NBER WORKING PAPER SERIES

ATTENTION ALLOCATION OVER THE BUSINESS CYCLE

Marcin Kacperczyk
Stijn Van Nieuwerburgh
Laura Veldkamp

Working Paper 15450
http://www.nber.org/papers/w15450

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2009

We thank Joseph Chen, Ralph Koijen, Matthijs van Dijk, and seminar participants at NYU Stern, University of Vienna, Australian National University, University of Melbourne, University of New South Wales, University of Sydney, University of Technology Sydney, Erasmus University, University of Mannheim, Duke University, the Amsterdam Asset Pricing Retreat, the Society for Economic Dynamics meetings in Istanbul, the CEPR Financial Markets conference in Gerzensee, and the UBC Summer Finance conference for useful comments and suggestions. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

Attention Allocation Over the Business Cycle
Marcin Kacperczyk, Stijn Van Nieuwerburgh, and Laura Veldkamp
NBER Working Paper No. 15450
October 2009
JEL No. E3,G2

ABSTRACT

The invisibility of information precludes a direct test of attention allocation theories. To surmount this obstacle, we develop a model that uses an observable variable -- the state of the business cycle -- to predict attention allocation. Attention allocation, in turn, predicts aggregate investment patterns. Because the theory begins and ends with observable variables, it becomes testable. We apply our theory to a large information-based industry, actively managed equity mutual funds, and study its investment choices and returns. Consistent with the theory, which predicts cyclical changes in attention allocation, we find that in recessions, funds' portfolios (1) covary more with aggregate payoff-relevant information, (2) exhibit more cross-sectional dispersion, and (3) generate higher returns. The results suggest that some, but not all, fund managers process information in a value-maximizing way for their clients and that these skilled managers outperform others.

Marcin Kacperczyk
Stern School of Business
New York University
44 West 4th Street
KMC 9-190
New York, NY 10012
and NBER
mkacperc@stern.nyu.edu

Stijn Van Nieuwerburgh
Stern School of Business
New York University
44 W 4th Street, Suite 9-120
New York, NY 10012
and NBER
svnieuwe@stern.nyu.edu

Laura Veldkamp
Stern School of Business
New York University
44 W Fourth Street, Suite 7-77
New York, NY 10012
and NBER
lveldkam@stern.nyu.edu

> "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)

Most decision makers are faced with an abundance of available information and must choose how to allocate their limited attention. Recent work has shown that introducing attention constraints into decision problems can help explain observed price-setting, consumption, and investment patterns.[1] Unfortunately, the invisibility of information precludes direct testing of whether agents actually allocate their attention in a value-maximizing way. To surmount this obstacle, we develop a model of investment that uses an observable variable – the state of the business cycle – to predict attention allocation. Attention, in turn, predicts aggregate investment patterns. Because the theory begins and ends with observable variables, it becomes testable. To carry out these tests, we use data on actively managed equity mutual funds. A wealth of detailed data on portfolio holdings and returns makes this industry an ideal setting in which to test the rationality of attention allocation.

A better understanding of attention allocation sheds 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.[2] This intermediation occurs despite a significant body of evidence that finds that actively managed portfolios tend to underperform passive investment strategies, on average, net of fees, and after controlling for differences in systematic risk exposure.[3] This evidence of negative average "alpha" has led many to conclude that investment managers have no skill. By devel-

[1] See, for example, Sims (2003) on consumption, Maćkowiak and Wiederholt (2009a, 2009b) on price-setting and Van Nieuwerburgh and Veldkamp (2009, 2010) on investment. Klenow and Willis (2007) and Gabaix, Laibson, Moloche, and Weinber (2006) test whether price-setting dynamics and experimental outcomes are consistent with inattention theories. A related investment literature on information choice includes Grossman and Stiglitz (1980), Verrecchia (1982), Admati (1985), Peress (2004, 2009), Amador and Weill (2008), and Veldkamp (2006). While in rational inattention models, agents typically choose the precision of their beliefs, Brunnermeier, Gollier, and Parker (2007) solve a portfolio problem in which investors choose the mean of their beliefs. In models of inattentiveness, e.g. Mankiw and Reis (2002) or Gabaix and Laibson (2002), agents update infrequently, but do not choose to to pay more attention to some risks than others.

[2] In 1980, 48% of U.S. equity was directly held by individuals – as opposed to being held through intermediaries; by 2007 that fraction has been down to 21.5%. See French (2008), Table 1. At the end of 2008, $9.6 trillion was invested with such intermediaries in the U.S. Of all investment in domestic equity mutual funds, about 85% is actively managed (2009 Investment Company Factbook). A related theoretical literature studies delegated portfolio management; e.g., Basak, Pavlova, and Shapiro (2007), Cuoco and Kaniel (2007), Vayanos and Woolley (2008), and Chien, Cole, and Lustig (2009).

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

oping 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.[4] However, the model is also consistent with the empirical literature's finding that skill is hard to detect, on average. The model identifies recessions as times when information choices lead to investment choices that are more revealing of skill.

We argue that recessions and expansions imply different optimal attention allocation strategies for skilled investment managers. Different learning strategies, in turn, prompt different investment strategies, causing the differential performance in recessions and expansions. 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 the future values of risky assets. 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 of stock-specific signals as 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 most learning problems, risks that are large in *scale* and high in *volatility* are more valuable to learn about. In our model, aggregate shocks are large in scale, because many asset returns are affected by them, but they have low volatility. Stock-specific shocks are smaller in scale but have higher volatility. As in the data, aggregate shocks are more volatile in recessions, relative to stock-specific shocks.[5] The increased volatility of aggregate shocks makes it optimal to devote relatively more attention to aggregate shocks in recessions and stock-specific shocks in expansions.

The second category of predictions pertains to portfolio dispersion. In expansions, when skilled managers pay more attention to stock-specific shocks, they hold portfolios that are

[4]The finding that some managers have skill 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).

[5]We show below that the idiosyncratic risk in stock returns, averaged across stocks, does not vary significantly over the business cycle. In contrast, the aggregate risk averaged across stocks is almost forty percent higher in recessions. Consistent with this fact, Ang and Chen (2002), Ribeiro and Veronesi (2002), and Forbes and Rigobon (2002) document that stocks exhibit more comovement in recessions.

largely similar to the market portfolio, except for their weights on the few stocks they follow. Therefore, the returns of the skilled and unskilled (who get no informative signals) differ only modestly from each other. 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 investor whose prior belief is that recession will continue. Consequently, fund returns are more dispersed in recessions. This is despite the fact that recessions are times when individual stock returns are less dispersed.

Third, the model predicts time variation in fund performance. The average fund can only outperform the market if there are other, non-fund investors who underperform. Therefore, the model also includes unskilled non-fund investors. Due to their lack of skill, they reside mostly in the left tail of the return distribution. When return dispersion rises, in recessions, left-tail investors underperform by more and the average fund's outperformance rises.

