DISCUSSION PAPER SERIES

No. 9025

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FINANCIAL ECONOMICS

Centre for Economic Policy Research

www.cepr.org

Available online at: www.cepr.org/pubs/dps/DP9025.asp

ISSN 0265-8003

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CEPR Discussion Paper No. 9025

ABSTRACT

Time-Varying Fund Manager Skill*

How to evaluate a fund manager's skill is a central question in empirical finance. Prior literature has defined skill as an ability to either pick stocks or time the market, at all times. We propose a new definition of skill as a general cognitive ability used in different ways at different times. We find evidence for stock picking in booms and for market timing in recessions. Moreover, the same fund managers that pick stocks well in expansions also time the market well in recessions. These fund managers significantly outperform other funds and passive benchmarks. Our results suggest a new metric of managerial ability that can be constructed in real time and can predict fund performance. The metric gives more weight to a fund's market timing in recessions and to a fund's stock picking in booms, and it displays far more persistence than either market timing or stock picking alone.

JEL Classification: G00, G11 and G2
Keywords: business cycle, mutual funds and skills

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* We thank the Q-group for their generous financial support.

Submitted 12 June 2012

A large literature studies whether investment managers add value for their clients and if so, how. One way to shed light on this question is to decompose fund performance into stock picking and market timing. Previous work has estimated picking and timing 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-evaluate 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 stock picking and market timing are tasks, not distinct and permanent talents. Skilled managers can successfully perform these tasks, but how much of each they choose to do depends on the market environment. As the financial blog 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.[3] The consensus view from that literature is that there is some evidence of stock-picking ability among best managers, but little evidence for market

[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).

[3]See 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 (2012), Baker, Litov, Wachter, and Wurgler (2010), Huang, Sialm, and Zhang (2011), Amihud and Goyenko (2011), and Cohen, Polk, and Silli (2011).

timing.[4] One reason these previous studies failed to detect market timing is because it is typically displayed only in recessions, which are a small fraction of the sample periods. 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. Once we condition on the state of the economy, we find a surprising result: Skilled managers successfully perform both tasks. 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 real-time measure for detecting managerial skill, one that gives more weight to a fund manager's market-timing success in recessions and her stock-picking success in booms. This new measure predicts performance and displays persistence.

To measure skill, we construct estimates of stock picking (the covariance of a fund's portfolio weights in deviation from market weights with the firm-specific component of stock returns) and market timing (the covariance of portfolio weights in deviation from market weights with the aggregate component of stock returns) for each firm. Then, we regress these timing and picking variables on a recession indicator variable to determine if the nature of skill changes significantly over the business cycle. We find that the average fund manager exhibits better stock picking in booms and better market timing 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.

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.

[4]See 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.

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 that are 70-90 basis points per year in excess of the other funds, before expenses and on a risk-adjusted basis. These results are consistent with the notion that only some managers have skill and it is those managers who decide how to apply that skill depending on the economic environment.

Using hand-collected data, we identify the characteristics of these 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 more likely to attract new money flows and are also more likely to depart later in their careers to hedge funds—presumably, both are market-based reflections of their ability.

We entertain many 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 the observed patterns in picking and timing measures. 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 levels. Fourth, we consider whether various forms of career concerns might explain our results. Fifth, we explore whether skill changes are a volatility or dispersion effect, rather than a business-cycle effect. Finally, this is not a composition effect. The same manager who picks stocks well in booms also times the market well in recessions. In short, none of these alternatives can explain the observed changes in fund portfolios over the business cycle.

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 over the business cycle.

Finally, our findings point to a new metric to identify skilled managers. We propose a Skill Index for each mutual fund which is a weighted average of that fund's market-timing and stock-picking metrics. The weight on market timing is the real-time probability of a recession, while the weight on stock picking is the complementary probability. This weighting scheme intuitively emphasizes the fund's market-timing prowess as recessions become more likely and its stock-picking ability when the likelihood of recession fades away. The Skill Index can be constructed in real time, on a monthly basis. We show that a one-standard-deviation increase in the Skill Index is associated with a 2.3% higher return performance over the next year, net of expenses and after controlling for exposure to the market, and a 1.1% higher performance after additionally controlling for size, value, and momentum factor exposure. We then sort all funds into quintiles according to their Skill Index and track each quintile over time. We find that the difference in Skill Index reading between the highest and the lowest quintiles remains large and positive for up to one year. In contrast, similar differences for market timing and stock picking mean revert quickly. In principle, similar skill indices could be constructed for hedge funds, other professional investment managers, or even individual investors.

