Attention Allocation Over the Business Cycle: Evidence from the Mutual Fund Industry

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Abstract

The world of actively managed mutual funds, a multi-billion information-processing industry, provides a rich laboratory to study the link between information and investment choices. We develop a model that characterizes how investment managers ought to allocate their limited attention. Because aggregate asset payoff shocks are relatively more volatile than stock-specific shocks in recessions, learning about the aggregate payoff shocks is more valuable in recessions. Since the optimal attention allocation varies with the state of the economy, so do investment strategies and fund returns. As long as a subset of investment managers has skill (non-zero information processing capacity), the model predicts a higher covariance of portfolio holdings with aggregate payoff shocks, more dispersion in returns across funds, and a higher average fund performance in recessions than in expansions. We find the same patterns in observed investment strategies and portfolio returns of actively managed U.S. mutual funds. Hence, the data are consistent with a world in which some investment managers have skill, but also one in which that skill is hard to detect, on average. Recessions are times when information choices lead to investment choices that are more revealing of skill.

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> "What information consumes is rather obvious: It consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention, and a need to allocate that attention efficiently among the overabundance of information sources that might consume it." Simon (1971)

Much of what the financial sector does is to gather and process information. Understanding how this sector operates requires studying the decisions its actors make. The difficulty is that information choices are not directly observable. To overcome this hurdle, we develop a model that uses an observable variable – the state of the business cycle – to predict information choices. Since information choices determine observable investment strategies, the model tells us how to test the information-based theory of financial intermediation. To carry out these tests, we use data on actively managed domestic equity mutual funds, an important part of the U.S. financial sector.[1] A wealth of detailed data makes this industry the perfect setting to test our theory of attention allocation. Its predictions for how the portfolios of investment managers should change over the business cycle are supported by the mutual fund data.

A better understanding of information choices sheds a new light on a central question in the financial intermediation literature: Do investment managers add value for their clients? What makes this an important question is that a large and growing fraction of individual investors delegate their portfolio management to professional investment managers. This intermediation occurs despite a large body of evidence that finds that actively managed funds tend to underperform passive investment strategies, on average, net of fees, and after controlling for differences in systematic risk exposure.[2] This evidence of negative average "alpha" has led many to conclude that investment managers have no skill. By developing a theory of managers' information and investment choices and finding evidence for its predictions in the mutual fund industry data, we conclude that the data are consistent with a world in which a small fraction of investment managers have skill.[3] However, the model is also consistent with the empirical literature's finding that skill is hard to detect, on average.

[1]At the end of 2007, $12 trillion was invested with such intermediaries in the U.S. Of all investment in domestic equity mutual funds, about 80% is actively managed (2008 Investment Company Factbook), while 100% of hedge fund money is actively managed. Intermediation has gained in importance over time. In 1980, 48% of U.S. equity was directly held by individuals –as opposed to being held through intermediaries–; by 2007 that fraction was down to 21.5%. See French (2008), Table 1.

[2]Among many others, see Jensen (1968), Malkiel (1995), Gruber (1996), Fama and French (2008).

[3]The finding that some managers is consistent with a number of recent papers in the empirical mutual fund literature, e.g., Cohen, Coval, and Pástor (2005), Kacperczyk, Sialm, and Zheng (2005, 2008), Kacperczyk and Seru (2007), Koijen (2008), Baker, Litov, Wachter, and Wurgler (2009), Huang, Sialm, and Zhang (2009).

The model identifies recessions as times when information choices lead to investment choices that are more revealing of skill.

Specifically, we build a general equilibrium model in which a fraction of investment managers have skill, meaning that they can acquire and process informative signals about future value of risky assets' payoffs. These skilled managers can observe a fixed number of signals and choose what fraction of those signals will contain aggregate versus stock-specific information. We think of aggregate signals as macroeconomic data that affect future cash flows of all firms, and stock-specific signals are firm-level data that forecast the part of firms' future cash flows that is independent of the aggregate shocks. Based on their signals, skilled managers form portfolios, choosing larger portfolio weights for assets that are more likely to have high returns.

The model's predictions fall into three categories. The first one relates to attention allocation. As in any learning problem, risks that are large in *scale* and high in *volatility* are more valuable to learn about.[4] In this case, aggregate shocks are large in scale, because many asset returns are affected by them, but they have low volatility. Stock-specific shocks, in turn, are smaller in scale but of high volatility. The key driving force in the model is that aggregate shocks become more volatile relative to stock-specific shocks in recessions.[5] The higher volatility of aggregate shocks makes it optimal to learn more about them, and less about stock-specific shocks.

The second category is predictions about portfolio dispersion. In addition to skilled fund managers, we consider two other types of investors: unskilled portfolio managers and unskilled other investors. The portfolios of skilled and unskilled investors differ more from each other in recessions. This makes portfolio return dispersion rise, despite the fact that individual stock return dispersion falls. In expansions, when managers pay more attention to stock-specific shocks, they hold portfolios that are largely similar to those of unskilled managers, except that they place different weights on the few stocks they follow. Fund

[4]Our model is in the tradition of the noisy rational expectations equilibrium literature. See for example Grossman and Stiglitz (1980), Verrecchia (1982), Admati (1985), Peress (2004), Veldkamp (2006), and Van Nieuwerburgh and Veldkamp, (2009, 2010). A related theoretical literature studies delegated portfolio management; e.g., Basak, Pavlova, and Shapiro (2007), Cuoco and Kaniel (2007), Vayanos and Woolley (2008). Brunnermeier, Gollier, and Parker (2007) solve a portfolio problem in which investors choose the mean of their beliefs, while Maćkowiak and Wiederholt (2009) solve a price setting problem where firms choose the variance of their beliefs (allocate attention), as do our investment managers. Finally, Van Nieuwerburgh and Veldkamp (2006) study information production over time in a real business cycle model.

[5]We show below that the idiosyncratic risk in stock returns, averaged across stocks, is no higher in recessions than in expansions. In contrast, the aggregate risk averaged across stocks is almost forty percent higher in recessions. Consistent with this fact, Ribeiro and Veronesi (2002) and Forbes and Rigobon (2002) document that stocks exhibit more comovement in recessions.

managers' and other investors' portfolio holdings differ only modestly. In recessions, skilled managers follow the macroeconomy and use their signals to adjust their holdings of every stock. A skilled manager who observes a positive aggregate signal (e.g., that recession is almost over) would take an opposite portfolio position from that of an unskilled manager or other investor whose prior belief is that recession will continue. Consequently, the returns earned by both types of managers are more dispersed in recession.

Third, the model predicts differences in fund performance. In recession, more portfolio return dispersion implies higher average fund returns. The reason is that returns of unskilled other investors end up primarily in the left tail of the return distribution. Focusing on investment managers only removes some of the left tail from the return distribution, and consequently raises its mean. The higher the dispersion of that distribution, the larger that increase is. Thus, the mean of the distribution of investment managers' fund returns is higher in recessions when its dispersion is larger.

We test the model's three main predictions on the universe of actively managed U.S. mutual funds. First, we look for evidence of cyclical changes in attention allocation. We estimate the covariance of investment managers' portfolio holdings with the aggregate payoff shock, proxied by innovations in industrial production growth. We call this covariance *reliance on aggregate information* (RAI). RAI indicates a manager's ability to time the market by increasing (decreasing) her portfolio positions in anticipation of good (bad) macroeconomic news. We find that the average RAI across funds is higher in recessions. We also calculate the covariance of funds' portfolio holdings with asset-specific shocks, proxied by innovations in earnings. We call this variable *reliance on stock-specific information* (RSI). RSI measures managers' ability to pick stocks that subsequently experience unexpectedly high earnings. We find that RSI is higher in expansions.

Second, we look for evidence of more portfolio dispersion in recessions. In recessions, we find higher portfolio concentration of funds, measured as the sum of squared deviation of portfolio weights from those of the market portfolio. Given that funds hold portfolios that differ more from the market portfolio, they are also holding portfolios that differ more from one another. Concentration and dispersion are two sides of the same coin because of market clearing. Consistent with more concentrated portfolios, we also find higher idiosyncratic risk for fund returns in recessions. The increased dispersion also appears in fund returns, fund alphas, and fund betas. All these are predictions of the theory. Figure 1 shows the 30% increase of the cross-sectional standard deviation of fund alphas in recessions for our mutual fund data.

Third, we document fund outperformance in recessions.[6] Risk-adjusted excess fund returns (alphas) are around 0.15 to 0.20% per month higher in recessions, depending on the specification. Gross alphas (before fees) are not statistically different from zero in expansions, but they are positive in recessions. Net alphas (after fees) are negative in expansions and positive in recessions. These cyclical differences are statistically and economically significant. Indeed, Figure 2 shows that, over the period 1980-2005, actively managed mutual funds have earned 2.1% risk-adjusted excess returns (alphas) per year in recessions but only 0.3% in expansions. What remains for the investors (net of fees) is 1.0% in recessions and -0.9% in expansions; the difference of 1.9% per year is both economically and statistically significant.

The model tells us what the application of investment management skill looks like in the data. We can use its insights to construct metrics that help to identify skilled managers. To show that such managers exist, we select the top 25 percent of funds in terms of their stock picking in expansions and show that the same group has significant market-timing ability in recessions; the other managers show no such market-timing ability.[7] Furthermore, these managers have higher *unconditional* returns. They tend to run smaller, more actively managed funds. By matching fund-level to manager-level data, we find that these skilled managers are more likely to have an MBA and are more likely to depart later in their careers to hedge funds, presumably a market-based signal of their ability. Finally, we construct a skill index based on observables and show that it predicts future outperformance.

The rest of the paper is organized as follows. Section 1 lays out our model. After describing the setup, we characterize the optimal information and investment choices of skilled and unskilled investors. We show how equilibrium asset prices are formed. We derive theoretical predictions for funds' attention allocation, portfolio dispersion, and performance. Section 2 contains the empirical analysis for actively managed mutual funds and tests the model's predictions. Section 3 uses the model's insights to identify a group of skilled mutual funds in the data. Section 4 briefly discusses alternative explanations. Section 5 concludes.

[6]Kosowski (2006), Lynch and Wachter (2007), and Glode (2008) also document such evidence.

[7]This is quite different from the typical approach in the literature, which has studied stock picking and market timing in isolation, and unconditional on the state of the economy. The consensus view from that literature is that there is some evidence for stock-picking ability (on average over time and across managers), but no evidence for market timing (e.g., Graham and Harvey (1996), Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (2000), Kacperczyk and Seru (2007), and Breon-Drish and Sagi (2008).

1 Model

We develop a stylized model whose purpose is to understand the optimal attention allocation of investment managers, its implications for asset holdings and for equilibrium asset prices.

1.1 Setup

We consider a three-period static model. At time 1, skilled investment managers choose how to allocate their attention. At time 2, all investors choose their portfolios of risky and riskless assets. At time 3, asset payoffs and utility are realized. Since this is a static model, the investment world is either in the recession (R) or in the expansion state (B).[8] Our main model holds fixed each manager's amount of attention. We study the problem of how the investment manager allocates a *given* amount of attention. In Section 1.3, we extend the model by considering the problem of *how much* capacity for attention to acquire.

Assets The model features three assets. Assets 1 and 2 have random payoffs f with respective loadings b_1, b_2 on an aggregate shock a, and face an idiosyncratic shock s_1, s_2. The third asset c is a composite asset. Its payoff has no idiosyncratic shock and a loading on the aggregate shock equals one. This composite asset is a stand-in for all other assets. This simplification is necessary because of the curse of dimensionality we face in the optimal attention allocation problem below. Formally,

$$\begin{aligned} f_i &= \mu_i + b_i a + s_i, \ i \in \{1, 2\} \\ f_c &= \mu_c + a. \end{aligned}$$

where the shocks $a \sim N(0, \sigma_a)$ and $s_i \sim N(0, \sigma_i)$, for $i \in \{1, 2\}$. At time 1, the distribution of payoffs is common knowledge; all investors have common priors about payoffs $f \sim N(\mu, \Sigma)$. Let E_1, V_1 denote expectations and variances conditioned on this information. Specifically, $E_1[f_i] = \mu_i$. The prior covariance matrix of the payoffs Σ has the following entries: $\Sigma_{ii} =$

[8] We do not consider transitions between recessions and expansions, although such an extension would be trivial in our setting because assets are short lived and their payoffs are realized and known to all investors at the end of each period. Thus, a dynamic model simply amounts to a succession of static models that are either in the expansion or in the recession state.

$b_i^2\sigma_a + \sigma_i$ and $\Sigma_{ij} = b_i b_j \sigma_a$. In matrix notation:

$$\Sigma = bb'\sigma_a + \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & 0 \end{bmatrix},$$

where the vector b is defined as $b = [b_1, b_2, 1]'$. In addition to the three risky assets, there is a risk-free asset that pays a gross return r.

The key driving force of the model is that there is more aggregate risk in recessions. That is, the prior variance of the aggregate shock in a recession is higher than it is in an expansion: $\sigma_a(R) > \sigma_a(B)$. This assumption is justified by the well-known fact that the aggregate stock market return is more volatile in recessions. In Table 1 and Section 2.2 below, we formally show that stocks' aggregate risk increases substantially in recessions whereas the change in their idiosyncratic risk is not economically nor statistically different from zero.

Investors We consider a continuum of atomless investors. In the model, the only ex-ante difference between investors is that a fraction χ of them have *skill*, measured by a total endowment $K > 0$ of signal precision they can acquire by processing information. The complementary fraction have no skill: $K = 0$. In order to match the model with data, we will call all of the skilled investors and some of the unskilled investors "investment managers." The remainder are "other investors," who are exclusively unskilled.

At time 1, a skilled investment manager j chooses the precisions of the signals about the payoff-relevant shocks a, s_1, or s_2 that she will receive at time 2. We denote these signal precisions by $\sigma_{\eta aj}^{-1}$, $\sigma_{\eta 1j}^{-1}$, and $\sigma_{\eta 2j}^{-1}$, respectively. This attention allocation decision is subject to two constraints. The first one is the *information capacity constraint*: The sum of the signal precisions may not exceed the information capacity,

$$\sigma_{\eta 1j}^{-1} + \sigma_{\eta 2j}^{-1} + \sigma_{\eta aj}^{-1} \leq K. \tag{1}$$

In Bayesian updating with normal variables, observing one signal with precision σ^{-1} or two signals, each with precision $\sigma^{-1}/2$, is equivalent. Therefore, one interpretation of the capacity constraint is that it allows the manager to observe N signal draws, each with precision K/N, for large N. The investor is then choosing how many of those N signals will be about each shock.

The second constraint is the *no-forgetting constraint*, which ensures that the chosen precisions are non-negative:

$$\sigma_{\eta 1j}^{-1} \geq 0 \qquad \sigma_{\eta 2j}^{-1} \geq 0 \qquad \sigma_{\eta aj}^{-1} \geq 0. \tag{2}$$

It prevents the manager from erasing any prior information – to make room to gather new information about another shock.

Bayesian Updating At time 2, each skilled investment manager observes signal realizations. Signals are random draws from a distribution that is centered around the true payoff shock, with a variance equal to the inverse of the signal precision that was chosen at time 1. Thus, skilled manager j's signals are $\eta_{aj} = a + e_{aj}$, $\eta_{1j} = s_1 + e_{1j}$, and $\eta_{2j} = s_2 + e_{2j}$, where $e_{aj} \sim N(0, \sigma_{\eta aj})$, $\eta_{1j} \sim N(0, \sigma_{\eta 1j})$, and $\eta_{2j} \sim N(0, \sigma_{\eta 2j})$ are mutually independent and independent across fund managers. Managers combine signal realizations with priors to update their beliefs, using Bayes' law. Asset prices are not a separate source of information. Of course, managers can observe asset prices and infer asset-payoff relevant information from them. But making that inference requires allocating attention to prices, in order to process in the information they contain. In other words, learning from prices requires using capacity. The information gleaned from prices is already included in the signals.

Since the resulting posterior beliefs are such that payoffs are normally distributed, they can be fully described by a posterior mean and variance: $\hat{a}_j$, $\hat{\sigma}_{aj}$, $\hat{s}_{ij}$, and $\hat{\sigma}_{ij}$. More precisely, the posterior precisions are the sum of prior and signal precisions: $\hat{\sigma}_{aj}^{-1} = \sigma_a^{-1} + \sigma_{\eta aj}^{-1}$ and $\hat{\sigma}_{ij}^{-1} = \sigma_i^{-1} + \sigma_{\eta ij}^{-1}$. The posterior means of the idiosyncratic shocks $\hat{s}_{ij}$ are a precision-weighted linear combination of the prior belief that $s_i = 0$ and the signal η_i: $\hat{s}_{ij} = \sigma_{\eta 1j}^{-1}/(\sigma_{\eta ij}^{-1} + \sigma_i^{-1})\eta_{1j}$. Simplifying yields $\hat{s}_{ij} = (1 - \hat{\sigma}_{ij}\sigma_i^{-1})\eta_{ij}$. Likewise, $\hat{a}_j = (1 - \hat{\sigma}_{aj}\sigma_a^{-1})\eta_{aj}$. Posterior beliefs about the payoff shocks translate into posterior beliefs on the asset payoffs themselves. Let $\hat{\Sigma}_j$ be the posterior variance-covariance matrix of payoffs f, i.e., conditional on time-2 information:

$$\hat{\Sigma}_j = bb'\hat{\sigma}_{aj} + \begin{bmatrix} \hat{\sigma}_{1j} & 0 & 0 \\ 0 & \hat{\sigma}_{2j} & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

Likewise, let $\hat{\mu}_j$ be the vector of posterior expected payoffs:

$$\hat{\mu}_j = [\mu_1 + b_1\hat{a}_j + \hat{s}_{1j},\ \mu_2 + b_2\hat{a}_j + \hat{s}_{2j},\ \mu_c + \hat{a}_j]'. \tag{3}$$

Obviously, for an investment manager or an other investor with no capacity, $\hat{\mu}_j = \mu$ and

$\hat{\Sigma}_j = \Sigma$.

Portfolio Choice Problem We solve this model by backward induction. We first solve for the optimal portfolio at time 2 and substitute in that solution into the time-1 optimal attention allocation problem.

Investors are each endowed with initial wealth, W_0. They have mean-variance preferences over time-3 wealth, with risk aversion coefficient ρ. Let E_2, V_2 denote expectations and variances conditioned on all information known at time 2. Thus, investor j chooses q_j to maximize time-2 expected utility U_{2j}:

$$U_{2j} = \rho E_2[W_j] - \frac{\rho^2}{2} V_2[W_j],$$

subject to the budget constraint[9]

$$W_j = rW_0 + q_j'(f - pr). \tag{4}$$

After having received the signals and having observed the prices of the risky assets p, the investment manager chooses risky asset holdings q_j, where p and q_j are 3-by-1 vectors. The first-order condition reveals that optimal holdings are increasing in the investor's risk tolerance, precision of beliefs, and expected return on the assets:

$$q_j = \frac{1}{\rho} \hat{\Sigma}_j^{-1} (\hat{\mu}_j - pr). \tag{5}$$

Since uninformed managers and other investors have identical beliefs $\hat{\mu}_j = \mu$ and $\hat{\Sigma}_j = \Sigma$, they hold identical portfolios $\rho^{-1}\Sigma^{-1}(\mu - pr)$.

Asset Prices Equilibrium asset prices are determined by market clearing:

$$\frac{1}{\rho} \int \hat{\Sigma}_j^{-1} (\hat{\mu}_j - pr) di = \bar{x} + x, \tag{6}$$

where the left-hand side is the vector of aggregate demand and the right-hand side is the aggregate supply vector. As in the standard noisy rational expectations equilibrium model, the asset supply is random in order to prevent the price from fully revealing the information

[9]For professional managers who invest only on behalf of clients, wealth would equal a fee times the assets under management.

of informed investors. We denote the 3×1 noisy asset supply vector by $\bar{x} + x$, with random component $x \sim N(0, \sigma_x I)$.

Appendix A.2 manipulates (6) to prove that equilibrium asset prices are linear in payoffs and supply shocks and to derive expressions for the coefficients A, B, and C in the following proposition:

Proposition 1. $p = \frac{1}{r}(A + Bf + Cx)$.

Attention Allocation Problem Turning to the optimal attention allocation problem, the skilled investment manager chooses $\sigma_{\eta aj}^{-1}$, $\sigma_{\eta 1j}^{-1}$, and $\sigma_{\eta 2j}^{-1}$ to maximize time-1 expected utility U_{1j} over her fund's terminal wealth:

$$U_{1j} = E_1\left[\rho E_2[W_j] - \frac{\rho^2}{2} V_2[W_j]\right]$$

subject to the constraints (1) and (2). Substituting in optimal risky asset holdings from equation (5), yields $U_{1j} = \frac{1}{2} E_1\left[(\hat{\mu}_j - pr)\hat{\Sigma}_j^{-1}(\hat{\mu}_j - pr)\right]$. Because asset prices are linear functions of normally distributed payoffs and asset supplies, expected excess returns, $\hat{\mu}_j - pr$, are normally distributed as well. Therefore, $(\hat{\mu}_j - pr)\hat{\Sigma}_j^{-1}(\hat{\mu}_j - pr)$ is a non-central χ^2-distributed variable, with mean[10]

$$U_{1j} = \frac{1}{2} trace(\hat{\Sigma}_j^{-1} V_1[\hat{\mu}_j - pr]) + \frac{1}{2} E_1[\hat{\mu}_j - pr]' \hat{\Sigma}_j^{-1} E_1[\hat{\mu}_j - pr]. \tag{7}$$

1.2 Model Predictions for Attention, Dispersion, and Performance

This section explains the model's three key predictions: for optimal attention allocation, the resulting equilibrium dispersion in investors' portfolios, and average performance. For each prediction, we first state a proposition. Since our aim is to connect the theory as closely as possible to the empirical work in the next section, we then introduce alternate measures of attention, dispersion, and performance. These alternate measures correspond to the objects we can measure in the data. Using a numerical simulation of the model, we verify that these alternate measures have the same comparative statics as the measures for which we are able to prove the propositions.

[10]If $z \sim N(E[z], Var[z])$, then $E[z'z] = trace(Var[z]) + E[z]'E[z]$, where $trace$ is the matrix trace (the sum of its diagonal elements). Setting $z = \hat{\Sigma}_j^{-1/2}(\hat{\mu}_j - pr)$ delivers the result. Appendix A contains the expressions for $E_1[\hat{\mu}_j - pr]$ and $V_1[\hat{\mu}_j - pr]$ as part of Section A.2.

1.2.1 Attention Allocation

Each skilled fund ($K > 0$) solves for the choice of signal precisions $\sigma_{\eta aj}^{-1} \geq 0$ and $\sigma_{\eta 1j}^{-1} \geq 0$ that maximize time-1 expected utility (7). The signal precision choice $\sigma_{\eta 2j}^{-1} \geq 0$ is implied by the capacity constraint (1). A robust prediction of our model is that it becomes relatively more valuable to learn about the aggregate shock a when the prior aggregate variance increases, i.e., in recessions.

