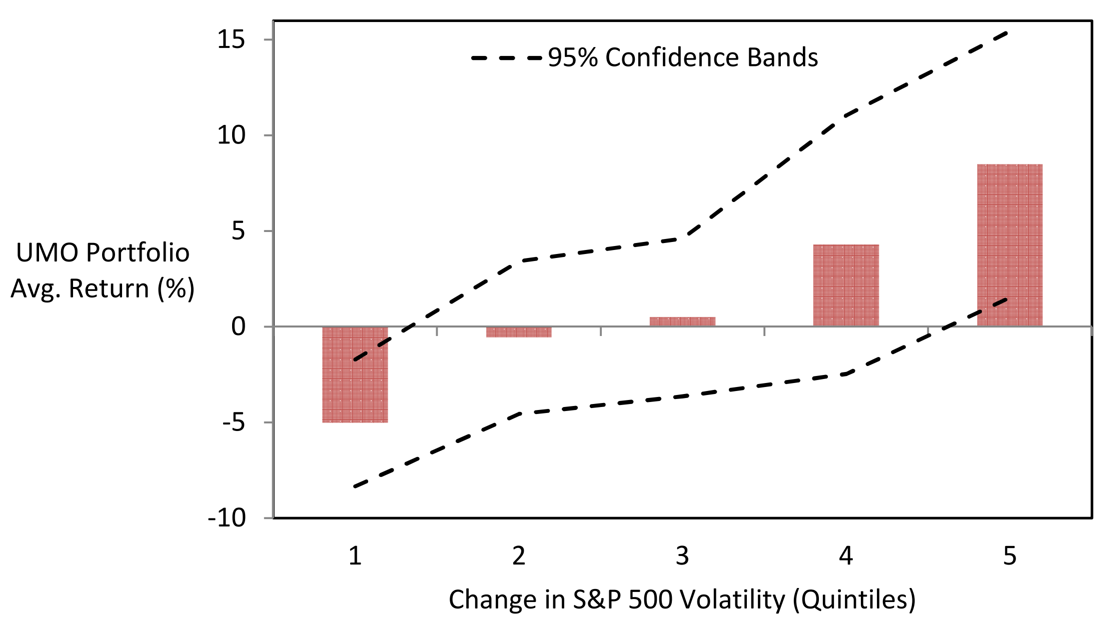


Figure 3

This figure plots the predicted responses of the institution's deviation from benchmark weight ($\theta_i^I - b_i$) in stock i and the price of stock i to changes in the aggregate component of return volatility ($\bar{\sigma}^R$), according to the model detailed in section 2. The other model parameters are held fixed: $\mu_i = 10; \gamma = 4;$ $R_f = 1$, and $W_0 = 100$. The plots are typical. Several values for the benchmark weight (b_i) are plotted on the same axes. The parameter values are such that $b_i > 0.1$ implies the stock is underweight, and $b_i < 0.1$ implies that it is overweight.

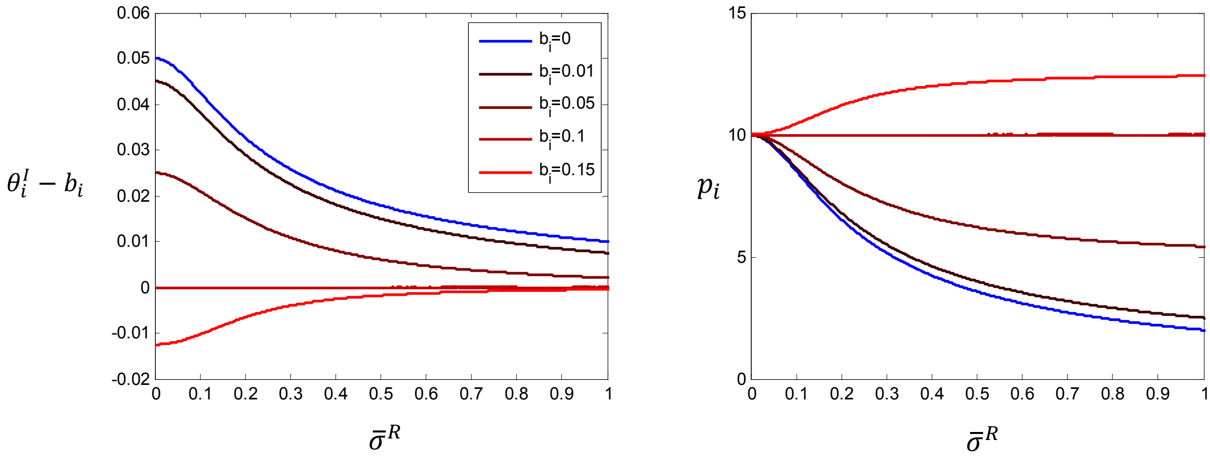


Table 1

Benchmarks

Mutual fund benchmarks reported in Morningstar Direct (US equity only), ranked by share of total assets under management (average over 1980-2014). Also shown is the number of funds reporting each benchmark.