We test the model's three main predictions on the universe of actively managed U.S. mutual funds. To detect evidence of cyclical changes in attention, we estimate the covariance of each fund's 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 a fund's 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 test for cyclical changes in portfolio dispersion. In recessions, we find a higher portfolio concentration, measured as the sum of squared deviations of portfolio weights from those of the market portfolio. When funds hold portfolios that differ more from the market, which is the average portfolio, they are also holding portfolios that differ more from one another. Also consistent with the concentration hypothesis, we find higher idiosyncratic risk in fund returns in recessions. The increased dispersion additionally appears in fund returns, alphas, and betas. All these are predictions of our theory. Figure 1 shows a 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 re-

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

turns (alphas) are around 1.8 to 2.4% per year 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 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.

Because our theory tells us how skilled managers should invest, it suggests how to construct metrics that could help us identify skilled managers. To show that skilled managers exist, we select the top 25 percent of funds in terms of their stock-picking ability in expansions and show that the same group has significant market-timing ability in recessions; the other funds show no such market-timing ability.[7] Furthermore, these funds have higher *unconditional* returns. They tend to manage smaller, more active funds. By matching fund-level to manager-level data, we find that these skilled managers are more likely to attract new money flows and are more likely to depart later in their careers to hedge funds. Presumably, both are market-based reflections of their ability. Finally, we construct a skill index based on observables and show that it is persistent and that it predicts future performance.

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. While there might be other potential alternative explanations for each of the three main predictions of the model, none of the alternatives can account for all three predictions *jointly.*

focus is solely on performance.

[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 across aggregate and idiosyncratic shocks. 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 (E).[8] Our main model holds each manager's total attention fixed and studies its allocation in recessions and expansions. In Section 1.7, we allow a manager to choose 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 of one on the aggregate shock. We use this composite asset as a stand-in for all other assets to avoid the curse of dimensionality in the optimal attention allocation problem. 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 exists a risk-free asset that pays a gross return, r.

We model recessions as periods with higher aggregate risk, that is, the prior variance of the aggregate shock in recessions is higher than the one in expansions: $\sigma_a(R) > \sigma_a(E)$. Section 2.2 justifies this assumption by showing that aggregate risk of stocks increases substantially in recessions while idiosyncratic risk does not.

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*, meaning that they can choose to observe a set of informative signals about the payoff shocks a or s_i. We describe this signal choice problem below. The remaining unskilled investors observe no information other than their prior beliefs.

Some of the unskilled investors are investment managers. As in reality, there are also non-fund investors, all of whom we assume are unskilled.[9] The reason for modeling non-fund investors is that without them, the sum of all funds' holdings would have to equal the market (market clearing) and therefore, the average fund return would have to equal the market return. There could be no excess return in expansions or recessions.

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 $e_{aj} \sim N(0, \tau_{aj})$, $e_{1j} \sim N(0, \tau_{1j})$, and $e_{2j} \sim N(0, \tau_{2j})$ are independent of each other and 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 infor-

[9]For our results, it is sufficient that the fraction of them that are unskilled is higher than for the investment managers (funds).

mation they contain. In other words, learning from prices requires using capacity. Whatever information managers choose to infer from prices is already included in the signals.

Since the resulting posterior beliefs (conditional on time-2 information) are such that payoffs are normally distributed, they can be fully described by posterior means, $(\hat{a}_j, \hat{s}_{ij})$, and variances, $(\hat{\sigma}_{aj}, \hat{\sigma}_{ij})$. More precisely, posterior precisions are the sum of prior and signal precisions: $\hat{\sigma}_{aj}^{-1} = \sigma_a^{-1} + \tau_{aj}^{-1}$ and $\hat{\sigma}_{ij}^{-1} = \sigma_i^{-1} + \tau_{ij}^{-1}$. 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: $\hat{s}_{ij} = \tau_{1j}^{-1}\eta_{1j}/(\tau_{ij}^{-1} + \sigma_i^{-1})$. Simplifying yields $\hat{s}_{ij} = (1 - \hat{\sigma}_{ij}\sigma_i^{-1})\eta_{ij}$ and $\hat{a}_j = (1-\hat{\sigma}_{aj}\sigma_a^{-1})\eta_{aj}$. Next, we convert posterior beliefs about the underlying shocks into posterior beliefs about the asset payoffs. Let $\hat{\Sigma}_j$ be the posterior variance-covariance matrix of payoffs f:

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

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

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

For any unskilled manager or investor: $\hat{\mu}_j = \mu$ 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 a risk aversion coefficient ρ. Let E_2 and 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}:

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

subject to the budget constraint:

$$W_j = rW_0 + q_j'(f - pr) \tag{3}$$

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.

Asset Prices Equilibrium asset prices are determined by market clearing:

$$\int q_j dj = \bar{x} + x, \tag{4}$$

where the left-hand side of the equation is the vector of aggregate demand and the right-hand side is the vector of aggregate supply. As in the standard noisy rational expectations equilibrium model, the asset supply is random to prevent the price from fully revealing the information of informed investors. We denote the 3×1 noisy asset supply vector by $\bar{x} + x$, with a random component $x \sim N(0, \sigma_x I)$.

Attention Allocation Problem At time 1, a skilled investment manager j chooses the precisions of 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 τ_{aj}^{-1}, τ_{1j}^{-1}, and τ_{2j}^{-1}, respectively. These choices maximize time-1 expected utility, U_{1j}, over the fund's terminal wealth:

$$U_{1j} = E_1\left[\rho E_2[W_j] - \frac{\rho^2}{2} V_2[W_j]\right], \tag{5}$$

subject to two constraints.

The first constraint is the *information capacity constraint*. It states that the sum of the signal precisions must not exceed the information capacity:

$$\tau_{1j}^{-1} + \tau_{2j}^{-1} + \tau_{aj}^{-1} \leq K. \tag{6}$$

Unskilled investors have no information capacity $K = 0$. In Bayesian updating with normal variables, observing one signal with precision τ^{-1} or two signals, each with precision $\tau^{-1}/2$, 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 investment manager then chooses 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:

$$\tau_{1j}^{-1} \geq 0 \qquad \tau_{2j}^{-1} \geq 0 \qquad \tau_{aj}^{-1} \geq 0. \tag{7}$$

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

1.2 Model Solution

Substituting the budget constraint (3) into the objective function (2) and taking the first-order condition with respect to q_j reveals that optimal holdings are increasing in the investor's risk tolerance, precision of beliefs, and expected return on the assets:

$$q_j = \frac{1}{\rho}\hat{\Sigma}_j^{-1}(\hat{\mu}_j - pr). \tag{8}$$

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

Appendix S.1 utilizes the market-clearing condition (4) 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:[10]

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

Substituting optimal risky asset holdings from equation (8) into the first-period objective (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[11]

$$U_{1j} = \frac{1}{2}trace(\hat{\Sigma}_j^{-1}V_1[\hat{\mu}_j - pr]) + \frac{1}{2}E_1[\hat{\mu}_j - pr]'\hat{\Sigma}_j^{-1}E_1[\hat{\mu}_j - pr]. \tag{9}$$

1.3 Bridging The Gap Between Model and Data

The following three sections explain the model's three key predictions: attention allocation, dispersion in investors' portfolios, and average performance. For each prediction, we state a hypothesis and explain how to test it. But the payoffs and quantities that have analytical

[10] References denoted S are in the paper's separate appendix, available from the authors' websites or at `http://pages.stern.nyu.edu/~lveldkam/pdfs/mfund_KVNV_appdx.pdf`

[11] 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 S.1.2 contains the expressions for $E_1[\hat{\mu}_j - pr]$ and $V_1[\hat{\mu}_j - pr]$.

expressions in a CARA-normal model do not correspond neatly to the returns and portfolio weights that are commonly measured in the data. To bridge this gap, we introduce empirical measures of attention, dispersion, and performance. These standard 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. Therefore, Appendix S.2 uses a numerical example to demonstrate that the empirical and theoretical measures have the same comparative statics.

