Attention Allocation Over the Business Cycle

Marcin Kacperczyk[*]   Stijn Van Nieuwerburgh[†]   Laura Veldkamp[‡]

First version: May 2009, This version: March 2010[§]

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.

[*]Department of Finance Stern School of Business and NBER, New York University, 44 W. 4th Street, New York, NY 10012; mkacperc@stern.nyu.edu; `http://www.stern.nyu.edu/∼mkacperc`.

[†]Department of Finance Stern School of Business, NBER, and CEPR, New York University, 44 W. 4th Street, New York, NY 10012; svnieuwe@stern.nyu.edu; `http://www.stern.nyu.edu/∼svnieuwe`.

[‡]Department of Economics Stern School of Business, NBER, and CEPR, New York University, 44 W. 4th Street, New York, NY 10012; lveldkam@stern.nyu.edu; `http://www.stern.nyu.edu/∼lveldkam`.

> "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 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 portfolio 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 do not outperform passive investment strategies, on average, net of fees, and after controlling for differences in systematic risk exposure.[3] This evidence of zero average "alpha" has led many to conclude that investment managers have no skill. By developing a theory of

---

[1]See, for example, Sims (2003) on consumption, Maćkowiak and Wiederholt (2009a, 2009b) on price setting, and Van Nieuwerburgh and Veldkamp (2009, 2010) on financial 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 financial 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 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% (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 (2010).

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 and helps distinguish our theory from a non-informational one. In recessions, when aggregate shocks to asset payoffs are larger in magnitude, asset payoffs exhibit more comovement. Thus, any portfolio

---

[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 (2010), 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 twenty-five percent higher in recessions in our sample.

strategies that put (exogenously) fixed weights on assets would have returns that also comove more in recessions. In contrast, when investment managers learn about asset payoffs and manage their portfolios according to what they learn, recessionary fund returns comove less. The reason is that when aggregate shocks become more volatile, and less predictable, managers who learn about aggregate shocks end up having more heterogeneous beliefs. They put less weight on their common prior beliefs, which have less predictive power, and more weight on their heterogeneous signals. More heterogeneous beliefs in recessions generate more heterogeneous investment strategies and fund returns.

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 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 covariance *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 also hold 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]Moskowitz (2000), Kosowski (2006), Lynch and Wachter (2007), and Glode (2008) also document such

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.

In our model, recessions are periods of high aggregate payoff and return volatility. The same is true in the data. Identifying these periods as recessions allows us to make contact with the existing macroeconomics literature on rational inattention, e.g., Maćkowiak and Wiederholt (2009a, 2009b). But there also is an effect of recessions above and beyond that which comes from volatility alone. When we use both a recession indicator and aggregate volatility as explanatory variables, we find that both contribute about equally to our three main results. Our explanation for the additional recession effect is that recessions are times in which not only the quantity of risk, but also the price of risk rises. An extended model shows why a recession that embodies both effects generates more attention reallocation than an increase in volatility alone.

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

---

evidence, but their focus is solely on performance.

[7]This is quite different from a 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 of 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)).

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 tests the model's predictions using the context of actively managed mutual funds.
Section 3 discusses the results that use volatility as a conditioning variable instead of or in
addition to the recession indicator. Section 4 uses the model's insights to identify a group
of skilled mutual funds in the data. Section 5 discusses alternative explanations.

1   Model

We develop a stylized model whose purpose is to understand the optimal attention allocation
of investment managers and its implications for asset holdings and 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 asset-specific 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 a stock-specific shock s_1, s_2. The
third asset, c, is a composite asset. Its payoff has no stock-specific 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,

$$f_i = \mu_i + b_i a + s_i, \ i \in \{1, 2\}$$
$$f_c = \mu_c + a$$

---

[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.

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: $\Sigma_{ii} = b_i^2 \sigma_a + \sigma_i$ 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 high 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 $e_{aj} \sim N(0, K_{aj}^{-1})$, $e_{1j} \sim N(0, K_{1j}^{-1})$, and $e_{2j} \sim N(0, K_{2j}^{-1})$ are independent of each other

---

[9]For our results, it is sufficient to assume that the fraction of non-fund investors that are unskilled is higher than that for the investment managers (funds).

and across fund managers. Managers combine signal realizations with priors to update their beliefs, using Bayes' law. Of course, asset prices contain payoff-relevant information as well. We could allow managers to infer this information and subtract the amount of attention required to infer this information from their total attention endowment. However, Lemma S.2 in the Supplementary Appendix[10] establishes that managers always prefer not to use their attention to process the information in prices, when they could instead use the same amount of capacity to process private signals. Therefore, we model managers as if they observed prices, but did not exert the mental effort required to infer the payoff-relevant 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: $\hat{\sigma}_{aj}^{-1} = \sigma_a^{-1} + K_{aj}$ and $\hat{\sigma}_{ij}^{-1} = \sigma_i^{-1} + K_{ij}$. The posterior means of the stock-specific shocks, $\hat{s}_{ij}$, are a precision-weighted linear combination of the prior belief that $s_i = 0$ and the signal η_i: $\hat{s}_{ij} = K_{ij}\eta_{ij}/(K_{ij} + \sigma_i^{-1})$. 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 3×1 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

