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ABSTRACT

Mutual fund managers can outperform the market by picking stocks or timing the market successfully. Previous work has estimated picking and timing skill, assuming that each manager is endowed with a fixed amount of each and found some evidence of picking skills and little evidence of timing skills among successful managers. This paper estimates skill separately in booms and recessions and finds that the extent to which managers focus on stock picking or market timing fluctuates with the state of the economy. Stock picking is more prevalent in booms, while market timing dominates in recessions. We use this finding to develop a new methodology for detecting managerial skill. The results suggest that some but not all managers have skill. We describe the characteristics of the skilled managers and show that skilled managers significantly outperform the market.

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An enormous literature asks whether investment managers add value for their clients and if so, how. One way to answer this question is to decompose fund performance into stock-picking ability and market-timing ability. Previous work has estimated picking and timing skills implicitly assuming that each manager is endowed with a fixed amount of each skill. But stock picking and market timing are not talents one is born with. They are the result of time spent working, analyzing data. Like workers in other jobs, fund managers may choose to focus on different tasks at different points in time. This simple idea leads us to re-estimate fund manager skill in a way that allows its nature to change, depending on economic conditions. Our results show that successful managers pick stocks well in booms and time the market well in recessions. This suggests that skills such as stock picking and market timing are not distinct and permanent, but instead reflect a cognitive ability that can be applied in different ways depending on the market environment. As a financial web site ZeroHedge writes: "It is hard for a portfolio manager to focus on the nuances of stock selection when the prospects of a U.S. recession keep rising. ...Simply put, the macro is overwhelming the micro."[1]

Understanding exactly how managers add value for their clients is important because a large and growing fraction of individual investors delegate their portfolio management to professional investment managers.[2] Yet, a significant body of evidence finds that the average actively managed fund does not outperform passive investment strategies, net of fees, and after controlling for differences in systematic risk exposure. Instead, there is a small subset of funds that persistently outperform. Most previous work has argued that this

[1]Published on September 25, 2011.

[2]In 1980, 48% of U.S. equity was directly held by individuals – as opposed to being held through intermediaries; by 2007, that fraction was down to 21.5% (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% was actively managed (2009 Investment Company Factbook).

outperformance comes from stock picking and not market timing. Our results suggest that the reason previous studies failed to detect market- timing ability is because it is typically displayed only in recessions, which are a small fraction of the sample periods. Once we condition on the state of the economy, we find that most skilled managers exhibit both types of skill: Those who are good stock-pickers in booms are also good market-timers in recessions.

The fact that only a subset of managers add value makes it important to be able to identify these skilled managers. Therefore, a second contribution of the paper is to develop a new measure for detecting managerial skill, that gives more weight to fund manager's market-timing ability in recessions and her stock-picking ability in booms. This new measure predicts performance. We show that a subset of managers with the highest value of our skill measure significantly outperform the passive benchmarks by 70-90 basis points per year, in a persistent way.

To measure skill, we construct estimates of stock picking (the covariance of portfolio weights with the firm-specific component of stock returns) and market timing (the covariance of portfolio weights with the aggregate component of stock returns) for each firm in each 12-month rolling window. Then, we regress these timing and picking variables on a recession indicator variable to determine if skills change significantly over the business cycle. We find that the average fund manager exhibits greater stock-picking ability in booms and a better market-timing ability in recessions. Moreover, results from quantile regressions show that it is the most skilled managers that vary the use of their skills most over the business cycle. This is consistent with the idea that only some managers have skill and it is those managers who decide how to apply that skill depending on the economic environment. Importantly, this is not a composition effect. It is the *same* manager who picks stocks well in booms that times the market well in recessions.

Our skill measures allow us to further investigate the nature of this stock-picking and market-timing skill. First, do managers correctly anticipate the demands of other market participants or do they acquire information that helps them to forecast market fluctuations or firm earnings? To answer these questions, we try to distinguish a manager's ability to forecast market or firm-specific fundamentals from her ability to forecast market sentiment (movements in returns that are orthogonal to fundamentals). Therefore, we estimate the covariance of each fund's portfolio holdings with an aggregate fundamental shock—the innovations in industrial production growth. This covariance measures a manager's ability to time the market by increasing (decreasing) her portfolio positions in anticipation of good (bad) macroeconomic news. We find that this fundamentals-based timing covariance rises in recessions. Likewise, we also calculate the covariance of a fund's portfolio holdings with asset-specific fundamental shocks—the unexpected innovations in earnings. This covariance measures managers' ability to pick stocks that subsequently experience high earnings. We find that this fundamentals-based stock-picking covariance increases in expansions. Figure 1 summarizes our findings.

Not only do we find that managers correctly forecast firm-specific fundamentals in booms and market fundamentals in recessions, these results are even stronger than those in which timing and picking are based on stock market information. Thus, another contribution of the paper is to show that skilled managers are learning about the fundamental strengths and weaknesses of firms and of the economy and are using that information to time the market and pick stocks.

Next, we explore several investment strategies managers use to time the market. We find that, on average, they hold more cash in recessions, their portfolios have lower market betas, and they tend to engage in sector rotation by investing more money into defensive industries in recessions and into cyclical industries in booms. All three results suggest that managers are actively varying their investment behavior along the business cycle.

We entertain five non-skill-related alternative explanations for our main findings. First, we consider whether mechanical effects from cyclical fluctuations in means or variances of *stock* returns could generate changes in picking and timing measure. After all, expected stock returns vary with the state of the business cycle (e.g., Ferson and Harvey (1991) and Dangl and Halling (2011)). Second, we explore the possibility that fund strategies change because the fund manager changes. Third, we study potential selection effects both at the fund and the manager level. Fourth, we consider whether various forms of career concerns might explain our results. Finally, we look at an explanation based on time-varying marginal utility. None of these alternatives can explain the observed changes in fund portfolios over the business cycle.

Our findings suggest a new way to construct metrics that would help us to 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 remaining funds show no such market-timing ability. Conversely, we can select the top 25 percent of funds in terms of their market-timing ability in recessions and show that this same group has significant stock-picking ability in booms. These top funds produce *unconditional* fund returns in excess of passive benchmarks. Our approach is quite different from a typical approach in the literature, which has studied stock picking and market timing in isolation, unconditional on the state of the economy. The consensus view from that literature is that there is some evidence of stock-picking ability among best managers, but little evidence for market timing (e.g., Graham and Harvey (1996), Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (2000) and Kacperczyk and Seru (2007)). Notable exceptions are Mamaysky, Spiegel, and Zhang (2008) who find evidence for market timing using Kalman filtering techniques, and Bollen and Busse (2001) and Elton, Gruber, and Blake (2011) who find evidence of market timing using higher frequency holdings data. Our finding that some managers have skill is consistent with a number of recent papers in the empirical mutual fund literature, e.g., Pástor and Stambaugh (2002), Kacperczyk, Sialm, and Zheng (2005, 2008), Kacperczyk and Seru (2007), Christoffersen, Keim, and Musto (2007), Cremers and Petajisto (2009), Koijen (2010), Baker, Litov, Wachter, and Wurgler (2010), Huang, Sialm, and Zhang (2011), Amihud and Goyenko (2011), and Cohen, Polk, and Silli (2011).