Specifically, our empirical measures use conventional definitions of asset returns, portfolio returns, and portfolio weights. Risky asset returns are defined as $R^i \equiv \frac{f_i}{p_i} - 1$, for $i \in \{1, 2, c\}$, while the risk-free asset return is $R^0 \equiv \frac{1+r}{1} - 1 = r$. We define the market return as the value-weighted average of the individual asset returns: $R^m \equiv \sum_{i=1}^{3} w_i^m R^i$, where $w_i^m \equiv \frac{p_i q_i^j}{\sum_{i=1}^{3} p_i q_i^j}$. Likewise, a fund j's return is $R^j \equiv \sum_{i=0}^{3} w_i^j R^i$, where $w_i^j \equiv \frac{p_i q_i^j}{\sum_{i=0}^{3} p_i q_i^j}$. It follows that end-of-period wealth (assets under management) equals beginning-of-period wealth times the fund return: $W^j = W_0^j (1 + R^j)$.

1.4 Hypothesis 1: Attention Allocation

Each skilled manager ($K > 0$) solves for the choice of signal precisions $\tau_{aj}^{-1} \geq 0$ and $\tau_{1j}^{-1} \geq 0$ that maximize her time-1 expected utility (9). The choice of signal precision $\tau_{2j}^{-1} \geq 0$ is implied by the capacity constraint (6). 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, that is, in recessions.

Proposition 2. *If all informed managers learn about aggregate risk and capacity is not too high ($K \leq \sigma_a^{-1}$), then 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 proofs of this and all further Propositions are in Appendix S.1. Intuitively, in most learning problems, investors prefer to learn about large shocks that are an important component of the overall asset supply, and volatile shocks that have high prior payoff variance. Aggregate shocks are larger in scale, but are less volatile than stock-specific shocks. Recessions are times when aggregate volatility increases, which makes aggregate shocks more valuable to learn about. As a result, in recessions, skilled investment managers allocate a relatively larger fraction of their attention to learning about the aggregate shock. The converse is true in expansions.

Appendix S.2 presents a detailed numerical example in which parameters are chosen to match the observed volatilities of the aggregate and individual stock returns in expansions and recessions. For our benchmark parameter values, all skilled managers exclusively allocate attention to idiosyncratic shocks in expansions. In contrast, the bulk of skilled managers learn about the aggregate shock in recessions (87%, with the remaining 13% equally split between shocks 1 and 2). Thus, managers may want to reallocate their attention over the business cycle.

We have verified that similarly large swings in attention allocation occur for a wide range of parameters. The result breaks down when assets become very asymmetric so that one learning decision is dominant in recessions and expansions. For example, if the average supply of the composite asset, $\bar{x}_c$, is too large relative to the supply of the individual asset supplies, $\bar{x}_1$ and $\bar{x}_2$, the aggregate shock will be so valuable to learn about that all skilled managers will want to learn about it all the time. Similarly, if the aggregate volatility, σ_a, is too low, then nobody ever wants to learn about the aggregate shock.

Investors' optimal attention allocation decisions are 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 from equation (8) in which q is increasing in $\hat{\mu}_j$ and from equation (1) in which $\hat{\mu}_j$ is increasing in $\hat{a}_j$, which is further increasing in a. The positive covariances between the aggregate shock and funds' portfolio holdings in recessions, on the one hand, and between idiosyncratic shocks and the portfolio holdings in expansions, on the other hand, 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.

We define a fund's *reliance on aggregate information*, 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:

$$RAI_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(a_{t+1}), \tag{10}$$

where N is the number of individual assets. The subscript t on the portfolio weights and the subscript $t+1$ on the aggregate shock signify that the aggregate shock is unknown at the time of portfolio formation. In our static model, time t is period 2 and time $t+1$ is period 3. Relative to the market, a fund with a high RAI overweighs assets that have high (low) sensitivity to the aggregate shock in anticipation of a positive (negative) aggregate shock realization and underweighs assets with a low (high) sensitivity.

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

$$Timing_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(\beta_{it+1}R_{t+1}^m), \tag{11}$$

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. Before the market return rises, a fund with a high *Timing* ability overweighs assets that have high beta. Likewise, it underweighs assets with a high beta in anticipation of a market decline.

To confirm that *RAI* and *Timing* accurately represent the model's prediction that skilled investors allocate more attention to the aggregate state in recessions, we resort to a numerical simulation. Appendix S.2 details the procedure and the construction of the empirical measures. 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 they are in expansions. Because of market clearing, not all investors can time the market. Unskilled investors have negative timing ability in recessions. When the aggregate state a is low, most skilled investors sell, pushing down asset prices, p, and making prior expected returns, $(\mu - pr)$, high. Equation (8) shows that uninformed investors' asset holdings increase in $(\mu - pr)$. Thus, their holdings covary negatively with aggregate payoffs, making their *RAI* and *Timing* measures negative. Since no investors learn about the aggregate shock in expansions, *RAI* and *Timing* are close to zero for both skilled and unskilled. When averaged over all funds (including both skilled and unskilled funds but excluding non-fund investors), we find that *RAI* and *Timing* are higher in recessions than in expansions.

When skilled investment managers allocate attention to stock-specific payoff shocks, s_i, information about s_i allows them to choose portfolios that covary with s_i. We define *reliance on stock-specific information*, *RSI*, which measures the covariance of a fund's portfolio weights of each stock, relative to the market, with the stock-specific shock, s_i:

$$RSI_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(s_{it+1}) \tag{12}$$

How well the manager can choose portfolio weights in anticipation of future asset-specific payoff shocks is closely linked to her 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:

$$Picking_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m) \tag{13}$$

A fund with a high *Picking* ability overweighs assets that have subsequently high idiosyncratic returns and underweighs assets with low subsequent idiosyncratic returns. In our simulation, we find that skilled funds have positive *RSI* and *Picking* ability in expansions, when they allocate their attention to stock-specific information. Unskilled investors have negative *Picking* in expansions for the same reason that they have negative *Timing* 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.