Our approach is related to recent studies that link fund performance to business-cycle variation (Ferson and Schadt (1996) Christopherson, Ferson, and Glassman (1998) and Moskowitz (2000)). 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–this 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. de Souza and Lynch (2012) investigate cyclical performance by mutual fund style using a GMM technique.

The rest of the paper is organized as follows. Section 1 describes our data. Section 2 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. It also 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 proposes a real-time Skill Index and uses it to predict fund returns. Section 5 concludes.

1 Data and Measurement

We begin by describing our data on active mutual funds, their portfolios, and their returns. We describe our measures of skill and then use the data to estimate them in booms and recessions.

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 our analysis on domestic open-end diversified equity funds, for which the holdings data are most complete and reliable.[5] In addition, we exclude index funds and sector funds. Since the reported objectives do not always indicate whether a fund portfolio is balanced or not, we also exclude funds that, on average, hold

[5]We base our selection criteria on the objective codes and on the disclosed asset compositions. We exclude funds with CRSP Database objective codes : International, Municipal Bonds, Bond and Preferred, and Balanced. We include funds with the following ICDI objectives: AG, GI, LG, or IN. If a fund does not have any of the above ICDI objectives, we select funds with the following Strategic Insight objectives: AGG, GMC, GRI, GRO, ING, or SCG. If a fund has neither the Strategic Insight nor the ICDI objective, then we go to the Wiesenberger Fund Type Code and pick funds with the following objectives: G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG. If none of these objectives are available and the fund has the CS policy (Common Stocks are the mainly held securities by the fund), then the fund will be included.

less than 80% in stocks. For mutual funds with different share classes, we aggregate all the observations pertaining to different share classes into one observation, since they have the same composition.[6]

To address the possibility of incubation bias,[7] we exclude the observations for which the year of the observation is prior to the reported fund starting year and exclude observations for which the names of the funds are missing in the CRSP database. Incubated funds also tend to be smaller, which motivates us to exclude funds that had in the previous month less than $5 million in assets under management or fewer than 10 stocks.

Next, we merge the CRSP mutual fund data with the Thomson Reuters stock holdings database and the CRSP stock price data using the methodology of Kacperczyk, Sialm, and Zheng (2008). We are able to match about 95% of the CRSP funds to the Thomson database. These stock holdings data are collected both from reports filed by mutual funds with the SEC and from voluntary reports generated by the funds. During most of our sample period, funds are required by law to disclose their holdings semiannually. Nevertheless, about 49% disclose quarterly.[8] To calculate fund returns, we link reported stock holdings to the CRSP stock database. The resulting sample includes 3477 distinct funds and 250,219 fund-month observations. The number of funds in each month varies between 158 in May 1980 and 1670 in July 2001.

Finally, 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 stock returns, market capitalizations, book-to-market ratios, momentum, and liquidity. The aggregate stock market

[6] We sum the total net assets under management (TNA) of share classes. For the qualitative attributes of funds (e.g., name, objectives, year of origination), we retain the observation of the oldest fund. Finally, for the other attributes of funds (e.g., returns, expenses, loads), we take the weighted average, where the weights are the lagged TNAs of each share class.

[7] Bias can arise when fund families incubate several private funds and then only make public the track record of the surviving incubated funds, not the terminated funds.

[8] For 4.6% of observations with valid CRSP data, the previous 6 months of holdings data are not available.

return is the value-weighted average return of all stocks in the CRSP universe.

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%). The Online Appendix considers several alternative recession indicators.

1.2 Defining measures of skill

Investors with skills use them to form portfolios that outperform the average investor. We measure two uses of skill: market timing and stock picking. If an investor times the market, it means that he is more exposed to 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 is holding more of a stock in periods when that firm's realized stock return will be high. To this end, we define the following measures.

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

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

where β_i measures the covariance of stock i's return, R^i, with the market return, R^m, divided by the variance of the market return. The portfolio weight w_{it}^j is the fraction of fund j's total assets held in risky asset i, at the start of time t. The market weight w_{it}^m is the fraction of total market capitalization in asset i. The product of β_i and R^m measures the systematic component of returns of asset i. Asset i's $\beta_{i,t}$ is computed using a rolling-window regression of asset i's excess returns on market excess returns, using return data between $t-11$ and t.[9]

[9] An alternative assumption, also consistent with our notion of ability, is to assume that, since the manager is forecasting time $t+1$ returns anyways, she computes the beta from return data between $t-11$ and $t+1$, treating her forecast for month $t+1$ as actual data to estimate the beta. Consistent with the manager's

The return R^m_{t+1} is the realized return between the start of period t and the start of period $t+1$. This means 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.