Finally, using hand-collected data, we identify the characteristics of the superior funds and their managers. They tend to be smaller and more active. By matching fund-level to manager-level data, we find that these skilled managers are also more likely to attract new money flows and 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 predicts future performance over one-month and one-year horizons.

The rest of the paper is organized as follows. Section 1 tests the hypothesis that fund managers' stock-picking and market-timing skill varies over the business cycle, using the universe of actively managed U.S. equity mutual funds. Section 2 delves more deeply into how managers pick stocks and time the market. Section 3 considers alternative explanations, not based on time-varying use of skill. Section 4 uses the paper's insights to identify a group of skilled mutual funds in the data and measures their outperformance. Section 5 concludes.

1 Skill Varies Over Time

We begin by describing our data on active mutual fund managers, their portfolios, and their returns. We describe our measures of skill and then use the data to estimate them in booms and recessions. In principle, similar tests could be conducted for hedge funds, other professional investment managers, or even individual investors.

1.1 Data

Our sample builds upon several data sets. We begin with the Center for Research on Security Prices (CRSP) survivorship bias-free mutual fund database. The CRSP database provides comprehensive information about fund returns and a host of other fund characteristics, such as size (total net assets), age, expense ratio, turnover, and load. Given the nature of our tests and data availability, we focus on actively managed open-end U.S. equity mutual funds. We further merge the CRSP data with fund holdings data from Thomson Financial. The total number of funds in our merged sample is 3477.

In addition, for some of our exercises, we map funds to the names of their managers using information from CRSP, Morningstar, Nelson's Directory of Investment Managers, Zoominfo, and Zabasearch. This mapping results in a sample with 4267 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.[3]

1.2 Defining measures of skill

Investors who have skill use them to form portfolios that covary with realized returns. If an investor has skill in timing the market, it means that he holds more of the market portfolio in periods when the realized market return will be high and holds less when the realized market return will be low. Similarly, stock-picking ability is the ability to hold more of a stock in periods when that firm's realized stock return will be high. To this end, we define the following measures of skill.

For fund j at time t, $Timing^j$ measures how a fund's holdings of each asset, relative to the market, covary with the systematic component of the stock return, over the next T periods:

$$Timing_t^j = \frac{1}{TN^j} \sum_{i=1}^{N^j} \sum_{\tau=0}^{T-1} (w_{it+\tau}^j - w_{it+\tau}^m)(\beta_{it+\tau+1} R_{t+\tau+1}^m), \tag{1}$$

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 product of β_i and R^m measures the systematic component of returns of asset i. The time subscripts indicate that the systematic component

[3]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. These results are omitted for brevity but are available from the authors upon request.

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.

Similarly, $Picking_t^j$ measures how a fund's holdings of each stock, relative to the market, covary with the idiosyncratic component of the stock return:

$$Picking_t^j = \frac{1}{N^j} \sum_{i=1}^{N^j} (w_{it}^j - w_{it}^m)(R_{t+1}^i - \beta_i R_{t+1}^m) \tag{2}$$

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

1.3 Main result: Skill is time varying

We begin by testing the main claim of the paper, that skilled investment managers deploy their skills differently over the business cycle. Our aim is to show that because managers analyze the aggregate payoff shock in recessions, it allows them to choose portfolio holdings that covary more with the aggregate shock. Conversely, in expansions, their holdings covary more with stock-specific information. To this end, we estimate the following regression model:

$$Picking_t^j = a_0 + a_1 Recession_t + \mathbf{a_2 X_t^j} + \epsilon_t^j, \tag{3}$$

$$Timing_t^j = b_0 + b_1 Recession_t + \mathbf{b_2 X_t^j} + \varepsilon_t^j, \tag{4}$$

where $Recession_t$ 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.[4] 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 skill variable in expansions, and a_1 indicates how much the variable increases in recessions.

First, we examine the variation in market-timing, $Timing_t^j$, and stock-picking ability,

[4]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).

$Picking^j_t$, defined in equations (1) and (2). 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. Table 1 presents the results.

Columns 1 and 2 show that the average market-timing ability across funds increases significantly in recessions. The increase is 25 percent of a standard deviation of the *Timing* measure, which is economically meaningful. Likewise, columns 3 and 4 show that stock-picking ability deteriorates substantially in recessions. The reduction in recessions is about 20 percent of a standard deviation of the *Picking* measure. In sum, we observe strong differences in average skills across market conditions.

1.4 Do all managers have time-varying skill?

Since markets have to clear, not everyone can outperform the market. Fama and French (2010) have used such adding-up constraint to argue that the average actively managed mutual fund cannot outperform passively managed funds. Therefore, the average fund cannot be a profitable stock-picker.[5] Our claim is not that all funds outperform, or even that the average fund outperforms. We only claim that there is a subset of funds with skilled managers who deliver valuable services to their clients, before fees, at the expense of all other investors (unskilled fund and non-fund investors). A second part of the Fama and French argument is that the R^2 of a regression of the aggregate mutual fund return on the market return is close to one. In other words, when we average across active funds, that average fund is passive. Our conclusions are consistent with this finding, because it does not condition investment strategies on the state of the business cycle and does not preclude the existence of a subset

[5] Savov (2010) argues that the same is not true for market timing, since investors in index funds capture less than the buy-and-hold returns of index funds through their dynamic trading strategies.

of skilled managers.

If we believe that there is a subset of skilled managers and that these skilled managers vary the way they use skill over the business cycle, then we should see most of the time variation in the use of skill among the most skilled managers. We test this prediction using quantiles of the cross-sectional fund distribution. Our hypothesis is that the distribution of picking and timing skills should be more sensitive to recession variable in the right tail than at the median. We evaluate this hypothesis formally by estimating the models in (3) and (4) using quantile regressions. We consider three different quantiles: 50 (median), 75, and 95. Table 2 presents the results.

Consistent with our hypothesis, we find that the effect of business cycle on skill is much stronger for extremely successful fund managers, residing in quantile 95, than for the median fund. The effect is statistically significant and economically strong, both for stock picking and market timing. For example, for market timing the effect of recession for extremely successful managers is about four times larger than that for the median manager (0.251 vs. 0.059). A similar comparison for stock picking returns about two times magnitude difference (-0.173 vs. -0.084). In sum, we conclude that the effect of market conditions on skill matters more for top-performing managers, which is consistent with the view that only a subset of fund managers hones skills.