1.5 Hypothesis 2: Dispersion

The model's second prediction is a higher cross-sectional dispersion in funds' investment strategies and in funds' 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, 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* $\bar{q} \equiv \int q_j dj$*.*

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.[12] 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

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

position in either asset 1 or 2. Hence, optimal information choice in expansions leads to less heterogeneous investment strategies.

To connect our model to the data, we use several measures of portfolio dispersion, commonly used in the empirical literature. The first one is the sum of squared deviations 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 all assets:

$$Concentration_t^j = \sum_{i=1}^{N} \left(w_{it}^j - w_{it}^m \right)^2 \tag{14}$$

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. Because markets must clear, funds cannot all hold concentrated portfolios without dispersion across their portfolios. Our numerical example shows that *Concentration* is higher for all funds in recessions than it is 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 a skilled fund's returns contain higher idiosyncratic risk in recessions.[13] We define idiosyncratic portfolio risk as the residual standard deviation, σ_ε^j, from a CAPM regression for fund j:

$$R_t^j = \alpha^j + \beta^j R_t^m + \sigma_\varepsilon^j \varepsilon_t^j \tag{15}$$

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

The higher dispersion across funds' portfolio strategies translates into a higher cross-sectional dispersion in fund returns. We look at dispersion in the funds' abnormal returns, $R^j - R^m$, CAPM alphas, α^j from equation (15), and CAPM betas, β^j. To facilitate comparison with the data, 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 a higher

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

dispersion of fund abnormal returns, alphas, and betas.

1.6 Hypothesis 3: Performance

The third prediction of the model is that the average performance of investment managers is higher in recessions than it is 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, that is, 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 $\bar{q} \equiv \int q_j dj$.*

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, because our data only include mutual funds, our model calculations similarly exclude non-fund investors. Since investment managers are skilled or unskilled, while other investors are only unskilled, an increase in the skill premium implies that the average manager's alpha rises in recessions. 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 ones have negative excess returns. Aggregating across skilled and unskilled funds results in higher average alphas in recessions, the third main prediction of the model.

1.7 Endogenous Capacity Choice

So far, we have assumed that skilled investment managers choose how to allocate a fixed information-processing capacity, K. We now extend the model to allow for skilled managers to add capacity at a cost $\mathcal{C}(K)$.[14] We draw three main conclusions. First, the proofs of

[14] 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 modeling a cost of capacity through the budget constraint. For a richer treatment of information production modeling, see Veldkamp (2006).

Propositions 2-4 hold for any chosen level of capacity K, below an upper bound, no matter the functional form of $\mathcal{C}$. Endogenous capacity only has quantitative, not qualitative implications. Second, because the marginal utility of learning about the aggregate shock is increasing in its prior variance (Proposition 2), skilled managers choose to acquire higher capacity in recessions. This extensive-margin effect amplifies our benchmark intensive-margin results. Third, the degree of amplification depends on the convexity of the cost function, $\mathcal{C}(K)$. The convexity determines how elastic equilibrium capacity choice is to the cyclical changes in the marginal benefit of learning. Appendix S.2.4 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 attention allocation over the business cycle, and its consequences for investors' strategies. 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 for 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 about fund returns and a host of other fund characteristics, such as 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 using information from CRSP, Morningstar, Nelson' Directory of Investment Managers, Zoominfo, and Zabasearch. 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. Industrial production is seasonally adjusted; the data are from the Federal Reserve Statistical Release.

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. Our aggregate sample spans 312 months of data from January 1980 until December 2005, among which 38 are NBER recession months (12%). In robustness analysis, we consider several alternative recession indicators (see Section 2.6).

2.2 Recessions Are Periods of Higher Aggregate Risk

Before testing our main hypotheses, we present empirical evidence for the main assumption in our model: Recessions are periods in which individual stocks contain more aggregate risk. Table 1 shows that an average stock's aggregate risk increases substantially in recessions whereas the change in 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 regression, delivering 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 monthly as the realized volatility from daily return observations. Panel A reports 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 indicator variable.[15] The aggregate risk is one-third higher in recessions than it is in expansions (0.69 versus 0.48), an economically and statistically significant difference. In contrast, the stock's idiosyncratic risk is essentially identical in expansions and in recessions. The results are similar whether one controls for other aggregate risk factors (Columns 2 and 4) or not (Columns 1 and 3). Panel B reports estimates from panel regressions of a stock's aggregate risk (Columns 1 and 2) or idiosyncratic risk (Columns 3 and 4) on the recession indicator variable, *Recession*, and additional stock-specific control variables including size, book-to-market ratio, and leverage. The panel results confirm the time-series findings.

2.3 Testing Hypothesis 1: 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 more with

[15]The reported results are for equally weighted averages. Unreported results confirm that value-weighted averaging across stocks delivers the same conclusion.

the aggregate shock. Conversely, in expansions their holdings covary more with stock-specific information. To this end, we estimate the following regression model:

$$Attention_t^j = a_0 + a_1 Recession_t + \mathbf{a_2 X_t^j} + \epsilon_t^j, \tag{16}$$

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.[16] 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) 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) and Thompson (2009)). 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 indicates how much the variable increases in recessions.

The first attention variable we examine is reliance on aggregate information, RAI, as in equation (10). We proxy for the aggregate payoff shock with the innovation in log industrial

[16]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 twelve-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).

production growth.[17] A time series for RAI_t^j is obtained by computing the covariance of the innovations and each fund j's portfolio weights using twelve-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.

Our estimates of the parameters appear in Table 2. Column 1 shows the results for a univariate regression. In expansions, RAI is not different from zero, implying that funds' portfolios do not comove with future macroeconomic information in those periods. In recessions, RAI increases. Both findings are consistent with the model. The increase amounts to ten percent of a standard deviation of RAI. It is measured precisely, with a t-statistic of 3. To remedy 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 our analysis using funds' reliance on stock-specific information (RSI) as a dependent variable. Using equation (12), the RSI metric is computed in each month t as a cross-sectional covariance across the assets between the fund's portfolio weights and firm-specific earnings shocks.[18] In the model, the fund's portfolio holdings and its 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. 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.

Next, we examine market-timing, $Timing_t^j$, and stock-picking ability, $Picking_t^j$, defined in equations (11) and (13). 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, β_i, in $Timing$ and $Picking$ are computed using the twelve-month rolling-window regressions of stock excess returns on

[17] 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 $t+1$.

[18] 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 in months t, $t+1$, and $t+2$ are computed using portfolio weights from month t and earnings surprises from month $t+3$.

market excess returns.

Columns 5 and 6 of Table 2 show that the average market-timing ability across funds increases significantly in recessions. In turn, 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 S.5 performs several robustness checks. First, we compute an alternative *RAI* measure, in which the aggregate shock is proxied by surprises in non-farm employment growth, another salient macroeconomic variable, instead of industrial production growth. Second, we compute an alternative *RSI* measure in which earnings surprises are defined as the residual from a regression of earnings per share in a given year on earnings per share in that same quarter one year earlier (instead of one quarter earlier), as in Bernard and Thomas (1989). Third, to check the market-timing results, we also study the R^2 from a CAPM regression at the fund level, as in equation (15). It measures how the funds' excess returns (as opposed to their portfolio weights) covary with the aggregate state, as measured by the market's excess return. All the results are similar to our benchmark result, and in the case of employment growth, are estimated even more precisely.