Primary Prospectus Benchmark	% of AUM	No. of Funds
S&P 500	57.49	5860
CRSP indices	8.95	38
Other S&P indices	6.68	1437
Russell 1000 Value	5.57	1039
Other Russell indices	5.47	1176
Russell 1000 Growth	4.37	1109
Other US Equity indices	3.17	587
Russell 3000	1.84	636
Russell 1000	1.41	437
Russell 2000	1.35	723
Russell 3000 Growth	1.21	169
Russell 2000 Value	1.00	485
Russell 2000 Growth	0.70	575
Russell 3000 Value	0.67	155
No reported benchmark	0.12	11572

Table 2

Active share and aggregate volatility

This table reports the estimated coefficients from a regression of end-of-quarter-t active share ($AS_{i,t}$) on S&P 500 volatility forecasts using information up to quarter t ($\hat{\sigma}_t^{S\&P}$) and fund-level control variables: the fund's previous-quarter active share ($AS_{i,t-1}$), the log of assets under management ($aum_{i,t-1}$), and fund-level fixed effects. The sample consists only of actively-managed funds that appear in both the Morningstar Direct database and the Thomson Reuters S12 file (formerly CDA/Spectrum database), and who report the S&P 500 as their primary benchmark. The formal regression specification is given in equation 28. T-statistics are reported in parentheses below the coefficient estimates, based on standard errors clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Dependent Variable: $AS_{i,t}$

	(1)	(2)	(3)	(4)
$\sigma_t^{S\&P}$	-0.122***	-0.045***	-0.227***	-0.076***
	(-13.48)	(-15.81)	(-14.11)	(-16.56)
$AS_{i,t-1}$		0.695***		0.691***
		(44.81)		(44.40)
$aum_{i,t-1}$		-0.007***		-0.007***
		(-12.62)		(-12.60)
$Intercept$	0.816***	0.320***	0.834***	0.329***
	(182.81)	(20.51)	(185.04)	(20.76)
Fund Fixed Effects	No	Yes	No	Yes
Vol. estimator	Std. Dev.	Std. Dev.	GARCH(1,1)	GARCH(1,1)
Observations	59,877	52,563	59,877	52,563
Adj. R^2	0.005	0.918	0.007	0.919

Table 3

Absolute deviations and cross-sectional stock volatility

This table reports the estimated coefficients from a stock-level regression of *absolute* aggregate deviation from benchmark in quarter t—$|Dev_{n,t}|$—on the volatility of the individual stock ($\hat{\sigma}_{n,t}$), and various other stock characteristics measured as of quarter $t-1$ (see equations 30 and 31). Aggregate deviation from benchmark is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (approximately equal to the average percentage deviation from the benchmark). Only the holdings of investment advisors (type 4 in Thomson Reuters S34 file) are used to compute the average portfolio weight. *Beta* is the single-factor market beta estimated from monthly returns over a five-year rolling window; *log(Size)* is the natural logarithm of the stock's market capitalization; *log(B/M)* is the natural logarithm of the stock's book-to-market ratio; *div. yield* is the ratio of dividends paid in the past year to the current market price; *turnover* is the stock's quarterly trading volume as a fraction of shares outstanding; and *ret(t)* is the stock's return in quarter t. Standard errors are clustered by quarter. T-statistics are reported in parentheses below the coefficient estimates. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Dependent Variable: $|Dev_{n,t}|$