1.5 The same managers exhibit both skills

One possible explanation for the findings reported thus far is that some managers have timing ability and others have picking ability, but that no managers both pick stocks and time the market well. To show that some managers are good at both tasks, we test the prediction that the *same* mutual funds that exhibit stock-picking ability in expansions display market-timing ability in recessions. 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 (equation 2). We then 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 (months) in that top group , relative to the total number of observations for that fund (months in expansions). Then, we estimate the following pooled regression model, separately for expansions and recessions:

$$Ability_t^j = c_0 + c_1 SP_t^j + \mathbf{c_2 X_t^j} + \epsilon_t^j, \tag{5}$$

where *Ability* denotes either *Timing* or *Picking*. X is a vector of previously defined control variables. The coefficient of interest is c_1.

In Table 3, 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 positive coefficient on SP in column 2, that 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.

2 How Do Funds Outperform The Market?

This section explores in greater detail how managers time the market and pick stocks, opening up the black box of fund outperformance. First, it looks at whether picking and timing are based on fundamental analysis or not. Second, to further explain how funds time the market in recessions, we show that they significantly increase their cash holdings, reduce their holdings of high-beta stocks, and tilt their portfolios towards more defensive sectors. Lastly, it explores alternative ways of measuring business cycles and skills.

2.1 Is skill from fundamental analysis?

The finding that some fund managers have skill raises questions about the nature of this skill. Is it an ability to forecast changes in market or firms fundamentals or rather some intuitive understanding of market psychology (sentiment)? To isolate the part of skill that comes from an ability to analyze fundamentals, we construct two new additional measures of skill, $Ftiming$ and $Fpicking$, where the first F stands for *fundamentals-based* timing and picking skills. While timing and picking measure the covariance of a fund's portfolio with market and firm-specific returns, $Ftiming$ measures the covariance of the portfolio with a measure of real economic performance (market fundamentals) and $Fpicking$ measures the covariance with firm earnings (firm-specific fundamentals).

Suppose that the time-t return on stock i depends on an aggregate shock a_t and a stock-specific shock $s_{i,t}$. Asset i's loading on the aggregate shock is b_i and the mean return is μ_i:

$$R_{i,t} = \mu_i + b_i a_t + s_{i,t},\ i \in \{1, \cdots, N\} \tag{6}$$

where the shocks a and $s_{i,t}$ are mean-zero and mutually independent $\forall\ i \in \{1, \cdots, N\}$. We define a fund's fundamentals-based market timing skill, $Ftiming$, 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, over a T-period horizon, averaged across assets:

$$Ftiming_t^j = \frac{1}{TN^j}\sum_{i=1}^{N^j}\sum_{\tau=0}^{T-1}(w_{it+\tau}^j - w_{it+\tau}^m)(a_{t+\tau+1}), \tag{7}$$

where N^j is the number of individual assets held by fund j. The subscript $\tau + t$ on the portfolio weights and the subscript $\tau+t+1$ on the aggregate shock signify that the aggregate shock is unknown at the time of portfolio formation. Relative to the market, a fund with a high $Ftiming$ 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. Put differently, in times when they learn that a is likely to be high, skilled managers who do fundamental analysis should hold more risky assets whose returns are increasing in a. $Ftiming$ is closely related to measures of market-timing ability, but it extracts the part of skill that is due to fundamental market analysis.

When skilled investment managers use their skill to analyze stock-specific payoff shocks, s_i, their analysis allows them to choose portfolios that covary with s_i. We define fundamentals-based stock picking skill, $Fpicking$, which measures the covariance of a fund's portfolio weights of each stock, relative to the market, with the stock-specific shock, s_i:

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

How well the manager can choose portfolio weights in anticipation of future asset-specific payoff shocks is closely linked to her stock-picking ability. But in contrast to $Picking$, $Fpicking$ extracts the part of skill that is due to analysis of fundamental determinants of firms' payoffs.

We now examine how the fundamentals-based skill measures vary over the business cycle.

In the construction of $Ftiming$, we proxy for the aggregate payoff shock a with the innovation in log industrial production growth.[6] A time series for $Ftiming_t^j$ is obtained by computing the covariance of the innovations and each fund j's portfolio weights using twelve-month rolling windows. Our hypothesis is that $Ftiming$ should be higher in recessions, which means that the coefficient on $Recession$, should be positive. Our estimates appear in Table 4. Column 1 shows the results for a univariate regression. The intercept is not different from zero, implying that funds' portfolios do not comove with future macroeconomic information in expansion. In contrast, in recessions, $Ftiming$ increases. The increase amounts to ten percent of a standard deviation of $Ftiming$. 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 in column 2. The slope coefficient of recession remains largely unaffected by the inclusion of the control variables.

Next, we repeat our analysis using funds' reliance on stock-specific fundamental information (Fpicking) as a dependent variable. Following equation (8), $Fpicking$ 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. To form the latter, 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.[7,8] 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 $Fpicking$ should fall in recessions. Columns 3 and 4 of Table 4 show

[6] 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 $t+1$.

[7] Suppose month t and $t+3$ are end-of-quarter months. Then $Fpicking$ in months t, $t+1$, and $t+2$ are computed using portfolio weights from month t and earnings surprises from month $t+3$.

[8] 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.

that the average *Fpicking* 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: *Fpicking* 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.

2.2 Cash holdings and market timing

To get further insight into why the *Timing* and *Ftiming* measures increase in recessions, we conduct several other exercises. First, we ask whether managers actively change their cash holdings in recessions. Cash is measured either as Reported Cash, from CRSP, or Implied Cash, backed out from fund size and its equity holdings. Table 5 shows a higher cash position in recessions than in expansions. In expansions, funds hold about 5% of their portfolio in cash. In recessions, the fraction of their holdings in cash rises by about 0.3% for the Reported Cash measure and by about 3% for the Implied Cash measure. Both increases are statistically significant, and each represents a change of about ten percent of a standard-deviation. We also investigate the month-over-month change in the Implied Cash position. In recessions, cash holdings increase by 0.5%. The effect is modest, but measured precisely. In sum, one way in which funds lower their portfolio beta in recessions is to increase their cash positions.

2.3 Portfolio beta and sector rotation

The second question we ask is whether fund managers invest in lower-beta stocks in recessions. For each individual stock, we compute the beta (from twelve-month rolling-window regressions). Based on the individual stock holdings of each mutual fund, we construct the funds' (value-weighted) *equity betas*. Columns 7 and 8 of Table 5 show that this beta is 1.11 in expansions and 0.99 in recessions; the 0.12 difference has a t-statistic of 4.5. This means that funds not only keep more cash in recessions, they also hold different types of stocks, namely lower-beta stocks.

Finally, we investigate whether funds change their portfolio allocations towards *defensive* sectors over the business cycle. Table 6 shows that, in recessions, funds increase their portfolio weights (relative to those in the market portfolio) in low-beta sectors such as Healthcare, Non-Durables (which includes Food and Tobacco), Wholesale, and Utilities. They reduce their portfolio weights (relative to those in the market portfolio) in high-beta sectors such as Telecom, Business Equipment and Services, Manufacturing, Energy, and Durables. Hence, funds engage in sector rotation over the course of the business cycle in a way consistent with market timing.