To further understand how funds improve their market timing in recessions, we conduct several exercises. We find they increase their cash holdings, reduce their holdings of high-beta stocks, and tilt their portfolios towards more defensive sectors. Tables S.6, S.7, and S.8 present the results; a more detailed discussion is in Appendix S.3.1.

2.4 Testing Hypothesis 2: Dispersion

The second 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 regression specification, using various return and investment heterogeneity measures, denoted as $Dispersion_t^j$, the dispersion of fund j at month t.

$$Dispersion_t^j = b_0 + b_1 Recession_t + \mathbf{b_2 X_t^j} + \epsilon_t^j, \tag{17}$$

The definitions of *Recession* and other control variables mirror those in regression (16). 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 (14). Funds whose holdings deviate more from the S&P 500 portfolio, and therefore from other investors, have higher levels of portfolio concentration; they pursue more active investment strategies. In contrast, when all funds hold the market portfolio, average concentration and portfolio dispersion are zero. 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, according to the CAPM regression (15). Columns 3 and 4 show that the idiosyncratic volatility increases in recessions. The increase is highly significant, statistically and economically. One concern with the CAPM-based measure of idiosyncratic risk is that it might not capture the possibility that some fund returns load on passive factors besides the market return. Therefore, we recompute idiosyncratic volatility, controlling for a fund's exposure to size (SMB), value (HML), and momentum (UMD) factors. The resulting *Recession* coefficient in a univariate regression is 0.347 and the intercept is 1.189. 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 use the absolute deviation between fund j's value and the equally weighted cross-sectional average, $|X_t^j - \overline{X}_t|$, as the dependent variable in (17). Columns 5 and 6 of Table 3 present the results for the dispersion in the funds' CAPM alphas, which are obtained from twelve-month rolling-window regressions of fund excess returns on market excess returns. Comparing the slope b_1 to the intercept b_0, we find a 50% dispersion increase 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 S.9 (in the Appendix) considers additional measures of portfolio and return dispersion. For example, we show that managers shift their investment styles more in recessions, consistent with more active portfolio management. Their funds also exhibit greater industry concentration in recessions. Next, we show that the dispersion of fund returns minus the market return nearly doubles in recessions. In unreported results, we obtain similar results for the dispersion of CAPM alpha and betas that are calculated by estimating their dependence on the aggregate dividend-price ratio, 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. These results further strengthen the evidence of the increased dispersion in recessions.

2.5 Testing Hypothesis 3: Performance

The third prediction of our model is that recessions are times when information allows funds to earn higher average risk-adjusted returns, on average. We evaluate this hypothesis using the following regression specification:

$$Performance_t^j = c_0 + c_1 Recession_t + \mathbf{c_2 X_t^j} + \epsilon_t^j \tag{18}$$

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 the control variables, X, are defined as before. All returns are expressed net of management fees. Our coefficient of interest is c_1.

Table 4, Column 1, shows that the average fund's net return is 3bp per month less than the market return in expansions, but it is 34bp per month higher in recessions. This difference is highly statistically significant and becomes even larger (42bp), after we control for fund characteristics (Column 2). Similar results (Columns 3 and 4) obtain when we use the CAPM alpha as a measure of fund performance, except that the alpha in expansions becomes negative. When we use alphas based on the three-factor and four-factor models, the recession return premium diminishes (Columns 5 through 8). But in recessions, the four-factor alpha still represents a non-trivial 1% per year risk-adjusted excess return, 1.6% higher than the -0.6% recorded in expansions (significant at the 1% level).

The cross-sectional regression model allows us to include a host of fund-specific control variables, making use of rich panel data. But because performance is measured using past twelve-month rolling-window regressions, a given observation for the dependent variable can be classified as a recession when some or even all of the remaining eleven months of the window are expansions. To verify the robustness of our results, we also employ a time-series approach. In each month, we form the equally weighted portfolio of funds and calculate its net return, in excess of the risk-free rate. We then regress this time series of fund portfolio returns on *Recession* and common risk factors. We adjust standard errors for heteroscedasticity and autocorrelation (Newey and West 1987). Table S.10 shows that our previous results remain largely unchanged.

Our results are robust to alternative performance measures. Table S.13 uses *gross* fund returns and alphas. In unreported results, we also use the information ratio (the ratio of the CAPM alpha to the CAPM residual volatility) as a performance measure. It increases sharply in recessions. Finally, we find similar results when we lead alpha on the left-hand side by one month instead of using a contemporaneous alpha. All results point in the same direction: Outperformance clusters in periods of recessions.

2.6 Identifying Recessions

So far, we have measured the state of the business cycle using an indicator variable based on the NBER definition of recessions. While this choice seems quite natural in light of its salience as an indicator of observed economic activity, it suffers from two potential problems. First, the information on NBER recessions is available only after the recession has already started. Second, measuring business cycles using a discrete variable contains less information than using a continuous counterpart. To address these concerns, we confirmed our results using various contemporaneous recession indicators such as a dummy for negative real consumption growth, or, alternatively, for the 25% lowest stock market returns. We also assessed the robustness of our results using the Chicago Fed National Activity Index (CFNAI), a continuous and contemporaneous indicator of the strength of economic activity, as our independent variable. Table S.11 shows that the results on performance are, if anything, stronger than those for our baseline measure. The other two hypotheses, on RAI/RSI and on dispersion, also hold for the CFNAI, but are omitted for brevity.

Another question is whether recession is the right conditioning variable. Since a key feature of recessions is high payoff volatility, we could replace the recession indicator with a dummy variable for high payoff volatility. The latter equals one in months with the highest volatility of aggregate earnings growth.[19] As predicted by the theory, we find that RAI,

[19]We chose the volatility cutoff such that 12% of months are selected, the same fraction as NBER recession

dispersion, and performance all rise in high volatility months, while RSI falls. For illustration, Table S.12 describes the performance results. Yet, we prefer to think of attention allocation as a cyclical phenomenon and believe that using our current definition of recession is more suitable, for the following reasons. First, it allows us to make contact with the existing macroeconomics literature on rational inattention, e.g., Maćkowiak and Wiederholt (2009a, 2009b). Second, our data suggests that attention allocation is more of a cyclical phenomenon: Cyclical attention reallocation is more pronounced than volatility-based attention allocation. Third, periods of low and high economic activity are common knowledge whereas measuring earnings volatility requires paying close attention to aggregate earnings data, which our theory predicts not all managers choose to do. A downturn in economic activity has such wide-ranging implications for investors, and as a binary variable, is so easy to learn, that knowing about the start or end of a recession is almost inescapable.