Proposition 2. *If all informed managers learn about aggregate risk and capacity is not too high ($K \leq \sigma_a^{-1}$), the marginal value of additional capacity K devoted to learning about the aggregate shock is increasing in the aggregate shock variance: $\partial^2 U / \partial K \partial \sigma_a > 0$.*

The proof is in Appendix A.3. In any learning problem, investors prefer to learn about shocks that affect assets that are large, i.e., that are an important component of the overall asset supply, and about shocks that are volatile, i.e., that generate a lot of payoff risk (high prior payoff variance). The most valuable shock to learn about is one that has both a large scale and a high volatility. On average, the aggregate shock is larger but not as volatile as the stock-specific shocks. Recessions are times in which the aggregate payoff shock becomes more volatile relative to the idiosyncratic payoff shocks. This is not so much an assumption as it is a fact in the data; see Section 2.2 below. The aggregate shock is still large, but now also more volatile, which makes it more valuable to learn about. As a result, skilled investment managers will allocate a larger fraction of their attention to learning about the aggregate shock in recessions. The converse is true in booms.

Under "natural" parameter conditions, the optimal attention allocation decision switches over the business cycle, with most skilled managers allocating their attention to the aggregate shock in recessions and to the idiosyncratic shocks in expansions. Thee conditions are that the average supply of the composite asset $\bar{x}_c$ cannot be too large relative to the supply of the individual asset supplies $\bar{x}_1$ and $\bar{x}_2$. This would make the aggregate shock so valuable to learn about that all skilled managers would want to learn about it all the time. Nor can its volatility σ_a be so low relative to the volatilities of the idiosyncratic shocks σ_i that nobody ever wants to learn about the aggregate shock. Appendix B presents a detailed numerical example where parameters are chosen to match the observed volatilities of the aggregate and individual stock returns in booms and recessions. At our benchmark parameter values, all skilled managers exclusively allocate attention to idiosyncratic shocks in expansions. In contrast, the bulk of skilled managers (87%) learn about the aggregate shock in recessions (with the remaining 13% equally split between shocks 1 and 2). We have verified that similar large swings in attention allocation occur for a wide range of parameters.

Investors' optimal attention allocation decision is reflected in their portfolio holdings. In recessions, skilled investors predominantly allocate attention to the aggregate payoff shock a. They use the information they observe to form a portfolio that covaries with a. In times when they learn that a will be high, they hold more risky assets whose returns are increasing in a. This positive covariance can be seen in equation (5) where q is increasing in $\hat{\mu}_j$ and from equation (3) where $\hat{\mu}_j$ is increasing in $\hat{a}_j$, which is increasing in a. The positive covariance between the aggregate shock and funds' portfolio holdings in recessions and, conversely, between idiosyncratic shocks and the portfolio holdings in expansions directly follow from optimal attention allocation decisions switching over the business cycle. As such, these covariances are the key moments that enable us to test the attention allocation predictions of the model.

To bridge the gap between the model and the data, we use the definitions for asset returns, portfolio returns, and portfolio weights conventionally used in the empirical literature. Risky asset returns are defined as $R^i = \frac{f_i}{p_i} - 1$, for $i \in \{1, 2, c\}$, while the risk-free asset return is $R^0 = \frac{1+r}{1} - 1 = r$. We define the market return as the value-weighted average of the individual asset returns: $R^m = \sum_{i=1}^3 w_i^m R^i$, where $w_i^m = \frac{p_i q_i^j}{\sum_{i=1}^3 p_i q_i^j}$. We define a fund j's return as $R^j = \sum_{i=0}^3 w_i^j R^i$, where $w_i^j = \frac{p_i q_i^j}{\sum_{i=0}^3 p_i q_i^j}$. It follows that end-of-period wealth (assets under management) equals beginning-of-period wealth times the fund return: $W^j = W_0^j(1 + R^j)$. While standard in the empirical literature, these definitions of returns and portfolio weights have no known moment generating functions in our model. For example, the asset return is a ratio of normally distributed variables. The role of the numerical example is to demonstrate that the empirical objects of interest have the same comparative statics as the objects in the propositions.

We define a fund's *reliance on aggregate information* or RAI as the covariance between its portfolio weights in deviation from the market portfolio weights, $w_i^j - w_i^m$, and the aggregate payoff shock a:

$$RAI_t^j = \frac{1}{N} \sum_{i=1}^{N} (w_{it}^j - w_{it}^m)(a_{t+1}) \tag{8}$$

The subscript t on the portfolio weights and the subscript $t+1$ on the aggregate shock are meant to indicate that the aggregate shock is unknown at the time of portfolio formation. In the context of our static model, time t is period 2 and time $t+1$ is period 3. A fund with a high RAI over-weights assets that have high (low) sensitivity to the aggregate shock in anticipation of a positive (negative) aggregate shock realizes and under-weights assets with a low (high) sensitivity.

RAI is closely related to measures of market-timing ability used in empirical work. *Timing* measures how a fund's holdings of each asset, relative the market, covary with the systematic component of the stock return:

$$Timing_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(\beta_{it+1}R_{t+1}^m), \tag{9}$$

where β_i measures the covariance of asset i's return R^i with the market return R^m, divided by the variance of the market return. The object $\beta_i R^m$ measures the systematic component of returns of asset i. The time subscripts indicate that the systematic component of the return is unknown at the time of portfolio formation. A fund with a high *Timing* ability over-weighs assets that have high beta before the market return rises. Likewise, it under-weighs assets with a high beta in anticipation of a market decline.

In order to confirm that the *RAI* and *Timing* measures adequately represent the model's prediction that skilled investors allocate more attention to the aggregate state in recessions, we resort to numerical simulation. The details of the simulation procedure are presented in Appendix B.1 while details on the construction of the main measures of interest in the simulation are discussed in Appendix B.2. For brevity, we only discuss the comparative statics in the main text. The simulation results show that *RAI* and *Timing* are higher for skilled investors in recessions than in expansions. Because of market clearing, unskilled investors are the flip side of the skilled. Since they have no information, they cannot design investment strategies that covary with the aggregate payoff shock (or aggregate market return). However, in times of low aggregate payoff shock realizations, when most skilled investors sell, asset prices p are low, and prior expected returns $\mu - pr$ are high. Equation (5) shows that uninformed investors' resulting asset holdings are high. Hence, the uninformed overweigh assets when payoffs are likely to be low making their assets' weights negatively covarying with the aggregate payoff shock. Hence, their *RAI* and *Timing* measures are negative. Since no investors learn about the aggregate shock in expansions, the *RAI* and *Timing* measures are essentially zero for both skilled and unskilled. When averaged over all funds (including both skilled and unskilled funds but excluding other unskilled investors), we find that *RAI* and *Timing* are higher in recessions than in expansion.

In expansions, skilled investment managers allocate attention to stock-specific payoff shocks s_i. We define a measure we label *reliance on stock-specific information*, or *RSI*, which measures the covariance of a fund's portfolio weights of each stock, relative to the market, with the stock-specific shock:

$$RSI_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(s_{it+1}) \tag{10}$$

This measure captures the increased attention to stock-specific information in expansions. How well the fund chooses portfolio weights in anticipation of future asset-specific payoff shocks is closely linked to the concept of stock-picking ability. $Picking_t^j$ measures how a fund's holdings of each stock, relative to the market, covary with the idiosyncratic component of the stock return:

$$Picking_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m). \tag{11}$$

A fund with a high *Picking* ability over-weighs assets that have subsequently high idiosyncratic returns and under-weighs assets with a low subsequent idiosyncratic return. In our simulation, we find that skilled funds have a high RSI and *Picking* ability in expansions, when they allocate their attention to stock-specific information. Unskilled investors have a negative *Picking* measure in expansions for the same reason that they have a negative *Timing* measure in recessions: Price fluctuations induce them to buy when returns are low and sell when returns are high. Across all funds, the model predicts lower RSI and *Picking* in recessions.

1.2.2 Dispersion

The model's second main prediction is a higher cross-sectional dispersion in funds' investment strategies and fund returns in recessions than in expansions. The following proposition shows that funds' portfolio returns, $q_j'(f - pr)$, display higher cross-sectional dispersion when aggregate risk is higher, i.e., in recessions.

Proposition 3. *If some investment managers are uninformed* $\chi < 1$*, but all informed managers learn about aggregate risk, and the average manager has sufficiently low capacity* $\chi K < \sigma_a^{-1}$*, then an increase in aggregate risk* σ_a *increases the dispersion of funds' portfolio returns* $E[((q_j - \bar{q})'(f - pr))^2]$*, where* $\bar{q} \equiv \int q_j dj$*.*

The proof is in Appendix A.4. When skilled fund managers learn, they observe different signal realizations, each of which is the truth plus some orthogonal signal noise. This signal noise is a key source of dispersion in the portfolios they hold. In recessions, the funds with aggregate signals that are more positive than average hold more than the market share of all risky assets (in proportion to their b loadings), while the funds with more negative draws hold less.[11] The key insight is that aggregate information affects an investor's holdings of *all assets*, making portfolio dispersion high in recessions. In contrast, in expansions, informed investors learn about stock-specific shocks which affect only a small component of their portfolios, namely their position in either asset 1 or 2. Hence, optimal information choice in expansions leads to less heterogeneous investment strategies.

To map model into data, we define several measures of portfolio dispersion which are common in the empirical literature. The first one is measured as the squared deviation of fund j's portfolio weight in asset i at time t from the average fund's portfolio weight in asset i at time t, summed over assets:

$$Concentration_t^j = \sum_{i=1}^{N} \left(w_{it}^j - w_{it}^m \right)^2 . \tag{12}$$

We label this measure *Concentration* because, as any Herfindahl index, it is a measure of portfolio concentration. Cross-sectional dispersion and concentration are two sides of the same coin. In equilibrium markets must clear so that funds cannot all be holding concentrated portfolios without dispersion across their portfolios. Our numerical example shows that *Concentration* is higher for all funds in recessions than in expansions. This increase is driven entirely by the informed; the uninformed are all holding the exact same portfolio because of common prior beliefs.

Because more concentrated portfolios are less diversified, the model predicts that skilled fund's returns contain higher idiosyncratic risk in recessions.[12] We define idiosyncratic portfolio risk as the residual standard deviation σ_ε^j from a CAPM regression for fund j:

$$R_t^j = \alpha^j + \beta^j R_t^m + \sigma_\varepsilon^j \varepsilon_t^j \tag{13}$$

In simulation, the skilled funds take on more idiosyncratic risk than the unskilled, and more in recessions than in booms. As a result, idiosyncratic risk, our second measure of portfolio dispersion, is higher in recessions than in booms for all funds.

[11] The equilibrium typically does not feature large short positions because assets are in positive net supply and markets must clear.

[12] The terminology idiosyncratic *risk* is slightly misleading in our context. In fact, the portfolio is not more risky because skilled managers obtain information which reduces risk. They optimally trade off the benefits from information with the costs of a reduction in diversification. The standard CAPM equation does not capture this because it does not condition on what the manager knows.

Dispersion across funds' portfolio strategies translates into cross-sectional return dispersion. We look at cross-sectional dispersion in the funds' abnormal return ($R^j - R^m$), CAPM alpha (α^j from equation 13), and CAPM beta (β^j). To facilitate comparison with the data in Section 2, we define the dispersion of variable X as the average over funds of $|X^j - \bar{X}|$. The notation $\bar{X}$ denotes the equally-weighted cross-sectional average across all investment managers (excluding the other investors). Our numerical results show higher dispersion in the dispersion of abnormal returns, fund alphas, and fund betas, confirming the result in Proposition 3 for a slightly different dispersion metric.

1.2.3 Performance

The third main prediction of the model is that the average performance of investment managers is higher in recessions than in expansions. The following proposition shows that skilled funds' abnormal portfolio returns, defined as their portfolio return $q_j'(f - pr)$ minus the market return $\bar{q}'(f - pr)$, are higher when aggregate risk is higher, i.e., in recessions.

Proposition 4. *If some managers are uninformed $\chi < 1$, but all informed managers learn about aggregate risk, and the average manager has sufficiently low capacity $\chi K < \sigma_a^{-1}$, then an increase in aggregate risk σ_a increases the expected profit of an informed fund, $E[(q_j - \bar{q})'(f - pr)]$, where $\bar{q} \equiv \int q_j dj$.*

The proof is in Appendix A.5. Because asset payoffs are more uncertain, recessions are times when information is more valuable. Therefore, the advantage of the skilled over the unskilled increases in recessions. This informational advantage generates higher (risk-adjusted) excess returns for informed managers. In equilibrium, market clearing dictates that alphas average to zero across all investors. However, our moments of interest exclude the unskilled "other investors" (those 20% of investors that are not investment managers), since that is what we have data on. Since investment managers include skilled and unskilled, while other investors are only unskilled, an increase in the skill premium implies that the average manager's alpha rises. The same argument holds for the abnormal return.

Our numerical simulations confirm that abnormal returns and alphas, defined as in the empirical literature and averaged over all funds, are higher in recessions than in expansions. Skilled investment managers have positive excess returns, while the uninformed have negative excess returns. Aggregating across skilled and unskilled funds results in higher average alphas in recessions than booms, the third main prediction of the model.

1.3 Endogenous Capacity Choice

So far we have assumed that skilled investment managers choose how to allocate a fixed information processing capacity K. We now briefly discuss an extension of our model where information processing capacity is endogenous. Skilled managers can add capacity at a cost, where $\mathcal{C}(K)$ is the cost function.[13] We draw three main conclusions. First, the proofs of Propositions 2-4 hold for any given level of capacity K (below a high upper bound). Hence, no matter the functional form of the cost function, these propositions continue to hold in the model with endogenous capacity. Endogenous capacity only has quantitative, not qualitative implications. Second, because the marginal utility of learning more about the aggregate shock is increasing in its prior variance (Proposition 2), skilled managers choose to acquire higher capacity in recessions than in booms. This extensive margin effect amplifies our benchmark intensive margin results. Third, the exact magnitude of the amplification is crucially dependent on the functional form of the cost function $\mathcal{C}(K)$. The steepness of the marginal cost function determines how elastic equilibrium capacity choice is to changes in the marginal benefit of learning. Appendix B.4 discusses numerical simulation results from the endogenous K model; they are similar to our benchmark results.

2 Evidence from Equity Mutual Funds

Our model studies the optimal attention allocation decisions with respect to the aggregate state of the economy, and its consequences for investment managers' strategies and asset prices, in general. We now turn to a specific set of investment managers, mutual fund managers, to test the predictions of the model. The richness of the data makes the mutual fund industry a great laboratory to perform this test. In principle, similar tests could be conducted for hedge funds, other professional investment managers, or even individual investors.

2.1 Data

Our sample builds upon several data sets. We begin with the Center for Research on Security Prices (CRSP) survivorship bias-free mutual fund database. The CRSP database provides comprehensive information on fund returns and a host of other fund characteristics, such as

[13] We model this cost as a utility penalty, akin to the disutility from labor in business cycle models. Since there are no wealth effects in our setting, it would be equivalent to model a cost of capacity through the budget constraint. For a richer treatment of the modeling of information production, see Veldkamp (2006).

size (total net assets), age, expense ratio, turnover, and load. Given the nature of our tests and data availability, we focus on actively managed open-end U.S. equity mutual funds. We further merge the CRSP data with fund holdings data from Thomson Financial. The total number of funds in our merged sample is 3,477. In addition, for some of our exercises, we map funds to the names of their managers. This mapping results in a sample with 4,267 managers. We also use the CRSP/Compustat stock-level database, which is a source of information on individual stocks' return, market capitalization, book-to-market ratio, momentum, liquidity, and standardized unexpected earnings (SUE). We use changes in monthly industrial production as a proxy for aggregate shocks. Finally, we measure recessions using the definition of the National Bureau of Economic Research (NBER) business cycle dating committee. The start of the recession is the peak of economic activity and its end is the trough. In robustness analysis, we use months with negative real consumption growth as an alternative measures of recession. In unreported results, we have also used months with lowest 25% of aggregate stock market returns, again with similar results. Our aggregate sample spans 312 months of data from January 1980 until December 2005, among which 38 are NBER recession months.

2.2 Motivating the Key Assumption

Before turning to the empirical tests of our main model predictions, we present empirical evidence for the main driving force in the model: the fact that individual stocks have more aggregate risk in recessions. Table 1 shows that stocks' aggregate risk increases substantially in recessions whereas the change in their idiosyncratic risk is not statistically different from zero. The table uses monthly returns for all stocks in the CRSP universe. For each stock and each month, we estimate a CAPM equation based on a twelve-month rolling window regressions; this delivers the stock's beta β_t^i and its residual standard deviation $\sigma_{\varepsilon t}^i$. We define the aggregate risk of stock i in month t as $|\beta_t^i \sigma_t^m|$ and its idiosyncratic risk as $\sigma_{\varepsilon t}^i$, where σ_t^m is formed as the realized volatility from daily return observations. Panel A report the results from a time-series regression of the aggregate risk averaged across stocks (Columns 1 and 2) and of the idiosyncratic risk averaged across stocks (Columns 3 and 4) on the NBER recession dummy. It shows that the aggregate risk is a third higher in recessions than in expansions (0.69 versus 0.47), an economically and statistically significant difference. In contrast, the idiosyncratic stock risk is essentially identical in booms and recessions.[14] The

[14]Averages across stocks are computed as equally-weighted averages. Unreported results confirm that value-weighted averaging across stocks delivers the same conclusion.

results are similar when one controls for other aggregate risk factors (Columns 2 and 4) or not (Columns 1 and 3). Panel B reports panel regressions of a stock's aggregate risk (Columns 1 and 2) or idiosyncratic risk (Columns 3 and 4) on the recession dummy and additional stock-specific control variables. The panel results confirm the time-series findings. We now turn to the results for mutual funds.

2.3 Attention Allocation

We begin by testing the first and most direct prediction of our model, that skilled investment managers reallocate their attention over the business cycle. Learning about the aggregate payoff shock in recessions makes managers choose portfolio holdings that covary relatively more with the aggregate shock. Conversely, in expansions, their holdings covary relatively more with the stock-specific information. To this end, we estimate the following regression:

$$Attention_t^j = a_0 + a_1 Recession_t + \mathbf{a_2 X_t^j} + \epsilon_t^j, \tag{14}$$

where $Attention_t^j$ denotes a generic attention variable, observed at month t for fund j. $Recession_t$ is an indicator variable equal to one if the economy in month t is in recession, as defined by the NBER, and zero otherwise. X is a vector of fund-specific control variables, including the fund age (natural logarithm of age in years since inception, $\log(Age)$), the fund size (natural logarithm of total net assets under management in millions of dollars, $\log(TNA)$), the average fund expense ratio (in percent per year, *Expenses*), the turnover rate (in percent per year, *Turnover*), the percentage flow of new funds (defined as the ratio of $TNA_t^j - TNA_{t-1}^j(1 + R_t^j)$ to TNA_{t-1}^j, *Flow*), and the fund load (the sum of front-end and back-end loads, additional fees charged to the customers to cover marketing and other expenses, *Load*). Also included are the fund style characteristics along the size, value, and momentum dimensions.[15] To mitigate the impact of outliers on our estimates, we winsorize *Flow* and *Turnover* at the 1% level.

We estimate this and most of our subsequent regression specifications using pooled (panel)

[15]The size style of a fund is the value-weighted score of its stock holdings' percentile scores calculated with respect to their market capitalizations (1 denotes the smallest size percentile; 100 denotes the largest size percentile). The value style is the value-weighted score of its stock holdings' percentile scores calculated with respect to their book-to-market ratios (1 denotes the smallest B/M percentile; 100 denotes the largest B/M percentile). The momentum style is the value-weighted score of a fund's stock holdings' percentile scores calculated with respect to their past 12-month returns (1 denotes the smallest return percentile; 100 denotes the largest return percentile). These style measures are similar in spirit to those defined in Kacperczyk, Sialm, and Zheng (2005) and Huang, Sialm, and Zhang (2009).

regression and calculating standard errors by clustering at the fund and time dimensions. This approach addresses the concern that the errors, conditional on independent variables, might be correlated within fund and time dimensions (e.g., Moulton (1986)). Addressing this concern is especially important in our context since our variable of interest, *Recession*, is constant across all fund observations in a given time period. Also, we demean all control variables so that the constant a_0 can be interpreted as the level of the attention variable in expansions, and a_1 how much the variable increases in recessions.

Our estimates of the parameters in equation (14) appear in Table 2. In columns 1 and 2, the dependent variable is the mutual funds' reliance on aggregate information (RAI). Recalling equation (8), the RAI for fund j in month t, is the covariance between the fund's portfolio weights in each stock i net of the weight of that stock in the market in month t, $w_{ti}^j - w_{ti}^m$, and the aggregate payoff shock in month $t+1$. We proxy the latter by the innovation in log industrial production growth in month $t+1$.[16] A time series for RAI_t^j is obtained by computing this covariance from 12-month rolling windows. Our hypothesis is that RAI should be higher in recessions, which means that the coefficient on *Recession*, a_1, should be positive.

Column 1 shows the results of a univariate regression on the recession dummy. In expansions, RAI is not different from zero, implying that funds' portfolios do not comove with future macroeconomic information in those periods. This is consistent with the model's prediction. In recessions, RAI increases, again consistent with the model. The increase amounts to ten percent of a standard deviation of RAI. It is measured precisely, with a t-stat of 3. To rule out the possibility of a bias in the coefficient due to omitted fund characteristics correlated with recession times, we turn to a multivariate regression. Our findings, presented in Column 2, remain largely unaffected by the inclusion of the control variables.

Next, we repeat the above regression analysis using the mutual funds' reliance on stock-specific information (RSI) as a dependent variable. Recalling equation (10), the RSI for fund j in month t, RSI_t^j is the covariance between the fund's portfolio weights in each stock i net of the weight of that stock in the market, $w_{ti}^j - w_{ti}^m$, and the innovation in that stock's earnings at time $t+1$.[17] Hence, the RSI metric is computed in each month t

[16] We regress log industrial production growth at $t+1$ on log industrial production growth in month t, and use the residual from this regression. Because industrial production growth is nearly i.i.d, the same results obtain if we simply use the log change in industrial production between t and $t+1$. Industrial production is seasonally adjusted; the data are from the Federal Reserve Statistical Release.

[17] We regress earnings per share in a given quarter on earnings per share in the previous quarter (earnings are reported quarterly), and use the residual from this regression. Suppose month t and $t+3$ are end-of-quarter months. Then RSI is months t, $t+1$, and $t+2$ are computed using portfolio weights from month t

as a cross-sectional covariance across the assets in the fund's portfolio. In the model, the fund's portfolio holdings and returns covary more with subsequent firm-specific shocks in expansions. Therefore, our hypothesis is that RSI should fall in recessions, meaning that a_1 should be negative.