2.4 Fund skill or fund manager skill?

Is skill embodied in the manager or does it come from the employee human capital and the organizational setup the fund provides that manager? To answer this question, we follow a manager over time, even as (s)he switches funds. This allows us to investigate to what extent our results reflect skill at the level of the fund versus at the level of the manager. Columns 1 and 2 of Table 7 show how $Ftiming$ and $Fpicking$ change in recessions when the unit of observation is the manager. The results without the control variables are similar to the results with controls, which we present. The table indicates significantly higher $Ftiming$ and significantly lower $Fpicking$ in recessions. The magnitudes of the recession effect are similar at the manager level as they were at the fund level. In columns 3 and 4, we add manager-fixed effects to control for any unobserved manager characteristics that may drive the results. The results remain essentially unchanged. We conclude that our results hold both at the fund level and at the manager level.

2.5 Skill measures: Robustness

This section explores various robustness tests to our measures of fund manager skill. The first two exercises address measurement issues in $Ftiming$ and $Fpicking$, the measures of fundamental-analysis skill. The third one explores another metric of market timing.

Industrial production vs. aggregate economic activity. Our measure of fundamental timing utilizes industrial production innovations to proxy for the aggregate payoff shock. Industrial production is useful because it is available monthly, as opposed to most other macro-economic variables such as GDP, which are released only quarterly. But it has a possible limitation that it does not cover non-industrial economic activity, which accounts for a large share of economic activity in the U.S. To explore the importance of this issue for our measure, we compute an alternative $Ftiming2$ measure in which the aggregate shock is proxied by surprises in non-farm employment growth, another salient monthly macroeconomic variable, instead of industrial production growth. The effect of recessions on the fundamentals-based timing ability listed in columns 1 and 2 of Table 8 is four times larger and even more statistically significant than the original result.

Unexpected earnings and seasonal fluctuations. In our measure of stock-specific skill we use shocks to firm earnings from an AR(1) process as stock-specific shocks. But firm earnings might not be well described by a one-quarter AR(1) process. We allow for seasonality or more lags in the dynamic earnings process by using data one year earlier to forecast earnings and define what constitutes an earnings surprise. To implement this, we compute an alternative $Fpicking2$ measure in which earnings surprises are defined as the residual from a regression of earnings per share in a given year on earnings per share in that same quarter one year earlier (instead of one quarter earlier), as in Bernard and Thomas (1989). The effect of recessions on the fundamentals-based stock-picking ability listed in columns 3 and 4 of Table 8 is even more negative (-0.89 vs -0.68) and just as statistically significant as the original result.

Market timing could also be captured by an R^2. In some settings, the comovement of a portfolio with a shock is not measured using a covariance of the portfolio weights with the shock, but via the R^2 of a fund-level CAPM regression:

$$R_t^j = \alpha^j + \beta^j R_t^m + \sigma_\varepsilon^j \varepsilon_t^j. \tag{9}$$

The R^2 of this regression measures how the funds' *excess returns* covary with the market excess return. In contrast, the $Timing$ variable measures how funds' *portfolio weights* covary with the market excess return. The results in columns 5 and 6 show that the average R^2 across all funds rises from 77% in expansions to 80% in recessions, an effect that is statistically significant. In summary, using other measures of skills, we continue to conclude that recessions are times when fund managers use their skill to analyze aggregate market conditions. This makes their portfolio choices and therefore their fund returns more sensitive to changes in market returns.

3 Alternative Explanations

This section explores whether our time-varying covariance results could arise from other effects unrelated to managerial skill. Specifically, we explore whether it could be a mechanical effect, a composition effect or a result of time-varying incentives.

This estimation employs a difference-in-differences approach. Since the average investor must hold the market portfolio in order for the market to clear, whatever the average manager in our sample holds must be the mirror image of what the investors not in our sample (non-fund investors) hold. Thus, anything that affects all investors equally cannot result in any portfolio effects. That would mean that markets do not clear. So, we are implicitly looking at differences in the portfolios of fund versus non-fund investors. And furthermore, we are interested in how those portfolio differences change in booms and recessions. An alternative mechanism that just generates a higher picking measure in booms or timing measure in recessions will not generate our results unless it affects funds more than non-funds. The alternatives explored below cannot generate the diff-in-diff results we have documented.

3.1 Stock price patterns generate mechanical effects

The first alternative is that our results at the mutual fund level arise mechanically from the properties of returns at the stock level. To rule this out, we generate artificial return data for a panel of 1000 stocks and the same number of periods as our sample. We assume that stock returns follow a CAPM with time-varying parameters. The mean and volatility of the market return, the idiosyncratic volatility, and the cross-sectional standard deviation of the alpha and beta are chosen to match the properties of stock-level data. Using a simulation for 500 funds, we verify that mechanical mutual fund strategies cannot reproduce the observed features of fund returns. The mechanical strategies include an equally weighted portfolio of 75 (or 50 or 100) randomly chosen stocks by all funds, half the funds choosing 75 random stocks from the top half of the alpha distribution and the other half 75 stocks from the bottom half of the alpha distribution, or similar strategies where half the funds pick from the top half of the total return or the beta distribution with the other half of funds choosing from the bottom half. None of these strategies generates higher market timing measures in recessions and higher stock picking readings in expansions.

3.2 Composition effects

A second possible explanation for our results is that each fund pursues a fixed strategy, but the composition of funds changes over the business cycle in such a way as to make the average fund strategy change. Such composition effects could come from changes in the set of active funds, from changes in the size of each of those funds, or from entry and exit of fund managers. We explore each in turn.

Fund-level composition effects First, we redo our results with fund-fixed effects to control for changes in the set of active funds. Including fixed effects in a regression model is a standard response to sample selection concerns. The results are qualitatively similar and slightly stronger quantitatively. For example, the coefficient of $Fpicking$ is equal to -0.92 (as opposed to -0.70 before), while the coefficient of $Ftiming$ equals 0.010 (as opposed to 0.011 before). Both coefficients are significant at the 1% level of statistical significance. The results are omitted for brevity.

Next, we consider if this is a composition effect related to fund size. It could be that the average mutual fund changes strategy over the business cycle only because relative fund size changes. Some fund managers might become more successful in recessions and manage larger funds, while others become successful in booms and accumulate more assets in those times. But our results showing that the same funds that do well at stock picking in expansions are good at market timing in recessions (Table 3) is incompatible with this explanation. And furthermore, this effect should also be picked up with a fund fixed-effect. Yet, when we include fund fixed effects, our cyclical skill results persist.

Manager-level composition effects Similarly, we can rule out the alternative explanation that the composition of managers changes over the cycle; recall our manager-level results with manager-level fixed effects as explanatory variables (columns 3 and 4 of Table 7). If a selection/composition effect drives the increase in $Ftiming$ in recessions, we should not find any effect from recession once we control for fixed effects. However, our results show that all our manager-level results survive the inclusion of manager-fixed effects.

More specifically, if we think that the composition of managers is changing over the business cycle through entry and exit of managers, we should see some difference in observable manager characteristics.[9] However, when we examine manager characteristics over the business cycle, we find no systematic differences in age, experience, or educational background of fund managers in recessions versus expansions.