3 Using Theory and Data to Identify Skilled Managers

Our analysis so far 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 display market-timing ability in recessions and stock-picking ability in expansions. We define market-timing and stock-picking ability as in equations (11) and (13). Since the funds' portfolio holdings in each stock are observed at most quarterly, we assume that funds use buy-and-hold strategies in non-disclosure periods. 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 test the prediction that the *same* investment managers with stock-picking ability in expansions display market-timing ability in recessions. To this end, we first identify funds with superior stock-picking ability in expansions: For all expansion months, we select all fund-month observations that are in the highest 25% of the $Picking_t^j$ distribution. We form an indicator variable *Skill Picking* ($SP_j \in \{0, 1\}$) that is equal to 1 for the 25% of funds (884 funds) with the highest fraction of observations in the top, relative to the total number of observations (in expansions) for that fund. Then, we estimate the following pooled regression

months.

model, separately for expansions and recessions:

$$Ability_t^j = d_0 + d_1 SP_t^j + \mathbf{d_2 X_t^j} + \epsilon_t^j, \tag{19}$$

where *Ability* denotes either *Timing* or *Picking*. X is a vector of previously defined control variables. Our coefficient of interest is d_1.

Table 5, Column 3, confirms that SP funds are significantly better at picking stocks in expansions, after controlling for fund characteristics. This is true by construction. The main point, however, is that these same SP funds are also good at market timing in recessions. This result is evident from the recession-based market-timing regression in Column 2, in which the coefficient on SP is statistically significant at the 5% level. 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 confirms that SP funds switch strategies.

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 6 compares the *unconditional* performance of the SP portfolio to that composed 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.

In Panel A of Table 7, we further compare the characteristics of the funds in the *Skill-Picking* 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 wealth under management (by $400 million), 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), suggesting rent extraction from customers for the skill they provide. Fourth, they exhibit much higher turnover rates (about 130% per year, versus 80% per year for other funds), consistent with their more active-management styles. Fifth, they receive higher inflows of new assets to manage, consistent with their superior performance, and presumably a market-based reflection of their skill. Sixth, the SP funds tend to hold more concentrated portfolios, with fewer stocks and higher stock-level and industry-level Herfindahl concentration. Seventh, their betas deviate more from their 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 observable characteristics predict skill (SP)? Table S.14 reports the estimates from a linear-probability regression model of the SP indicator on *fund* characteristics, such as age, TNA, expenses, and turnover. The regression R^2 equals 14%. Including attributes that our theory links to skilled managers, such as stock and industry concentration, beta deviation, and RAI, increases the R^2 to 19%. Table 7, Panel B, examines *manager* characteristics. SP fund managers are 2.6% more likely to have an MBA, are one year younger, and have 1.7 fewer years of experience. Interestingly, they are much more likely to depart for hedge funds later in their careers, suggesting that the market judges them to have superior skills.

The existence of skilled mutual funds with cyclical learning and investment strategies is not a fragile result. First, the results continue to hold if we change the cutoff levels for the inclusion in the SP portfolio. Second, we show that the top 25% RSI funds in expansions have higher RAIs in recessions and higher unconditional alphas (Tables S.15 and S.16). Third, we verify our results using Daniel, Grinblatt, Titman, and Wermers (1997)'s definitions of market timing (CT) and stock picking (CS). Finally, we reverse the sort, to show that funds in the top 25% of market-timing ability in recessions, have statistically higher stock-picking ability in expansions and higher unconditional alphas (Tables S.17 and S.18).

3.2 Creating a Skill Index

If one is going to use the model to identify skilled investment managers, it is important that she can identify these managers in real time, without 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, in which the weights we place on each measure depend on the state of the business cycle:

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

We demean $Timing$ and $Picking$, divide each by its standard deviation, and set $w(R) = 0.8 > w(E) = 0.2$ (the exact number is not crucial).

Subsequently, we examine whether the time-t Index can predict future fund performance, measured by the CAPM, three-factor, and four-factor alphas one month (and one year) later. Table 8 shows that funds with a higher Skill Index have on average higher alphas. For example, when $Skill\ Index$ is zero (its mean), the alpha is -4bp per month. However, when the *Skill Index* is one standard deviation (0.83%) above its mean, the alpha is 1.1% (four-factor) or 2.4% (CAPM) higher per year. The three most right columns show similar predictive power of the *Skill Index* for one-year ahead alphas. As a robustness check, we construct a second skill index based on *RAI* and *RSI* instead of *Timing* and *Picking*. A one-standard-deviation increase in this skill index increases one-month-ahead alphas by 0.3-0.5% per year, a statistically significant effect (Table S.19).

A large literature investigates whether measures of skill persist through time (e.g., Carhart (1997), Brown and Goetzmann (1995)). To investigate whether the skill we identify exhibits persistence, we sort funds into quintiles based on their values of the *Skill Index*. We then track the *Skill Index* of the funds in each quintile over the next twelve months. Figure 3 shows a substantial amount of skill persistence, which is slowly declining over time. One interesting observation is that the best funds display the most persistence, which is in contrast with most of the literature, which usually finds persistence among the worst but not the best funds.

4 Alternative Explanations

We briefly explore other candidate explanations. The first alternative is that no skill exists. In that case, all the recession effects in fund returns would have to arise mechanically from the properties of asset returns. To rule this out, we calculate means, volatilities, alphas, betas, and idiosyncratic volatilities of individual stock returns, in the same way as we do it for mutual fund returns. None of these moments differ between expansions and recessions (except for higher volatility of asset returns in recessions, our driving force). Using a simulation, we verify that a mechanical mutual fund investment policy that randomly selects 50, 75, or 100 stocks cannot produce the observed counter-cyclical fund returns.

Second, we consider labor market explanations. In recessions, fund managers' labor-market options deteriorate. Not only do their assets under management and therefore their wages shrink, they are also less likely to get promoted or picked off by a hedge fund and more likely to get fired or demoted (Table S.20). In a model with risk-averse investment managers who are compensated based on their relative performance, larger downsides and smaller upsides would make optimal investment choices more conservative and less dispersed. To see why, 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 fewer 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 and deviate from the pack, in an attempt to get promoted. This explanation counterfactually generates higher portfolio dispersion in expansions. While labor market considerations may be important to understand many aspects of the behavior of mutual fund managers, the above argument suggests that they cannot account for the dispersion patterns we document.

Another labor-market 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. Table S.21 shows no difference between the age, educational background or experience of our managers in recessions versus expansions.

Fourth, Glode (2008) argues that funds outperform in recessions because their investors' marginal utility is highest in such periods. While complementary to our explanation, his work remains silent on what strategies investment managers pursue to achieve this differential performance, and hence on our first and second hypothesis. In sum, while various explanations can account for some of the facts, we conclude that they cannot account for all facts jointly.

5 Conclusion

Do investment managers add value for their clients? The answer to this question matters for problems ranging from the discussion of 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 can process information about future asset payoffs, the model predicts a higher covariance of portfolio holdings with aggregate information, more dispersion in returns across funds, and a higher average outperformance, in recessions. We observe these patterns in investments and returns of actively managed U.S. mutual funds. Hence, the data are consistent with a world in which some investment managers have skill, but that skill is often hard to detect. Recessions are times when differences in performance are magnified and skill is easier to detect.