	(1)	(2)	(3)	(4)	(5)
$\hat{\sigma}_{n,t}$	-0.039	-0.068***	-0.139***	-0.039**	-0.047**
	(-1.49)	(-3.51)	(-5.04)	(-1.97)	(-2.08)
Beta			-0.035***		-0.043***
			(-7.07)		(-6.18)
Log(Size)			-0.179***		-0.155***
			(-40.14)		(-32.38)
Log(B/M)			0.036***		0.013***
			(8.73)		(2.66)
Div. Yield			-0.063		-0.209***
			(-1.43)		(-3.41)
Turnover			0.006		-0.039***
			(0.97)		(-4.35)
Ret(t-1)			0.080***		0.061***
			(6.06)		(2.94)
Ret(t-2)			0.081***		0.078***
			(6.29)		(3.60)
Ret(t-3)			0.051***		0.055**
			(4.44)		(2.51)
Ret(t-4)			0.053***		0.058***
			(4.76)		(2.90)
Ret(t-12,t-4)			0.005**		0.006**
			(2.10)		(2.02)
Constant	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	No	No
Year Fixed Effects	No	Yes	Yes	No	No
Stock × Year Fixed Effects	No	No	No	Yes	Yes
Observations	67,489	67,489	57,743	67,489	57,743
Adj. R^2	0.531	0.582	0.668	0.590	0.639

Table 4

Absolute deviations, stock volatility, and fund flows

This table reports the estimated coefficients from a stock-level regression of *absolute* aggregate deviation from benchmark in quarter t—$|Dev_{n,t}|$—on the volatility of the individual stock ($\hat{\sigma}_{n,t}$), aggregate percentage fund flows to/from investment advisors who hold the stock ($Aggflow_{n,t}$), and various stock characteristics measured as of quarter $t-1$ (see equations 34 and 35). Aggregate deviation from benchmark is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (approximately equal to the average percentage deviation from the benchmark). Only the holdings of investment advisors (type 4 in Thomson Reuters S34 file) are used to compute the average portfolio weight. Stock characteristics are the same as in table 3, but are not reported for brevity. Standard errors are clustered by quarter in panel A and by stock in panel B. T-statistics are reported in parentheses below the coefficient estimates. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Dependent Variable: $|Dev_{n,t}|$

	(1)	(2)	(3)	(4)	(5)
Panel A: Clustering by Quarter					
$\hat{\sigma}_{n,t}$	-0.038	-0.069***	-0.153***	-0.039**	-0.047**
	(-1.51)	(-3.53)	(-5.44)	(-1.98)	(-2.11)
$Aggflow_{n,t}$	0.235***	0.058	0.053	0.183**	0.108
	(2.79)	(0.90)	(0.87)	(2.55)	(1.50)
Panel B: Clustering by Stock					
$\hat{\sigma}_{n,t}$	-0.038**	-0.069***	-0.153***	-0.039***	-0.047***
	(-2.33)	(-3.49)	(-7.77)	(-2.59)	(-2.70)
$Aggflow_{n,t}$	0.235***	0.058	0.053	0.183***	0.108**
	(4.44)	(1.18)	(1.12)	(3.56)	(2.35)
Constant	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	No	No
Year Fixed Effects	No	Yes	Yes	No	No
Stock × Year Fixed Effects	No	No	No	Yes	Yes
Stock Characteristics	No	No	Yes	No	Yes
Observations	67,489	67,489	57,743	67,489	57,743
Adj. R^2	0.533	0.585	0.627	0.593	0.640

Table 5

Determinants of aggregate overweight/underweight

This table reports coefficient estimates from a regression that relates *signed* aggregate institutional deviations from benchmark (in each stock) to a set of stock characteristics recorded one quarter prior (see equation 36). Aggregate deviation from benchmark is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (equation 29). Only the holdings of investment advisors (type 4 in Thomson Reuters S34 file) are used to compute the average portfolio weight. *Beta* is the single-factor market beta estimated from monthly returns over a five-year rolling window; *log(Size)* is the natural logarithm of the stock's market capitalization; *log(B/M)* is the natural logarithm of the stock's book-to-market ratio; *div. yield* is the ratio of dividends paid in the past year to the current market price; *turnover* is the stock's quarterly trading volume as a fraction of shares outstanding; and *ret(t)* is the stock's return in quarter t. Standard errors are clustered by quarter. T-statistics are reported in parentheses below the coefficient estimates. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Beta	0.184***						0.056***
	(9.17)						(3.63)
Log(Size)		-0.253***					-0.270***
		(-24.55)					(-21.67)
Log(B/M)			0.125***				-0.042***
			(6.83)				(-4.05)
Div. Yield				-0.029			-2.916***
				(-0.79)			(-4.95)
Turnover					0.007		0.082**
					(0.19)		(2.61)
Ret(t-1)						0.032	0.076**
						(0.43)	(2.09)
Ret(t-2)						0.053	0.095***
						(0.69)	(3.77)
Ret(t-3)						0.029	0.076*
						(0.39)	(1.90)
Ret(t-4)						-0.003	0.052*
						(-0.06)	(1.75)
Ret(t-12,t-4)						-0.017	0.007
						(-1.03)	(0.99)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,811	67,480	65,106	66,970	67,224	59,660	57,743
Adj. R^2	0.019	0.354	0.024	0.000	0.000	0.001	0.415