[9] Our data do show that outside labor market options of investment fund managers deteriorate in recessions. Not only do assets under management–and therefore managerial compensation–shrink, managers are also more likely to get fired or demoted. There is a smaller incidence of promotion to a larger mutual fund in a different fund family, a higher incidence of demotion to a smaller mutual fund in a different fund family, and a lower incidence of departure to a hedge fund. Results are available on request.

3.3 Career concerns

In the previous section, we considered the possibility that the composition of funds changes. Now, we consider the possibility that the behavior or funds changes over the business cycle, but not because of attention allocation. One reason for the change in behavior might be because of cyclical career concerns.

Chevalier and Ellison (1999) show that career concerns give managers an incentive to herd. This pressure is strongest on young managers. It would seem logical that the concern for being fired would be greatest in recessions; in fact, our data bear this out as mentioned in footnote 9. What does herding imply for picking and timing? Stock picking is an activity that skilled managers might do very differently: Some might analyze pharmaceutical stocks and others energy stocks. But market timing is something that managers would expect other skilled managers to do in the same way at the same time. It is better suited to herding. So, according to this alternative explanation, market timing in recessions arises because of the stronger pressure on young managers to herd.

In order to investigate this hypothesis, we estimate portfolio dispersion–a measure of the inverse of herding–in recessions and booms. Our measure of dispersion 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:

$$Portfolio\ Dispersion_t^j = \sum_{i=1}^{N^j} \left(w_{it}^j - w_{it}^m \right)^2 . \tag{10}$$

If we regress this dispersion measure on a regression indicator variable and a constant, the recession coefficient is 0.347 and is significant at the 5% confidence level. Controlling for the fund characteristics listed in Table 1 changes this estimate by less than a percent. Thus, instead of finding more portfolio herding in recessions, we find the opposite, more cross-sectional portfolio dispersion.

It is worth noting that we do find that manager age is positive and significantly related to the fund's portfolio dispersion metric, meaning that younger managers are more likely to herd. This confirms the findings of Chevalier and Ellison (1999) in our data set. But this herding is weaker in recessions, not stronger.

Since we just showed that recessions are times when managers are more likely to deviate from the pack, one might be tempted to construct a story whereby career concerns are actually stronger in expansions instead of recessions. But if that is true, then there should be an interaction effect: Younger managers should be more likely to hold portfolios with low dispersion in booms. In recessions, their portfolio dispersion should increase by more. Conversely, older managers' portfolio dispersion should change less over the cycle. This suggests that when we regress portfolio dispersion on recession, age of the manager and the interaction of recession and age, the interaction term should have a negative sign (dispersion for older managers decreases less in recessions). Instead, we find a significantly positive interaction effect. The coefficient of the interaction term equals 0.40 (with a standard error or 0.08). If instead of portfolio dispersion, we look at the dispersion in funds' portfolio betas, the coefficient of the interaction term is -0.047 with standard error of 0.038, which is not statistically different from zero.

In sum, the results do not support the hypothesis that cyclical changes in skill are driven by cyclical changes in career concerns. 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 specific patterns we document.

3.4 Time-varying marginal utility

Two recent studies link fund performance to business-cycle variation. Glode (2011) argues that funds outperform in recessions because their investors' marginal utility is highest in such periods. While complementary to our explanation–and a good explanation for why households choose to delegate their portfolio to mutual funds–his work remains silent on what strategies investment managers pursue to achieve this differential performance. Similarly, Kosowski (2006) shows that fund performance varies over the business cycle but he does not distinguish between the sources of skill as we do here.

4 Identifying Skilled Managers

The time variation in skill we have detected can now be used to form an indicator of who the skilled managers are.

4.1 Why not judge managers only on performance?

The most obvious way to assess skill is to look at a fund's average return. To avoid confusing risky investment with skilled investment, we need to adjust returns for risk. The difficulty is that measuring risk in the presence of private information is nearly impossible. Information that helps a manager to forecast a market's future return, makes the return less uncertain to the manager. By its nature, information reduces uncertainty and resolves risk. But that means we can only accurately judge a manager's risk-adjusted returns if we know what information he has. Therefore, it is useful to couple performance measures with other measures of skill that do not rely on one's ability to accurately measure risk.

To see more clearly what the problem is, imagine that a fund manager's portfolio return is a normally-distributed random variable $f \sim N(\mu, \sigma^2)$. Now, suppose the fund manager does research that uncovers information about his future return. He sees an unbiased but noisy signal, $s = f + e$, where the signal noise e is also normally distributed $s \sim N(0, \eta^2)$. According to Bayes' law, the manager's updated best estimate of his portfolio return, conditional on seeing his signal is $E[f|s] = (\mu\sigma^{-2} + s\eta^{-2})/(\sigma^{-2} + \eta^{-2})$. But more importantly, the variance of that estimate is $V[f|s] = 1/(\sigma^{-2} + \eta^{-2})$. For any finite signal variance $\eta^2 \in [0, \infty)$ this variance is always less than the prior variance: $V[f|s] < \sigma^2$. Suppose that fund performance is judged by a Sharpe ratio. The econometrician, who is unaware of the manager's information, estimates this Sharpe ratio as the prior expected return, divided by the prior standard deviation: μ/σ. But the manager's true Sharpe ratio is the one conditional on his information: $E[f|s]/V[f|s]^{1/2}$. By the law of iterated expectations, $E[E[f|s]] = \mu$. But we know that $V[f|s]^{1/2} < \sigma$. Thus, the true Sharpe ratio of the manager is systematically higher than what the econometrician estimates.

Not only will the conditional variance be lower, by the same token, the conditional covariance of that return with the market return will also be reduced when the manager observes his signal. Suppose that the portfolio return at time t is $f_t = \alpha + \beta r_t^m + \nu_t$, where r_t^m is the time-t market return and $\nu_t \sim N(0, \phi^2)$. The covariance of the portfolio return and the market return is $\beta Var[r^m]$. But the manager's signal about his portfolio return is also informative about the market return. Specifically, $(s - \alpha)/\beta$ is an unbiased, normally distributed signal about r^m. Conditioning on this signal will lower the uncertainty about the market return: $Var[r^m|s] < Var[r^m]$. If the true conditional variance is lower, the true conditional covariance is lower as well. The same logic explains why the conditional covariances in a multi-factor model would be overestimated as well. Thus, an econometrician who uses a factor model to measure performance and does not account for the manager's superior information, will over-estimate risk and under-estimate the true risk-adjusted return.[10]

Whether he measures skill with a Sharpe ratio or an alpha, the econometrician's estimate of skill is downward biased for truly skilled managers. Of course, ultimately we also want to know what the manager's realized portfolio return is, so that we know if picking and timing are generating outperformance. But also considering measures of picking and timing ability is a way to avoid relying solely on biased measures of risk.