Beyond the mutual fund industry, a sizeable fraction of GDP now comes from industries that produce and process information. Increasing access to information through the internet has made the problem of how to best allocate a limited amount of information-processing capacity even more relevant. While information choices have consequences for real outcomes, they are often poorly understood because they are difficult to measure. By predicting how information choices are linked to observable variables (such as the state of the economy) and by tying information choices to real outcomes (such as portfolio investment), we show how models of information choices can be brought to the data. This information-choice-based approach could be useful in examining other information-processing sectors of the economy.

References

Admati, A. (1985): "A noisy rational expectations equilibrium for multi-asset securities Markets," *Econometrica*, 53(3), 629–57.

Amador, M., and P.-O. Weill (2008): "Learning from prices: public communication and welfare," Working Paper Stanford University and UCLA.

Ang, A., and J. Chen (2002): "Asymmetric correlations of equity portfolios," *Journal of Financial Economics*, 63 (3), 443–494.

Avramov, D., and R. Wermers (2006): "Investing in mutual funds when returns are predictable," *Journal of Financial Economics*, 81, 339–377.

Baker, M., L. Litov, J. Wachter, and J. Wurgler (2009): "Can mutual fund managers pick stocks? Evidence from their trades prior to earnings announcements," *Journal of Financial and Quantitative Analysis*, 44, forthcoming.

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

Berk, J., and R. C. Green (2004): "Mutual fund flows and performance in rational markets," *Journal of Political Economy*, 112, 1269–1295.

Bernard, V. L., and J. K. Thomas (1989): "Post-earnings announcement drift: delayed price response or risk premium?," *Journal of Accounting Research*, 27, 1–36.

Breon-Drish, B., and J. S. Sagi (2008): "Do fund managers make informed asset allocation decisions," Working Paper, Vanderbilt University.

Brown, S., and W. Goetzmann (1995): "Performance persistence," *Journal of Finance*, 50, 679–698.

Brunnermeier, M., C. Gollier, and J. Parker (2007): "Optimal beliefs, asset prices and the preferences for skewed returns," *American Economic Review, Papers and Proceedings*, 97(2), 159–165.

Carhart, M. M. (1997): "On persistence in mutual fund performance," *Journal of Finance*, 52, 57–82.

Chen, J., H. Hong, M. Huang, and J. Kubik (2004): "Does fund size erode mutual fund performance? The role of liquidity and organization," *American Economic Review*, 94, 1276–1302.

Chien, Y., H. Cole, and H. Lustig (2009): "Macro implications of household finance," Working Paper UCLA.

Cohen, R. B., J. D. Coval, and L. Pástor (2005): "Judging fund managers by the company they keep," *Journal of Finance*, 60, 1057–1096.

Cuoco, D., and R. Kaniel (2007): "Equilibrium prices in the presence of delegated portfolio management," Working Paper, Duke University.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers (1997): "Measuring mutual fund performance with characteristic based benchmarks," *Journal of Finance*, 52, 1035–1058.

Fama, E. F., and K. French (1997): "Industry costs of equity," *Journal of Financial Economics*, 43, 153–193.

Fama, E. F., and K. R. French (2008): "Mutual fund performance," Working Paper, University of Chicago.

Forbes, K., and R. Rigobon (2002): "No contagion, only interdependence: measuring stock co-movements," *Journal of Finance*, 57, 2223–2261.

French, K. (2008): "The cost of active investing," *Journal of Finance*, 63 (4), 1537–1573.

Gabaix, X., and D. Laibson (2002): "The 6D Bias and the Equity Premium Puzzle," *NBER Macroeconomics Annual*, 47(4), 257–312.

Gabaix, X., D. Laibson, G. Moloche, and S. Weinber (2006): "Costly Information Acquisition: Experimental Analysis of a Boundedly Rational Model," *American Economic Review*, 96 (4), 1043–1068.

GLODE, V. (2008): "Why mutual funds underperform?," Working Paper, Carnegie Mellon University.

GRAHAM, J. R., AND C. R. HARVEY (1996): "Market timing ability and volatility implied in investment newsletters' asset allocation recommendations," *Journal of Financial Economics*, 42 (3), 397–421.

GROSSMAN, S., AND J. STIGLITZ (1980): "On the impossibility of informationally efficient markets," *American Economic Review*, 70(3), 393–408.

GRUBER, M. J. (1996): "Another puzzle: the growth in actively managed mutual funds," *Journal of Finance*, 51, 783–810.

HUANG, J., C. SIALM, AND H. ZHANG (2009): "Risk shifting and mutual fund performance," Working Paper, University of Texas Austin.

JENSEN, M. C. (1968): "The performance of mutual funds in the period 1945-1964," *Journal of Finance*, 23, 389–416.

KACPERCZYK, M., AND A. SERU (2007): "Fund manager use of public information: new evidence on managerial skills," *Journal of Finance*, 62, 485–528.

KACPERCZYK, M., C. SIALM, AND L. ZHENG (2005): "On the industry concentration of actively managed equity mutual funds," *Journal of Finance*, 60, 1983–2012.

——— (2008): "Unobserved actions of mutual funds," *Review of Financial Studies*, 21, 2379–2416.

KLENOW, P. J., AND J. L. WILLIS (2007): "Sticky Information and Sticky Prices," *Journal of Monetary Economics*, 54, 79–99.

KOIJEN, R. (2008): "The cross-section of managerial ability and risk preferences," Working Paper, University of Chicago.

KOSOWSKI, R. (2006): "Do mutual funds perform when it matters most to investors? US mutual fund performance and risk in recessions and expansions," Working Paper, Imperial College.

LYNCH, A. W., AND J. WACHTER (2007): "Does mutual fund performance vary over the business cycle?," Working Paper, New York University.

MAĆKOWIAK, B., AND M. WIEDERHOLT (2009a): "Business Cycle Dynamics under Rational Inattention," Working Paper Northwestern University.

——— (2009b): "Optimal sticky prices under rational inattention," *American Economic Review*, 99 (3), 769–803.

Malkiel, B. G. (1995): "Returns from investing in equity mutual funds 1971 to 1991," *Journal of Finance*, 50, 549–572.

Mankiw, G., and R. Reis (2002): "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve," *Quarterly Journal of Economics*, 117, 1295–1328.

Moulton, B. R. (1986): "Random group effects and the precision of regression estmates," *Journal of Econometrics*, 32, 385–397.

Newey, W. K., and K. D. West (1987): "A simple positive-definite heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica*, 55, 703–708.

Pástor, L., and R. F. Stambaugh (2003): "Liquidity risk and expected stock returns," *Journal of Political Economy*, 111, 642–685.

Peress, J. (2004): "Wealth, information acquisition and portfolio choice," *The Review of Financial Studies*, 17(3), 879–914.

——— (2009): "The tradeoff between risk sharing and information production in financial markets," *Journal of Economic Theory*, Forthcoming, INSEAD Working Paper.

Ribeiro, R., and P. Veronesi (2002): "Excess co-movement of international stock markets in bad times: a rational expectations equilibrium model," Working Paper, University of Chicago.