Table 6

Regression test for price distortions

This table reports the estimated coefficients from a regression of quarterly stock returns ($Ret_{n,t}$) on the interaction between investment advisors' beginning-of-period aggregate deviation from benchmark ($Dev_{n,t-1}$) and the change in S&P500 quarterly standard deviation over the quarter ($\Delta\sigma_t^{S\&P}$). The formal specification is given in equation 37. Stocks are indexed by n and calendar quarters by t. Aggregate deviation from benchmark is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (equation 29). The benchmark is the S&P 500 index. Only the holdings of investment advisors (type 4 in Thomson Reuters S34 file) are used to compute the average portfolio weight. Also included as explanatory variables are volatility interactions with estimated market beta of the stock ($\hat{\beta}_{n,t}$), the natural logarithm of the stock's market capitalization ($Log(Size_{n,t})$) and other stock characteristics (see section 5.2). T-statistics are reported in parentheses below the coefficient estimates, based on standard errors clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Dependent variable: $Ret_{n,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
$Dev_{n,t-1} \times \Delta\hat{\sigma}_t^{S\&P}$	-75.31***	-19.90***	-34.38***	-108.71***	-40.22***	-39.80***
	(-3.63)	(-2.86)	(-3.59)	(-4.89)	(-5.57)	(-4.30)
$Dev_{n,t-1}$		-0.04	-1.08**		-0.76	-1.80***
		(-0.10)	(-2.58)		(-1.31)	(-3.14)
$\Delta\hat{\sigma}_t^{S\&P}$		-58.30***	257.60***		-64.16***	190.60**
		(-3.87)	(3.17)		(-3.02)	(2.15)
$\Delta\hat{\sigma}_t^{S\&P} \times \hat{\beta}_{n,t}$			-47.15***			-53.20***
			(-5.82)			(-5.99)
$\Delta\hat{\sigma}_t^{S\&P} \times Log(Size_{n,t})$			-11.52***			-8.59**
			(-3.37)			(-2.47)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Stock Characteristics	No	No	Yes	No	No	Yes
Char. Interactions	No	No	Yes	No	No	Yes
Start of Sample	1980	1980	1980	1997	1997	1997
Observations	66,367	66,367	57,303	34,525	34,525	32,555
Adj. R^2	0.047	0.096	0.110	0.080	0.124	0.151

Table 7

Price distortions and fund flows

This table reports the estimated coefficients from the regression in table 5, but also adds the interaction between investment advisors' beginning-of-period aggregate deviation from benchmark ($Dev_{n,t-1}$) and aggregate fund flows to the advisors holding this particular stock ($Flow_{n,t}$). The formal specification is given in equation 38. Stocks are indexed by n and calendar quarters by t. Aggregate deviation from benchmark is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (equation 29). The benchmark is the S&P 500 index. Only the holdings of investment advisors (type 4 in Thomson Reuters S34 file) are used to compute the average portfolio weight. Aggregate fund flows are computed as the AUM-weighted average percentage change in assets (after adjusting for returns) among investment advisors who hold the stock (see equation 33). Also included as explanatory variables are volatility interactions with estimated market beta of the stock ($\hat{\beta}_{n,t}$), the natural logarithm of the stock's market capitalization ($Log(Size_{n,t})$) and other stock characteristics (see section 5.2). T-statistics are reported in parentheses below the coefficient estimates, based on standard errors clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Dependent variable: $Ret_{n,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
$Dev_{n,t-1} \times \Delta\hat{\sigma}_t^{S\&P}$	-68.86***	-19.38***	-26.35***	-108.6***	-40.83***	-40.90***
	(-5.12)	(-2.95)	(-3.37)	(-4.93)	(-5.94)	(-4.77)
$Dev_{n,t-1} \times Flow_{n,t}$	19.96**	18.96***	20.25***	-1.79	23.78*	26.50**
	(2.00)	(3.06)	(3.21)	(-0.08)	(1.81)	(2.33)
$Dev_{n,t-1}$		-0.44	-1.40***		-1.17*	-2.35***
		(-1.14)	(-3.08)		(-1.95)	(-3.62)
$\Delta\hat{\sigma}_t^{S\&P}$		-58.65***	145.85		-63.28***	198.10**
		(-3.95)	(1.52)		(-3.03)	(2.27)
$Flow_{n,t}$		8.52	3.21		-22.54	-21.37
		(0.39)	(0.16)		(-1.15)	(-1.17)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Stock Characteristics	No	No	Yes	No	No	Yes
Char. Interactions	No	No	Yes	No	No	Yes
Start of Sample	1980	1980	1980	1997	1997	1997
Observations	66,878	66,878	57,774	34,532	34,532	32,562
Adj. R^2	0.058	0.098	0.132	0.080	0.125	0.153