Columns 3 and 4 of Table 2 show that the average RSI across funds is positive in expansions and substantially lower in recessions than in expansions. This is conform the model's predictions. The effect is statistically significant at the 1% level. It is also economically significant: RSI decreases by approximately ten percent of one standard deviation. Overall, the data support the model's prediction that portfolio holdings are more sensitive to aggregate shocks in recessions and more sensitive to firm-specific shocks in expansions.

The reliance on aggregate and stock-specific information (RAI and RSI) are intimately connected to our measures of market-timing $Timing_t^j$ and stock-picking ability $Picking_t^j$, defined in equations (9) and (11), respectively. The benefit of using these variables is that they have an exact analog in the model. In contrast, for RAI and RSI, we need to take a stance on the empirical proxy for the aggregate and idiosyncratic shocks. The stock betas in the Timing and Picking definitions, β_i, are computed using the 12-month rolling-window regressions of stock returns net of the risk-free rate on market excess returns.

Columns 5 and 6 of Table 2 show that the average market-timing ability across funds increases significantly in recessions. In fact, we find no evidence of market timing in expansions. Since expansion months make up the bulk of our sample, this result is consistent with the literature which fails to find evidence for market timing, on average. However, we find that market timing is positive and statistically different from zero in recessions. The increase is 25 percent of a standard deviation of the $Timing$ measure, which is economically meaningful. Likewise, columns 7 and 8 show that stock-picking ability deteriorates substantially in recessions, again consistent with the theory. The reduction in recessions is about 20 percent of a standard deviation of the $Picking$ measure.

Table 14 performs several robustness checks. First, we compute a second RSI measure where the aggregate shock is proxied by surprises in non-farm employment growth, another salient macroeconomic variable, instead of industrial production growth. The results are similar, and if anything, estimated even more precisely. Second, we compute a second RSI measure where earnings surprises are defined as the residual from a regression of earnings per share in that same quarter one year earlier (instead of one quarter earlier). Such a definition is more common in the literature (Bernard and Thomas 1989). The results are very similar

and earnings surprises from month $t + 3$.

to our benchmark RSI results. Third, as a robustness check on the market timing results, we also study the R^2 from a CAPM regression at the fund level (as in equation 13). It measures how the fund's excess return (as opposed to the fund's portfolio weights) covaries with the aggregate state measured by the market's excess return. The average R^2 across all funds rises from 77% in expansions to 80% in recessions. This is consistent with the hypothesis that recessions are times when funds learn about the aggregate shock, making their portfolio choices and therefore their fund return more sensitive to changes in market returns.

2.4 Dispersion

The second main prediction of the model is that heterogeneity in fund investment strategies and portfolio returns rises in recessions. To test this hypothesis, we estimate the following pooled cross-sectional regression specification, using heterogeneity measures of funds' investment strategies and properties of their resulting returns as $Dispersion_t^j$, the dispersion of fund j at month t.

$$Dispersion_t^j = b_0 + b_1 Recession_t + \mathbf{b_2 X_t^j} + \epsilon_t^j, \tag{15}$$

The definitions of $Recession$ and other control variables mirror those in regression (14). Our coefficient of interest is b_1.

We begin by examining dispersion in investment strategies. The results are in Table 3. Our first measure is a fund's portfolio $Concentration$, defined in equation (12). A fund whose holdings deviate more from the market portfolio, and therefore from other investors, has a higher stock concentration; it pursues a more active investment strategy. In contrast, when all funds' stock holdings perfectly track the market portfolio, each fund is perfectly diversified, average concentration is zero, and so is dispersion in fund strategies. Concentration and dispersion are two sides of the same coin. The results in columns 1 and 2 indicate an increase in average $Concentration$ across funds in recessions. The increase is statistically significant at the 1% level. It is also economically significant: The value of stock concentration in recessions goes up by about 15% of a standard deviation.

An alternative way to assess a fund's concentration level is to look at its degree of idiosyncratic risk. A more concentrated portfolio carries more idiosyncratic risk σ_ε^j, at least according to the CAPM regression (13). Columns 3 and 4 show that the idiosyncratic volatility increases substantially in recessions. The increase is again highly significant, both statistically and economically. One concern with the CAPM-based measure of idiosyncratic risk is that it might not capture the possibility that some funds have passive loadings on factors besides the market return. Therefore, we re-compute idiosyncratic volatility, controlling for a fund's exposure to size (SMB), value (HML), and momentum (UMD) risk factors. When we use the new idiosyncratic volatility as our dependent variable, the *Recession* coefficient (standard error) in a univariate regression is 0.347 (0.070) and the intercept is 1.189 (0.029). Controlling for fund characteristics changes the coefficients by 1% or less.

Since dispersion in fund strategies should generate dispersion in fund returns, we next look for evidence of higher return dispersion in recessions. To measure dispersion in return variable X, we construct the absolute deviation between fund j's value and the equally weighted cross-sectional average, $|X_t^j - \overline{X}_t|$. Subsequently, we estimate the regression model in (15) using the deviation measures as dependent variables. Columns 5 and 6 of Table 3 presents the results for the dispersion in the funds' CAPM alphas, which are obtained from 12-month rolling-window regressions of fund excess returns on market excess returns, as in equation (13). Comparing the slope b_1 to the intercept b_0, we find a 50 percent increase in portfolio dispersion in recessions. The effect is measured precisely. Columns 7 through 8 show that using four-factor alphas in place of CAPM alphas does not change the result. Finally, columns 9 and 10 show that the CAPM beta dispersion also increases by about 30% in recessions, as investment managers take different directional bets in their investment strategies. The increased dispersions in abnormal returns, alphas, and betas are all consistent with the predictions of our model.

Table 15 in Appendix C considers additional measures of portfolio dispersion and return dispersion. For example, we show that managers shift their investment styles more in recessions, consistent with them pursuing a more active portfolio management. The results are again highly significant, both economically and statistically. Investment managers also display somewhat greater sector concentration in recessions. Next, we show that the dispersion of abnormal returns (fund returns minus the market return) nearly doubles in recessions. In unreported results, we obtained similar results for the dispersion in CAPM alpha and beta when funds' alphas and betas were calculated, not by using 12-month rolling-window regressions, but by estimating their dependence on several state variables (the dividend-price ratio on the aggregate stock market, the term spread, the short-term interest rate, and the default spread) in one full-sample regression (Avramov and Wermers 2006). Finally, we study the dispersion in the information ratio, defined as the ratio of the CAPM alpha to the CAPM residual volatility. Its dispersion increases from 0.31 in expansion to 0.39 in recessions. The increase is measured precisely (t-stat of 4.7). These results further strengthen the evidence for increased dispersion in recessions.

2.5 Performance

The third main prediction of our model is that recessions are times when information is more valuable. The hypothesis is that this informational advantage translates into higher average risk-adjusted returns across funds in recessions than in booms. We evaluate this hypothesis using the following pooled (panel) regression specification:

$$Performance_t^j = c_0 + c_1 Recession_t + \mathbf{c_2 X_t^j} + \epsilon_t^j, \tag{16}$$

where $Performance_t^j$ denotes the fund j's performance in month t using previously introduced measures of abnormal fund returns, CAPM, three-factor, and four-factor alphas. *Recession* and a vector of control variables, X, are defined as before. Since all returns are expressed net of management fees, they effectively measure the return the end-investor would obtain in each state of the economy. Our coefficient of interest is c_1. Table 4 presents the results.

Column 1 shows that the fund average (net) abnormal return in excess of the market return is negative 3bp per month in expansions, but it is 34bp per month higher in recessions. The difference in returns is highly statistically significant. The impact of recessions becomes even stronger, and equal to 42bp per month, after we control for various fund characteristics, as reported in Column 2. Similar results, presented in Columns 3 and 4, obtain when we use the CAPM alpha as a measure of fund performance, with the exception that now the alpha in expansions is negative and statistically different from zero. The incremental return in recessions diminishes somewhat when we use alphas based on the three-factor and four-factor models, as evidenced in Columns 5 through 8. In particular, we obtain a 7bp higher three-factor alpha (Column 6) and a 14bp higher four-factor alpha (Column 8). Nevertheless, the level of a monthly four-factor alpha still amounts to an economically significant 1% per year risk-adjusted excess return in recessions, 1.6% higher than the -0.6% recorded in expansions. This difference is statistically significant at the 1% level of significance.

The cross-section regression model allows us to include a host of fund-specific control variables. It also makes use of rich panel data. One disadvantage of such a specification, however, is that it relies on measures of alpha that are estimated using past 12-month rolling regression windows. A potential problem with such a specification is that a given observation for the dependent variable can be classified as a recession even when only the last month of the rolling window is a recession month. It does not preclude that the remaining eleven months used in estimation could be expansions.

To verify the robustness of our results, we follow a time-series approach, which is free of this issue. As such, the time-series approach provides a cleaner estimate of the economic magnitudes we measure. In each month, we form the equally-weighted portfolio of funds and calculate its (net) return in excess of the risk-free rate. This procedure results in a time series of portfolio returns which we then use to estimate a time-series regression model of the portfolio returns on *Recession* and common risk factors. We adjust standard errors for any heteroscedasticity and autocorrelation using the procedure in Newey and West (1987). Table 5 presents the results.

In Column 1, we control for the excess market return. The intercept of the regression, equal to -6bp per month, measures the CAPM alpha in expansions. The coefficient *Recession* measures the incremental CAPM alpha in recessions, and is equal to 27bp per month. This result is equivalent to an economically large and statistically positive alpha in recessions of around 2.5% per year. In Columns 2 and 3, we include additional two and three factors. The respective three- and four-factor alphas are both estimated to be 16bp per month higher in recessions than in expansions; they are also fairly negative in expansions. As an extension of the cross-section approach, the time-series approach allows us to include an additional illiquidity factor, defined in Pástor and Stambaugh (2003). The results, in Column 4, show that fund returns do not load significantly on this factor; consequently, our previous results remain largely unchanged.

To allow for the possibility that factor loadings may vary over the business cycle, we re-estimate the regression specifications in Columns 1 through 4, allowing for interactions of the factors with *Recession*. The results, in Columns 5 through 8, show that the coefficients on the interaction terms are typically statistically insignificant, with the exception of the interaction term with the value factor. Our results are largely unaffected by the time-varying factor exposures of fund returns. If anything, the magnitudes of the incremental return in recessions become slightly stronger. As an example, in Column 8, the risk-adjusted excess return is 1.7% per year in recessions, 2.7% higher than the -1% return in expansions. This difference is statistically and economically significant. The magnitudes of the estimates in Table 5 are reassuring as they are quite consistent with our panel regression estimates in Table 4.

Table 16 in Appendix C details additional robustness checks to our performance results. In particular, we show that the average fund outperformance in recessions is even stronger when we replace the NBER recession indicator with a recession indicator which is one when real consumption growth is negative. Table 17 uses *gross* fund returns and alphas instead of returns and alphas net-of-fees. They are constructed by adding back in the management fees. Gross returns are about zero in expansions and substantially higher in recessions. All results point in the same direction: Outperformance clusters in periods of recessions. Finally, in unreported results we also study the information ratio, defined as the ratio of the CAPM alpha to the CAPM residual volatility, another often-used performance measure. The results are, if anything, stronger. The information ratio is -0.07 in expansions and increases by 0.14 (t-stat of 7.8) to 0.072. The 0.14 increase in recessions can be interpreted as a Sharpe ratio gain.

3 Using Theory and Data to Identify Skilled Managers

The previous analysis shows that the data are consistent with the three main predictions of the model. This suggests we can use it to identify skilled investment managers. In particular, we exploit the model's prediction that skilled managers allocate their attention to aggregate information in recessions and to stock-specific information in expansions. Equivalently, they display market-timing ability in recessions and stock-picking ability in expansions. We define market-timing ability as we did in the model, using the $Timing_t^j$ measure in equation (9). Likewise, the stock-picking ability is measured by $Picking_t^j$, as in equation (11). In the empirical implementation, the funds' portfolio holdings in each stock are observed at most with a quarterly frequency. We thus assume that funds follow a buy-and-hold strategy during the non-disclosure periods. Hence, in these periods, the portfolio weights w_{it}^j would only vary to the extent that market prices vary.

3.1 The Same Managers Do Switch Strategies

We first look for any empirical support for the prediction that the *same* investment managers with stock-picking ability in expansions display market-timing ability in recessions. For all expansion months, we select all fund-month observations that are in the highest 25% of the $Picking_t^j$ distribution. Then, from these observations, we form a *Switching Portfolio* of funds based on the 25% of funds with the highest *presence*, where *presence* is defined as the fraction of fund-month observations in the top, relative to the total number of observations (in expansions) for that fund. In total, 884 funds or 23 percent of funds in our universe are included in the switching portfolio. These are the funds selected by their superior stock-picking ability in expansions. Subsequently, we estimate the following pooled regression model, separately for expansions and recessions:

$$Ability_t^j = d_0 + d_1 SP_t^j + \mathbf{d_2 X_t^j} + \epsilon_t^j, \tag{17}$$

where *Ability* denotes either $Timing$ or $Picking$. SP is an indicator variable equal to one for funds included in the *Switching Portfolio*, and zero otherwise. X is a vector of previously defined control variables. Our coefficient of interest is d_1. Table 6 presents the results.

Column 3 confirms that the stock-picking ability of the funds in the SP portfolio is higher than that of the rest of funds, after controlling for fund characteristics. This is true by construction. The difference is statistically significant. The main point, however, is that this same group of managers also has a higher market-timing ability in recessions. This result is evident from Column 2. The coefficient on SP is significant at the 5% level. So, the same funds that are good at stock-picking in expansions are good at market-timing in recessions. Finally, we note that the funds in SP do not exhibit superior market-timing ability in expansions (Column 1) nor superior stock-picking ability in recessions (Column 4), which validates the label Switching Portfolio.

Having identified a subset of skilled funds based on their time-varying investment strategies, the model predicts that this group should outperform the unskilled funds not only in recessions but also in expansions. Table 7 compares the *unconditional* performance of the SP portfolio to that of all other funds. After controlling for various fund characteristics, the CAPM, three-factor, and four-factor alphas are 70-90 basis points per year higher for the SP portfolio, a difference that is statistically and economically significant.

Panel A of Table 8 further compares the characteristics of the funds in the *Switching Portfolio* to those not included in the portfolio. We note several salient differences. First, funds in SP are on average younger (by five years). Second, they have less assets under management (by $400 million), a finding potentially suggestive of decreasing returns to scale at the fund level, as in Berk and Green (2004) and Chen, Hong, Huang, and Kubik (2004). Third, they tend to charge higher expenses (by 0.26% per year), consistent with the idea of their extracting rents from customers for the skill they provide. Fourth, they exhibit much higher turnover rates of about 130% per year, as compared to 50% per year for other funds, which is consistent with them having a more active management style. Fifth, the SP funds tend to hold more concentrated portfolios, with fewer stocks and higher stock-level and industry-level Herfindahl concentration indices. Sixth, their beta deviates more from its peers suggesting a strategy with different systematic risk exposure. Finally, they rely significantly more on aggregate information. Taken together, these findings begin to paint a picture of what a typical skilled fund looks like.

To what extent can these fund characteristics explain a fund's selection to the SP portfolio? Table 18 in Appendix C reports the estimation results from the linear probability regression model of the SP indicator variable on fund age, TNA, expenses, and turnover. The R^2 of the baseline regression is 14%. Interestingly, extending the regression model with attributes that our theory connects to skilled managers, such as stock and industry concentration, beta deviation, and RAI, improves the model's fit to 19%.

Panel B of Table 8 compares the characteristics of *managers* of the funds in the SP portfolio to those of funds not included in the SP portfolio. For that reason, we link individual managers to funds they manage. We find that the managers in charge of the funds in the SP portfolio are slightly (2.6%) more likely to have an MBA; they are one year younger, and have 1.7 fewer years of experience. Finally, on average, they are substantially more likely to depart for hedge funds later in their careers. The latter may suggest that the market judges them to have superior skill.

We perform several additional robustness checks for these findings. First, we investigate a different cutoff level for the inclusion in the SP portfolio. Including more than 25% of funds in the SP portfolio considerably weakens the funds' average market-timing ability in recessions as well as their unconditional alpha, because skill dissipates with the size of the group. Conversely, including fewer than 25% of funds strengthens both results. Second, we examine funds that are among the top 25% in terms of their RSI metric in expansions. These funds have higher RAI in recessions and higher unconditional alphas (Tables 19 and 20 in Appendix C). Third, we verify our results using alternative definitions of market timing (CT) and stock picking (CS) originally proposed in Daniel, Grinblatt, Titman, and Wermers (1997). The funds that are among the 25% best in terms of their CS metric in expansions have significantly higher CT in recessions. They also have have higher unconditional alphas (Tables 21 and 22).[18] Fourth, we also perform the reverse sort. We verify that funds in the top 25% of market-timing ability in recessions, have statistically higher stock-picking ability, $Picking$, in expansions (Table 23) and higher unconditional alphas (Table 24). In sum, the existence of a group of skilled mutual funds who switch in terms of their learning and investment strategies between recessions and expansions is not very sensitive to the exact

[18] Additional, unreported results, show the same results for fund and manager characteristics as those in Table 8, but using the SP_3 variable instead. Fund age, size, expenses, and turnover explain 8% of the selection into the SP_3 portfolio. Adding stock concentration, beta deviation, and RAI improves that R^2 to 18%.

specification.

3.2 Creating a Skill Index

We now consider a more practical implication of our model. We examine whether it is possible to identify skilled investment managers without the benefit of looking at the full sample of the data. To this end, we construct a *Skill Index* that is informed by the main predictions of our model that attention allocation and investment strategies change over the business cycle. We define the Skill Index as a weighted average of *Timing* and *Picking* measures, where the weights we place on each measure depend on the state of the business cycle:

$$Skill\,Index\,1_t^j(z) = w(z_t)Timing_t^j + (1 - w(z_t))Picking_t^j, \text{ with } z_t \in \{E, R\}.$$

We standardize the *Timing* and *Picking* measures by demeaning them and dividing them by their respective standard deviation. In the implementation, we assume that $w(R) = 0.8 > w(E) = 0.2$, but the exact number is not important.

Subsequently, we examine whether such an index can predict future fund performance, measured by CAPM, three-factor, and four-factor alphas. In our model, the holdings information that enters the construction of *Timing* and *Picking* is dated t, which then implies that the alphas in Table 9 are dated $t + 2$. The table shows that funds with a higher skill index have on average higher alphas. For example, when *Skill Index* is at its mean of zero, the alpha is negative at around -4bp per month. However, when the index is one standard deviation (0.83%) above its mean, the alpha is between 1.1% (four-factor) and 2.4% (CAPM) higher per year. The three most columns show similar predictive power of the *Skill Index* for one-year ahead alphas.

In table 25 in Appendix C we construct an alternative skill index based on the relative importance of *RAI* and *RSI* measures. The effects of the resulting *Skill Index* 2 on alphas are a bit weaker. Nevertheless, one-month ahead alphas are still between 0.3 and 0.5% per year higher for a one-standard-deviation increase in this skill index, a statistically significant effect.

4 Alternative Explanations

We briefly discuss two other candidate explanations for our findings, but conclude that none of them can account for the full set of facts we find in the data.

The first, and most obvious alternative, is that there is no skill whatsoever. In that case all the recession effects in the properties of mutual fund returns we find would have to follow mechanically from the underlying properties in asset returns themselves. This turns out not to be the case. We use individual stock returns and calculate means, volatilities, alphas, betas, idiosyncratic volatility, in the same way as we do for mutual fund returns. None of the moments of stock returns differ between expansions and recessions (other than higher volatility of asset returns in recessions, our key driving force). Using a simulation, we also verify that a mechanical mutual fund investment policy that randomly selects 50, 75, or 100 stocks cannot produce the differences in fund returns we observe between expansions and recessions.

Second, we consider a couple of labor market-related explanations. The data show that outside labor market options of investment managers deteriorate in recessions. Not only do their assets under management and therefore their wages shrink, they are also more likely to get fired or demoted. Table 26 in Appendix C shows that there is less turnover in the labor market for investment managers in recessions (columns 1 and 2), there is a smaller incidence of promotion to a larger mutual fund in a different fund family (columns 3 and 4), a higher incidence of demotion to a smaller mutual fund in a different fund family (columns 5 and 6), and a lower incidence of departure to a hedge fund (columns 7 and 8). One might then conclude that the change in managers' outside options over the business cycle could be an alternative explanation of our results. We argue that this is not the case.

In a model with risk-averse investment managers, like ours, the greater chance of them getting fired or demoted and the smaller chance of them being promoted or being picked off by a hedge fund in recessions will make their investment choices more conservative. After all, a strategy that is too concentrated or that deviates too much from that of its peers has a much higher chance of underperforming in relative terms than does a more diversified strategy. To see this, imagine that a manager implements a small deviation from the strategy of all other managers; then she has an approximately 50% chance of underperforming. If less than 50% of managers are fired, following peers is better. The opposite is true in expansions: There is a lot of upside and little downside, giving managers incentives to gamble. Likewise, they have more incentives in booms to deviate from the pack in an attempt to get picked off by a hedge fund. In other words, the labor market explanation generates the opposite pattern in dispersion from our model and from what we find in the data. While labor market considerations may be important to understand the behavior of mutual fund managers, the above argument suggests that the differences in incentives between booms and recessions may be too small to account for the patterns we document.

Another labor market-based alternative explanation could be that the quality of fund managers improves during recessions because better fund managers survive (or self-select) into the mutual fund industry in such periods. We find no evidence for such an effect in the data. Table 27 in Appendix B shows no difference between the age, educational background or experience of our managers in recessions versus in expansions.

5 Conclusion

Do investment managers add value for their clients? The answer to this question matters for problems ranging from the discussion on market efficiency to a practical portfolio advice for households. The large amount of randomness in financial asset returns makes it a difficult question to answer. The multi-billion investment management business is first and foremost an information-processing business. We model investment managers not only as agents making optimal portfolio decisions, but also as ones who optimally allocate a limited amount of attention or information-processing capacity. Since the optimal attention allocation varies with the state of the economy, so do investment strategies and fund returns. As long as a subset of investment managers is skilled (can process information about future asset payoffs), the model predicts a higher correlation of portfolio holdings with aggregate information, more dispersion in returns across funds, and a higher average outperformance in recessions than in expansions. We find exactly these patterns in observed investment strategies and portfolio returns of actively managed U.S. mutual funds. Hence, the data are consistent with a world in which some investment managers have skill, but also one in which that skill is hard to detect, on average. Recessions are times when information choices lead to investment choice that are more revealing of skill.