---

[10]References denoted by 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`

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 K_{aj}, K_{1j}, and K_{2j}, 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:

$$K_{1j} + K_{2j} + K_{aj} \leq K. \tag{6}$$

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.[11]

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

$$K_{1j} \geq 0 \qquad K_{2j} \geq 0 \qquad K_{aj} \geq 0. \tag{7}$$

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 non-fund 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 lemma:

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

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

---

[11]The results are not sensitive to the additive nature of the information capacity constraint. They also hold, for example, for a product constraint on precisions. The entropy constraints often used in information theory take this multiplicative form.

distributed variable, with mean[12]

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

1.3 Bridging The Gap Between Model and Data

The following three sections explain the model's three key predictions: attention alloca-tion, dispersion in investors' portfolios, and average performance. For each prediction, we state a hypothesis and explain how we test it. But the payoffs and quantities that have analytical expressions in a model with CARA preferences and normally distributed asset payoffs 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 exam-ple 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 $K_{aj} \geq 0$ and $K_{1j} \geq 0$ that maximize her time-1 expected utility (9). The choice of signal precision $K_{2j} \geq 0$ 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.

---

[12]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 $V_1[\hat{\mu}_j - pr]$.

Proposition 1. *If aggregate variance is not too high ($\sigma_a \leq 1$), then the marginal value of a given investor j reallocating an increment of capacity from stock-specific shock $i \, \epsilon \, \{1, 2\}$ to the aggregate shock is increasing in the aggregate shock variance: If $K_{aj} = \tilde{K}$ and $K_{ij} = K - \tilde{K}$, then $\partial^2 U / \partial \tilde{K} \partial \sigma_a > 0$.*

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. The converse is true in expansions. The parameter restriction $\sigma_a < 1$, is a sufficient, but not a necessary condition.[13]

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 stock-specific 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 reallocate their attention over the business cycle. Such large swings in attention allocation occur for a wide range of parameters.

As long as the investor's capacity allocation choice is not a corner solution ($K_{aj} \neq 0$ or $K_{aj} \neq K$), a rise in the marginal utility of aggregate shock information increases the optimal K_{aj}. In these environments, skilled investment managers allocate a relatively larger fraction of their attention to learning about the aggregate shock in recessions. But, that effect can break down when assets become very asymmetric because corner solutions arise. 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 exclusively ($K_{aj} = K$) in booms and recessions. Similarly, if the aggregate volatility, σ_a, is too low, then nobody ever learns about the aggregate shock ($K_{aj} = 0$ always).

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

---

[13]Of the seven terms in expected utility, six can be signed without parameter restrictions and one requires this restriction for the derivative to be positive.This constraint does not seem tight in the sense that a value for σ_a of 0.13 in expansions and 0.25 in recessions are the parameter choices that replicate the observed volatility of aggregate stock market returns in our simulation.

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 stock-specific 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:

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

where N^j is the number of individual assets held by fund j. 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 overweights assets that have high (low) sensitivity to the aggregate shock in anticipation of a positive (negative) aggregate shock realization and underweights 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:

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

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 overweights assets that have high betas. Likewise, it underweights assets with high betas 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 simu-

lation 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:

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

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:

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

A fund with a high $Picking$ ability overweights assets that have subsequently high idiosyncratic returns and underweights 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.

13

1.5 Hypothesis 2: Dispersion

A second, more fundamental question is whether investment managers are processing information at all. One prediction that speaks directly to that question is portfolio dispersion. In recessions, as aggregate shocks become more volatile, the idiosyncratic shocks to assets' payoffs account for less of the variation, and the comovement in stock payoffs rises. Since asset payoffs comove more, the payoffs to all investment strategies that put fixed weights on assets should also comove more.

When investment managers are processing information, this prediction is reversed. To see why, consider the Bayesian updating formula for the posterior mean of asset payoffs. It is a weighted average of the prior mean μ and the fund j's signal $\eta_j | f \sim N(f, \Sigma_\eta)$, where each is weighted by their relative precision:

$$E[f|\eta_j] = \left(\Sigma^{-1} + \Sigma_\eta^{-1}\right)^{-1} \left(\Sigma^{-1}\mu + \Sigma_\eta^{-1}\eta_j\right) \tag{14}$$

In recessions, when the variance of the aggregate shock, σ_a, rises, the prior beliefs about asset payoffs are more uncertain: Σ rises and Σ^{-1} falls. This makes the weight on prior beliefs μ decrease and the weight on the signal η_j increase. The prior μ is common across agents, while the signal η_j is heterogeneous. When informed managers weigh their heterogeneous signals more, their resulting posterior beliefs become more different from each other and more different from the beliefs of uninformed managers. More disagreement about asset payoffs results in more heterogeneous portfolios and portfolio returns.