Table 8

Portfolio sorts: returns in quarter t

This table reports quarter-t returns on five value-weighted portfolios formed by ranking stocks on aggregate deviation from benchmark in quarter $t-1$. Low quintiles indicate underweight stocks and high quintiles indicate overweight stocks. Aggregate deviation is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (approximately equal to the average percentage deviation from the benchmark). The benchmark is the S&P 500 index. Only the holdings of investment advisors (type 4 in Thomson Reuters S34 file) are used to compute the average portfolio weight. Returns are reported for different S&P 500 volatility-change quintiles, with low quintiles representing declines in volatility and high quintiles representing volatility increases. Returns on the underweight-minus-overweight portfolio, formed by subtracting the fifth from the first underweight/overweight quintile portfolio, are shown in the final column. T-statistics are reported in parentheses below the coefficient estimates, based on standard errors clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

		Return on Quintile Portfolios					
		Underweight/Overweight Quintiles					
		1	2	3	4	5	1-5
		Panel A: 1980 – 2014					
Volatility Change Quintile	1	5.379***	8.021***	8.114***	7.292***	7.919***	-2.540**
		(2.78)	(6.78)	(5.34)	(5.29)	(5.85)	(-2.15)
	2	3.805***	4.518***	4.785***	4.051***	3.684**	0.121
		(3.73)	(4.04)	(4.99)	(3.32)	(2.39)	(0.10)
	3	0.328	1.420	1.305	0.111	1.539	-1.211
		(0.22)	(1.23)	(1.14)	(0.06)	(0.95)	(-0.66)
	4	0.836	1.725	1.807	-0.801	-1.597	2.433*
		(0.38)	(0.84)	(1.00)	(-0.28)	(-0.58)	(1.87)
	5	-5.143***	-6.772**	-7.418***	-9.644***	-12.195***	7.052**
		(-2.68)	(-2.56)	(-2.66)	(-3.57)	(-3.74)	(2.26)
		Panel B: 1997 – 2014					
Volatility Change Quintile	1	5.610**	8.575***	8.757***	8.263***	10.631***	-5.021***
		(2.54)	(6.57)	(4.89)	(4.71)	(7.49)	(-3.03)
	2	3.733***	4.571***	4.954***	4.411**	4.292	-0.559
		(3.08)	(3.36)	(4.19)	(2.54)	(1.53)	(-0.28)
	3	-0.050	0.975	0.598	-1.391	-0.545	0.495
		(-0.03)	(0.78)	(0.48)	(-0.68)	(-0.29)	(0.24)
	4	-0.116	1.075	1.290	-2.774	-4.408	4.292
		(-0.04)	(0.39)	(0.49)	(-0.62)	(-0.78)	(1.27)
	5	-5.418***	-7.133**	-7.591**	-9.882***	-13.917***	8.499**
		(-2.69)	(-2.57)	(-2.56)	(-3.35)	(-3.74)	(2.44)

Table 9

Portfolio sorts: returns in quarter $t + 1$

This table reports quarter $t + 1$ returns on five value-weighted portfolios formed by ranking stocks on aggregate deviation from benchmark in quarter $t - 1$. Low quintiles indicate underweight stocks and high quintiles indicate overweight stocks. Aggregate deviation is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (approximately equal to the average percentage deviation from the benchmark). The benchmark is the S&P 500 index. Only the holdings of investment advisors (type 4 in Thomson Reuters S34 file) are used to compute the average portfolio weight. Returns are reported for different S&P 500 volatility-change quintiles, with low quintiles representing declines in volatility and high quintiles representing volatility increases. Returns on the underweight-minus-overweight portfolio, formed by subtracting the fifth from the first underweight/overweight quintile portfolio, are shown in the final column. T-statistics are reported in parentheses below the coefficient estimates, based on standard errors clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