4.2 Funds that switch strategies earn higher returns

Instead of using performance metrics to select fund managers, we exploit the prediction that skilled managers display market-timing ability in recessions and stock-picking ability in expansions to develop a new skill metric. First, we show that this metric is correlated with performance. Then we show that, unlike performance alone, this measure of skill is persistent and can therefore predict future returns.

If skilled funds switch between market timing and stock picking, then these strategy switchers should outperform the unskilled funds both in recessions and in expansions. Table 3 showed that there exists a set of SP funds that have high stock-picking skill in booms and that also have market-timing skill in recessions. Table 9 compares the *unconditional* performance of these SP funds to that of all other funds. After controlling for various fund characteristics, the CAPM, three-factor, and four-factor alphas are 70-90 basis points per year higher for the SP portfolio, a difference that is statistically and economically significant.

The existence of skilled mutual funds with cyclical investment strategies is a robust result. First, the results survive if we change the cutoff levels for the inclusion in the SP

[10] See Koijen (2010) for a detailed exploration of this argument, as well as earlier versions of this argument in Ferson and Schadt (1996), Ferson and Harvey (1999), and Mamaysky, Spiegel, and Zhang (2008).

portfolio. Second, we find that the top 25% *Fpicking* funds (as opposed to the top 25% *Picking* funds) in expansions also have higher *Ftiming* in recessions and that they earn higher unconditional alphas. 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. All these results are available upon request.

4.3 The characteristics of skilled funds and managers

In Panel A of Table 10, we 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. 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 asset 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 portfolio dispersion. 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 the skill indicator SP (not reported). Including attributes that we could link to skilled funds, such as stock and industry portfolio dispersion, beta deviation, and *Ftiming*, increases the R^2 to 19%. Thus, these findings paint a rough picture of what a typical skilled fund looks like.

Table 10, 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.

4.4 Creating a Skill Index

If one is going to use our approach to identify skilled investment managers, it is important that these managers can be identified in real time, without the benefit of looking at the full sample of the data. To this end, we construct a *Skill Index* that is informed by our main result that the nature of skill 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 specific value for $w(R) - w(E)$ we choose is not crucial for the results.

Subsequently, we examine whether the time-t $Skill\ Index$ can predict future fund performance, measured by the CAPM, three-factor, and four-factor alphas one month (and one year) later. Table 11 shows that funds with a higher $Skill\ Index$ 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 2.4% (CAPM) or 1.1% (four-factor) 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 *Ftiming* and *Fpicking* 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.

5 Conclusion

Do investment managers add value for their clients? The answer to this question matters for question ranging from discussions on the efficiency of markets to practical portfolio advice for households. The large amount of randomness in financial asset returns and the unobservable nature of risk make this a difficult question to answer. We argue that previous studies have ignored the fact that the skill funds exhibit might change with the state of the business cycle. When we condition on the state of the business cycle, we find that managers exhibit stock-picking skills in booms and market-timing skills in recessions. Furthermore, we show that this skill comes from anticipating changes in firm-specific or market fundamentals, not from reading market sentiment, front-running the market, or using momentum strategies. This suggests that the nature of fund managers' skill is to conduct value-adding research and analysis on individual firms in expansions or on the state of the aggregate economy in recessions, and to trade on that information. Finally, we show that managers who exhibit this time-varying skill outperform the market by 70-90 basis points per year and we identify the observable characteristics of these managers.

Our findings raise the question, why do skilled fund managers change the nature of their activities over the business cycle? Kacperczyk, Van Nieuwerburgh, and Veldkamp (2011) extend this research agenda by providing a theoretical answer to that question. They argue that recessions are times when aggregate payoff shocks are more volatile and when the price of risk is higher. Both of these forces make acquiring and processing information about aggregate shocks more valuable. Thus, if a firm has some general cognitive ability that it can allocate to processing information about specific stocks or to processing information about the aggregate economy, it will optimally change the allocation between booms and recessions. The paper lays out this theory in an equilibrium model, derives some additional testable implications from the model and shows that those hypotheses are supported in the data.

Like workers in all jobs, mutual fund managers can focus on different tasks at different points in time. The task of a mutual fund manager is to uncover information. Stock-picking and market-timing "skills" result from expending time and effort to analyze news and data. When we re-estimate fund manager skill in a way that allows its nature to change with economic conditions, we find evidence that skilled managers indeed readjust how they use their skills as circumstances change. Thus, our approach uncovers new evidence in support of the idea that a subset of managers process information about firm and economy-wide fundamentals in a way that creates value.

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Figure 1: Market timing and stock picking, based on market and firm fundamentals.

This figure shows funds' reliance on stock-specific information ($Fpicking$) and reliance on aggregate information ($Ftiming$) in economic expansions ($Boom$) and contractions ($Recession$). The data are from CRSP and available monthly from January 1980 until December 2005.

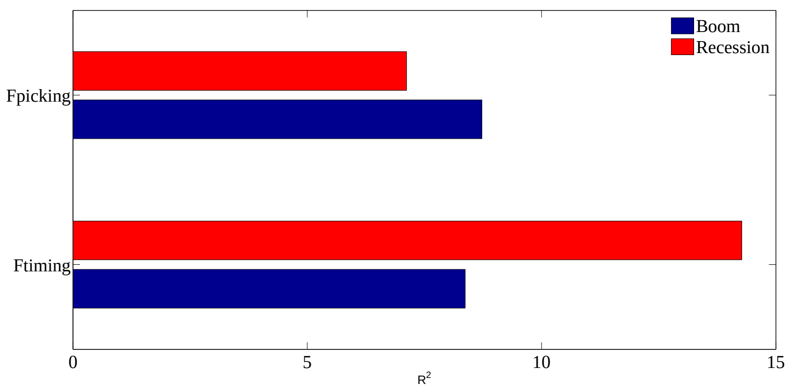

Table 1: **Timing and Picking Skills are Cyclical**

Dependent variables: Fund j's $Ftiming_t^j$ is defined in equation (7), where the rolling window T is 12 months and the aggregate shock a_{t+1} is the change in industrial production growth between t and $t+1$. A fund j's $Fpicking_t^j$ is defined as in equation (8), where s_{it+1} is the change in asset i's earnings growth between t and $t+1$. $Timing_t^j$ and $Picking_t^j$ are defined in equations (1) and (2), where each stock's β_{it} is measured over a twelve-month rolling window. All are multiplied by 10,000 for readability.
Independent variables: *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 in years. $Log(TNA)$ 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 by fund and time.