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

$$Picking^j_t = \frac{1}{N^j} \sum_{i=1}^{N^j} (w^j_{it} - w^m_{it})(R^i_{t+1} - \beta_i R^m_{t+1}) \tag{2}$$

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

Our picking and timing measures are a version of the performance measures in Grinblatt and Titman (1993) and Daniel, Grinblatt, Titman, and Wermers (1997). Picking and timing distinguish performance based on aggregate market returns from that derived from the idiosyncratic components of returns. They are different from the measures developed by Ferson and Schadt (1996), Becker, Ferson, Myers, and Schill (1999), and Ferson and Khang (2002) because these compute covariances conditional on all available public information. We use unconditional covariances instead. Conceptually, these measures differ: For example, in Ferson and Schadt (1996), skill means executing a trading strategy that outperforms a hypothetical investor who optimally combined all publicly available information. In this paper, skill means using either public or private information in a way that generates higher risk-adjusted returns. We think of managers as having to spend limited time and effort acquiring and processing any type of information, whether it is private or public, firm specific or aggregate (Sims 2003). This cognitive ability to process information is what we call skill

procedure, the *econometrician* takes the ex-post realized value of the return at $t+1$ to estimate the beta, just like she uses time $t+1$ returns to form the $Timing_t$ and $Picking_t$ measures. The timing and picking results are essentially unaffected when we use this alternative construction of beta.

and what allows the manager to construct a high-performance portfolio. We now show that the nature of that skill varies over time.

2 Skill Varies Over Time

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:

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

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

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.[10] To mitigate the impact of outliers on our estimates, we winsorize

[10]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

Flow and *Turnover* at the 1% level. Finally, 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.

Table 1 examines the cyclical variation in market-timing and stock-picking ability. 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 meaningful differences in average skills across market conditions.

We estimate this and most of our subsequent specifications using pooled (panel) regression model, 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. Because our variable of interest, *Recession*, is constant across all fund observations in a given time period, addressing cross-fund correlation is important. At the same time, this approach generates standard errors which may well be overly conservative.

To ensure the robustness of our results, we also explore three alternative ways of clustering (a detailed table is in the Online Appendix). First, we only cluster at the fund level and not at the time dimension. We find that all coefficients of the NBER recession indicator variable are strongly significant, with much larger t-statistics between 3.5 and 35 in absolute value. Second, we cluster by fund style. For this exercise, we sort funds into 64 style bins, based on a 4 by 4 by 4 grouping of the size, value, and momentum characteristics of the stocks they hold. This clustering allows for dependence within each of the 64 style bins. All coefficients

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).

of the NBER recession indicator are more significant, with t-statisics between 3.5 and 12 in absolute value. Third, we cluster standard errors at the fund family level. In this estimation, the standard errors on the recession coefficient are about ten times lower than in the original results. All of these results reinforce the statistical significance of our findings.

2.1 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. 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. 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 of skilled managers.

If there is a subset of skilled managers and they deploy different skills over the business cycle, then we should observe most of the time variation in the use of skill among the most skilled managers. We test this prediction using the quantiles of the cross-sectional distribution of fund skills. Our hypothesis is that the distribution of picking and timing skills should be more sensitive to the 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. In this regression, standard errors are calculated using block bootstrap (with 2,000 repetitions), which takes into account cross-sectional dependence across funds. Table 2 presents the results.

Consistent with our hypothesis, we find that the effect of the 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). 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 hone skills.

2.2 The same manager exhibits 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 manager both picks stocks and times 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 one 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:

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

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 the same SP funds are on average also better at market timing in recessions. This result is evident from the positive coefficient of SP in column 2, which 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.

How can a fund manager execute such switching strategy when NBER recessions are not known until several months after the fact? She need not know NBER turning points. Just like she is trying to forecast future market returns or future abnormal returns of individual stocks, she is forecasting the future state of the macroeconomy. We might think of her as updating the probability of recession (estimating a two-state regime switching model) based on all public and private information she has gathered and processed, and formulating an investment strategy that is a weighted average of her market-timing and stock-picking strategies, with weights that are a function of that estimated real-time recession probability.

The econometrician who wants to assess managers' ability to do this forecasting, will want to know when the recession truly took place, not just when real-time public information would lead one believe there was a recession. Because the NBER Business Cycle Dating Committee uses information available well after the boom or recession has ended, it produces a more accurate assessment of the state of the business cycle. This makes the NBER recession indicator the best metric for the econometrician to investigate ex post whether the fund pursued the right trading strategy at the right time, and why we use it for our headline results.

2.3 Fund skill or fund manager skill?

Is skill embodied in the manager or does it come from the human capital and the organizational setup the fund provides for that manager? To answer this question, we follow a manager over time, even as she 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 4 show how *Timing* and *Picking* 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 *Timing* and significantly lower *Picking* 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.