		Return on Quintile Portfolios					
		Overweight/Underweight Quintiles					
		1	2	3	4	5	1-5
		Panel A: 1980 – 2014					
Volatility Change Quintile	1	2.652*	4.363**	4.003**	2.924	0.348	2.304
		(1.72)	(2.46)	(2.15)	(1.40)	(0.13)	(1.06)
	2	1.113	0.892	0.421	1.016	1.222	-0.109
		(0.83)	(0.53)	(0.22)	(0.46)	(0.54)	(-0.10)
	3	0.821	0.614	1.169	1.785	2.956	-2.135
		(0.57)	(0.33)	(0.62)	(0.97)	(1.27)	(-1.02)
	4	2.194*	2.416**	3.424***	2.644	2.489	-0.295
		(1.93)	(2.23)	(3.06)	(1.54)	(1.45)	(-0.32)
	5	0.795	1.082	1.029	2.430	8.555***	-7.76***
		(0.33)	(0.39)	(0.31)	(0.98)	(3.40)	(-3.05)
		Panel B: 1997 – 2014					
Volatility Change Quintile	1	3.022	5.329**	5.494**	4.682**	-0.811	3.833
		(1.54)	(2.56)	(2.48)	(2.01)	(-0.38)	(1.48)
	2	0.232	0.160	-0.225	0.498	2.809	-2.577
		(0.12)	(0.06)	(-0.08)	(0.14)	(0.50)	(0.58)
	3	-1.262	-1.227	-0.813	-0.499	-2.073	0.811
		(-0.65)	(-0.49)	(-0.31)	(-0.18)	(-0.49)	(0.20)
	4	2.418	2.541	3.912*	2.825	3.644	-1.226
		(0.98)	(1.28)	(1.73)	(0.61)	(0.51)	(0.26)
	5	-0.728	0.184	-0.236	0.713	6.244**	-6.972***
		(-0.25)	(0.06)	(-0.06)	(0.22)	(2.29)	(3.06)

Table 10

Volatility changes in quarter $t + 1$

This table reports the change in S&P500 volatility from quarter t to quarter $t + 1$ for each volatility-change quintile from table 6. T-statistics are reported in parentheses below the coefficient estimates. Standard errors are clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

		Average subsequent ($t + 1$) change in volatility	
		1980 – 2014	1997 – 2014
Volatility Change Quintile (t)	1	0.011	-0.009
		(0.55)	(-0.39)
	2	0.010	0.013
		(1.36)	(0.87)
	3	0.020*	0.027
		(1.76)	(1.51)
	4	-0.005	0.006
		(-0.70)	(0.35)
	5	-0.032***	-0.038**
		(-3.36)	(-2.89)

Table 11

Portfolio sorts: alphas

This table reports quarter-t *risk-adjusted* returns on five value-weighted portfolios formed by ranking stocks on aggregate deviation from benchmark in quarter $t-1$. Low quintiles indicate underweight stocks and high quintiles indicate overweight stocks. Aggregate deviation is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (approximately equal to the average percentage deviation from the benchmark). The benchmark is the S&P 500 index. Only the holdings of investment advisors (type 4 in Thomson Reuters S34 file) are used to compute the average portfolio weight. Returns are reported for different S&P 500 volatility-change quintiles, with low quintiles representing declines in volatility and high quintiles representing volatility increases. Returns on the underweight-minus-overweight portfolio, formed by subtracting the fifth from the first underweight/overweight quintile portfolio, are shown in the final column. I use four standard asset pricing factor models to adjust returns: the Fama-French three-factor model (FF), the Fama-French three-factor model plus the Pástor-Stambaugh liquidity factor (FF+LIQ), the Fama-French-Carhart four-factor model (FFC), and the Fama-French-Carhart model plus the Pástor-Stambaugh liquidity factor (FFC+LIQ). T-statistics are reported in parentheses below the coefficient estimates, based on standard errors clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Panel A: 1980 – 2014