The world of actively managed mutual funds provides a rich laboratory to study the link between information and investment choices. But, in a knowledge economy like ours, investment managers are hardly the only agents in the business of acquiring and processing information. The increasing volume of information has made the problem of how to best allocate a limited amount of information-processing capacity, if anything, more relevant. While information choices have consequences for real outcomes, they are poorly understood.

By predicting how information choices are linked to observables (such as the state of the economy) and by tying information choices to real outcomes (such as portfolio investment), models of information choices can be brought to the data. We expect that this recipe will be useful in other applications.

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A Proofs of Propositions

A.1 Mathematical Preliminaries

Expressing matrices in terms of fundamental variances In order to determine the effect of changes in aggregate shock variance on dispersion and profits, we need to express some of the matrices in terms of σ_a^{-1}. If we can decompose the matrices into components that depend on σ_a and those that do not, we can differentiate the expressions more easily.

First, we decompose the payoff precision matrices. To do this decomposition, we need to invert Σ. Doing it by hand yields

$$\Sigma^{-1} = \begin{bmatrix} \sigma_1^{-1} & 0 & \frac{-b_1}{b_3}\sigma_1^{-1} \\ 0 & \sigma_2^{-1} & \frac{-b_2}{b_3}\sigma_2^{-1} \\ \frac{-b_1}{b_3}\sigma_1^{-1} & \frac{-b_2}{b_3}\sigma_2^{-1} & \frac{1}{b_3^2}(\sigma_a^{-1} + b_1^2\sigma_1^{-1} + b_2^2\sigma_2^{-1}) \end{bmatrix}.$$

Similarly, the posterior precision matrix for an agent j that learns only about aggregate risk is

$$\hat{\Sigma}_j^{-1} = \begin{bmatrix} \sigma_1^{-1} & 0 & \frac{-b_1}{b_3}\sigma_1^{-1} \\ 0 & \sigma_2^{-1} & \frac{-b_2}{b_3}\sigma_2^{-1} \\ \frac{-b_1}{b_3}\sigma_1^{-1} & \frac{-b_2}{b_3}\sigma_2^{-1} & \frac{1}{b_3^2}(\sigma_a^{-1} + K + b_1^2\sigma_1^{-1} + b_2^2\sigma_2^{-1}) \end{bmatrix}$$

It is useful to separate out the terms that depend on σ_a from those that do not. Define

$$S \equiv \begin{bmatrix} \sigma_1^{-1} & 0 & \frac{-b_1}{b_3}\sigma_1^{-1} \\ 0 & \sigma_2^{-1} & \frac{-b_2}{b_3}\sigma_2^{-1} \\ \frac{-b_1}{b_3}\sigma_1^{-1} & \frac{-b_2}{b_3}\sigma_2^{-1} & \frac{1}{b_3^2}(b_1^2\sigma_1^{-1} + b_2^2\sigma_2^{-1}) \end{bmatrix}$$

and

$$\tilde{B} \equiv \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \frac{1}{b_3^2} \end{bmatrix}.$$

Then,

$$\Sigma^{-1} = S + \sigma_a^{-1}\tilde{B} \tag{18}$$

$$\hat{\Sigma}_j^{-1} = S + (\sigma_a^{-1} + K)\tilde{B} \tag{19}$$

The average precision matrix when a fraction χ of investment managers have capacity is

$$(\hat{\Sigma}^a)^{-1} = \chi\hat{\Sigma}_j^{-1} + (1-\chi)\Sigma^{-1}.$$

Thus,

$$(\hat{\Sigma}^a)^{-1} = S + (\sigma_a^{-1} + \chi K)\tilde{B}. \tag{20}$$

An expression that recurs frequently below is the difference between the precision of an informed manager's posterior beliefs and the precision of the average manager's posterior beliefs. This difference becomes

$$\Sigma^{-1} - (\hat{\Sigma}^a)^{-1} = (1-\chi)K\tilde{B}. \tag{21}$$

Second, we decompose the variance matrices. In particular, we need to know average variance, which requires inverting $(\hat{\Sigma}^a)^{-1}$. Replacing σ_a with $(\sigma_a^{-1} + \chi K)^{-1}$, and following the same inversion steps backwards, we get

$$\hat{\Sigma}^a = (\sigma_a^{-1} + \chi K)^{-1} bb' + \Phi, \tag{22}$$

where

$$\Phi \equiv \begin{bmatrix} \sigma_1^{-1} & 0 & 0 \\ 0 & \sigma_2^{-1} & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

and b is the 3×1 vector of loadings of each asset on aggregate risk. This also implies that $\hat{\Sigma}^a = \Sigma - \chi K \sigma_a (\sigma_a^{-1} + \chi K)^{-1} bb'$. Finally, let $\tilde{\sigma}_a \equiv (\sigma_a^{-1} + \chi K)^{-1}$.

Portfolio holdings The optimal portfolio for investor j is

$$q_j = \frac{1}{\rho} \hat{\Sigma}_j^{-1} (\hat{\mu}_j - pr). \tag{23}$$

This comes from the first order condition and is a standard expression in any portfolio problem with CARA or mean-variance utility.

Next, compute the portfolio of the average investor. Let the average of all investors' signal precision be $(\hat{\Sigma}^a)^{-1} \equiv \int \hat{\Sigma}_j^{-1} dj$. Use the fact that $\hat{\mu}_j = \hat{\Sigma}_j \Sigma^{-1} \mu + (I - \hat{\Sigma}_j \Sigma^{-1}) \eta_j$ and the fact that the signal noise is mean-zero to get that $\int \hat{\Sigma}_j^{-1} \hat{\mu}_j dj = \Sigma^{-1} \mu + ((\hat{\Sigma}^a)^{-1} - \Sigma^{-1}) f$. This is true because the mean of all investors' signals are the true payoffs f and because the signal errors are uncorrelated with (but of course, not independent of) signal precision.

$$\bar{q} \equiv \int q_j dj = \frac{1}{\rho} \left(\Sigma^{-1} \mu + ((\hat{\Sigma}^a)^{-1} - \Sigma^{-1}) f - (\hat{\Sigma}^a)^{-1} pr \right). \tag{24}$$

Using Bayes' rule for the posterior variance of normal variables, we can rewrite this as

$$\bar{q} \equiv \int q_j dj = \frac{1}{\rho} \left(\Sigma^{-1} \mu + (\Sigma_\eta^a)^{-1} f - (\hat{\Sigma}^a)^{-1} pr \right). \tag{25}$$

A.2 Proof of Proposition 1

Proof. Following Admati (1985), we conjecture that the price vector p is linear in the payoff vector f and the supply vector x: $pr = A + Bf + Cx$. We now verify that conjecture by imposing market clearing

$$\int q_j dj = \bar{x} + x. \tag{26}$$

Using (24) to substitute out the left hand side, and rearranging,

$$pr = -\rho\hat{\Sigma}^a(\bar{x}+x) + f + \hat{\Sigma}^a\Sigma^{-1}(\mu - f).$$

Thus, the coefficients A, B, and C are given by

$$A = -\rho\hat{\Sigma}^a\bar{x} + \hat{\Sigma}^a\Sigma^{-1}\mu \tag{27}$$

$$B = I - \hat{\Sigma}^a\Sigma^{-1} \tag{28}$$

$$C = -\rho\hat{\Sigma}^a, \tag{29}$$

which verifies our conjecture. □

A.3 Proof of Proposition 2

If capacity is not too high ($K_j \leq \sigma_a^{-1}$), the marginal value of additional capacity K devoted to learning about the aggregate shock is increasing in the aggregate shock variance: $\partial^2 U/\partial K\partial\sigma_a > 0$.

Proof. From the main text (7), we know that expected utility is

$$U_{1j} = \frac{1}{2}trace(\hat{\Sigma}_j^{-1}V_1[\hat{\mu}_j - pr]) + \frac{1}{2}E_1[\hat{\mu}_j - pr]'\hat{\Sigma}_j^{-1}E_1[\hat{\mu}_j - pr].$$

The first step is to work out the variance $V_1[\hat{\mu}_j - pr]$.

$$\hat{\mu}_j - pr = \hat{\Sigma}_j(\Sigma^{-1}\mu + \Sigma_{\eta j}^{-1}\eta_j) - A - Bf - Cx$$

The signal η can be expressed as the true asset payoff f, plus orthogonal signal noise ϵ_j.

$$\hat{\mu}_j - pr = \hat{\Sigma}_j\Sigma^{-1}\mu - A + (\hat{\Sigma}_j\Sigma_{\eta j}^{-1} - B)f + \hat{\Sigma}_j\Sigma_{\eta j}^{-1}\epsilon_j - Cx.$$

Since μ and A are known constants and f, ϵ_j and x are independent, with variances Σ, $\Sigma_{\eta j}$ and σ_x respectively,

$$V_1[\hat{\mu}_j - pr] = (\hat{\Sigma}_j\Sigma_{\eta j}^{-1} - B)\Sigma(\hat{\Sigma}_j\Sigma_{\eta j}^{-1} - B)' + \hat{\Sigma}_j\Sigma_{\eta j}^{-1}\hat{\Sigma}_j + CC'\sigma_x.$$

Substituting in for the price coefficients using (27), (28) and (29) yields

$$V_1[\hat{\mu}_j - pr] = (\hat{\Sigma}^a - \hat{\Sigma}_j)\Sigma^{-1}(\hat{\Sigma}^a - \hat{\Sigma}_j)' + \hat{\Sigma}_j\Sigma_\eta^{-1}\hat{\Sigma}_j + \rho^2\hat{\Sigma}^a\hat{\Sigma}^a\sigma_x.$$

Next, work out the second term by using the expression above for $\hat{\mu}_j - pr$ and taking the expectation: $E[\hat{\mu}_j - pr] = \hat{\Sigma}_j\Sigma^{-1}\mu - A + (\hat{\Sigma}_j\Sigma_{\eta j}^{-1} - B)\mu$. Substituting in the coefficients A and B and simplifying reveals that $E[\hat{\mu}_j - pr] = \rho\hat{\Sigma}^a\bar{x}$. Thus,

$$E_1[\hat{\mu}_j - pr]'\hat{\Sigma}_j^{-1}E_1[\hat{\mu}_j - pr] = \rho^2\bar{x}'\hat{\Sigma}^a\hat{\Sigma}_j^{-1}\hat{\Sigma}^a\bar{x}$$

Thus, expected utility is

$$U_{1j} = \frac{1}{2} trace\left(\hat{\Sigma}_j^{-1}(\hat{\Sigma}^a - \hat{\Sigma}_j)\Sigma^{-1}(\hat{\Sigma}^a - \hat{\Sigma}_j)' + \Sigma_{\eta j}^{-1}\hat{\Sigma}_j + \rho^2\hat{\Sigma}_j^{-1}\hat{\Sigma}^a\hat{\Sigma}^a\sigma_x\right) + \frac{\rho^2}{2}\bar{x}'\hat{\Sigma}^a\hat{\Sigma}_j^{-1}\hat{\Sigma}^a\bar{x}.$$

In the next step, we want to take a cross-partial derivative of utility with respect to σ_a and capacity for a given investor j. To do this, substitute out the $\hat{\Sigma}_j^{-1}$ terms using (19), (18) and (20), which tell us that $\hat{\Sigma}_j^{-1} = \Sigma^{-1} + K_j\tilde{B}$ and $\Sigma_{\eta j}^{-1} = K_j\tilde{B}$, where K_j is the capacity investor j devotes to learning about the aggregate shock. Also, substitute out $\hat{\Sigma}^a - \hat{\Sigma}_j = ((\sigma_a^{-1} + \chi K)^{-1} - (\sigma_a^{-1} + K_j)^{-1})bb'$ to get

$$U_{1j} = \frac{1}{2} Tr\left(\left(\frac{1}{\sigma_a^{-1} + \chi K} - \frac{1}{\sigma_a^{-1} + K_j}\right)^2 (\Sigma^{-1} + K_j\tilde{B})bb'\Sigma^{-1}bb' + K_j\tilde{B}((\sigma_a^{-1} + K_j)^{-1}bb' + \Phi)\right.$$

$$\left. +\rho^2\sigma_x(\Sigma^{-1} + K_j\tilde{B})\hat{\Sigma}^a\hat{\Sigma}^a\right) + \frac{\rho^2}{2}\bar{x}'\hat{\Sigma}^a(\Sigma^{-1} + K_j\tilde{B})\hat{\Sigma}^a\bar{x}.$$

Since $\hat{\Sigma}^a$ and $\tilde{B}$ are positive semi-definite matrices, the last term is linearly increasing in K_j, with derivative $\rho^2/2\bar{x}'\hat{\Sigma}^a\tilde{B}\hat{\Sigma}^a\bar{x}$. Since $\hat{\Sigma}^a$ has every entry increasing in σ_a (equation 22), this term has a positive cross-partial derivative $\partial^2/\partial K_j\partial\sigma_a$.

Thus, a sufficient condition for $\partial^2 U/\partial K_j\partial\sigma_a > 0$ is for the trace term to have a positive cross-partial. We can break the trace term up into 6 additive trace terms.

$$Tr(\cdot) = \left(\frac{1}{\sigma_a^{-1} + \chi K} - \frac{1}{\sigma_a^{-1} + K_j}\right)^2 Tr(\Sigma^{-1}bb'\Sigma^{-1}bb') + \left(\frac{1}{\sigma_a^{-1} + \chi K} - \frac{1}{\sigma_a^{-1} + K_j}\right)^2 K_j Tr(\tilde{B}bb'\Sigma^{-1}bb')$$

$$+\frac{K_j}{\sigma_a^{-1} + K_j} Tr(\tilde{B}bb') + K_j Tr(\tilde{B}\Phi) + \rho^2\sigma_x Tr(\Sigma^{-1}\hat{\Sigma}^a\hat{\Sigma}^a) + K_j\rho^2\sigma_x Tr(\tilde{B}\hat{\Sigma}^a\hat{\Sigma}^a)$$

Differentiating the squared scalar term in front reveals that

$$\frac{\partial^2}{\partial K_j\partial\sigma_a}\left(\frac{1}{\sigma_a^{-1} + \chi K} - \frac{1}{\sigma_a^{-1} + K_j}\right)^2 > 0$$

Since the first trace term does not contain K_j, but is positive because it contains a product of positive definite matrices, the first term has a positive cross-partial.

To sign the cross-partial derivative of the second term, let $g \equiv 1/(\sigma_a^{-1} + \chi K)$ and let $h = 1/(\sigma_a^{-1} + K_j)$. Then, the second term becomes $(g-h)^2 K_j$, times a positive constant. The derivative with respect to K_j is $2(g-h)h^2K_j + (g-h)^2$. Taking a derivative again, this time with respect to the precision σ_a^{-1} delivers $-4h^3(g-h) - 2h^2(g^2-h^2)K_j - 2(g-h)(g^2-h^2)$. Every term in this expression is negative, meaning that $\partial^2/\partial K_j\partial\sigma_a^{-1} < 0$. Since the cross-partial for the precision σ_a^{-1} is negative, the chain rule tells us that the cross partial for the variance is positive: $\partial^2/\partial K_j\partial\sigma_a > 0$.

The third term is a positive trace term of constants, times $K_j/(\sigma_a^{-1} + K_j)$. The derivative with respect to K_j is $\sigma_a^{-1}/(\sigma_a^{-1} + K_j)^2$ and the cross partial $\partial^2/\partial K_j\partial\sigma_a^{-1}$ is $(K_j - \sigma_a^{-1})/(\sigma_a^{-1} + K_j)^3$. This is negative when $K_j < \sigma_a^{-1}$, which makes $\partial^2/\partial K_j\partial\sigma_a > 0$.

The fourth and fifth terms have zero cross-partials. The fourth term does not depend on σ_a and the fifth term does not depend on K_j.

Finally, the partial derivative of the sixth term with respect to K_j is $\rho^2\sigma_x Tr(\tilde{B}\hat{\Sigma}^a\hat{\Sigma}^a)$. Using (22), and multiplying out $\hat{\Sigma}^a\hat{\Sigma}^a$ reveals that all the diagonal entries of $\hat{\Sigma}^a\hat{\Sigma}^a$ are increasing in σ_a.

In sum, when $K_j < \sigma_a^{-1}$, all six trace terms have non-negative cross-partial derivatives and therefore $\partial^2 U/\partial K_j \partial\sigma_a > 0 > 0$.

□

A.4 Proof of Proposition 3

If some managers are uninformed $\chi < 1$, but all informed managers learn about aggregate risk, and the average manager has sufficiently low capacity $\chi K < \sigma_a^{-1}$, then an increase in aggregate risk σ_a increases the dispersion of fund profits $E[((q_j - \bar{q})'(f - pr))^2]$, where $\bar{q} \equiv \int q_j dj$.

Proof. Define expected excess profits for trader j to be $E[(q_j - x - \bar{x})'(f - pr)]$, where the expectation is conditioned on prior information (time-0 expectation). Using the optimal portfolio expressions, (23) and (25), and Bayes' rule ($\hat{\mu}_j = \hat{\Sigma}_j(\Sigma^{-1}\mu + \Sigma_\eta^{-1}\eta_j)$), this is

$$(q_j - \bar{q})'(f - pr) = \frac{1}{\rho}\left[\Sigma_\eta^{-1}\eta_j - (\Sigma_\eta^a)^{-1}f + ((\hat{\Sigma}^a)^{-1} - \hat{\Sigma}_j^{-1})pr\right]'(f - pr),$$

where $(\Sigma_\eta^a)^{-1} \equiv \int \Sigma_{\eta,j}^{-1} dj$ is the average manager's signal precision.

Next, we need to take into account that signals and payoffs are correlated. To do this, replace the signal η_j with the true payoff, plus signal noise: $\eta_j = f + e_j$,

$$(q_j - \bar{q})'(f - pr) = \frac{1}{\rho}\left[\Sigma_\eta^{-1}e_j + (\Sigma_\eta^{-1} - (\Sigma_\eta^a)^{-1})f + ((\hat{\Sigma}^a)^{-1} - \hat{\Sigma}_j^{-1})pr\right]'(f - pr).$$

Bayes' rule for variances of normal variables is $\hat{\Sigma}_j^{-1} = \Sigma^{-1} + \Sigma_\eta^{-1}$. Integrating the left and right sides of this expression yields $(\hat{\Sigma}^a)^{-1} = \Sigma^{-1} + (\Sigma_\eta^a)^{-1}$. Subtracting one expression from the other yields $\hat{\Sigma}_j^{-1} - (\hat{\Sigma}^a)^{-1} = \Sigma_\eta^{-1} - (\Sigma_\eta^a)^{-1}$. Furthermore, equation (21) tells us that both of these quantities are equal to $(1-\chi)K\tilde{B}$. Substituting this in and combining terms yields

$$(q_j - \bar{q})'(f - pr) = \frac{1}{\rho}\left[\Sigma_\eta^{-1}e_j + (1-\chi)K\tilde{B}(f - pr)\right]'(f - pr). \tag{30}$$

Now replace pr with $A + Bf + Cx$, where A, B and C are given by appendix A.2,

$$(q_j - \bar{q})'(f - pr) = \frac{1}{\rho}\left[\Sigma_\eta^{-1}e_j + (1-\chi)K\tilde{B}((I - B)f - A - Cx)\right]'((I - B)f - A - Cx). \tag{31}$$

This is fund j's realized profit, in excess of the average fund's profit.

To work out the expectation of this quantity squared, it is helpful to define some new notation and to transform the random variables into standard normal variables. First, collect the constants,

$$D \equiv (I - B)\mu - A = \rho\hat{\Sigma}^a\bar{x}$$

where the second equality comes from substituting in B and A from the pricing equation.

Next, collect the normal variables that appear squared. These are $(I-B)(f-\mu)-Cx$. If z is a standard multi-variate normal, then this is equal to $G^{1/2}x$, where

$$G \equiv (I-B)'\Sigma(I-B) + \sigma_x C'C = \hat{\Sigma}^a \Sigma^{-1} \hat{\Sigma}^a + \rho^s \sigma_x \hat{\Sigma}^a \hat{\Sigma}^a.$$

Again, the second equality comes from substituting in the pricing coefficients.

Now, If y and z are independent standard normal variables, we can write profit dispersion as

$$\rho(q_j - x - \bar{x})'(f - pr) = [\Sigma_\eta^{-1/2} y + (1-\chi K)\tilde{B}(D + G^{1/2}z)]'(D + G^{1/2}z)$$

$$= (1-\chi K)D'\tilde{B}D + 2(1-\chi K)D'\tilde{B}G^{1/2}z + D'\Sigma_\eta^{-1/2}y + y'\Sigma_\eta^{-1/2}G^{1/2}z + (1-\chi K)z'G\tilde{B}z$$

Next, square the whole expression, and take the expectation, canceling out all the cross-terms that have products of independent random variables.

$$\rho^2 E[((q_j - x - \bar{x})'(f - pr))^2] = (1-\chi K)^2 (D'\tilde{B}D)^2 + 4(1-\chi K)^2 D'\tilde{B}G\tilde{B}D + D'\Sigma_\eta^{-1}D$$

$$+ Tr(\Sigma_\eta^{-1}G) + 2(1-\chi K)^2 D'\tilde{B}DTr(G\tilde{B}) + (1-\chi K)^2 E[z'G\tilde{B}zz'G\tilde{B}z]$$

Evaluate this term-by-term. Here, we exploit the fact that $\tilde{B}$ is all zeros, except for the (3,3) entry. This reflects the fact that when all informed managers learn only about aggregate shocks, the posterior precision matrix of an informed manager and of the average manager differ only in their (3,3) entry. Let D_3 denote the 3rd entry of the vector D and let $G_{i,j}$ be the (i,j) entry of the matrix G.