Simon, H. (1971): *Computers, communications, and the public interest*chap. Designing organizations for an information-rich world. The Johns Hopkins Press.

Sims, C. (2003): "Implications of Rational Inattention," *Journal of Monetary Economics*, 50(3), 665–90.

Thompson, S. (2009): "Simple formulas for standard errors that cluster by both firm and time," *Journal of Financial Economics*, Forthcoming.

Van Nieuwerburgh, S., and L. Veldkamp (2009): "Information immobility and the home bias puzzle," *Journal of Finance*, 64 (3), 1187–1215.

——— (2010): "Information acquisition and under-diversification," *Review of Economic Studies*, April.

Vayanos, D., and P. Woolley (2008): "An institutional theory of momentum and reversal," Working Paper, London School of Economics.

Veldkamp, L. (2006): "Media frenzies in markets for financial information," *American Economic Review*, 53 (4), 577–601.

Verrecchia, R. (1982): "Information acquisition in a noisy rational expectations economy," *Econometrica*, 50(6), 1415–1430.

Wermers, R. (2000): "Mutual fund performance: an empirical decomposition into stock-picking talent, style, transactions costs, and expenses," *Journal of Finance*, 55, 1655–1703.

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.

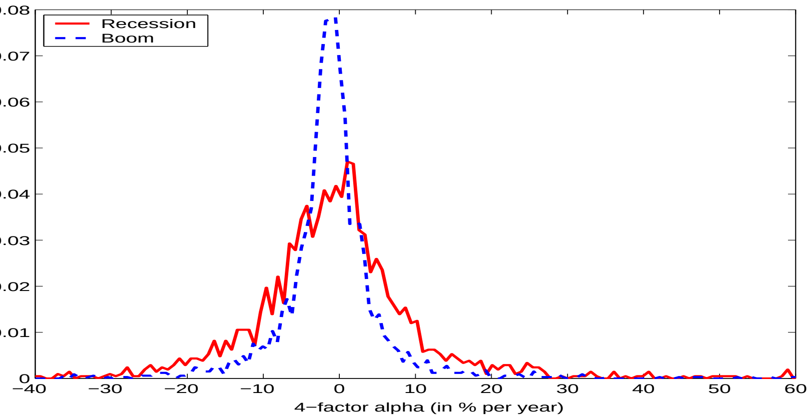

Figure 2: Investment Performance in Recessions vs. Expansions

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 fund alpha is the intercept of that regression. In a second step, we regress the fund alphas on a recession indicator variable 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 them by twelve. The data are from CRSP and available monthly from January 1980 until December 2005.

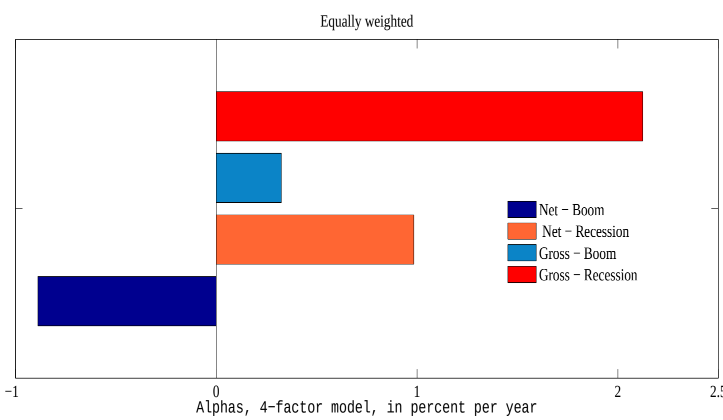

Figure 3: Skill Index Persistence

In a given month, all funds are ranked into quintiles based on their Skill Index, defined as $Skill\,Index_t^j(z) = w(z_t)Timing_t^j + (1 - w(z_t))Picking_t^j$, with $z_t \in \{E, R\}$. Skill Index is standardized cross-sectionally to have mean zero and standard deviation one. We then compute and plot the Skill Index of the funds in each quintile in the subsequent twelve months. The data cover the period from January 1980 until December 2005.

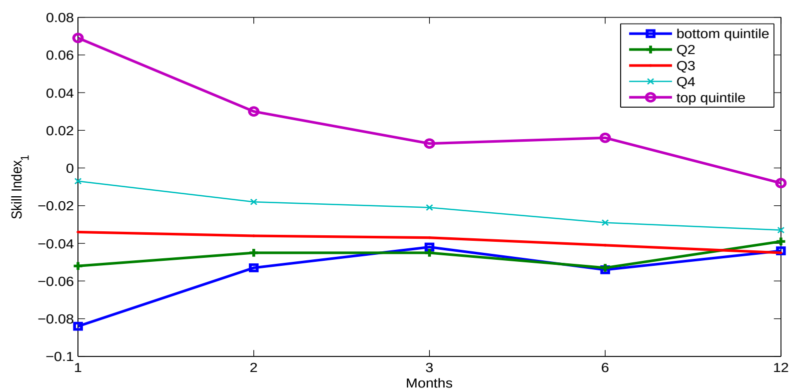

Table 1: **Individual Stocks Have More Aggregate Risk in Recessions**

For each stock i and each month t, we estimate a CAPM equation based on twelve months of data (a twelve-month rolling-window regression). This estimation 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 reports the results from a time-series regression of the aggregate risk averaged across stocks, $\frac{1}{N}\sum_{i=1}^N \left|\beta_t^i \sigma_t^m\right|$, in Columns 1 and 2, and of the idiosyncratic risk averaged across stocks, $\frac{1}{N}\sum_{i=1}^N \sigma_{\varepsilon t}^i$, in Columns 3 and 4 on *Recession*. *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 *Recession*. 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 an indicator variable, $NASDAQ$, equal to one if 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 (twelve-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 twelve-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. *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 twelve-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 twelve-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: **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 a fund's market timing, $Timing_t^j$, and our measure of the fund's stock-picking ability, $Picking_t^j$. 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 $Picking_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. *Skill Picking* 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
Skill Picking	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 6: **Unconditional Performance of "Skill-Picking" Funds**

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 $Picking_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. Skill Picking, 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 twelve-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
Skill Picking	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 7: **Comparing "Skill-Picking" Funds to Other Funds**

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 $Picking_t^j = \sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. *Skill Picking* 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. *Flows* is the fund's net inflow of new assets to manage. *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 *Skill Picking* equals one and zero, respectively. The data are monthly and cover the period 1980 to 2005. $p - values$ measure statistical significance of the difference.

	Skill Picking = 1			Skill Picking = 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
Flows	0.22	7.39	-0.76	-0.07	6.47	-0.73	0.300	0.008
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 8: **Skill Index Predicts Performance**

The dependent variable is the fund's cumulative CAPM, three-factor, or four-factor alpha, calculated from a twelve-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 $Picking_t^j = \frac{1}{N}\sum_{i=1}^{N}(w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m)$. $Picking$ and $Timing$ are normalized so that they are mean zero and have a standard deviation of one 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