Thus, the model's second prediction is that in recessions, the cross-sectional dispersion in funds' investment strategies and returns rises. 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 2. *If the average manager has sufficiently low capacity, $\chi K < \sigma_a^{-1}$, then for given K_{aj} and K_{ij}, an increase in aggregate risk, σ_a, increases the dispersion of funds' portfolios $E[(q_j - \bar{q})'(q_j - \bar{q})']$, and their portfolio returns $E[((q_j - \bar{q})'(f - pr))^2]$, where $\bar{q} \equiv \int q_j dj$.*

As before, the parameter restriction is sufficient, but not necessary and is not very tight when calibrated to the data.

To connect this proposition to the data, we use several measures of portfolio dispersion, commonly used in the empirical literature. The first one, proposed by Kacperczyk, Sialm, and Zheng (2005), is the sum of squared deviations of fund j's portfolio weight in asset i at

time t, w_{it}^j, from the average fund's portfolio weight in asset i at time t, , w_{it}^m, summed over all assets held by fund j, N^j:

$$Concentration_t^j = \sum_{i=1}^{N^j} \left(w_{it}^j - w_{it}^m\right)^2 \qquad (15)$$

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. In recessions, the portfolios of the informed managers differ more from each other and more from the uninformed investors. Part of this difference comes from a change in the composition of the risky asset portfolio and part comes from differences in the fraction of assets held in riskless securities. Fund j's portfolio weight w_{it}^j is a fraction of the fund's assets, including both risky and riskless, held in asset i. Thus, when one informed fund gets a bearish signal about the market, its w_{it}^j for all risky assets i falls. Concentration can rise when funds take different positions in risky assets, even if the fractional allocation among the risky assets remains identical.

The higher dispersion across funds' portfolio strategies translates into a higher cross-sectional dispersion in fund returns. We form a CAPM regression for fund j:

$$R_t^j = \alpha^j + \beta^j R_t^m + \sigma_\varepsilon^j \varepsilon_t^j \qquad (16)$$

and look at dispersion in the funds' abnormal returns, $R^j - R^m$, alphas, α^j, and betas, β^j. To facilitate comparison with the data, we define the dispersion of variable X as $|X^j - \bar{X}|$. The notation $\bar{X}$ denotes the equally weighted cross-sectional average across all investment managers (excluding non-fund investors). Our numerical results show a higher dispersion of fund abnormal returns, alphas, and betas.

Betas are more dispersed in recessions because funds get signals about the aggregate state a that are heterogenous. Some funds get no signal; others get a signal that a is positive and others will get a signal that a is much lower than expected. This causes some funds to tilt their portfolios to high-beta assets and other funds to low-beta assets, thus creating dispersion. Likewise, the abnormal and risk-adjusted returns of these funds are very different because some funds will have taken the correct bet, while others will not.

The numerical results also reveal that the regression residual variance $(\sigma_\varepsilon^j)^2$ is higher in

recessions. This effect arises because a fund that gets different signal draws (information) in each period holds a portfolio with a beta that varies over time. The CAPM equation (16) estimates an unconditional beta instead. The difference between the true, conditional beta and the estimated, constant beta shows up in the regression residual. Since recessions are times when funds learn more new information each period about the aggregate shock, these are times when true fund betas fluctuate more and the regression residuals are more volatile.

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. To measure performance, we want to measure the portfolio return, adjusted for risk. One risk adjustment that is both analytically tractable in our model and often used in empirical work is the certainty equivalent return, which is also an investor's objective (5). The following proposition shows that the average certainty equivalent of skilled funds' returns exceeds that of unskilled funds by more when aggregate risk is higher, that is, in recessions.

Proposition 3. *If investor j knows more about the aggregate shock than the average investor does ($\hat{\sigma}_{aj} < \bar{\sigma}_a$), then an increase in aggregate shock variance increases the difference between j's expected certainty equivalent return and the expected certainty equivalent return of an uninformed investor: $\partial(U_j - U^U)/\partial\sigma_a > 0$.*

Corollary 1 in Appendix S.1.7 shows that a similar result holds for (risk unadjusted) abnormal portfolio returns, defined as the fund's portfolio return, $q_j'(f - pr)$, minus the market return, $\bar{q}'(f - pr)$.