The first term is a constant times $(D'\tilde{B}D)^2$. Substituting in the definition of D and of $\tilde{B}$, $D'\tilde{B}D$ is a constant times the third element of the vector $\hat{\Sigma}^a \bar{x}$, squared. Therefore,

$$(D'\tilde{B}D)^2 = \rho^4 \frac{1}{b_3^4} (\bar{x}_1 \hat{\Sigma}^a_{1,3} + \bar{x}_2 \hat{\Sigma}^a_{2,3} + \bar{x}_3 \hat{\Sigma}^a_{3,3})^4.$$

The second term is a constant times

$$D'\tilde{B}G\tilde{B}D = \frac{1}{b_3^4} G_{3,3} D_3^2$$

Bayes' rule tells us that $\Sigma_\eta^{-1} = \hat{\Sigma}_j^{-1} - \Sigma^{-1}$. Substituting in (19) and (18), delivers $\Sigma_\eta^{-1} = K\tilde{B}$. Therefore, the third and fourth terms can be expressed as

$$D'\Sigma_\eta^{-1}D + Tr(\Sigma_\eta^{-1}G) = KD'\tilde{B}D + Tr(K\tilde{B}G)$$

$$= K\frac{1}{b_3^2}(D_3^2 + G_{3,3})$$

The second-to-last term is a constant times

$$D'\tilde{B}DTr(G\tilde{B}) = \frac{1}{b_3^4} D_3^2 G_{3,3}$$

The last term is the expectation of a squared chi-square. To work out its value, write it out as a sum, squared $z'Gz = \sum_i \sum_j G_{ij} z_i z_j$. If you square this double sum, all the products of z's to the odd powers will drop out. $z^2 = 1$, because it is a standard normal variable, while $z^4 = 3$ (kurtosis of a standard normal). This leaves all the terms $\sum_i \sum_j (G_{ij} z_i z_j)^2$, plus all the combinations of diagonal elements multiplied by each other $\sum_i \sum_j G_{ii} G_{jj}$. Rewriting this in matrix notation, it is [19] $2n + n^2$.

$$E[z'Gzz'Gz] = Tr(G'G) + Tr(G)^2.$$

Since there is also a $\tilde{B}$ matrix in the middle, applying the same formula yields

$$E[z'G\tilde{B}zz'G\tilde{B}z] = Tr(G\tilde{B}\tilde{B}G) + Tr(G\tilde{B})^2.$$

$$= \frac{1}{b_3^4}(G_{1,3}^2 + G_{2,3}^2 + G_{3,3}^2) + \frac{1}{b_3^2} G_{3,3}^2$$

Combining terms, and using the assumption that $b_3 = 1$, we get

$$\rho^2 E[((q_j - x - \bar{x})'(f - pr))^2] = K(D_3^2 + G_{3,3}) + (1 - \chi K)[D_3^4 + 4G_{3,3}D_3^2 + 2G_{3,3}D_3^2 + G_{1,3}^2 + G_{2,3}^2 + 2G_{3,3}^2]$$

where $D_3 = (\bar{x}_1 \hat{\Sigma}_{1,3}^a + \bar{x}_2 \hat{\Sigma}_{2,3}^a + \bar{x}_3 \hat{\Sigma}_{3,3}^a)$ and $G = \hat{\Sigma}^a (\Sigma^{-1} + \rho^2 \sigma_x I) \hat{\Sigma}^a$.

Can I show that D_3, $G_{1,3}$, $G_{2,3}$ and $G_{3,3}$ are all increasing in σ_a? Yes. Start with D_3.

$$D_3 = \sum_{i=1}^{3} \bar{x}_i \hat{\Sigma}_{i,3}^a.$$

Recall that $\hat{\Sigma}^a = (\sigma_a^{-1} + \chi K)^{-1} bb' + \Phi$, where Φ is all zeros in the 3rd row and column. Therefore,

$$D_3 = \frac{1}{\sigma_a^{-1} + \chi K} \sum_{i=1}^{3} \bar{x}_i b_i b_3.$$

For b_1, b_2, $b_3 > 0$, this is decreasing in σ_a^{-1} and therefore increasing in σ_a.

Next, show that $G_{1,3}$, $G_{2,3}$ and $G_{3,3}$ are increasing in σ_a. Recall that $G = \hat{\Sigma}^a(\Sigma^{-1} + \rho^2 \sigma_x I)\hat{\Sigma}^a$. Note that for b_1, b_2, $b_3 > 0$, every element of $\hat{\Sigma}^a$ is increasing in σ_a. Therefore, the second term $\rho^2 \sigma_x \hat{\Sigma}^a \hat{\Sigma}^a$ is increasing in σ_a. The first term can be written as

$$\hat{\Sigma}^a \Sigma^{-1} \hat{\Sigma}^a = \hat{\Sigma}^a \left(S + \sigma_a^{-1} \tilde{B} \right) \hat{\Sigma}^a.$$

$$= \hat{\Sigma}^a S \hat{\Sigma}^a + \sigma_a^{-1} \hat{\Sigma}^a \tilde{B} \hat{\Sigma}^a.$$

Since $\tilde{B}$ is only non-zero in its (3,3) entry, the second term will take the form $\sigma_a^{-1}/b_3^2 \sum_i (\hat{\Sigma}_{i,3}^a)^2$. This only depends on the $\hat{\Sigma}^a$ entries in the 3rd column. Recall that $\hat{\Sigma}^a = (\sigma_a^{-1} + \chi K)^{-1} bb' + \Phi$, where Φ is all zeros in

[19] I verified this in two ways. First, I worked out an example with a 2x2 matrix. Second, I know that if $G = I$, this is the squared mean plus variance of a standard chi-square. That has known value

the 3rd row and column. Therefore, $\hat{\Sigma}^a \tilde{B} \hat{\Sigma}^a = (\sigma_a^{-1} + \chi K)^{-2} bb' \tilde{B} bb' / b_3^2$. Substituting this back in, we get

$$\hat{\Sigma}^a \Sigma^{-1} \hat{\Sigma}^a = \hat{\Sigma}^a S \hat{\Sigma}^a + \frac{1}{b_3^2} \frac{\sigma_a^{-1}}{(\sigma_a^{-1} + \chi K)^2} bb' \tilde{B} bb'$$

Since S has no σ_a terms in it, we know that the first term is increasing in σ_a. Likewise, $bb'\tilde{B}bb'$ does not depend on σ_a. Note that $\sigma_a^{-1}/(\sigma_a^{-1} + \chi K)^2$ is decreasing in σ_a^{-1} if $\sigma_a^{-1} > \chi K$. This is a sufficient condition (but not a necessary one) to make the whole expression decreasing in σ_a^{-1} and therefore increasing in σ_a. The interpretation of this sufficient condition is that the average agent must not have enough capacity to double the precision of his information about the aggregate risk.

□

A.5 Proof of Proposition 4

If some managers are uninformed $\chi < 1$, but all informed managers learn about aggregate risk, and the average manager has sufficiently low capacity $\chi K < \sigma_a^{-1}$, then an increase in aggregate risk σ_a increases the expected profit of an informed fund, $E[(q_j - \bar{q})'(f - pr)]$, where $\bar{q} \equiv \int q_j dj$.

Proof. Assume that all informed investors use all their capacity K to learn about the aggregate risk. We show that when σ_a^{-1} falls (in recessions), that expected excess returns of the informed traders rises.

Begin by take the expectation of (31) to get expected profits. Since the supply shocks and the signal noise are mean-zero and independent of all other shocks, we can take their expectations separately. Using the formula for the expectation of a chi-square variable,

$$E[(q_j - \bar{q})'(f - pr)] = \frac{-\sigma_x}{\rho} Tr[C'(1-\chi)K\tilde{B}C] + \frac{(1-\chi)K}{\rho} E\left\{((I-B)f - A)'\tilde{B}'((I-B)f - A)\right\}. \quad (32)$$

Since $((I - B)f - A)$ is normally distributed, the remaining expectation is also the mean of a chi square

$$\begin{aligned} E[(q_j - x - \bar{x})'(f - pr)] &= \frac{\sigma_x(1-\chi)K}{\rho} Tr[C'\tilde{B}C] + \frac{(1-\chi)K}{\rho}((I-B)\mu - A)'\tilde{B}((I-B)\mu - A) \\ &+ \frac{(1-\chi)K}{\rho} Tr[(I-B)'\tilde{B}\Sigma(I-B)]. \end{aligned}$$

Finally, substitute in for A, B and C from (27), (28) and (29).

$$E[(q_j - x - \bar{x})'(f - pr)] = (1-\chi)K \left\{ \sigma_x \rho Tr[\hat{\Sigma}^a \tilde{B} \hat{\Sigma}^a] + \rho \bar{x}' \hat{\Sigma}^a \tilde{B} \hat{\Sigma}^a \bar{x} + \frac{1}{\rho} Tr[\hat{\Sigma}^a \Sigma^{-1} \tilde{B} \hat{\Sigma}^a] \right\}.$$

$\hat{\Sigma}^a$ is equal to $1/(\sigma_a^{-1} + \chi K)bb'$ in its 3rd column and 3rd row entries, which are the only entries that the $\tilde{B}$ matrix does not zero out. Therefore, $\hat{\Sigma}^a \tilde{B} \hat{\Sigma}^a = (1/(\sigma_a^{-1} + \chi K))^2 bb'\tilde{B}bb'$, and

$$E[(q_j - x - \bar{x})'(f - pr)] = (1-\chi)K \left\{ \frac{\sigma_x \rho}{(\sigma_a^{-1} + \chi K)^2} Tr[bb'\tilde{B}bb'] + \frac{\rho}{(\sigma_a^{-1} + \chi K)^2} \bar{x}' bb' \tilde{B} bb' \bar{x} + \frac{1}{\rho} Tr[\hat{\Sigma}^a \Sigma^{-1} \tilde{B} \hat{\Sigma}^a] \right\}.$$

Since $bb'\tilde{B}bb'$ does not depend on σ_a, but is positive semi-definite, and $(1/(\sigma_a^{-1} + \chi K))^2$ in increasing in σ_a, the first two terms are increasing in σ_a.

The last term can be rewritten using the relationship that $\Sigma^{-1} = S + \sigma_a^{-1}\tilde{B}$.

$$Tr[\hat{\Sigma}^a \Sigma^{-1} \tilde{B} \hat{\Sigma}^a] = Tr[\hat{\Sigma}^a S \tilde{B} \hat{\Sigma}^a] + \sigma_a^{-1} Tr[\hat{\Sigma}^a \tilde{B} \tilde{B} \hat{\Sigma}^a].$$

Note that $\hat{\Sigma}^a$ and S are both positive definite matrices and therefore have positive eigenvalues. Even $\tilde{B}$ has non-negative eigenvalues. Since the trace is the sum of the eigenvalues and sums and products of non-negative eigenvalues are non-negative, the first term is positive. Furthermore, $\hat{\Sigma}^a$ has every entry increasing in σ_a. Therefore, the first trace term is increasing in σ_a.

In the second trace term, the matrix $\tilde{B}\tilde{B} = 1/b_3^2 \tilde{B}$. Using the value derived for $Tr[\hat{\Sigma}^a \tilde{B} \hat{\Sigma}^a]$ above, we can rewrite the remaining term as

$$\sigma_a^{-1} Tr[\hat{\Sigma}^a \tilde{B} \tilde{B} \hat{\Sigma}^a] = \frac{\sigma_a^{-1}}{b_3^2 (\sigma_a^{-1} + \chi K)^2} Tr[bb' \tilde{B} bb'].$$

This is increasing in σ_a if $\partial / \partial \sigma_a^{-1} (\sigma_a^{-1} / b_3^2 (\sigma_a^{-1} + \chi K)^2) < 0$, which is true if

$$\frac{\partial}{\partial \sigma_a^{-1}} \frac{\sigma_a^{-1}}{(\sigma_a^{-1} + \chi K)^2} = \frac{\chi K - \sigma_a^{-1}}{(\sigma_a^{-1} + \chi K)^3} < 0.$$

Thus,

$$\chi K < \sigma_a^{-1}$$

is a sufficient, but not necessary, condition for profits to be increasing in σ_a.

□

Figure 1: Cross-Sectional Distribution of Outperformance

This figure shows the cross-sectional distribution in recessions (red) and in expansions (blue) of the four-factor alpha for the mutual funds in our sample. The data are from CRSP and are available monthly from January 1980 until December 2005.

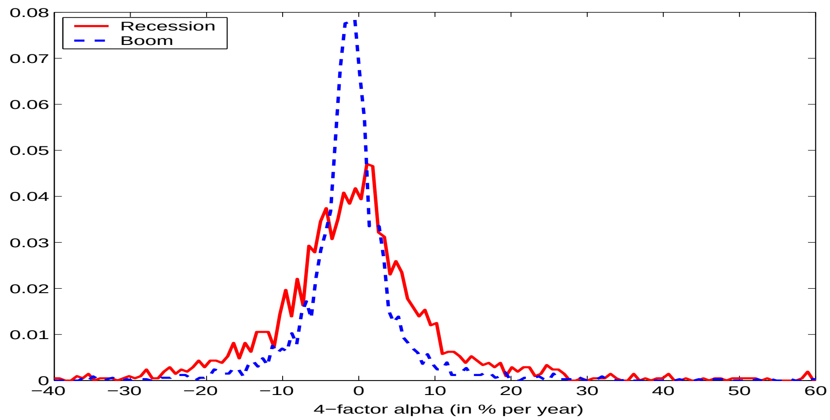

Figure 2: Investment Performance in Recessions vs. Expansions

This figure shows four-factor alphas for all domestic equity mutual funds. They are obtained by, first, regressing fund returns in excess of the risk-free rate on the market return in excess of the risk-free rate, the return on a portfolio that is long in small firms and short in large firms (SMB), the return on a portfolio that is long in value firms and short in growth firms (HML), and the return on a portfolio that is long in winners and short in losers (UMD) in twelve-month rolling-window regressions. The alpha of a fund is the intercept of that regression. In a second step, we regress the fund alphas on a recession dummy in a panel regression, controlling for other fund characteristics. The intercept of that regression is the alpha in expansions, the sum of the coefficient on the dummy and the intercept is the alpha in recessions. We annualize monthly alphas by multiplying by twelve. The data are from CRSP and available monthly from January 1980 until December 2005.

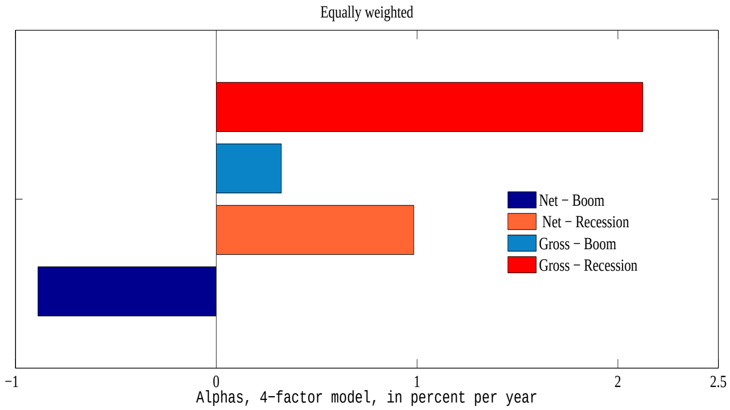

Table 1: **Individual Stocks Have More Aggregate Risk in Recessions**

For each stock i and each month t, we estimate a CAPM equation based on twelve months of data (a twelve-month rolling window regressions). This delivers the stock's beta β_t^i and its residual standard deviation $\sigma_{\varepsilon t}^i$. We define stock i's aggregate risk in month t as $\left|\beta_t^i \sigma_t^m\right|$ and its idiosyncratic risk as $\sigma_{\varepsilon t}^i$, where σ_t^m is formed as the realized volatility from daily return observations. Panel A report the results from a time-series regression of the aggregate risk averaged across stocks, $\frac{1}{I}\sum_{i=1}^N \left|\beta_t^i \sigma_t^m\right|$, in Columns 1 and 2 and of the idiosyncratic risk averaged across stocks, $\frac{1}{I}\sum_{i=1}^N \sigma_{\varepsilon t}^i$, in Columns 3 and 4 on the *Recession* dummy. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. In Columns 2 and 4 we include several aggregate control variables: We regress the portfolio (net) return in excess of the risk-free rate on *Recession* and a set of four risk factors: the market excess return (MKTPREM), the return on the small-minus-big portfolio (SMB), the return on the high-minus-low book-to-market portfolio (HML), the return on the up-minus-down momentum portfolio (UMD). The data are monthly and cover the period 1980 to 2005 (309 months). Standard errors (in parentheses) are corrected for autocorrelation and heteroscedasticity. Panel B reports results of panel regressions of the aggregate risk of an individual stock, $\left|\beta_t^i \sigma_t^m\right|$, in Columns 1 and 2 and of its idiosyncratic risk, $\sigma_{\varepsilon t}^i$, in Columns 3 and 4 on the *Recession* dummy. In Columns 2 and 4 we include several firm-specific control variables: the log market capitalization of the stock $log(Size)$, the ratio of book equity to market equity $B-M$, the average return over the past year $Momentum$, the stock's leverage $Leverage$ measured as the ratio of book debt to book debt plus book equity, and a dummy of whether the stock is traded on NASDAQ. All control variables are lagged one month. The data are monthly and cover all stocks in the CRSP universe for the period 1980 to 2005. Standard errors (in parentheses) are clustered at the stock and time dimensions.

	(1)	(2)	(3)	(4)
	Aggregate Risk		Idiosyncratic Risk	
	Panel A: Time-Series Regression			
Recession	0.213	0.207	0.058	0.016
	(0.120)	(0.118)	(1.018)	(1.016)
MKTPREM		-0.678		-1.865
		(0.487)		(3.043)
SMB		1.251		12.045
		(0.593)		(4.293)
HML		0.015		9.664
		(0.842)		(8.150)
UMD		-0.684		-1.112
		(0.372)		(3.888)
Constant	0.475	0.484	13.229	13.196
	(0.030)	(0.031)	(0.286)	(0.276)
Observations	309	309	309	309
	Panel B: Pooled Regression			
Recession	0.212	0.253	0.064	0.510
	(0.058)	(0.057)	(0.493)	(0.580)
Log(Size)		-0.029		-1.544
		(0.004)		(0.037)
B-M Ratio		-0.160		-2.691
		(0.012)		(0.086)
Momentum		0.029		2.059
		(0.021)		(0.177)
Leverage		-0.095		-1.006
		(0.015)		(0.119)
NASDAQ		0.150		1.937
		(0.017)		(0.105)
Constant	0.447	0.442	12.641	12.592
	(0.015)	(0.015)	(0.122)	(0.144)
Observations	1,312,216	1,312,216	1,312,216	1,312,216

Table 2: **Attention Allocation**

The dependent variables are funds' reliance on aggregate information (RAI), funds' reliance on stock-specific information (RSI), funds' market timing ability (Timing), and funds' stock picking ability (Picking). A fund j's RAI_t^j is defined as the (12-month rolling window time series) covariance between the funds' holdings in deviation from the market $(w_{it}^j - w_{it}^m)$ in month t and changes in industrial production growth between t and $t+1$. A fund j's RSI_t^j is defined as the (across stock) covariance between the funds' holdings in deviation from the market $(w_{it}^j - w_{it}^m)$ in month t and changes in earnings growth between t and $t+1$. Timing is defined as follows: $Timing_t^j = \sum_{i=1}^N (w_{it}^j - w_{it}^m)(\beta_{it} R_{t+1}^m)$ and $Picking_t^j = \sum_{i=1}^N (w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_{it} R_{t+1}^m)$, where the stocks' β_{it} is measured over a 12-month rolling window. RAI, RSI, $Timing$, and $Picking$ are all multiplied by 10,000 for ease of readability. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. $Log(Age)$ is the natural logarithm of fund age. $Log(TNA)$ is the natural logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Turnover* is the fund turnover ratio. *Flow* is the percentage growth in a fund's new money. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. Flow and Turnover are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RAI		RSI		Timing		Picking	
Recession	0.011	0.011	-0.682	-0.696	0.140	0.139	-0.144	-0.146
	(0.004)	(0.004)	(0.159)	(0.150)	(0.070)	(0.068)	(0.047)	(0.047)
Log(Age)		-0.002		0.423		0.006		0.004
		(0.001)		(0.060)		(0.006)		(0.004)
Log(TNA)		-0.001		-0.173		0.000		-0.003
		(0.000)		(0.029)		(0.004)		(0.003)
Expenses		-0.330		88.756		1.021		-0.815
		(0.244)		(11.459)		(1.280)		(0.839)
Turnover		-0.004		-0.204		0.007		0.017
		(0.001)		(0.053)		(0.013)		(0.010)
Flow		-0.008		1.692		-0.001		0.058
		(0.010)		(0.639)		(0.078)		(0.088)
Load		0.017		-9.644		0.033		0.156
		(0.023)		(1.972)		(0.180)		(0.131)
Constant	-0.001	-0.001	3.084	3.086	0.007	0.007	-0.010	-0.010
	(0.001)	(0.001)	(0.069)	(0.070)	(0.024)	(0.024)	(0.018)	(0.018)
Observations	224,257	224,257	166,328	166,328	221,306	221,306	221,306	221,306

Table 3: **Dispersion in Funds' Portfolio Strategies and Returns**

The dependent variables are *Concentration*, *Idio Vol*, and $|X_t^j - \bar{X}_t|$, where X_t^j is the *CAPM Alpha*, $4 - Factor\ Alpha$, or *CAPM Beta* and $\bar{X}$ denotes the (equally-weighted) cross-sectional average. *Portf Concentration* for fund j at time t is calculated as the Herfindahl index of portfolio weights in stocks $i \in \{1, \cdots, N\}$ in deviation from the market portfolio weights $\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)^2 \times 100$. *Idio Vol* is the idiosyncratic volatility from a 12-month rolling-window CAPM regression at the fund level. The CAPM alpha (and four-factor alpha) and the CAPM beta are obtained from twelve-month rolling window regressions of fund-level excess returns on excess market returns (and returns on SMB, HML, and MOM). *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *Log*(*Age*) is the natural logarithm of fund age. *Log*(*TNA*) is the logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Concentration		Idio Vol		CAPM Alpha		4-Factor Alpha		CAPM Beta	
Recession	0.205	0.147	0.348	0.359	0.275	0.298	0.140	0.150	0.082	0.083
	(0.027)	(0.026)	(0.127)	(0.104)	(0.054)	(0.050)	(0.028)	(0.025)	(0.015)	(0.014)
Log(Age)		0.203		-0.181		-0.045		-0.011		-0.009
		(0.028)		(0.017)		(0.004)		(0.002)		(0.002)
Log(TNA)		-0.179		0.039		0.017		-0.006		0.003
		(0.014)		(0.012)		(0.002)		(0.001)		(0.001)
Expenses		28.835		54.365		9.468		8.58		5.460
		(4.860)		(2.806)		(0.658)		(0.468)		(0.235)
Turnover		-0.092		0.358		0.050		0.059		0.020
		(0.025)		(0.023)		(0.004)		(0.003)		(0.001)
Flow		0.122		0.196		0.315		0.242		0.022
		(0.104)		(0.174)		(0.053)		(0.032)		(0.017)
Load		-1.631		-5.562		-1.123		-0.420		-0.444
		(0.907)		(0.490)		(0.095)		(0.070)		(0.042)
Constant	1.525	1.524	2.103	2.104	0.586	0.585	0.497	0.497	0.229	0.229
	(0.024)	(0.022)	(0.071)	(0.068)	(0.018)	(0.016)	(0.009)	(0.008)	(0.006)	(0.006)
Observations	230,185	230,185	227,159	227,159	226,745	226,745	226,745	226,745	227,159	227,159