2.4 Funds that switch strategies earn higher 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 *Skill-Picking* or *SP* funds that have both high stock-picking skills in booms and high market-timing skills in recessions. Table 5 compares the *unconditional* performance of these *SP* funds to that of all other funds. The dependent variables are CAPM, three-factor, and four-factor alphas, obtained from twelve-month rolling-window regression of a fund's excess returns, before expenses, on a set of common risk factors. After controlling for various fund characteristics, we find that the CAPM, three-factor, and four-factor alphas are 5.6 to 7.6 basis points per month or 67 to 91 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 portfolio. Second, we confirm 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.

2.5 The characteristics of skilled funds and managers

In Panel A of Table 6, we compare the characteristics of the funds in the SP 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 and beta deviation, increases the R^2 to 19%. Thus, these findings paint a rough picture of what a typical skilled fund looks like.

Table 6, 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.

2.6 Market timing: Varying cash or betas?

Next, we explore in greater detail how managers time the market. A fund manager can time the market, even if she only holds the market portfolio of risky assets. For example, if the manager invests 100% of her assets in the S&P 500 when market returns are high and holds only cash when the market is falling, she will score high on timing ability because her weight w_{it}^{j} will be high in booms and zero in market downturns. She can also time the market without holding any cash by holding a high-β portfolio (of stocks or industries) in booms and a low-β portfolio in downturns. We find that managers do some of each: They significantly increase their cash holdings and reduce their holdings of high-beta stocks. They tilt their portfolios away from high-beta stocks and towards more defensive sectors.

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. In expansions, funds hold about 5% of their portfolios in cash. In recessions, the fraction of their holdings in cash rises by about 0.3% for *Reported Cash* and by about 3% for *Implied Cash*. 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. Within one year from the end of the average recession, half of the *Implied Cash* buildup is reversed (1.5% of the 3%).

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*. 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. 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. In sum, funds time the market by lowering their portfolio beta, shifting to defensive sectors and increasing their cash positions in recessions.[11]

2.7 Ruling out composition effects

Suppose 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 and show that they do not drive our results.

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 Recession in the *Picking* equation is equal to -0.146 (identical to the estimate without fixed effects), while the recession coefficient in the *Timing* estimation is slightly higher 0.148 (as opposed to 0.139 before). Both coefficients are significant at the 1% level of statistical significance.

[11]The Online Appendix reports the complete set of results for each of these exercises.

Size-driven composition effects Next, we consider whether composition related to fund size could drive our effect. Mutual funds might change their strategies 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 fund-fixed effects. 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-fixed effects as explanatory variables (columns 3 and 4 of Table 4). If a selection/composition effect drives the increase in $Timing$ 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.[12] 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.

2.8 Skill measures: Robustness

This section explores various robustness tests to our findings on fund manager skill.

[12] Our data 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.

Alternative recession indicators Our results so far use the NBER dates to split the sample into boom and recession periods. While we believe this is a sensible way to capture business cycles, we also explored three other recession indicators, all of which are available in more timely fashion. The first is a recession probability measure, constructed by Chauvet and Piger (2008); the second is a recession probability measure from the Survey of Professional Forecaster; and the third is the Chicago Fed National Activity Index (CFNAI). For the probability measures, we classify periods with recession probabilities exceeding 20% as recessions. For the CFNAI, readings below -0.7 are considered recessions. The fraction of recession months for these three alternative indicators is comparable to the fraction of NBER recessions. The Online Appendix replicates all our main results with these three alternatives and reports results that are similar to those using NBER recessions.

Market timing could 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:

$$R_t^j = \alpha^j + \beta^j R_t^m + \sigma_\varepsilon^j \varepsilon_t^j. \tag{6}$$

While *Timing* measures how funds' *portfolio weights* covary with the market excess return, this R^2 measures how funds' *excess returns* covary with the market excess return. The average R^2 across all funds rises from 77% in expansions to 80% in recessions, an effect that is statistically significant. The higher R^2 is due to higher market return volatility in recessions. 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.

3 Alternative Explanations

This section explores whether our time-varying skill results could arise from other effects unrelated to managerial skill.

3.1 Stock price patterns generate mechanical effects

Our results at the mutual fund level could 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: (1) an equally weighted portfolio of 75 (or 50 or 100) randomly chosen stocks by all funds; (2) 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; (3) similar strategies in which 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 Career concerns

We consider the possibility that the behavior of funds changes over the business cycle, because of cyclical career concerns. Chevalier and Ellison (1999) show that career concerns give managers an incentive to herd. This pressure is strongest for young managers. It would seem logical that the concern for being fired would be greatest in recessions; in fact, our data bear this out (see footnote 12). 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.