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 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 an average manager's risk-adjusted return rises in recessions.

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 returns 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 Propositions 1-3 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 1), skilled managers choose to acquire higher capacity in recessions. This extensive-margin effect amplifies our benchmark, intensive-margin result. 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, active mutual fund managers, to test the predictions of the model. The richness of the data makes the mutual fund industry a great laboratory for these tests. 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

---

[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).

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' returns, market capitalizations, book-to-market ratios, momentum, liquidity, and standardized unexpected earnings (SUE). The aggregate stock market return is the value-weighted average return of all stocks in the CRSP universe.

We use changes in monthly industrial production, obtained from the Federal Reserve Statistical Release, as a proxy for aggregate shocks. Industrial production is seasonally adjusted. 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%). We consider several alternative recession indicators and find our results to be robust.[15]

2.2 Recessions Are Periods of Higher Aggregate Risk

At the outset, 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

---

[15]We have confirmed our results using an indicator variable for negative real consumption growth, the Chicago Fed National Activity Index (CFNAI), and an indicator variable for the 25% lowest stock market returns as alternative recession indicators. While its salience makes the NBER indicator a natural benchmark, the other measures may be available in a more timely manner. Also, the CFNAI has the advantage that it is a continuous variable, measuring the strength of economic activity. As an example, Table S.12 shows that the results on performance are, if anything, stronger using the CFNAI measure than they are with the NBER indicator. Other results are omitted for brevity but are available from the authors upon request.

the aggregate (Columns 1 and 2) and the idiosyncratic risk (Columns 3 and 4), both averaged across stocks, on the NBER recession indicator variable.[16] The aggregate risk is twenty percent higher in recessions than it is in expansions (6.69% versus 8.04% per month), 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 pooled (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.

A large literature in economics and finance presents evidence supporting the results in Table 1. First, Ang and Chen (2002), Ribeiro and Veronesi (2002), and Forbes and Rigobon (2002) document that stocks exhibit more comovement in recessions, consistent with stocks carrying higher systematic risk in recessions. Second, Schwert (1989), Hamilton and Lin (1996), Campbell, Lettau, Malkiel, and Xu (2001), and Engle and Rangel (2008) show that aggregate stock market return volatility is much higher during periods of low economic activity. Diebold and Yilmaz (2008) find a robust cross-country link between volatile stock markets and volatile fundamentals. Third, Bloom, Floetotto, and Jaimovich (2009) find that the volatilities of GDP and industrial production growth, obtained from GARCH estimation, and the volatility implied by stock options are much higher during recessions. The same result holds for the uncertainty in several establishment-, firm- and industry-level payoff measures they consider.[17]

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 the aggregate shock. Conversely, in expansions, their holdings covary more with stock-

---

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

[17]Several other pieces of evidence also corroborate the link between volatility and recessions. First, labor earnings volatility is substantially counter-cyclical (Storesletten, Telmer, and Yaron (2004) and Shin and Solon (2008)). This mechanism has been exploited in generating equity risk premium by Mankiw (1986), Constantinides and Duffie (1996), Lustig and Van Nieuwerburgh (2005), and Storesletten, Telmer, and Yaron (2007), among others. Second, small firms face more risk in recessions (Perez-Quiros and Timmermann (2000)). Finally, the notion of Shumpeterian creative destruction is also consistent with such link.

specific information. To this end, we estimate the following regression model:

$$Attention_t^j = a_0 + a_1 Recession_t + \mathbf{a_2}\mathbf{X_t^j} + \epsilon_t^j, \tag{17}$$

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.[18] 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 specifications using pooled (panel) regression model 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 production growth.[19] A time series for RAI_t^j is obtained by computing the covariance of the

---

[18]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).

[19]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 $t+1$.

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, 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. Following equation (12), RSI 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.[20,21] 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, or 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 the variation in market-timing, $Timing_t^j$, and stock-picking ability, $Picking_t^j$, defined in equations (11) and (13). The benefit of using these measures 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, utilized in $Timing$ and $Picking$, are computed using the twelve-month rolling-window regressions of stock excess returns on market excess returns.

Columns 5 and 6 of Table 2 show that the average market-timing ability across funds

---

[20]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 $t + 3$.

[21]We have verified that the firm-specific earnings shocks are uncorrelated with the aggregate earnings shocks. The median correlation across stocks is below 0.01, with a cross-sectional standard deviation of 0.28.

increases significantly in recessions. In turn, we find no evidence of market timing in expansions. Since expansion months constitute 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 our theory. The reduction in recessions is about 20 percent of a standard deviation of the $Picking$ measure.