Table 4: **Fund Performance: Cross-Section Approach**

The dependent variables are funds' *Abnormal Return*, *CAPM Alpha*, $3 - Factor\ Alpha$, and $4 - Factor\ Alpha$. All are obtained from 12-month rolling-window regressions of fund-level excess returns on excess market returns for the CAPM alpha, additionally on the SMB and the HML factors for the three-factor alpha, and additionally on the UMD factor for the four-factor alpha. The abnormal return is the fund return minus the market return. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. $Log(Age)$ is the natural logarithm of fund age. $Log(TNA)$ is the natural logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimension, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Abnormal Return		CAPM Alpha		3-Factor Alpha		4-Factor Alpha	
Recession	0.342	0.425	0.337	0.404	0.043	0.073	0.107	0.139
	(0.056)	(0.058)	(0.048)	(0.047)	(0.034)	(0.028)	(0.041)	(0.032)
Log(Age)		-0.031		-0.036		-0.028		-0.039
		(0.009)		(0.008)		(0.006)		(0.006)
Log(TNA)		0.046		0.033		0.009		0.012
		(0.005)		(0.004)		(0.003)		(0.003)
Expenses		-1.811		-2.372		-7.729		-7.547
		(1.046)		(0.945)		(0.782)		(0.745)
Turnover		-0.023		-0.044		-0.074		-0.065
		(0.016)		(0.010)		(0.010)		(0.008)
Flow		2.978		2.429		1.691		1.536
		(0.244)		(0.172)		(0.097)		(0.096)
Load		-0.809		-0.757		-0.099		-0.335
		(0.226)		(0.178)		(0.131)		(0.141)
Constant	-0.027	-0.033	-0.059	-0.063	-0.059	-0.060	-0.050	-0.052
	(0.027)	(0.026)	(0.025)	(0.024)	(0.020)	(0.018)	(0.023)	(0.021)
Observations	226,745	226,745	226,745	226,745	226,745	226,745	226,745	226,745

Table 5: **Fund Performance: Time-Series Approach**

Each month, we form an equally weighted portfolio of all funds. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. We regress the portfolio (net) return in excess of the risk-free rate on *Recession* and a set of four risk factors: the market excess return (MKTPREM), the return on the small-minus-big portfolio (SMB), the return on the high-minus-low book-to-market portfolio (HML), the return on the up-minus-down momentum portfolio (UMD), and the return on the illiquid-minus-liquid stock portfolio (LIQ) of Pástor and Stambaugh (2003). We also consider specifications in which the risk factors are interacted with Recession. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are corrected for autocorrelation and heteroscedasticity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Recession	0.274	0.151	0.156	0.157	0.265	0.215	0.198	0.222
	(0.105)	(0.079)	(0.076)	(0.074)	(0.104)	(0.094)	(0.097)	(0.081)
MKTPREM	1.000	0.976	0.978	0.981	0.998	0.979	0.980	0.984
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
SMB		0.169	0.168	0.168		0.170	0.169	0.169
		(0.024)	(0.025)	(0.026)		(0.026)	(0.027)	(0.027)
HML		-0.007	-0.003	-0.001		0.001	0.005	0.007
		(0.030)	(0.030)	(0.030)		(0.032)	(0.033)	(0.033)
UMD			0.014	0.014			0.015	0.015
			(0.019)	(0.020)			(0.021)	(0.022)
LIQ				-0.008				-0.007
				(0.007)				(0.008)
Recession*MKT					0.011	-0.029	-0.018	-0.025
					(0.024)	(0.023)	(0.025)	(0.024)
Recession*SMB						-0.027	-0.024	-0.013
						(0.047)	(0.049)	(0.041)
Recession*HML						-0.088	-0.098	-0.124
						(0.049)	(0.050)	(0.044)
Recession*UMD							0.017	0.027
							(0.033)	(0.035)
Recession*LIQ								-0.046
								(0.026)
Constant	-0.064	-0.059	-0.074	-0.075	-0.062	-0.065	-0.079	-0.081
	(0.057)	(0.038)	(0.047)	(0.047)	(0.058)	(0.038)	(0.048)	(0.048)
Observations	309	309	309	309	309	309	309	309

Table 6: **Same Funds with Stock-Picking Ability in Expansions Have Market-Timing Ability in Recessions**

We divide all fund-month observations into Recession and Expansion subsamples. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise; *Expansion* is equal to one every month the economy is not in recession. The dependent variables are our measure of market timing of a fund, $Timing_t^j$, and our measure of the stock picking ability of a fund, $Picking_t^j$. They are defined as follows: $Timing_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(\beta_i R_{t+1}^m)$ and $Picking_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. *Switching Portfolio* is an indicator variable equal to one for all funds whose *Picking* measure in Expansion is in the highest 25th percentile of the distribution, and zero otherwise. *Log*(*Age*) is the natural logarithm of fund age. *Log*(*TNA*) is the natural logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)
	Market Timing		Stock Picking	
	Expansion	Recession	Expansion	Recession
Switching Portfolio	0.000	0.017	0.056	-0.096
	(0.004)	(0.009)	(0.004)	(0.017)
Log(Age)	0.009	-0.025	-0.001	0.029
	(0.002)	(0.006)	(0.002)	(0.007)
Log(TNA)	-0.001	0.005	0.000	-0.023
	(0.001)	(0.003)	(0.001)	(0.003)
Expenses	0.868	1.374	-1.291	-4.434
	(0.321)	(1.032)	(0.376)	(1.378)
Turnover	0.009	-0.011	0.017	-0.006
	(0.003)	(0.007)	(0.004)	(0.012)
Flow	0.056	-0.876	0.138	-0.043
	(0.024)	(0.112)	(0.037)	(0.093)
Load	0.094	-0.076	0.131	0.615
	(0.049)	(0.151)	(0.055)	(0.195)
Constant	0.016	0.059	-0.021	-0.148
	(0.001)	(0.004)	(0.001)	(0.005)
Observations	204,330	18,354	204,330	18,354

Table 7: **Unconditional Performance of the Switching Portfolio**

We divide all fund-month observations into Recession and Expansion subsamples. *Expansion* equals one every month the economy is not in recession according to the NBER, and zero otherwise. We define the stock picking ability of a fund as $Picking_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. Switching Portfolio, SP, is an indicator variable equal to one for all funds whose *Picking* measure in Expansion is in the highest 25th percentile of the distribution, and zero otherwise. The dependent variables are the CAPM alpha, three-factor alpha, or four-factor alpha of the mutual fund, obtained from a 12-month rolling-window regression of a fund's excess returns before expenses on a set of common risk factors. $Log(Age)$ is the natural logarithm of fund age. $Log(TNA)$ is the natural logarithm of a fund's total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)
	CAPM Alpha	3-Factor Alpha	4-Factor Alpha
Switching Portfolio	0.076	0.056	0.064
	(0.040)	(0.021)	(0.018)
Log(Age)	-0.039	-0.028	-0.038
	(0.008)	(0.006)	(0.006)
Log(TNA)	0.032	0.013	0.014
	(0.005)	(0.004)	(0.004)
Expenses	4.956	0.627	0.241
	(1.066)	(0.793)	(0.739)
Turnover	-0.009	-0.047	-0.041
	(0.014)	(0.012)	(0.009)
Flow	2.579	1.754	1.602
	(0.173)	(0.102)	(0.101)
Load	-0.744	-0.090	-0.289
	(0.214)	(0.136)	(0.145)
Constant	0.057	0.038	0.049
	(0.017)	(0.015)	(0.018)
Observations	227,183	227,183	227,183

Table 8: **Comparing Funds Inside and Outside the Switching Portfolio**

We divide all fund-month observations into Recession and Expansion subsamples. *Expansion* equals one every month the economy is not in recession according to the NBER, and zero otherwise. We define the stock picking ability of a fund as $Picking_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. *Switching Portfolio* is an indicator variable equal one for all funds whose *Picking* measure in Expansion is in the highest 25th percentile of the distribution, and zero otherwise. Panel A reports fund-level characteristics. *Age* is the fund age in years. *TNA* is the fund's total net assets. *Expenses* is the fund expense ratio. *Turnover* is the fund turnover ratio. *Beta* is the fund's CAPM beta. *Concentration* is the concentration of the fund's portfolio, measured as the Herfindahl index of portfolio weights in deviation from the market portfolio's weights. *Stock Number* is the number of stocks in the fund's portfolio. *Industry* is the industry concentration of the fund's portfolio, measured as the Herfindahl index of portfolio weights in a given industry in deviation from the market portfolio's weights. *Beta Deviation* is the absolute difference between the fund's beta and the average beta in its style category. *RAI* is the manager reliance on aggregate information, defined as the R-squared from the regression of the fund's portfolio returns on contemporaneous changes in industrial production. Panel B reports manager-level characteristics. *MBA* equals one if the manager obtained an MBA degree, and zero otherwise. *Ivy* equals one if the manager graduated from an Ivy League institution, and zero otherwise. *Age* is the fund manager age in years. *Experience* is the fund manager experience in years. *Gender* equals one if the manager is a male and zero if the manager is female. *Hedge Fund* equals one if the manager ever departed to a hedge fund, and zero otherwise. $SP1 - SP0$ is the difference between the mean values of the groups for which *Switching Portfolio* equals one and zero, respectively. The data are monthly and cover the period 1980 to 2005. $p - values$ measure statistical significance of the difference.

	Switching Portfolio = 1			Switching Portfolio = 0			Difference	
	Mean	Stdev.	Median	Mean	Stdev.	Median	SP1-SP0	p-value
				Panel A: Fund Characteristics				
Age	10.01	8.91	7	15.20	15.34	9	-5.19	0.000
TNA	621.13	2027.04	129.60	1019.45	4024.29	162.90	-398.32	0.002
Expenses	1.48	0.47	1.42	1.22	0.47	1.17	0.26	0.000
Turnover	130.41	166.44	101.00	79.89	116.02	58.00	50.52	0.000
Concentration	1.68	1.60	1.29	1.33	1.50	0.99	0.35	0.000
Stock Number	90.83	110.20	68	111.86	187.13	69	-21.03	0.000
Industry	8.49	7.90	6.39	5.37	7.54	3.54	3.12	0.000
Beta Deviation	0.18	0.38	0.13	0.13	0.23	0.10	0.05	0.000
RAI	4.13	5.93	1.82	2.77	3.97	1.26	1.37	0.000
				Panel B: Fund Manager Characteristics				
MBA	42.09	49.37	0	39.49	48.88	0	2.60	0.128
Ivy	25.36	43.51	0	27.94	44.87	0	-2.57	0.205
Age	53.02	10.42	50	54.11	10.06	52	-1.08	0.081
Experience	26.45	10.01	24	28.14	10.00	26	-1.69	0.003
Gender	90.89	28.77	100	90.50	29.31	100	0.39	0.681
Hedge Fund	10.43	30.57	0	6.12	23.96	0	4.31	0.000

Table 9: **Skill Index Predicts Performance**

The dependent variable is the fund's cumulative CAPM, three-factor, or four-factor alpha, calculated from a 12-month rolling regression of observations in month $t+2$ in the three left columns and in month $t+13$ in the three most right columns. For each fund, we form the following skill index in month t. $Skill\ Index_t^j = w(z_t)Timing_t^j + (1-w(z_t))Picking_t^j, z_t \in \{Expansion, Recession\}$, w(Recession)=0.8 > w(Expansion) = 0.2, where $Timing_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(\beta_i R_{t+1}^m)$ and $Picking_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. The variables $Picking$ and $Timing$ are normalized so that they have a mean of zero and a standard deviation of 1 over the full sample. $Log(Age)$ is the natural logarithm of fund age. $Log(TNA)$ is the natural logarithm of a fund total net assets. $Expenses$ is the fund expense ratio. $Flow$ is the percentage growth in a fund's new money. $Turnover$ is the fund turnover ratio. $Load$ is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. $Flow$ and $Turnover$ are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)	(5)	(6)
	One Month Ahead			One Year Ahead		
	CAPM Alpha	3-Factor Alpha	4-Factor Alpha	CAPM Alpha	3-Factor Alpha	4-Factor Alpha
Skill Index	0.239	0.118	0.107	0.224	0.104	0.106
	(0.044)	(0.022)	(0.019)	(0.031)	(0.025)	(0.014)
Log(Age)	-0.034	-0.024	-0.036	-0.019	-0.009	-0.024
	(0.009)	(0.006)	(0.007)	(0.008)	(0.005)	(0.006)
Log(TNA)	0.026	0.010	0.011	-0.016	-0.018	-0.011
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Expenses	-2.977	-7.063	-7.340	-5.793	-9.093	-9.308
	(1.620)	(1.004)	(0.957)	(1.578)	(0.917)	(0.887)
Turnover	-0.010	-0.047	-0.039	-0.001	-0.041	-0.036
	(0.016)	(0.014)	(0.010)	(0.016)	(0.014)	(0.010)
Flow	2.409	1.664	1.519	0.237	0.210	0.227
	(0.151)	(0.097)	(0.095)	(0.119)	(0.086)	(0.071)
Load	-0.762	-0.093	-0.313	-0.683	0.213	-0.044
	(0.233)	(0.144)	(0.157)	(0.225)	(0.129)	(0.149)
Constant	-0.030	-0.055	-0.041	-0.043	-0.070	-0.056
	(0.024)	(0.018)	(0.021)	(0.024)	(0.019)	(0.022)
Observations	219,338	219,338	219,338	187,668	187,668	187,668

B Model Simulation

In this appendix, we use a numerical example to illustrate the model's predictions for the same measures of attention, portfolio dispersion, and performance than the ones we measure in the data. The goal of this exercise is to confirm that the model makes the same predictions for these observables than for the slightly different measures of attention allocation, portfolio dispersion, and fund performance for which we can prove propositions. We do not attempt to quantitatively account for all time-series and cross-sectional moments of actively managed fund portfolio holdings and returns. Such a task is beyond the scope of this paper and indeed beyond the current state of the literature. Our model is too stylized along many dimensions to deliver on such a task. For example, it has only 3 assets and no heterogeneity in risk aversion, prior beliefs, or initial wealth among funds, and no heterogeneity in information capacity among skilled managers. Adding such bells and whistles could improve the predictions, but only at the cost of obscuring the main mechanisms operative in the model.

B.1 Parameter Choices

The following explains how we choose the parameters of our model. The simplicity of the model prevents a full calibration. Instead, we pursue a numerical example that matches some salient properties of stock return data. Our benchmark parameter choices are listed in Table 10. Section B.3 below shows that the qualitative results are robust to a wide range of alternative parameter choices.

Our procedure is to simulate $3,000$ draws of the shocks $(x_1, x_2, x_c, s_1, s_2, a)$ in recessions and $3,000$ draws of the shocks in expansions. Since our model is static, each simulation is best interpreted as different draws of a random variable, and not as a period (months). The model's recessions differ from expansions in *two respects*.

First, the variance of the aggregate payoff shock σ_a is higher. It is set to replicate the fact the market return volatility is 25% higher in recessions than in expansions. In the numerical example, the volatility of the market return is 4.0% in expansions and 5.0% in recessions, straddling the observed market return volatility of 4.5%. The variance of the asset supplies $\sigma_x = .05^2\bar{x}$ allows us to match this level of market return volatility.

Second, recessions are also characterized by lower *realized* stock market returns (despite high expected returns). In order to generate lower realized market returns and higher expected returns in a static model, we have to assume that agents are surprised by unexpected low returns in a recession. We accomplish this in the numerical example by replicating the bottom $m = 2.5\%$ of market return realizations among the 3000 simulations of the model in recessions, in effect simulating the economy in recessions for $3,000 * (1 + .025) >$ 3000 draws. This choice for m is conservative because the 0.03% difference between market returns in expansions (0.87% per month) and recessions (0.84% per month) it generates is lower than the 0.20% per month difference in the data. In the robustness section below, we consider a case that generates a 0.20% return difference. The results are qualitatively and quantitatively similar.

To get the average market return right, we choose the mean of asset payoffs μ (equal for all assets) and the coefficient of absolute risk aversion, ρ, to achieve an average equilibrium market return of about 0.85% per month.

We think of assets 1 and 2 as two large industries and the composite asset as summarizing all other industries. Therefore, we normalize the mean asset supply of assets 1 and 2 to 1, and set the supply of the composite asset, $\bar{x}_c$, to 7. The variance of the firm-specific shocks is chosen to match the fact that individual industry returns are about 30% more volatile than the market return over our sample of 1980-2005. We use data from the 30 industry portfolios of Fama and French (1997). In the example, the average volatility of assets 1 and 2 is 6.5% in recessions and 5.8% in expansions, 29% and 45% higher than that of the market return. This choice matches the proportion of the average industry's return variance that is idiosyncratic. We choose the asset loadings on the aggregate payoff shock, b_1 and b_2, to be different from each other so as to generate some spread in asset betas. The chosen values generate average market betas of 0.9 and a dispersion in betas of 33%. This is reasonably close to the average beta of 0.95 and the dispersion of 23% for the 30-industry portfolios.

We set the average risk-free rate equal to 0.22% per month, the average of the 1-month yield minus inflation in our sample. We set initial wealth, W_0, to generate average holdings in the risk-free asset around 0%.

For simplicity, we set capacity K for the skilled funds equal to 1. This implies that learning can increase the precision of one of the idiosyncratic shocks (aggregate shock) by 25% (18%). We will vary K in our robustness exercise below. Likewise, we have no strong prior on the fraction of skilled funds χ. In our benchmark, we set it equal to 20%, and we will vary it for robustness. The model is simulated for 800 investors, of which 175 are skilled (20%). We assume that 20% of all investors are non-investment managers ("other investors"). The unskilled managers (60% of the populations) and other investors differ in name only. We note that the parameter conditions in propositions 2 through 4 are satisfied by these parameter choices.

As in our empirical work on mutual funds in Section 2, we compute all statistics of interest as equally-weighted averages across all investment managers (i.e., without the of 20% other investors). We also report results separately for skilled and unskilled investment managers.

B.2 Main Simulation Results

Each skilled fund ($K > 0$) solves for the choice of signal precisions $\sigma^{-1}_{\eta aj} \geq 0$ and $\sigma^{-1}_{\eta 1j} \geq 0$ that maximize time-1 expected utility (7). In our numerical work, we assume that these choice variables lie on a 25×25 grid in $\mathbb{R}^2_+$. The signal precision choice $\sigma^{-1}_{\eta 2j} \geq 0$ is implied by the capacity constraint (1).

In our numerical exercise, we simulate a sequence of $T = 3,000$ draws (months) for the random variables in each of the recession and expansion states, as explained above. We form $T \times 1$ time-series for the three individual asset returns, for the market return, for each fund's return, and for each fund's (and the market's) portfolio weights in each asset. For each asset i, we then run a CAPM regression of the excess return on the asset on the excess return on the market. This delivers the asset's CAPM beta, CAPM β_i; one value in booms and one in recessions. We define the systematic component of returns as $\beta_i R^m_t$, for $t = 1, \cdots, T$ and $i = 1, 2, 3$. Stacking the different is and ts results in a $3T \times 1$ vector of systematic returns. Likewise, we define the unexpected returns $R^i_t - \beta_i R^m_t$.

To compute RAI in equation (8) for fund j, we stack its portfolio weights in deviation from the market's weights for the three assets and the T draws in a $3T \times 1$ vector. We also create a $3T \times 1$ vector of aggregate shocks by stacking three identical repetitions of each aggregate shock realization a. We calculate the RAI as the covariance between these two variables. Likewise, we form $Timing$ in equation (9) as the covariance between the time-series of portfolio weights, in deviation from the market's weights, and the systematic component of returns. The procedure delivers one RAI and one $Timing$ measure per fund in recessions and one set of measures in expansions. We multiply RAI by 1,000 and $Timing$ by 10,000 because the aggregate shocks are an order of magnitude larger than the systematic returns.

Table 11 summarizes the predictions of the model for the main statistics of interest. The left panel shows the results for recessions, while the right panel shows the results for expansions. In each panel, there are three columns. The column *skilled* reports the equally-weighted average of the statistic in question for the group of skilled investors (20% of investors have $K > 0$ in our benchmark parametrization). The column *unskilled* is the equally-weighted average across the unskilled funds (60% of investors are unskilled mutual funds). The column *all* is the equally-weighted average across all funds (80% of investors). The 20% unskilled other investors are excluded from the table because we do not observe them in the data either. However, the model's predictions for this group are identical to those for the unskilled funds. These two groups differ in name only.

Rows 1 and 2 of Table 11 show that RAI and $Timing$ are higher for skilled investors in recessions (left panel) than in expansions (right panel). Because of market clearing, unskilled investors are the flip side of the skilled, their RAI and $Timing$ measures are negative. Since no investors learn about the aggregate shock in expansions, the RAI and $Timing$ measures are essentially zero for both skilled and unskilled. The column "All" denotes the statistics across all mutual funds; it includes both skilled and unskilled funds but excludes other unskilled investors. The combination of all investment managers, skilled and unskilled, is what we have data on. Hence, the first testable implication of the model is that RAI and $Timing$ should be higher for all funds in recessions than in expansions.

In similar fashion, we construct the RSI measure, defined in equation (10), and the stock-picking measure $Picking$ in equation (11). That is, we stack the stock-specific shocks s_i, the unexpected returns $R^i_t - \beta_i R^m_t$, and the fund's portfolio weights in $3T \times 1$ vectors and compute covariances. Rows 3 and 4 summarize the predictions of the model for RSI (multiplied by 1,000) and $Picking$ (multiplied by 10,000). Across all funds (skilled and unskilled), the model predicts lower RSI and $Picking$ in recessions. Skilled funds have a high RSI and $Picking$ ability in expansions, when they allocate their attention to stock-specific information. Unskilled investors have a negative $Picking$ measure in expansions for the same reason that they have a negative $Timing$ measure in recessions: Price fluctuations induce them to buy when returns are low and sell when returns are high. The RSI and $Picking$ measures are close to zero for all investors in recessions. Hence, the second testable implication of the model is that RSI and $Picking$ should be lower for all funds in recessions than in expansions.

Next, we turn to the measures of portfolio and return dispersion. Row 5 of Table 11 shows the results from the $Concentration$ measure, defined in equation (12), in our numerical example. We calculate $Concentration^j$ for fund j by stacking all squared deviations of fund j's portfolio from the market's portfolio in a $3T \times 1$ vector, and by summing over its entries, and dividing by T. We obtain one number for recessions and one for booms. We find that $Concentration$ is higher for all funds in recessions than in expansions. This increase is driven entirely by the informed; the uninformed are all holding the exact same portfolio because of common prior beliefs.

More concentrated portfolios are also less diversified. For each fund j, we estimate the CAPM regression (13) at the fund level by regressing the fund's excess return on the market's excess return. This delivers the fund's α^j, β^j, and σ_ε^j. We use the idiosyncratic risk σ_ε^j as our second measure of portfolio dispersion. If all funds held the market portfolio, their idiosyncratic risk would be zero, and there would be zero cross-sectional dispersion. In simulation, the skilled funds take on more idiosyncratic risk than the unskilled, and more in recessions than in booms. As a result, idiosyncratic risk is higher in recessions than in booms for all funds.