"UMO" 1-5 Quintile Portfolios

Volatility Change Quintile	Raw Return	FF Alpha	FF+LIQ Alpha	FFC Alpha	FFC+LIQ Alpha
1	-2.540**	1.068**	1.23**	0.817	0.987
	(-2.15)	(2.08)	(2.33)	(1.43)	(1.63)
2	0.121	1.071*	1.073*	0.554	0.519
	(0.10)	(1.84)	(1.88)	(0.81)	(0.71)
3	-1.211	1.674**	1.564**	1.004	0.814
	(-0.66)	(2.41)	(2.20)	(1.45)	(1.23)
4	2.433*	1.020*	0.97	0.418	0.339
	(1.87)	(1.86)	(1.62)	(0.82)	(0.60)
5	7.052**	4.008***	3.965***	3.146***	3.061***
	(2.26)	(4.95)	(4.66)	(3.87)	(3.65)

Panel B: 1997 – 2014

"UMO" 1-5 Quintile Portfolios

Volatility Change Quintile	Raw Return	FF Alpha	FF+LIQ Alpha	FFC Alpha	FFC+LIQ Alpha
1	-5.021***	0.961	0.982	0.832	0.857
	(-3.03)	(0.93)	(0.59)	(1.44)	(1.25)
2	-0.559	0.24	0.476	0.075	0.238
	(-0.28)	(0.20)	(0.45)	(0.10)	(0.32)
3	0.495	2.549***	2.401**	1.688**	1.439
	(0.24)	(2.78)	(2.27)	(2.14)	(1.64)
4	4.292	1.330**	1.247**	0.298	0.144
	(1.27)	(2.59)	(2.10)	(0.62)	(0.22)
5	8.499**	5.047***	4.998***	3.963***	3.870***
	(2.44)	(6.05)	(5.67)	(4.44)	(4.06)

Table 12

Active share and volatility—index funds

This table reports the estimated coefficients from a regression of end-of-quarter-t active share ($AS_{i,t}$) on S&P 500 volatility forecasts using information up to quarter t ($\hat{\sigma}_t^{S\&P}$) and fund-level control variables: the fund's previous-quarter active share ($AS_{i,t-1}$), the log of assets under management ($aum_{i,t-1}$), and fund-level fixed effects. The sample consists only of S&P 500 index funds that appear in both the Morningstar Direct database and the Thomson Reuters S12 file (formerly CDA/Spectrum database). The formal regression specification is given in equation 28. T-statistics are reported in parentheses below the coefficient estimates, based on standard errors clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

	Dependent Variable $AS_{i,t}$			
	(1)	(2)	(3)	(4)
$\sigma_t^{S\&P}$	0.054**	0.021	0.066	-0.010
	(1.99)	(1.53)	(1.55)	(-0.49)
$AS_{i,t-1}$		0.113***		0.112***
		(6.36)		(6.31)
$aum_{i,t-1}$		-0.005**		-0.005*
		(-2.01)		(-1.94)
$Intercept$	0.102***	0.146***	0.100***	0.150***
	(7.24)	(5.57)	(6.69)	(5.65)
Constant	Yes	Yes	Yes	Yes
Fund Fixed Effects	No	Yes	No	Yes
Vol. estimator	Std. Dev.	Std. Dev.	GARCH	GARCH
Observations	59,877	52,563	59,877	52,563
Adj. R^2	0.005	0.918	0.007	0.919

Table 13

Placebo UMO portfolios

This table reports returns on underweight-minus-overweight (UMO) portfolios, formed by ranking on aggregate deviation from benchmark and subtracting the fifth deviation quintile from the first deviation quintile. Aggregate deviation is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (approximately equal to the average percentage deviation from the benchmark). The benchmark is the S&P 500 index. Holdings used to compute average portfolio weights are taken from institutions *not in the investment advisory sector*: insurance companies (Thomson Reuters S34 type 2), pension funds/endowments (type 5), banks (type 1), and index funds (extracted manually—see section 3). Returns are reported for different S&P 500 volatility-change quintiles, with low quintiles representing declines in volatility and high quintiles representing volatility increases. T-statistics are reported in parentheses below the coefficient estimates, based on standard errors clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