	(1)	(2)	(3)	(4)
	Timing		Picking	
Recession	0.140	0.139	-0.144	-0.146
	(0.070)	(0.068)	(0.047)	(0.047)
Log(Age)		0.006		0.004
		(0.006)		(0.004)
Log(TNA)		0.000		-0.003
		(0.004)		(0.003)
Expenses		1.021		-0.815
		(1.280)		(0.839)
Turnover		0.007		0.017
		(0.013)		(0.010)
Flow		-0.001		0.058
		(0.078)		(0.088)
Load		0.033		0.156
		(0.180)		(0.131)
Constant	0.007	0.007	-0.010	-0.010
	(0.024)	(0.024)	(0.018)	(0.018)
Observations	221,306	221,306	221,306	221,306

Table 2: **Whose skills are most cyclical?**

Dependent variables: Fund j's $Ftiming_t^j$ is defined in equation (7), where the rolling window T is 12 months and the aggregate shock a_{t+1} is the change in industrial production growth between t and $t+1$. A fund j's $Fpicking_t^j$ is defined as in equation (8), where s_{it+1} is the change in asset i's earnings growth between t and $t+1$. $Timing_t^j$ and $Picking_t^j$ are defined in equations (1) and (2), where each stock's β_{it} is measured over a twelve-month rolling window. All are multiplied by 10,000 for readability.
Independent variables: *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 in years. $Log(TNA)$ 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 by fund and time.

	(1)	(2)	(3)	(4)	(5)	(6)
	Q50	Q75	Q95	Q50	Q75	Q95
		Timing			Picking	
Recession	0.059	0.114	0.251	-0.084	-0.091	-0.173
	(0.070)	(0.003)	(0.015)	(0.003)	(0.002)	(0.014)
Log(Age)	0.000	-0.003	-0.020	0.003	-0.005	-0.057
	(0.000)	(0.001)	(0.005)	(0.001)	(0.001)	(0.005)
Log(TNA)	0.000	0.004	-0.004	-0.001	0.001	0.005
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.003)
Expenses	0.162	4.015	21.046	-0.588	3.096	18.869
	(0.027)	(0.178)	(0.942)	(0.102)	(0.182)	(0.941)
Turnover	0.001	0.053	0.404	0.001	0.042	0.305
	(0.000)	(0.001)	(0.004)	(0.001)	(0.001)	(0.005)
Flow	0.004	0.036	0.228	0.035	0.099	0.192
	(0.002)	(0.011)	(0.061)	(0.006)	(0.012)	(0.068)
Load	-0.013	-0.327	-1.404	0.108	-0.129	-1.213
	(0.005)	(0.030)	(0.166)	(0.017)	(0.031)	(0.166)
Constant	0.000	0.108	0.765	-0.015	0.126	0.722
	(0.000)	(0.001)	(0.004)	(0.000)	(0.001)	(0.004)
Observations	221,306	221,306	221,306	221,306	221,306	221,306

Table 3: **The Same Funds Switch Strategies**

We divide all fund-month observations into Recession and Expansion subsamples. $Expansion \equiv 1 - Recession$. *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. Control variables, sample period and standard errors are described in Table 1.

	(1)	(2)	(3)	(4)
	Timing		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 4: **Timing and Picking Skills are Driven by Fundamentals**

Dependent variables: Fund j's $Ftiming_t^j$ is defined in equation (7), where the rolling window T is 12 months and the aggregate shock a_{t+1} is the change in industrial production growth between t and $t+1$. A fund j's $Fpicking_t^j$ is defined as in equation (8), where s_{it+1} is the change in asset i's earnings growth between t and $t+1$. All are multiplied by 10,000 for readability.
Independent variables: *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 in years. $Log(TNA)$ 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 by fund and time.

	(1)	(2)	(3)	(4)
	Ftiming		Fpicking	
Recession	0.011	0.011	-0.682	-0.696
	(0.004)	(0.004)	(0.159)	(0.150)
Log(Age)		-0.002		0.423
		(0.001)		(0.060)
Log(TNA)		-0.001		-0.173
		(0.000)		(0.029)
Expenses		-0.330		88.756
		(0.244)		(11.459)
Turnover		-0.004		-0.204
		(0.001)		(0.053)
Flow		-0.008		1.692
		(0.010)		(0.639)
Load		0.017		-9.644
		(0.023)		(1.972)
Constant	-0.001	-0.001	3.084	3.086
	(0.001)	(0.001)	(0.069)	(0.070)
Observations	224,257	224,257	166,328	166,328

Table 5: **Funds Hold More Cash and Lower Portfolio Betas in Recessions**

The dependent variables are three measures of funds' cash holdings. *ReportedCash* is the cash position reported by mutual funds to CRSP in their quarterly statements, relative to the size of the fund (expressed as a percent). *ImpliedCash* is based on the portfolio holdings of the fund. In particular, it is the difference between the total size of the fund (monthly) as reported in the data and the implied size of the equity portio based on the observed holdings and their prices. It is also expressed as a percent of total holdings. *%ChangeCash* is defined as the percentage change in the implied cash measure. For *Equity Beta*, we first compute the market beta of each stock from a twelve-month rolling-window regression. We then construct the funds' equity beta as the value-weighted average of the individual stock betas, where the weights are the fund's dollar holdings in that stock divided by the dollar holdings in all stocks. Control variables, sample period and standard errors are described in Table 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Implied Cash		Reported Cash		% Change Cash		Equity Beta	
Recession	2.491	3.278	0.230	0.362	0.643	0.545	-0.118	-0.106
	(0.537)	(0.535)	(0.089)	(0.087)	(0.051)	(0.050)	(0.026)	(0.027)
Log(Age)		-0.453		0.309		-0.075		0.013
		(0.517)		(0.081)		(0.037)		(0.002)
Log(TNA)		1.676		-0.047		-0.092		0.008
		(0.277)		(0.040)		(0.018)		(0.001)
Expenses		163.772		-46.153		24.280		3.113
		(119.092)		(18.459)		(6.859)		(0.385)
Turnover		-0.059		-0.168		0.119		0.035
		(0.413)		(0.064)		(0.031)		(0.002)
Flow		13.794		3.893		0.189		0.056
		(2.840)		(0.315)		(0.301)		(0.037)
Load		-5.033		15.169		-1.144		0.561
		(14.366)		(2.837)		(1.196)		(0.062)
Constant	5.316	5.252	4.672	4.656	-1.505	-1.495	1.112	1.111
	(0.481)	(0.479)	(0.065)	(0.062)	(0.033)	(0.031)	(0.006)	(0.008)
Observations	230,185	230,185	209,516	209,516	225,374	225,374	226,094	226,094