Rows 7 through 9 report the results for the dispersion across funds' abnormal returns, CAPM alphas, and CAPM betas. All three metrics show increasing dispersion in recessions, driven largely by the heterogeneity in the choices of the skilled investors.

Finally, we study performance measures. Rows 10 and 11 of Table 11 show that skilled investment managers have large excess returns, as measured by abnormal fund returns or fund alphas ($R^j - R^m$ and α^j), at the expense of the uninformed. For the average investment manager, there is a slightly higher alpha in recessions than in expansions. While quantitatively small, the positive difference in average alphas between recessions and expansions is a robust finding of the model.

Table 10: **Numerical Example**

This table provides an overview of the parameters of the model. The first column lists the parameter in question, the second column is its symbol, the third column lists its numerical value, and the last column briefly summarizes how we chose that value.

Parameter	*Symbol*	*Value*	*How Chosen?*
CARA	ρ	0.525	*Asset return mean*
mean of payoffs 1,2,c	μ_1, μ_2, μ_c	10, 10, 10	*Asset return mean*
variance aggr. payoff comp. a	σ_a	0.1225 (B), 0.2625 (R)	*Market return vol in booms vs. recessions*
variance idio. payoff comp. s_i	σ_i	0.25	*Asset return vol vs. market return vol*
a-sensitivity of payoffs	b_1, b_2	0.25,0.50	*Asset beta level + dispersion*
mean asset supply 1,2	$\bar{x}_1 = \bar{x}_2$	1,1	*Normalization*
mean asset supply 1,2	$\bar{x}_c$	7	*Asset return volatility*
variance asset supply	σ_x	$(.05 * \bar{x})^2$	*Asset return idio vol*
risk-free rate	r	0.0022	*Average T-bill return*
initial wealth	W_0	90	*Average cash position*
difficulty learning aggr. info	ψ	1	*Simplicity*
information capacity	K	1	
skilled fraction	χ	0.20	

Table 11: **Benchmark Simulation Results from Model**

This table provides the main statistics for a simulation of the model under the benchmark parameter values summarized in Table 10. Panel A reports moments related to attention allocation, Panel B reports the moments related to portfolio dispersion, and Panel C reports moments related to performance. The first column lists the moments in question, as defined in the main text, the next three columns report the predictions for the model simulated in a recession, the last three columns report the results for the model simulated in an expansion. All moments are generated from a simulation of 3,000 draws and 800 investors. For both recessions and expansions, we list the equally-weighted average across *all* investment managers (the 20% skilled and the 60% investment managers), and separately for the *skilled* and the *unskilled* investment managers.

	Recessions			**Expansions**		
	All managers	Skilled	Unskilled	All managers	Skilled	Unskilled
Panel A: Attention Allocation						
1. RAI	10.55	162.54	-40.11	0.07	0.94	-0.22
2. Timing	9.91	155.78	-38.72	0.06	3.31	-1.02
3. RSI	2.15	33.46	-8.28	15.61	249.72	-62.42
4. Picking	1.66	25.84	-6.40	10.02	160.11	-40.01
Panel B: Dispersion						
5. Concentration	3.75	13.15	0.00	3.12	11.48	0.00
6. Idiosyn. volatility	5.09	15.21	1.72	4.33	13.50	1.28
7. Disp. in abnormal return	3.54	10.05	1.36	3.37	9.82	1.22
8. Disp. in CAPM alpha	2.52	5.05	1.68	2.28	4.55	1.52
9. Disp. in CAPM beta	6.37	13.20	4.09	1.46	4.30	0.51
Panel C: Performance						
10. Abnormal return	0.346	5.471	-1.363	0.302	4.867	-1.220
11. CAPM Alpha	0.353	5.401	-1.330	0.307	4.861	-1.211

B.3 Robustness of Simulation Results

This section discusses the robustness of the model results to alternative parameter choices. We conduct several experiments where we vary one key parameter at the time, while holding all other parameters fixed at their benchmark levels. Table 12 summarizes these robustness checks. For brevity, we only report the results averaged over all investment managers and omit the results broken out for skilled and unskilled managers separately.

In our benchmark model, we assumed that 20% ($\chi = .20$) of investors are skilled mutual funds (60% are unskilled mutual funds and 20% unskilled other investors). We first study two different values for the fraction of skilled investment managers: $\chi = 10\%$ and $\chi = 30\%$. When there are fewer skilled funds, they have a comparatively larger advantage over the unskilled. This results in investment choices that exploit their informational advantage more aggressively. The *Timing* measure for the skilled increases from 156 to 210 in recessions while their *Picking* reading in expansions increases from 160 in the baseline to 181. At the same time, there are fewer skilled investors exploiting more unskilled investors than in the baseline, so that the unskilled have less negative average *Timing* values in recessions and less negative *Picking* values in expansions. As a result, the *Timing* value in recession and *Picking* value in expansion, averaged across across *all* investment managers (80% of the investor population), fall relative to the benchmark (from 9.9 to 5.8). Similarly, the *RAI* increases in recessions for all funds and the *RSI* decreases, but the changes are smaller than in the benchmark case. Likewise, our measures of portfolio dispersion continue to be higher in recessions than in expansions, but all dispersion levels are somewhat lower than before. The reason is that there is no dispersion among the unskilled, and there are more of them than in the benchmark. Finally, the performance results remain in tact as well. The skilled investors make higher abnormal returns and alphas than in the benchmark, which means the unskilled loose more in total. However, they loose less per unskilled investor. As a result, alphas averaged across all funds are lower than in the benchmark: 18.6bp per month in recessions (versus 35.3bp) and 15.6bp in expansions (versus 30.7bp).

The opposite effects happen when we increase the fraction of skilled investors to 30 percent. The increase in *RAI* and *Timing* and the decrease in *RSI* and *Picking* in recessions are larger than in the benchmark model. The same is true for the measures of portfolio dispersion and performance. For example, the average alpha is now 50.6bp per month in recessions and 45.4bp in expansions; the difference is slightly higher than in the benchmark. In expansions, all skilled investors continue to learn about the stock-specific information. In recessions, about 70% of attention is allocated to the aggregate shock in recessions and 15% to each of the stock-specific shocks. This 70% is lower than the 87% of skilled managers who learn about the aggregate shock in recessions in our benchmark parametrization. This is a general equilibrium effect, which we label *strategic substitutability*. When many informed investors learn about the aggregate shock, and buy assets that load heavily on that shock, they push up the price of these assets, making it less desirable to learn about for other informed investors ceteris paribus. This leads some to learn about the stock specific shocks instead, hence the higher average RSI of the informed in recessions compared to the benchmark. Why is the reverse not happening in expansions? Because the volatility of the aggregate shock is low enough in expansions that it turns out not to be optimal for any of the 30% informed investors to deviate from the full attention allocation to the idiosyncratic shocks.

The second variational experiment is to decrease and increase the amount of attention allocation capacity K that skilled investors have. In the benchmark $K = 1$, which amounts to the ability to increase the precision on any one signal by 25% of the prior precision of the stock-specific information through learning. We now consider $K = .5$ and $K = 2$. When the 20% skilled have twice as much capacity, their RAI and $Timing$ measures increases substantially in recessions ($Timing$ goes up from 157 in the benchmark to 220), and their RSI and $Picking$ measure increases in expansions ($Picking$ goes up from 160 in the benchmark to 311). In contrast to the previous exercise, the $Timing$ measure for the unskilled becomes more negative in recessions and their $Picking$ more negative in expansions than in the benchmark. The reason is that there are as many unskilled as in the benchmark but they are now at a larger disadvantage. The net effect of the skilled and the unskilled is an increase in $Timing$ in recessions from 9.9 in the benchmark to 14.0. Likewise, $Picking$ in booms increases from 10.0 to 19.5. Given 30% of investors $K = 1$ has similar effects than giving 20% of investors $K = 2$. Portfolio dispersion increases substantially with higher K. The result is driven by the more concentrated portfolios of the skilled, which creates both more dispersion among the skilled and a bigger difference with the unskilled. The skilled investors make abnormal returns and alphas that are about twice as high as in the benchmark, and the unskilled loose about twice as much. The net effect are average fund alphas that are substantially higher than in the benchmark: 67.2bp per month in recessions (versus 35.3bp) and 59.3bp in expansions (versus 30.7bp). The opposite happens when we lower K to 0.5.

We recall that recessions in the model are periods with not only a higher variance of the aggregate shock, but also with lower realized market returns. We implement the latter by first simulating the model in recessions for 3,000 periods, then taking the bottom m% of return realizations, and adding them to the 3,000 draws when calculating the moments of interest. In our third robustness check we verify how robust our results are to different values for m. We explore $m = 0$ and $m = 0.08$, while our benchmark is $m = 0.025$. When $m = .08$, realized market returns are 22 basis points per month lower in recessions than in booms (0.54 versus 0.76% per month). This corresponds to the return difference in the data. The results for $Timing$, $Picking$, RAI, and RSI are slightly stronger, but the magnitudes are quite close to the benchmark. The same is true for all dispersion measures, except for the beta dispersion. The latter is quite a bit lower in recessions than in the benchmark (3.91 instead of 6.37), driven by a reduction in the beta dispersion of the skilled. Because of the lower returns in recessions, skilled managers have both lower betas and less differences in their betas with the unskilled in recessions. Finally, the performance results are similar to the benchmark. Alphas are slightly higher than in the benchmark: 38.5bp per month in recessions (versus 35.3bp) and 31.6bp in expansions (versus 30.7bp). The difference between recessions and booms grows to 7bp per month.

The case of $m = 0$ corresponds to a world where assets have realized payoffs that are symmetrically distributed around the same mean in booms and in recessions. However, because recessions are times in which returns are more volatile, *expected* (and unconditional average) returns must be higher to compensate the investors for the higher risk. In particular, the average market return is 1.30% in recessions and 0.95% in expansions. The results on the fund moments are opposite from the case with higher m, but still quantitatively similar to our benchmark case. For example, the difference in average alphas between recessions and booms is 4.1bp per month compared to 4.6bp in the benchmark.

Overall, none of the comparative statics are sensitive to variation in the key parameters of the model.

B.4 Endogenous Capacity Model

Finally, we consider the extended model where skilled managers can freely choose not only how to allocate their information processing capacity, but also how much capacity to acquire. We let the cost of acquiring K

units of capacity be $\mathcal{C}(K)$. Each skilled fund solves for the choice of signal precisions $\sigma_{\eta aj}^{-1} \geq 0$ and $\sigma_{\eta 1j}^{-1} \geq 0$, and capacity K that maximize time-1 expected utility, as in (7) but adjusted for a penalty term $-\mathcal{C}(K)$. In our numerical work, we assume that these choice variables lie on a 25×25 grid in $\mathbb{R}_{+}^{3}$. The signal precision choice $\sigma_{\eta 2j}^{-1} \geq 0$ is implied by the capacity constraint (1).

In our numerical exercise, we consider two different functional forms for $\mathcal{C}(K)$. The first one is $\mathcal{C}_1(K) = c_1 \exp(K)$ and the second one is $\mathcal{C}_2(K) = c_2 K^{\psi}$. For ease of comparison with our exogenous K results, we choose the scalars c_1 and c_2 such that the optimal capacity choice is $K = 1$ on average across booms and recessions. This is the same capacity choice we assumed in our benchmark parametrization. Clearly, increasing (lowering) the scalars c_1 and c_2 will lead to lower (higher) optimal capacity choice. These scalars can be interpreted as the (shadow) price of capacity. All other parameters are the same as in our benchmark model.

More interesting than the level of K that is chosen is how that choice differs between recessions and expansions. We find that for both cost functions, investors acquire more capacity in recessions than in booms. Nothing in the cost function makes it cheaper to acquire capacity in either booms or recessions. This results is solely driven by the fact that the higher (aggregate) uncertainty in recessions makes it optimal to acquire more capacity and to allocate it to the aggregate shock. This extensive margin effect acts as an amplification to our intensive margin effect. How elastic capacity choice is to changes in prior aggregate uncertainty, and hence how large the amplification effect is, *does* depend on the functional form of the cost function. For cost function 1, we find that capacity choice is 1.02 in recessions and 0.97 in expansions. For cost function 2, the elasticity is much higher, with a capacity choice of 1.15 in recessions and 0.92 in expansions. The reason for the higher elasticity is that the marginal cost function 2 is less steep in capacity. As a result, a given change in the marginal benefit of acquiring information leads to larger equilibrium changes in capacity. Since we have no strong prior over the functional form, we conduct our numerical simulation for both cost functions.

Table 13 summarizes the main moments of interest for the endogenous K model, alongside the benchmark exogenous K results. For brevity, we only report the results averaged over all investment managers and omit the results broken out for skilled and unskilled managers separately. Overall, we find that the results are very similar to those in our exogenous K model, not only qualitatively, but also quantitatively. The moments for cost function 2 (two most right columns) tend to be higher in recessions than the benchmark numbers, and lower in expansions. Hence, there is amplification of the difference between recessions and booms. For example, average fund alphas are somewhat higher than in the benchmark in recessions (40.7bp per month versus 35.3bp) and somewhat lower in expansions (27.7bp versus 30.7bp). The resulting difference between recessions and booms grows substantially from 4.6bp to 13bp per month. For cost function 1 (two middle columns), the moments are slightly higher in recessions since the skilled investment managers choose to acquire slightly more capacity than what they are endowed with in the benchmark ($K = 1.02$ versus 1). The moments are slightly lower in expansions, since they have slightly lower capacity ($K = 0.97$ versus 1). Overall, the difference between recessions and booms is usually very similar to our benchmark model.

Table 12: **Robustness of Predictions of the Model**

This table provides a robustness analysis of the main predictions of the model. Panel A reports moments related to attention allocation, Panel B reports the moments related to dispersion, and Panel C reports moments related to performance. The first column lists the moments in question, as defined in the main text. The other pairs of columns report results for the benchmark parameters and for six robustness exercises. In each pair of columns, the first column reports the predictions for the model simulated in a recession and the second column for the model simulated in an expansion. All moments are generated from a simulation of 4,000 draws and 750 investors. For both recessions and expansions, we list the equally-weighted average across all investment managers (the 20% skilled and the 60% investment managers). The parameters are the same as in the benchmark model, except for the parameter listed in the first row.

	baseline		$\chi = .10$		$\chi = .30$		$K = 0.5$		$K = 2$		$m = 0$		$m = .08$	
	R	B	R	B	R	B	R	B	R	B	R	B	R	B
Panel A: Attention Allocation														
1. RAI	10.55	0.07	6.11	0.04	12.96	-0.08	6.23	0.01	14.53	-0.08	9.30	-0.04	11.01	-0.02
2. Timing	9.91	0.06	5.77	-0.09	11.56	0.12	5.93	-0.05	13.96	0.13	9.34	0.09	10.93	0.06
3. RSI	2.15	15.61	0.01	7.76	7.23	23.21	-0.03	7.89	12.66	30.14	2.08	16.16	2.14	15.76
4. Picking	1.66	10.02	0.13	5.04	5.10	14.83	0.18	5.04	8.19	19.45	1.68	9.31	1.65	10.28
Panel B: Dispersion														
5. Concentration	3.75	3.12	1.99	1.59	5.27	4.62	1.78	1.50	7.71	6.74	3.74	3.12	3.77	3.14
6. Idiosyn. volatility	5.09	4.33	2.90	2.27	6.66	6.07	3.34	2.80	7.38	6.71	4.83	4.09	5.29	4.33
7. Disp. in abnormal return	3.54	3.37	1.93	1.82	4.94	4.71	2.21	2.13	5.97	5.51	3.42	3.21	3.74	3.44
8. Disp. in CAPM alpha	2.52	2.28	1.52	1.35	3.06	2.84	1.32	1.15	4.85	4.46	2.22	2.15	2.76	2.35
9. Disp. in CAPM beta	6.37	1.46	4.70	1.03	5.76	2.45	3.45	0.98	10.84	2.67	21.03	2.08	3.91	1.38
Panel C: Performance														
10. Abnormal return	0.346	0.302	0.178	0.150	0.500	0.450	0.184	0.151	0.664	0.589	0.330	0.283	0.379	0.312
11. CAPM Alpha	0.353	0.307	0.186	0.156	0.506	0.454	0.192	0.156	0.672	0.593	0.329	0.288	0.385	0.316

Table 13: **Endogenous Capacity Model**

This table provides the results from an extension of the model where skilled funds endogenously choose how much capacity to acquire. It reports on the main predictions of the model. Panel A reports moments related to attention allocation, Panel B reports the moments related to dispersion, and Panel C reports moments related to performance. The first column lists the moments in question, as defined in the main text. The other pairs of columns report results for the benchmark parameters and for two versions of the endogenous K model with different cost functions. The cost function in the first one is $\mathcal{C}_1(K) = c_1 \exp(K)$, while the cost function in the second one is $\mathcal{C}_2(K) = c_2 K^{\psi}$. We set $c_1 = 1.057$, $c_2 = 2.4$, and $\psi = 1.2$. All other parameters are the same as in the benchmark model. In each pair of columns, the first column reports the predictions for the model simulated in a recession and the second column for the model simulated in an expansion. All moments are generated from a simulation of 2,000 draws and 100 investors. For both recessions and expansions, we list the equally-weighted average across all investment managers (the 20% skilled and the 60% investment managers).

	baseline		$\mathcal{C}_1(K) = c_1 \exp(K)$		$\mathcal{C}_2(K) = c_2 K^{\psi}$	
	R	B	R	B	R	B
Panel A: Attention Allocation						
1. RAI	10.55	0.07	10.53	-0.12	11.58	-0.01
2. Timing	9.91	0.06	9.83	0.10	10.65	0.13
3. RSI	2.15	15.61	2.35	15.43	3.69	14.37
4. Picking	1.66	10.02	1.76	9.91	2.65	8.87
Panel B: Dispersion						
5. Concentration	3.75	3.12	3.82	3.13	4.37	2.85
6. Idiosyn. volatility	5.09	4.33	5.20	4.53	5.34	4.15
7. Disp. in abnormal return	3.54	3.37	3.59	3.34	3.97	3.16
8. Disp. in CAPM alpha	2.52	2.28	2.57	2.29	2.92	2.06
9. Disp. in CAPM beta	6.37	1.46	5.18	3.01	5.28	1.94
Panel C: Performance						
10. Abnormal return	0.346	0.302	0.348	0.302	0.399	0.271
11. CAPM Alpha	0.353	0.307	0.355	0.307	0.407	0.277

C Additional Empirical Results

Table 14: **Robustness: Attention Allocation**

The dependent variables are funds' reliance on aggregate information $RAI2$, funds' reliance on stock-specific information $RSI2$, and the CAPM $R-squared$. A fund j's $RAI2_t^j$ is defined as the (12-month rolling window time series) covariance between the funds' portfolio holdings in deviation from the market $(w_{it}^j - w_{it}^m)$ in month t and changes in non-farm employment growth between t and $t+1$. A fund j's $RSI2_t^j$ is defined as the (across stock) covariance between the funds' holdings in deviation from the market $(w_{it}^j - w_{it}^m)$ in month t and changes in earnings growth between $t-11$ and $t+1$. $R-squared$ is obtained from the 12-month rolling-window regression model of a fund's excess returns on excess market returns. $RAI2$, and $RSI2$ are multiplied by 10,000 and $R-sqyared$ is multiplied by 100 for ease of readability. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. $Log(Age)$ is the natural logarithm of fund age. $Log(TNA)$ is the natural logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Turnover* is the fund turnover ratio. *Flow* is the percentage growth in a fund's new money. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. Flow and Turnover are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)	(5)	(6)
	RAI2		RSI2		R-squared	
Recession	0.004	0.004	-0.886	-0.897	3.040	2.891
	(0.001)	(0.001)	(0.201)	(0.191)	(1.451)	(1.315)
Log(Age)		-0.001		0.452		2.126
		(0.000)		(0.076)		(0.190)
Log(TNA)		0.000		-0.229		0.258
		(0.000)		(0.034)		(0.074)
Expenses		-0.158		111.982		-582.087
		(0.058)		(12.954)		(26.684)
Turnover		0.000		-0.329		-1.242
		(0.000)		(0.074)		(0.110)
Flow		-0.001		2.570		-6.614
		(0.003)		(0.723)		(2.885)
Load		0.021		-12.614		68.883
		(0.007)		(2.317)		(5.434)
Constant	-0.001	-0.001	3.962	3.962	77.361	77.331
	(0.000)	(0.000)	(0.089)	(0.089)	(0.854)	(0.846)
Observations	224,257	224,257	166,328	166,328	227,159	227,159

Table 15: **Robustness: Dispersion in Funds' Portfolio Strategies and Returns**

The dependent variables are *Style Shifting*, *Sector Deviation*, and $|X_t^j - \bar{X}_t|$, where X_t^j is the *Abnormal Return* or $3 - Factor\ Alpha$ and $\bar{X}$ denotes the (equally-weighted) cross-sectional average. *Style Shifting* for fund j at time t is the absolute value of the change between time t and time $t-1$ in the the fund's investment style index, defined in footnote 15. *Sector Deviation* for fund j at time t is calculated as the mean square root of the sum of squared differences between the share of fund j's assets in each of 10 industry sectors and the mean share in each sector in quarter t among all funds in fund j's objective class (aggressive growth, growth, or value). To identify the investment objectives, we use the Thomson Financial's style categories 2, 3, and 4. Industry sectors are defined using a modified 10-industry classification of Fama and French, as in Kacperczyk, Sialm, and Zheng (2005). The three-factor alphas are obtained from twelve-month rolling window regressions of fund-level excess returns on excess market returns, SMB, and HML. The abnormal return is the fund return minus the market return, also from a 12-month rolling-window regression. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *Log(Age)* is the natural logarithm of fund age. *Log(TNA)* is the logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Style Shifting		Sector Deviation		Abnormal Return		3-Factor Alpha	
Recession	5.246	5.082	0.003	0.003	0.530	0.561	0.201	0.212
	(0.826)	(0.798)	(0.002)	(0.001)	(0.108)	(0.102)	(0.042)	(0.039)
Log(Age)		0.014		0.000		-0.064		-0.013
		(0.080)		(0.002)		(0.007)		(0.003)
Log(TNA)		-0.214		-0.006		0.029		-0.001
		(0.047)		(0.001)		(0.004)		(0.001)
Expenses		101.35		2.084		13.816		9.178
		(13.908)		(0.301)		(1.152)		(0.465)
Turnover		1.111		-0.001		0.074		0.064
		(0.109)		(0.002)		(0.006)		(0.004)
Flow		-1.749		0.008		0.479		0.227
		(1.101)		(0.007)		(0.088)		(0.034)
Load		-4.517		-0.175		-1.738		-0.622
		(2.284)		(0.052)		(0.182)		(0.076)
Constant	14.725	14.807	0.185	0.186	0.661	0.659	0.497	0.497
	(0.283)	(0.284)	(0.001)	(0.001)	(0.029)	(0.027)	(0.010)	(0.010)
Observations	191,109	191,109	72,708	72,708	226,745	226,745	226,745	226,745