Table S.5 reports 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. 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 (instead of one quarter) earlier, as in Bernard and Thomas (1989). Third, to check the market-timing results, we also compute the R^2 from a CAPM regression at the fund level, as in equation (16). It measures how the funds' excess returns (as opposed to their portfolio weights) covary with the aggregate state, defined by the market's excess return. All the results are similar to our benchmark results, 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 states 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, generically denoted as $Dispersion_t^j$, the dispersion of fund j at month t.

$$Dispersion_t^j = b_0 + b_1 Recession_t + \mathbf{b_2}\mathbf{X_t^j} + \epsilon_t^j, \tag{18}$$

The definitions of $Recession$ and other controls mirror those in regression (17). 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 (15). 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.

A common measure of portfolio dispersion is the variance of the CAPM residual (σ_ε^j in equation (16), often called idiosyncratic risk). As explained in Section 1.5, our model generates counter-cyclical residual variance. Columns 3 and 4 show that this residual variance increases in recessions in the data as well. The increase is highly significant, statistically and economically. One concern with the CAPM residual 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 (18). 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 and 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 considers additional measures of portfolio and return dispersion. 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 alphas 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. Taken together, these results support our 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:

$$Performance_t^j = c_0 + c_1 Recession_t + \mathbf{c_2}\mathbf{X_t^j} + \epsilon_t^j \tag{19}$$

where $Performance_t^j$ denotes fund j's performance in month t, measured as fund abnormal returns or CAPM, three-factor, or four-factor alphas. *Recession* and the control variables, X, are defined as before. All returns are 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 lower 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 premiums diminish (Columns 5-8). 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 advantage of this cross-sectional regression model is that it allows us to include a host of fund-specific control variables. The disadvantage is that performance is measured using past twelve-month rolling-window regressions. Thus, 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 cross-sectional results, we also employ a time-series ap-

proach. 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.11 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 recessions.

While our model is silent about the distinction between funds and fund managers, in practice, skill could be embodied in the manager or be produced by the organizational setup the fund provides that manager. We estimate our main results using the cross section of data at the manager level. Table S.14 shows that the recession effects on RAI/RSI, dispersion, and performance are essentially unchanged, suggesting that the distinction is not important for our results.

3   Recession versus Volatility

In our model, recessions are times of higher aggregate payoff volatility, and hence higher stock return volatility. In Section 2.2, we show that the same is true in the data. This motivates our use of recessions in the empirical work. The link between recessions and aggregate volatility, however, suggests an additional way of testing the model: We could replace the recession indicator with an indicator for high aggregate payoff volatility. The high-volatility indicator variable equals one in months with the highest volatility of aggregate earnings growth, where aggregate volatility is estimated from Shiller's S&P 500 earnings growth data.[22] As predicted by our theory, we find that RAI, dispersion, and performance all rise in high-volatility months, while RSI falls; see Table S.13.

Given that both recessions and aggregate volatility qualitatively deliver the same predictions, it is natural to ask which of the two effects is stronger. To that end, we include both NBER recession and high aggregate payoff volatility indicators as explanatory variables in

---

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

an empirical horse race. For brevity, Table 5 combines the headline results for RAI/RSI, portfolio dispersion, and performance. It shows that both recession and volatility contribute to a lower RSI in expansions and a higher RAI in recessions, to a higher portfolio dispersion in recessions (concentration, alpha dispersion, and beta dispersion), and to a higher performance in recessions (four-factor alpha).[23] For some of the results the recession effect is slightly stronger, while for others the volatility effect is slightly stronger. Clearly, there is an effect of recessions beyond the one coming through volatility.

To understand why recessions have an incremental effect over volatility in explaining attention allocation, we consider an augmented model in which both the quantity and the price of risk rise in recessions. The idea that the price of risk rises in recessions is supported by a large asset pricing literature (e.g., the external habit model of Campbell and Cochrane (1999) or the variable rare disasters model of Gabaix (2009)). The parameter that governs the price of risk in our model is risk aversion. The following result shows that an increase in the price of risk (risk aversion) in recessions is an independent force driving the reallocation of attention from stock-specific to aggregate shocks. Because of this additional channel, recessions should generate more attention reallocation than a rise in aggregate volatility alone, just as we see in the data. The proof is in Appendix S.1.8.

Proposition 4. *If the size of the composite asset $\bar{x}_c$ is sufficiently large, then an increase in risk aversion increases the marginal utility of reallocating a unit of capacity from the firm-specific shock to the aggregate shock:* $\partial/\partial\rho(\partial U/\partial(\hat{\sigma}_{aj}^{-1} - \hat{\sigma}_{1j}^{-1})) > 0$.

The intuition for this result is that aggregate shocks affect a large fraction of the value of one's portfolio. Therefore, a marginal reduction in the uncertainty about an aggregate shock reduces total portfolio risk by more than the same-sized reduction in the uncertainty about a stock-specific shock. In other words, learning about aggregate shocks is the most efficient way to reduce portfolio risk. The more risk averse an agent is, the more attractive aggregate attention allocation becomes.