Table 6: **Funds Change the Sector Weights in their Portfolios**

The dependent variable is the portfolio weight of fund j in sector l in deviation from the market portfolio's weight in sector l: $w_{lt}^{j} - w_{lt}^{m}$. Each column represent a different sector. The sectors are the ten Fama-French industry sectors: (1) Consumer non-durables, (2) Consumer durables, (3) Healthcare, (4) Manufacturing, (5) Energy, (6) Utilities, (7) Telecom, (8) Business Equipment and Services, (9) Wholesale and Retail, (10) Finance. *Recession* equals one for every month the economy is in the recession according to the NBER, and zero otherwise. Control variables, sample period and standard errors are described in Table 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	NDRBL	DRBL	HLTH	MFCT	ENER	UTIL	TEL	BUSEQ	WHLS	FIN
Recession	0.817	0.123	0.541	-0.278	-0.311	0.246	-0.493	-1.565	0.384	0.741
	(0.085)	(0.111)	(0.215)	(0.121)	(0.397)	(0.269)	(0.111)	(0.563)	(0.081)	(0.154)
Log(Age)	0.301	-0.022	0.728	-0.086	-0.557	-0.702	0.037	0.278	0.085	0.036
	(0.028)	(0.016)	(0.032)	(0.031)	(0.044)	(0.035)	(0.022)	(0.064)	(0.027)	(0.054)
Log(TNA)	-0.246	-0.076	-0.387	-0.114	0.270	0.247	0.257	0.001	-0.060	-0.003
	(0.014)	(0.013)	(0.013)	(0.013)	(0.025)	(0.016)	(0.010)	(0.025)	(0.015)	(0.016)
Expenses	42.310	2.132	-54.607	-72.195	67.829	28.997	22.623	-63.774	11.964	29.247
	(3.641)	(2.849)	(4.630)	(5.043)	(7.958)	(4.180)	(3.902)	(10.138)	(4.611)	(8.483)
Turnover	-0.181	-0.134	0.330	-0.586	0.328	0.040	0.307	1.276	0.021	-1.325
	(0.030)	(0.025)	(0.040)	(0.039)	(0.025)	(0.017)	(0.031)	(0.075)	(0.044)	(0.041)
Flow	-0.256	-0.423	-0.320	-1.241	-1.554	-1.298	1.308	3.289	0.057	0.450
	(0.314)	(0.296)	(0.443)	(0.431)	(0.602)	(0.503)	(0.423)	(1.219)	(0.377)	(0.580)
Load	-4.833	0.764	6.123	8.589	-12.164	-9.617	3.758	23.523	-1.886	-15.841
	(0.656)	(0.563)	(0.658)	(0.894)	(1.219)	(0.705)	(0.473)	(1.729)	(0.871)	(0.978)
Constant	-0.471	-0.777	0.173	2.499	-1.171	-1.769	-1.489	3.600	2.404	-2.660
	(0.046)	(0.065)	(0.050)	(0.073)	(0.080)	(0.084)	(0.053)	(0.201)	(0.059)	(0.101)
Observations	207,382	207,382	207,382	207,382	207,382	207,382	207,382	207,382	207,382	207,382

Table 7: **Managers as the Unit of Observation**

The dependent variables are reliance on aggregate information (*Ftiming*), reliance on stock-specific information (*Fpicking*), both tracked at the manager level. In columns 3 and 4, we include manager-level fixed effects as independent variables. Control variables, sample period and standard errors are described in Table 1.

	Ftiming	Fpicking	Ftiming	Fpicking
Recession	0.008	-0.701	0.007	-0.824
	(0.003)	(0.130)	(0.002)	(0.132)
Log(Age)	-0.002	0.460	-0.004	0.268
	(0.001)	(0.066)	(0.001)	(0.065)
Log(TNA)	-0.000	-0.126	-0.000	-0.139
	(0.000)	(0.032)	(0.000)	(0.033)
Expenses	0.130	127.222	0.060	45.894
	(0.105)	(13.972)	(0.146)	(13.867)
Turnover	-0.005	-0.287	-0.004	0.210
	(0.002)	(0.077)	(0.002)	(0.090)
Flow	-0.009	1.037	-0.016	1.186
	(0.009)	(0.613)	(0.009)	(0.554)
Load	-0.009	-16.064	-0.069	-5.832
	(0.017)	(2.393)	(0.023)	(2.307)
Manager Fixed Effect	N	N	Y	Y
Constant	-0.002	2.966	-0.002	2.977
	(0.001)	(0.072)	(0.001)	(0.068)
Observations	332,676	249,942	332,676	249,942

Table 8: **Alternative Measures of Skill**

The dependent variables are funds' reliance on aggregate information $Ftiming2$, funds' reliance on stock-specific information $Fpicking2$, and the CAPM $R-squared$. A fund j's $Ftiming2_t^j$ is defined as the (twelve-month rolling window time series) covariance between the funds' portfolio holdings in deviation from the market $(w_{it}^j - w_{it}^m)$ in month t and changes in non-farm employment growth between t and $t+1$. A fund j's $Fpicking2_t^j$ is defined as the (across stock) covariance between the funds' holdings in deviation from the market $(w_{it}^j - w_{it}^m)$ in month t and changes in earnings growth between $t-11$ and $t+1$. $R-squared$ is obtained from the twelve-month rolling-window regression model of a fund's excess returns on excess market returns. $Ftiming2$, and $Fpicking2$ are multiplied by 10,000 and $R-squared$ is multiplied by 100 for ease of readability. Control variables, sample period and standard errors are described in Table 1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ftiming2		Fpicking2		R-squared	
Recession	0.004	0.004	-0.886	-0.897	3.040	2.891
	(0.001)	(0.001)	(0.201)	(0.191)	(1.451)	(1.315)
Log(Age)		-0.001		0.452		2.126
		(0.000)		(0.076)		(0.190)
Log(TNA)		0.000		-0.229		0.258
		(0.000)		(0.034)		(0.074)
Expenses		-0.158		111.982		-582.087
		(0.058)		(12.954)		(26.684)
Turnover		0.000		-0.329		-1.242
		(0.000)		(0.074)		(0.110)
Flow		-0.001		2.570		-6.614
		(0.003)		(0.723)		(2.885)
Load		0.021		-12.614		68.883
		(0.007)		(2.317)		(5.434)
Constant	-0.001	-0.001	3.962	3.962	77.361	77.331
	(0.000)	(0.000)	(0.089)	(0.089)	(0.854)	(0.846)
Observations	224,257	224,257	166,328	166,328	227,159	227,159

Table 9: **Strategy Switchers Outperform**

The dependent variables CAPM alpha, three-factor alpha, and four-factor alpha are obtained from a twelve-month rolling-window regression of a fund's excess returns, before expenses, on a set of common risk factors. *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. Control variables, sample period and standard errors are described in Table 1.

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

Table 10: **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. *Skill Picking* is one for any fund with a *Picking* measure (defined in Table 1) in the highest 25th percentile in expansions, and zero otherwise. Panel A reports fund-level characteristics. *Age*, TNA, *Expenses*, *Turnover*, *Flow* and *Ftiming* are defined in Table 1. $Portfoliodispersion$ 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. Panel B reports manager-level characteristics. MBA or *Ivy* equals one if the manager obtained an MBA degree or graduated from an Ivy League institution, and equals zero otherwise. *Age* and *Experience* are the fund manager's age and experience in years. *Gender* equals one if the manager is a male and zero if 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. $p - values$ measure statistical significance of the difference. The data are monthly from 1980-2005.

	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
Flow	0.22	7.39	-0.76	-0.07	6.47	-0.73	0.300	0.008
Portfolio dispersion	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
Ftiming	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 11: **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. *Picking* and *Timing* are defined in Table 1, except that now they are normalized so that they are mean zero and have a standard deviation of one over the full sample. The other right-hand side variables, the sample period, and the standard error calculation are the same as in Table 1.

	(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