Table 16: **Fund Returns: Using Consumption Growth as Recession Indicator**

Each month, we form value-weighted or equally-weighted portfolio returns of all mutual funds. *CGD* equals one for every month real consumption growth from the national Income and Product Accounts is negative, and zero otherwise. We regress the returns on *Recession* and a set of four risk factors: the market excess return (MKTPREM), the return on the small-minus-big portfolio (SMB), the return on the high-minus-low book-to-market portfolio (HML), the return on the up-minus-down momentum portfolio (UMD), and the return on the illiquid-minus-liquid stock portfolio (LIQ) of Pástor and Stambaugh (2003). We also consider specifications where the risk factors are interacted with Recession. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are corrected for autocorrelation and heteroskedasticity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CGD	0.226	0.167	0.171	0.174	0.205	0.188	0.220	0.232
	(0.096)	(0.084)	(0.083)	(0.082)	(0.098)	(0.084)	(0.100)	(0.090)
MKTPREM	1.000	0.976	0.978	0.982	0.994	0.974	0.976	0.975
	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)
SMB		0.169	0.168	0.169		0.177	0.174	0.174
		(0.024)	(0.025)	(0.026)		(0.025)	(0.026)	(0.026)
HML		-0.006	-0.002	0.000		0.003	0.008	0.007
		(0.029)	(0.030)	(0.029)		(0.031)	(0.031)	(0.031)
UMD			0.014	0.014			0.020	0.020
			(0.019)	(0.019)			(0.020)	(0.020)
LIQ				-0.008				0.002
				(0.008)				(0.013)
CGD*MKT					2.766	0.811	0.214	1.162
					(2.292)	(2.234)	(2.681)	(2.688)
CGD*SMB						-4.573	-4.503	-2.423
						(3.078)	(3.325)	(3.210)
CGD*HML						-4.464	-5.363	-5.900
						(4.928)	(4.521)	(4.334)
CGD*UMD							-3.185	-3.554
							(3.160)	(2.848)
CGD*LIQ								-4.830
								(3.477)
Constant	-0.082	-0.079	-0.095	-0.096	-0.079	-0.083	-0.103	-0.103
	(0.063)	(0.037)	(0.043)	(0.044)	(0.063)	(0.037)	(0.045)	(0.045)
Observations	309	309	309	309	309	309	309	309

Table 17: **Fund Returns: Gross Returns**

Each month, we calculate value-weighted or equally weighted gross portfolio returns (returns + expenses) of all mutual funds. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. We regress the returns on *Recession* and a set of four risk factors: the market excess return (MKTPREM), the return on the small-minus-big portfolio (SMB), the return on the high-minus-low book-to-market portfolio (HML), the return on the up-minus-down momentum portfolio (UMD), and the return on the illiquid-minus-liquid stock portfolio (LIQ) of Pástor and Stambaugh (2003). We also consider specifications in which the risk factors are interacted with Recession. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are corrected for autocorrelation and heteroskedasticity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Recession	0.268	0.146	0.150	0.151	0.259	0.210	0.195	0.218
	(0.104)	(0.078)	(0.076)	(0.073)	(0.103)	(0.092)	(0.096)	(0.081)
MKTPREM	1.000	0.976	0.978	0.981	0.998	0.979	0.980	0.984
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
SMB		0.169	0.168	0.168		0.170	0.169	0.169
		(0.024)	(0.025)	(0.026)		(0.026)	(0.027)	(0.027)
HML		-0.007	-0.003	-0.002		0.001	0.005	0.007
		(0.030)	(0.030)	(0.030)		(0.032)	(0.033)	(0.033)
UMD			0.014	0.014			0.015	0.015
			(0.019)	(0.020)			(0.021)	(0.022)
LIQ				-0.008				-0.007
				(0.007)				(0.008)
Recession*MKTPREM					0.011	-0.029	-0.019	-0.026
					(0.024)	(0.023)	(0.025)	(0.024)
Recession*SMB						-0.028	-0.025	-0.014
						(0.047)	(0.048)	(0.040)
Recession*HML						-0.090	-0.099	-0.125
						(0.049)	(0.049)	(0.044)
Recession*UMD							0.016	0.026
							(0.033)	(0.035)
Recession*LIQ								-0.045
								(0.026)
Constant	0.037	0.042	0.027	0.026	0.039	0.036	0.022	0.020
	(0.058)	(0.038)	(0.047)	(0.047)	(0.058)	(0.038)	(0.048)	(0.048)
Observations	309	309	309	309	309	309	309	309

Table 18: **Fund Characteristics of the Switching Portfolio**

Expansion is every month the economy is not in recession. We define the stock picking ability of a fund as $Picking_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. *Switching Portfolio* is an indicator variable equal to one for all funds whose *Picking* measure in Expansion is in the highest 25th percentile of the distribution, and zero otherwise. *Age* is the fund's age. *TNA* is the fund 's total net assets. *Expenses* is the fund's expense ratio. *Turnover* is the fund's turnover ratio. *Industry Concentration* is the industry concentration of the fund's portfolio. *Stock Concentration* is the stock concentration of the fund's portfolio. *Beta Deviation* is the absolute difference between the fund beta and the average beta in its style category. *Number of Stocks* is the number of stocks in the fund portfolio. *RAI* is the fun manager's reliance on aggregate information (RAI), defined as the R-squared from the regression of fund portfolio returns on contemporaneous changes in industrial production. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)
	Switching Portfolio	Switching Portfolio
Log(Age)	-0.073	-0.069
	(0.010)	(0.010)
Log(TNA)	0.010	0.017
	(0.006)	(0.005)
Expenses	21.677	18.715
	(2.151)	(2.095)
Turnover	0.126	0.117
	(0.011)	(0.011)
Industry Concentration		1.063
		(0.170)
Stock Concentration		1.338
		(0.497)
Beta Deviation		0.146
		(0.054)
Number of Stocks		-0.002
		(0.002)
RAI		0.844
		(0.075)
Constant	0.255	0.255
	(0.010)	(0.010)
Observations	180,997	180,997
R-squared	0.14	0.19

Table 19: **Same Managers with High RSI in Expansions Have High RAI in Recessions**

We divide all mutual fund-month observations into Recession and Expansion subsamples. *Recession* is an indicator variable equal to one every month the economy is in recession according to the NBER, and zero otherwise; *Expansion* is one every month the economy is not in recession. The dependent variables are fund managers' reliance on aggregate information (RAI) and fund managers' reliance on stock-specific information (RSI). RAI is defined as the R-squared from the regression of fund portfolio returns on contemporaneous changes in industrial production. RSI is defined as the R-squared from the regression of changes in a mutual fund's stock holdings on contemporaneous changes in equity analysts' stock recommendations. *Switching Portfolio* 2 is an indicator variable equal to one for all funds whose RSI measure in Expansion is in the highest 25th percentile of the distribution, and zero otherwise. *Log*(*Age*) is the natural logarithm of fund age. *Log*(*TNA*) is the natural logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)
	RAI		RSI	
	Expansion	Recession	Expansion	Recession
Switching Portfolio 2	0.138	0.811	25.899	22.030
	(0.124)	(0.411)	(0.602)	(1.164)
Log(Age)	-0.178	-1.372	0.195	2.020
	(0.091)	(0.257)	(0.374)	(0.734)
Log(TNA)	0.122	0.530	-0.728	-1.459
	(0.038)	(0.110)	(0.185)	(0.374)
Expenses	111.586	140.244	217.636	505.439
	(16.334)	(41.952)	(75.370)	(164.300)
Turnover	0.054	2.304	-0.268	0.068
	(0.085)	(0.246)	(0.312)	(0.663)
Flow	1.189	-13.400	4.402	18.798
	(0.553)	(1.327)	(2.047)	(9.011)
Load	-11.771	4.776	-68.071	-91.943
	(2.366)	(6.244)	(13.560)	(30.653)
Constant	8.318	13.943	31.903	33.704
	(0.083)	(0.225)	(0.263)	(0.623)
Observations	206,204	18,264	111,198	8,463

Table 20: **Outperformance of the Switching Portfolio: RSI and RAI**

We divide all mutual fund-month observations into Recession and Expansion subsamples. *Expansion* is one every month the economy is not in recession according to the NBER, and zero otherwise. *Switching Portfolio* 2 is an indicator variable equal to one for all funds whose RSI measure in Expansion is in the highest 25th percentile of the distribution, and zero otherwise. The dependent variable is the CAPM alpha, three-factor alpha, or four-factor alpha of the mutual fund, obtained from a 12-month rolling-window regression. *Log*(*Age*) is the natural logarithm of fund age. *Log*(*TNA*) is the natural logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)
	CAPM Alpha	3-Factor Alpha	4-Factor Alpha
Switching Portfolio 2	0.144	0.009	0.037
	(0.039)	(0.013)	(0.015)
Log(Age)	-0.024	-0.030	-0.036
	(0.007)	(0.006)	(0.006)
Log(TNA)	0.027	0.013	0.013
	(0.005)	(0.004)	(0.003)
Expenses	-4.480	-6.791	-7.530
	(1.187)	(0.877)	(0.797)
Turnover	-0.005	-0.041	-0.036
	(0.016)	(0.013)	(0.010)
Flow	2.571	1.753	1.600
	(0.173)	(0.102)	(0.101)
Load	-0.412	-0.125	-0.251
	(0.150)	(0.130)	(0.129)
Constant	-0.091	-0.058	-0.057
	(0.013)	(0.015)	(0.017)
Observations	227,183	227,183	227,183

Table 21: **Same Managers with High CS in Expansions Have High CT in Recessions**

We divide all mutual fund-month observations into Recession and Expansion subsamples. *Recession* is an indicator variable equal to one every month the economy is in recession according to the NBER, and zero otherwise; *Expansion* is one every month the economy is not in recession. The dependent variables are characteristic selectivity (CS) and characteristic timing (CT) measures defined as in Daniel, Grinblatt, Titman, and Wermers (1997). *Switching Portfolio* 3 is an indicator variable equal to one for all funds whose CS measure in Expansion is in the highest 25th percentile of the distribution, and zero otherwise. $Log(Age)$ is the natural logarithm of fund age. $Log(TNA)$ is the natural logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)
	Characteristic Timing		Characteristic Selectivity	
	Expansion	Recession	Expansion	Recession
Switching Portfolio 3	-0.006	0.114	0.259	-0.040
	(0.008)	(0.019)	(0.015)	(0.064)
Log(Age)	-0.013	0.024	0.000	0.049
	(0.004)	(0.010)	(0.006)	(0.029)
Log(TNA)	0.003	-0.022	0.003	-0.076
	(0.002)	(0.004)	(0.003)	(0.013)
Expenses	-1.377	-2.192	-3.018	-21.831
	(0.756)	(1.851)	(1.295)	(5.240)
Turnover	0.008	0.022	0.030	-0.175
	(0.004)	(0.011)	(0.008)	(0.037)
Flow	0.012	-0.312	0.482	-0.629
	(0.049)	(0.112)	(0.102)	(0.340)
Load	-0.162	0.606	0.285	0.656
	(0.110)	(0.288)	(0.189)	(0.742)
Constant	0.021	-0.096	-0.001	0.012
	(0.003)	(0.008)	(0.005)	(0.022)
Observations	184,817	16,228	184,817	16,228

Table 22: **Outperformance of the Switching Portfolio: CS and CT**

We divide all fund-month observations into Recession and Expansion subsamples. *Expansion* is one every month the economy is not in recession according to the NBER, and zero otherwise. We define characteristic selectivity (CS) as in Daniel, Grinblatt, Titman, and Wermers (1997). *Switching Portfolio* 3 is an indicator variable equal to one for all funds whose CS measure in Expansion is in the highest 25th percentile of the distribution, and zero otherwise. The dependent variable is the CAPM alpha, three-factor alpha, or four-factor alpha of the mutual fund, obtained from a 12-month rolling-window regression of a fund's excess returns on excess market returns. *Log*(*Age*) is the natural logarithm of fund age. *Log*(*TNA*) is the natural logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)
	CAPM Alpha	3-Factor Alpha	4-Factor Alpha
Switching Portfolio 3	0.192	0.159	0.151
	(0.030)	(0.016)	(0.015)
Log(Age)	-0.034	-0.024	-0.035
	(0.008)	(0.006)	(0.006)
Log(TNA)	0.030	0.011	0.013
	(0.005)	(0.004)	(0.004)
Expenses	-5.373	-9.477	-9.577
	(1.153)	(0.815)	(0.768)
Turnover	-0.008	-0.048	-0.041
	(0.015)	(0.013)	(0.009)
Flow	2.545	1.725	1.575
	(0.171)	(0.100)	(0.100)
Load	-0.510	0.110	-0.109
	(0.203)	(0.132)	(0.140)
Constant	-0.079	-0.094	-0.079
	(0.018)	(0.016)	(0.019)
Observations	227,183	227,183	227,183

Table 23: **Same Funds with Market-Timing Ability in Recessions Have Stock-Picking Ability in Expansions**

We divide all fund-month observations into Recession and Expansion subsamples. *Recession* is one every month the economy is in recession according to the NBER; *Expansion* is one every month the economy is not in recession. The dependent variables are $Timing_t^j$ and $Picking_t^j$. They are defined as follows: $Timing_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(\beta_i R_{t+1}^m)$ and $Picking_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. $Switching\ Portfolio$ 4 is an indicator variable equal to one for all funds whose $Timing$ measure in recessions is in the highest 25th percentile of the distribution, and zero otherwise. $Log(Age)$ is the natural logarithm of fund age. $Log(TNA)$ is the natural logarithm of a fund total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)
	Market Timing		Stock Picking	
	Expansion	Recession	Expansion	Recession
Switching Portfolio 4	0.000	0.017	0.056	-0.096
	(0.004)	(0.009)	(0.004)	(0.017)
Log(Age)	0.009	-0.025	-0.001	0.029
	(0.002)	(0.006)	(0.002)	(0.007)
Log(TNA)	-0.001	0.005	0.000	-0.023
	(0.001)	(0.003)	(0.001)	(0.003)
Expenses	0.868	1.374	-1.291	-4.434
	(0.321)	(1.032)	(0.376)	(1.378)
Turnover	0.009	-0.011	0.017	-0.006
	(0.003)	(0.007)	(0.004)	(0.012)
Flow	0.056	-0.876	0.138	-0.043
	(0.024)	(0.112)	(0.037)	(0.093)
Load	0.094	-0.076	0.131	0.615
	(0.049)	(0.151)	(0.055)	(0.195)
Constant	0.016	0.059	-0.021	-0.148
	(0.001)	(0.004)	(0.001)	(0.005)
Observations	204,330	18,354	204,330	18,354

Table 24: **Unconditional Performance of the Reverse-Switching Portfolio**

We divide all fund-month observations into Recession and Expansion subsamples. *Expansion* equals one every month the economy is not in recession according to the NBER. $Picking_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. $Switching\ Portfolio$ 4 is an indicator variable equal to one for all funds whose $Timing$ measure in recessions is in the highest 25th percentile of the distribution, and zero otherwise. The dependent variable is the CAPM alpha, three-factor alpha, or four-factor alpha of the mutual fund, obtained from a 12-month rolling-window regression of excess gross fund returns on a set of various risk factors. $Log(Age)$ is the natural logarithm of fund age. $Log(TNA)$ is the natural logarithm of a fund total net assets. $Expenses$ is the fund expense ratio. $Flow$ is the percentage growth in a fund's new money. $Turnover$ is the fund turnover ratio. $Load$ is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. $Flow$ and $Turnover$ are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)
	CAPM Alpha	3-Factor Alpha	4-Factor Alpha
Switching Portfolio 4	0.076	0.056	0.064
	(0.040)	(0.021)	(0.018)
Log(Age)	-0.039	-0.028	-0.038
	(0.008)	(0.006)	(0.006)
Log(TNA)	0.032	0.013	0.014
	(0.005)	(0.004)	(0.004)
Expenses	4.956	0.627	0.241
	(1.066)	(0.793)	(0.739)
Turnover	-0.009	-0.047	-0.041
	(0.014)	(0.012)	(0.009)
Flow	2.579	1.754	1.602
	(0.173)	(0.102)	(0.101)
Load	-0.744	-0.090	-0.289
	(0.214)	(0.136)	(0.145)
Constant	0.057	0.038	0.049
	(0.017)	(0.015)	(0.018)
Observations	227,183	227,183	227,183

Table 25: **Robustness: Skill Index Based on RAI/RSI Predicts Performance**

The dependent variable is the fund's cumulative CAPM, three-factor, or four-factor alpha, calculated from a 12-month rolling regression of observations in month $t+2$ in the three left columns and in month $t+13$ in the three most right columns. For each fund, we form the following skill index in month t. $Skill\,Index\,2_t^j = w(z_t)RAI_t^j + (1-w(z_t))RSI_t^j, z_t \in \{Expansion, Recession\}$, w(Recession)=0.8 > w(Expansion)= 0.2, where RAI is the fund manager's reliance on aggregate information and RSI is the fund manger's reliance on stock-specific information. $Log(Age)$ is the natural logarithm of fund age. $Log(TNA)$ is the natural logarithm of a fund total net assets. $Expenses$ is the fund expense ratio. $Flow$ is the percentage growth in a fund's new money. $Turnover$ is the fund turnover ratio. $Load$ is the total fund load. The last three control variables measure the style of a fund along the size, value, and momentum dimensions, calculated from the scores of the stocks in their portfolio in that month. They are omitted for brevity. All control variables are demeaned. $Flow$ and $Turnover$ are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)	(5)	(6)
	One Month Ahead			One Year Ahead		
	CAPM Alpha	3-Factor Alpha	4-Factor Alpha	CAPM Alpha	3-Factor Alpha	4-Factor Alpha
Skill Index 2	0.021	0.035	0.020	0.005	0.011	0.011
	(0.009)	(0.009)	(0.007)	(0.008)	(0.006)	(0.007)
Log(Age)	-0.037	-0.025	-0.036	-0.024	-0.012	-0.027
	(0.009)	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)
Log(TNA)	0.028	0.011	0.012	-0.015	-0.017	-0.010
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Expenses	-2.489	-7.040	-7.199	-4.985	-8.916	-8.979
	(1.600)	(0.988)	(0.945)	(1.586)	(0.908)	(0.863)
Turnover	0.000	-0.043	-0.035	0.011	-0.035	-0.029
	(0.017)	(0.014)	(0.010)	(0.018)	(0.014)	(0.010)
Flow	2.483	1.691	1.546	0.329	0.252	0.270
	(0.173)	(0.106)	(0.104)	(0.115)	(0.083)	(0.067)
Load	-0.818	-0.074	-0.280	-0.698	0.251	0.001
	(0.238)	(0.144)	(0.157)	(0.223)	(0.129)	(0.148)
Constant	-0.034	-0.058	-0.044	-0.042	-0.070	-0.055
	(0.024)	(0.019)	(0.022)	(0.025)	(0.019)	(0.022)
Observations	218,104	218,104	218,104	183,845	183,845	183,845

Table 26: **Managerial Turnover**

The dependent variables are: The manager's departure (*Departure*) for any reason, the manager's promotion to a larger mutual fund in a different fund family (*Promotion*), the manager's departure to a smaller mutual fund in a different fund family (*Demotion*), and the manager's departure to a hedge fund (*Hedge Fund*). *Departure* includes those managers in the variables *Promotion*, *Demotion*, *Hedge Fund*, as well as the managers that disappear from the investment management industry. *Recession* is an indicator variable that equals one for every month the economy is in the recession according to the NBER, and zero otherwise. *Log*(*Age*) is the natural logarithm of a fund's age. *Log*(*TNA*) is the natural logarithm of a fund's total net assets. *Expenses* is the fund expense ratio. *Flow* is the percentage growth in a fund's new money. *Turnover* is the fund turnover ratio. *Load* is the total fund load. *Log*(*Manage*) is the natural logarithm of the fund manager's age in years. *Log*(*Experience*) is the natural logarithm of a manager experience in years. *Ivy* is an indicator variable equal to one if the manager graduated from an Ivy League academic institution, and zero otherwise. All control variables are demeaned. *Flow* and *Turnover* are winsorized at the 1% level. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at the fund and time dimensions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Departure		Promotion		Demotion		Hedge Fund	
Recession	-1.118	-1.470	-0.247	-0.263	0.333	0.326	-0.037	-0.041
	(0.616)	(0.602)	(0.095)	(0.099)	(0.130)	(0.131)	(0.013)	(0.014)
Log(Age)		-1.079		0.097		0.021		0.001
		(0.125)		(0.043)		(0.044)		(0.009)
Log(TNA)		0.600		-0.065		0.018		-0.001
		(0.094)		(0.021)		(0.022)		(0.005)
Expenses		239.641		-9.060		12.793		0.771
		(41.513)		(7.985)		(8.238)		(1.730)
Turnover		2.823		0.061		0.052		0.021
		(0.197)		(0.037)		(0.035)		(0.009)
Flow		-5.175		0.170		-0.605		-0.073
		(1.871)		(0.537)		(0.403)		(0.180)
Load		56.096		4.587		-1.945		0.322
		(5.244)		(1.601)		(1.203)		(0.308)
Log(Manage)		-5.210		-0.497		-0.699		-0.139
		(1.854)		(0.403)		(0.289)		(0.086)
Log(Experience)		4.157		-0.477		0.473		0.020
		(0.787)		(0.236)		(0.165)		(0.034)
Ivy		1.103		0.137		0.085		0.036
		(0.433)		(0.071)		(0.072)		(0.020)
Constant	7.598	7.624	0.548	0.549	0.419	0.420	0.037	0.038
	(0.332)	(0.320)	(0.056)	(0.058)	(0.056)	(0.056)	(0.013)	(0.013)
Observations	86,823	86,823	86,823	86,823	86,823	86,823	86,823	86,823

Table 27: **Managers' Age, Experience, and Education**

The dependent variables are: The natural logarithm of the fund manager's age in years ($Log(Manage)$); the natural logarithm of a manager experience in years ($Log(Experience)$); an indicator variable (Ivy) that is equal to one if the manager graduated from an Ivy League University, and zero otherwise. *Recession* is an indicator variable equal to one for every month the economy is in the recession according to the NBER, and zero otherwise. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered at both fund and time dimensions.

	(1)	(2)	(3)
	Log(Manage)	Log(Experience)	Ivy
Recession	-0.011	-0.023	0.003
	(0.009)	(0.017)	(0.004)
Constant	3.974	3.287	0.253
	(0.003)	(0.006)	(0.001)
Observations	91,879	91,879	91,879