4   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 could use it to successfully identify skilled investment managers in the data. In particular, we exploit the model's prediction that skilled managers display

---

[23]The results without controls are similar, as are the results for other dispersion and performance measures.

market-timing ability in recessions and stock-picking ability in expansions. Market-timing and stock-picking ability are defined by 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.

4.1 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 model, separately for expansions and recessions:

$$Ability_t^j = d_0 + d_1 SP_t^j + \mathbf{d_2} \mathbf{X_t^j} + \epsilon_t^j, \tag{20}$$

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

In Table 6, Column 3, we confirm that SP funds are significantly better at picking stocks in expansions, after controlling for fund characteristics. This is true by construction. The main point is that these same SP funds are on average better 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, the funds in SP do not exhibit superior market-timing ability in expansions (Column 1) nor superior stock-picking ability in recessions (Column 4), which validates the point that SP funds switch strategies.[24]

Having identified a subset of skilled ($SP_j = 1$) funds, the model predicts that this group

---

[24]The existence of skilled mutual funds with cyclical investment strategies is not a fragile result. First, the results survive 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.16 and S.17). 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.18 and S.19).

should outperform the unskilled funds both in recessions and in expansions. Table 7 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 8, we further compare the characteristics of the funds in the *Skill-Picking* portfolio to those of funds not included in the portfolio. We note several differences. First, funds in SP portfolio are younger (by five years on average). 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 higher turnover rates (130% per year, versus 80% for other funds), consistent with a more active management style. Fifth, they receive higher inflows of new assets to manage, presumably a market-based reflection of their skill. Sixth, the SP funds tend to hold portfolios with fewer stocks and higher stock-level and industry-level 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, fund characteristics, such as age, TNA, expenses, and turnover explain 14% of the variation in SP, the skill indicator (Table S.15). Including attributes that our theory links to skilled funds, such as stock and industry concentration, beta deviation, and RAI, increases the R^2 to 19%. Thus, these findings paint a rough picture of what a typical skilled fund looks like.

Table 8, 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.

4.2   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 9 shows that funds with a higher $SkillIndex$ have higher average 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.20).

5   Alternative Explanations

Mechanical effects   We briefly explore other candidate explanations. The first alternative is that our effects 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.

Sample selection   Suppose that managers have heterogeneous skill, but they do not display the cyclical variation in attention allocation we envision. Furthermore, suppose that the best managers leave the sample in good times, maybe because they go to a hedge fund. Then the composition effect would deliver lower alphas and less dispersion in expansions. If for some reason skill is associated with high RAI and low RSI, it could also explain the attention allocation results. There are at least three ways to refute this story. First, we redo our results with managers (instead of funds) as the unit of observation and include man-

ager fixed effects. Table S.21 shows that our results go through unchanged. Including fixed effects in a regression model is a standard response to sample selection concerns. We find that fund fixed effects do not change our fund-level results. Second, in Section 4 we show that the same managers who have high RSI in expansions also have high RAI in recessions, a finding supporting active behavior of fund managers and working against the composition effect explanation. Third, even though in Table S.22 we show a higher chance of being promoted or picked off by a hedge fund in expansions, we also show a higher likelihood of being fired or demoted in recessions. The latter effect works in the opposite direction of the first, especially with respect to the dispersion result. Fourth, we find no systematic differences in age, educational background, or experience of managers in recessions versus expansions (Table S.23).

Career concerns   Chevalier and Ellison (1999) show that young managers with career concerns may have an incentive to herd. Now imagine that in expansions the incentive to herd is strong, while in recessions young managers have to deviate from the pack to safeguard their jobs. We would then expect to see higher dispersion in strategies and performance in recessions. In order to investigate this hypothesis, we first run our dispersion regressions at the manager level adding the manager's log age and log age interacted with the recession indicator as independent variables. The career-concerns hypothesis predicts a negative sign on the interaction term: Younger managers should deviate more from the pack in recessions. Instead, we find a significantly positive interaction effect for our Concentration measure. The effect on idiosyncratic risk and beta dispersion is not statistically different from zero, while the effect on alpha dispersion is negative but only significant at the 10% level. It is worth noting that the sign on manager age itself is positive and significant, in line with the findings of Chevalier and Ellison (1999).[25] In sum, the results do not provide much evidence for the career-concerns hypothesis. Moreover, it is not clear how the hypothesis would account for the RAI/RSI and performance results. 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 patterns we document.

Time-varying marginal utility   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

---

[25]Detailed results are omitted for brevity, but available upon request.

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 are unlikely to account for all facts jointly.

6 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 currently 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.