		UMO 1-5 Quintile Portfolios					
		Advisors (Return)	Index Funds (Return)	Pensions (Return)	Insurance (Return)	Banks (Return)	Banks (FFC Alpha)
Panel A: 1980 – 2014							
Volatility Change Quintile	1	-2.540**	-0.240	2.482	1.069	-0.780	0.223
		(-2.15)	(-0.28)	(1.36)	(0.62)	(-0.41)	(0.37)
	2	0.121	-1.214	0.116	-0.666	0.588	-0.511
		(0.10)	(-1.50)	(0.10)	(-0.69)	(1.10)	(0.58)
	3	-1.211	-0.615	-2.996	-2.853*	-2.280	0.362
		(-0.66)	(-0.94)	(-1.53)	(-1.77)	(-1.37)	(0.22)
	4	2.433*	-1.035*	-0.678	-1.708	-2.177	-1.054*
		(1.87)	(-1.89)	(-0.35)	(-1.04)	(-1.44)	(1.84)
	5	7.052**	0.540	-1.011	0.313	-5.194	-1.064
		(2.26)	(0.48)	(-0.28)	(0.14)	(-1.30)	(0.79)
Panel B: 1997 – 2014							
Volatility Change Quintile	1	-5.021***	-1.948	-0.140	-1.086	0.777	0.920
		(-3.03)	(-1.28)	(-0.14)	(-1.42)	(0.35)	(0.98)
	2	-0.559	-2.246*	-1.447	-0.842	1.889	0.867
		(-0.28)	(-1.98)	(-1.60)	(-1.24)	(2.38)	(1.22)
	3	0.495	-1.504	1.572	-0.062	-0.892	-0.105
		(0.24)	(-1.12)	(0.98)	(-0.10)	(-0.81)	(-0.10)
	4	4.292	-0.040	-0.120	-0.442	-4.418*	-1.811*
		(1.27)	(-0.06)	(-0.06)	(-0.39)	(-1.94)	(-1.80)
	5	8.499**	0.640	2.041	1.641	-5.443**	-0.400
		(2.44)	(0.35)	(1.02)	(0.98)	(-2.35)	(-0.48)

Table A.1

Regression test for price distortions using GARCH(1,1) volatility forecast

This table reports the estimated coefficients from a regression of quarterly stock returns ($Ret_{n,t}$) on the interaction between investment advisors' beginning-of-period aggregate deviation from benchmark ($Dev_{n,t-1}$) and the change in a GARCH(1,1) forecast of S&P 500 index volatility over the quarter ($\Delta\sigma_t^{S\&P}$). The formal specification is given in equation 37. Stocks are indexed by n and calendar quarters by t. Aggregate deviation from benchmark is computed as the log of the AUM-weighted average portfolio weight minus the log of the benchmark weight (equation 29). The benchmark is the S&P 500 index. Only the holdings of investment advisors (type 4 in Thomson Reuters S34 file) are used to compute the average portfolio weight. Also included as explanatory variables are volatility interactions with estimated market beta of the stock ($\hat{\beta}_{n,t}$), the natural logarithm of the stock's market capitalization ($Log(Size_{n,t})$) and other stock characteristics (see section 5.2). T-statistics are reported in parentheses below the coefficient estimates, based on standard errors clustered by quarter. Statistical significance is indicated by asterisks: * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Dependent variable: $Ret_{n,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
$Dev_{n,t-1} \times \Delta\hat{\sigma}_t^{S\&P}$	-109.07***	-51.18***	-60.10**	-107.90***	-47.74***	-62.09***
	(-5.39)	(-5.41)	(-2.12)	(-4.43)	(-5.39)	(-2.76)
$Dev_{n,t-1}$		0.025	-1.76***		-0.66	-0.86**
		(0.06)	(-3.39)		(-1.13)	(-2.48)
$\Delta\hat{\sigma}_t^{S\&P}$		-62.38**	132.2		-58.42**	48.3
		(-2.58)	(0.99)		(-2.37)	(0.60)
$\Delta\hat{\sigma}_t^{S\&P} \times \hat{\beta}_{n,t}$			-52.85***			-44.85***
			(-5.80)			(-6.21)
$\Delta\hat{\sigma}_t^{S\&P} \times Log(Size_{n,t})$			-6.07			-2.55
			(-1.18)			(-0.75)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Stock Characteristics	No	No	Yes	No	No	Yes
Char. Interactions	No	No	Yes	No	No	Yes
Start of Sample	1980	1980	1980	1997	1997	1997
Observations	67,329	67,329	57,743	34,525	34,525	32,555
Adj. R^2	0.042	0.060	0.160	0.052	0.074	0.138