BLOOM, N., M. FLOETOTTO, AND N. JAIMOVICH (2009): "Really uncertain business cycles," Working Paper, Stanford University.

BREON-DRISH, B., AND J. S. SAGI (2008): "Do fund managers make informed asset allocation decisions?," Working Paper, Vanderbilt University.

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.

CAMPBELL, J., M. LETTAU, B. MALKIEL, AND Y. XU (2001): "Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk," *Journal of Finance*, 56 (1), 1–44.

CAMPBELL, J. Y., AND J. H. COCHRANE (1999): "By force of habit: A consumption-based explanation of aggregate stock market behavior," *Journal of Political Economy*, 107(2), 205–251.

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.

CHEVALIER, J., AND G. ELLISON (1999): "Career concerns of mutual fund managers," *Quarterly Journal of Economics*, 104, 389–432.

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.

CONSTANTINIDES, G. M., AND D. DUFFIE (1996): "Asset pricing with heterogeneous consumers," *Journal of Political Economy*, 104, 219–240.

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.

DIEBOLD, F., AND K. YILMAZ (2008): *Volatility and time-series econometrics: Essays in Honor of Robert F. Engle*chap. Macroeconomic volatility and stock market volatility world-wide. Oxford University Press.

ENGLE, R., AND J. RANGEL (2008): "The spline-GARCH model for low-frequency volatility and its global macroeconomic causes," *Review of Financial Studies*, 21 (3), 1187–1222.

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 (2010): "Luck versus skill in the cross section of mutual fund returns," *Journal of Finance*, Forthcoming.

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. (2009): "Variable rare disasters: An exactly solved framework for ten puzzles in macro finance," Workikng Paper, NYU Stern.

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, Wharton.

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.

HAMILTON, J. D., AND G. LIN (1996): "Stock market volatility and the business cycle," *Journal of Applied Econometrics*, 11 (5), 573–593.

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. (2010): "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.

LUSTIG, H., AND S. VAN NIEUWERBURGH (2005): "Housing collateral, consumption insurance and risk premia: An empirical perspective," *Journal of Finance*, 60(3), 1167–1219.

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.

MANKIW, G. N. (1986): "The equity premium and the concentration of aggregate shocks," *Journal of Financial Economics*, 17, 211–219.

MOSKOWITZ, T. J. (2000): "Discussion of mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses," *Journal of Finance*, 55, 1695–1704.

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.

PEREZ-QUIROS, G., AND A. TIMMERMANN (2000): "Firm size and cyclical variations in stock returns," *Journal of Finance*, 55, 1229–1262.

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.

SCHWERT, G. W. (1989): "Why does stock market volatility change over time?," *Journal of Finance*, 44(5), 1115–1153.

SHIN, D., AND G. SOLON (2008): "Trends in mens earnings volatility: What does the Panel Study of Income Dynamics show?," NBER Working paper 14075.

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.

STORESLETTEN, K., C. TELMER, AND A. YARON (2004): "Cyclical dynamics of idiosyncratic labor market risk," *The Journal of Political Economy*.

——— (2007): "Asset pricing with idiosyncratic risk and overlapping generations," *Review of Economic Dynamics*, 10 (4), 519–548.

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.
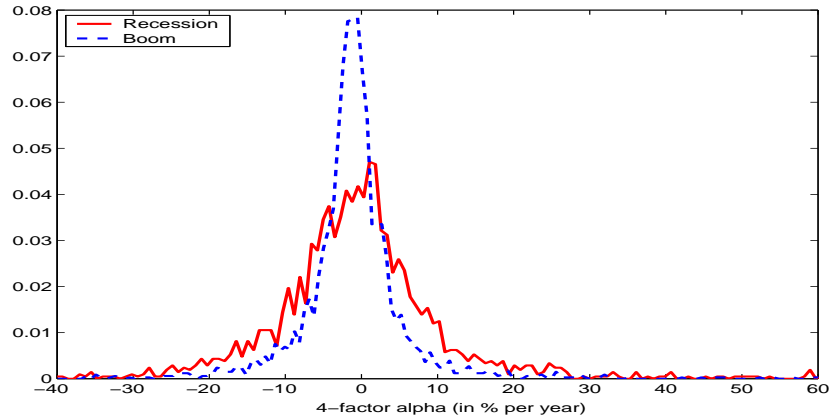
Figure 2: Investment Performance in Recessions vs. Expansions

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.

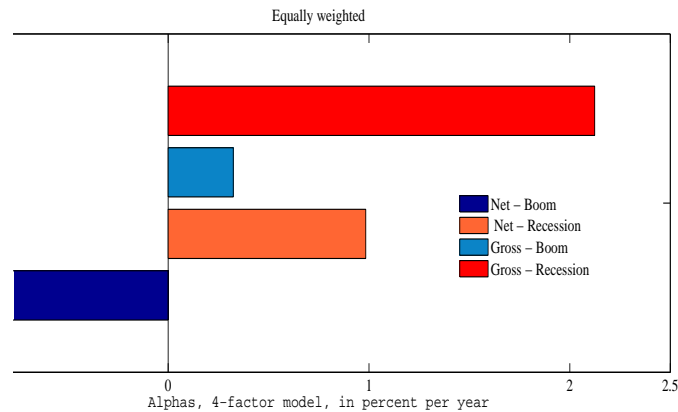Table 1: **Individual Stocks Have More Aggregate Risk in Recessions**

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	1.348	1.308	0.058	0.016
	(0.693)	(0.678)	(1.018)	(1.016)
MKTPREM		-4.034		-1.865
		(3.055)		(3.043)
SMB		8.110		12.045
		(3.780)		(4.293)
HML		0.292		9.664
		(5.458)		(8.150)
UMD		-4.279		-1.112
		(2.349)		(3.888)
Constant	6.694	6.748	13.229	13.196
	(0.204)	(0.212)	(0.286)	(0.276)
Observations	309	309	309	309
Panel B: Pooled Regression				
Recession	1.203	1.419	0.064	0.510
	(0.242)	(0.238)	(0.493)	(0.580)
Log(Size)		-0.145		-1.544
		(0.021)		(0.037)
B-M Ratio		-0.934		-2.691
		(0.056)		(0.086)
Momentum		0.097		2.059
		(0.101)		(0.177)
Leverage		-0.600		-1.006
		(0.074)		(0.119)
NASDAQ		0.600		1.937
		(0.075)		(0.105)
Constant	4.924	4.902	12.641	12.592
	(0.092)	(0.095)	(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: **Recession and Volatility**

The dependent variables are funds' reliance on aggregate information (RAI), funds' reliance on stock-specific information (RSI), funds' portfolio concentration (*Concentration*), the cross-sectional dispersion in fund CAPM alphas (CAPM Alpha Disp) and betas (CAPM Beta Disp), and the funds' four-factor alpha (4-Factor Alpha). The definitions of the dependent variables are listed in the captions of Tables 2, 3, and 4. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *Volatility* is a dummy variable indicating periods of high volatility in fundamentals. We calculate the twelve-month rolling-window standard deviation of aggregate earnings growth. Aggregate earnings growth is the year-to-year log change in the earnings of S&P 500 index constituents; the aggregate earnings data are from Robert Shiller for the period from 1926 until 2008. Volatility equals one if the standard deviation of aggregate earnings growth is in the highest 10% of months in the 1926-2008 sample. Twelve percent of months in our 1985-2005 sample are such high volatility months. *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)
	RAI	RSI	Concentration	CAPM Alpha Disp	CAPM Beta Disp	4-Factor Alpha
Recession	0.011	-0.503	0.185	0.217	0.062	0.100
	(0.004)	(0.166)	(0.027)	(0.050)	(0.013)	(0.035)
Volatility	0.000	-0.477	0.206	0.254	0.077	0.125
	(0.003)	(0.106)	(0.030)	(0.035)	(0.018)	(0.064)
Log(Age)	-0.002	0.416	0.198	-0.040	-0.004	-0.036
	(0.001)	(0.060)	(0.027)	(0.004)	(0.002)	(0.006)
Log(TNA)	-0.001	-0.167	-0.176	0.013	0.002	0.010
	(0.000)	(0.029)	(0.014)	(0.003)	(0.001)	(0.003)
Expenses	-0.331	90.911	29.859	8.166	3.695	-8.187
	(0.247)	(11.599)	(4.868)	(0.586)	(0.211)	(0.787)
Turnover	-0.004	-0.199	-0.089	0.044	0.012	-0.067
	(0.001)	(0.063)	(0.025)	(0.004)	(0.001)	(0.008)
Flow	-0.008	1.668	0.108	0.316	0.008	1.536
	(0.010)	(0.632)	(0.104)	(0.046)	(0.016)	(0.096)
Load	0.017	-10.009	-1.789	-0.895	-0.252	-0.223
	(0.023)	(1.984)	(0.909)	(0.100)	(0.040)	(0.141)
Constant	-0.001	3.124	1.546	0.561	0.221	-0.065
	(0.001)	(0.074)	(0.023)	(0.016)	(0.005)	(0.021)
Observations	224,257	166,328	226,745	226,745	226,745	226,745

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

We divide all fund-month observations into Recession and Expansion subsamples. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise; *Expansion* is equal to one every month the economy is not in recession. The dependent variables are our measure of 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 7: **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) CAPM Alpha	(2) 3-Factor Alpha	(3) 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 8: **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 9: **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