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}:

$$Portfolio\ Dispersion_t^j = \sum_{i=1}^{N^j} \left(w_{it}^{j} - w_{it}^{m} \right)^2 . \tag{7}$$

If we regress this dispersion measure on a recession indicator variable and a constant, the recession coefficient is 0.347 and is significant at the 5% confidence level.[13] 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 positively and significantly related to the fund's portfolio dispersion, 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

[13]This portfolio dispersion measure is similar in spirit to the concentration measure used in Kacperczyk, Sialm, and Zheng (2005) and the active share measure used in Cremers and Petajisto (2009). Because portfolio dispersion is a persistent variable, we might underestimate the standard error of our estimates. But this does not change the fact that the coefficient is not negative, as would be predicted by the career-concerns hypothesis.

be an interaction effect: Younger managers should hold portfolios with lower 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 with 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 of 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 a 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 career concerns. While labor market considerations may be important to understand many aspects of the behavior of mutual fund managers, they do not account for the specific patterns we document.

3.3 Skill varies with economic uncertainty

Another possibility is that skill is time varying, but it does not vary with the business cycle. Instead, changes in return dispersion or volatility explain changes in how managers exhibit skill.

Changes in picking and timing skill are not related to stock return dispersion. We begin by computing the cross-sectional dispersion of stock returns in each month. It has a low correlation (0.11) with recessions. When we regress $Timing$ on return dispersion, instead of our recession indicator (with our standard control variables), the coefficient is -0.76 with a standard error of 1.08. Similarly, when we regress $Picking$ on return dispersion, the coefficient is -0.34 with a standard error of 0.81. Hence, the relationship between picking or timing and return dispersion is not statistically significant.

Likewise, the evidence for volatility is weak. We define $Volatility$ as an indicator variable equal to one for periods of high volatility. We calculate the twelve-month rolling-window standard deviation of aggregate earnings growth.[14] Volatility equals one if the standard deviation of aggregate earnings growth is in the highest 10% of months. Volatility alone does have the same sign effect as recession, but it does not generate effects that are significant at the 5% level. When we include both recession and volatility as independent variables, both contribute to higher $Picking$ in expansions and to higher $Timing$ in recessions. However, the volatility effect is never statistically significant at the 5% level. And the point estimate of the recession indicator is larger in magnitude. In sum, the recession-only specification is the only one that produces a statistically significant change in timing and picking.

4 Identifying Skilled Managers in Real Time

The second contribution of the paper is to use the results on time variation in skill presented thus far to develop an indicator of who the skilled managers are. Instead of using performance metrics to select fund managers, we exploit the prediction that skilled managers time the market in recessions and pick stocks in expansions, to develop our *Skill Index*. Unlike in the previous sections, we now take the perspective of an investor (or an agency like Morningstar) who wants to form a timely gauge of how skilled funds are. Our monthly *Skill Index* is constructed based on real-time, publicly available information. We show that this index is correlated with future performance. Second, we show that, unlike market timing or stock picking alone, the skill index is persistent over time.

[14]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.

4.1 Creating a Skill Index

To use our approach as a way 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* for fund j in month $t+1$ as a weighted average of $Timing_t^j$ and $Picking_t^j$ measures, in which the weights we place on each measure depend on the state of the business cycle:

$$Skill\,Index_{t+1}^j = w_t Timing_t^j + (1 - w_t) Picking_t^j \tag{8}$$

We normalize $Timing$ and $Picking$ so that each has a mean of zero and a standard deviation one in the cross-section, each period. Then, we set the weight on $Timing$ equal to $0 \leq w_t \leq 1$, where w_t is the real-time recession probability of Chauvet and Piger (2008).[15] This continuous weighting scheme is quite intuitive: Linearly weight $Timing$ more whenever the probability of a recession increases. $Picking$ always gets the complementary weight $1 - p_t$. The resulting *Skill Index* is mean-zero with standard deviation close to one (0.96). The Online Appendix shows that our results are robust to using alternative weighting schemes.

Notice that $Timing_t^j$ and $Picking_t^j$ are both constructed using fund portfolio weights at the beginning of time t and asset returns realized between the start of period t and $t+1$. All of this information is known at time $t+1$. Also, the real-time recession probability p_t is known at time $t+1$. Thus, this is a fund score that can be computed at the end of each period $t+1$ and contains no future information (beyond time $t+1$) that would generate spurious predictability.

[15] Real time recession probabilities for the United States are obtained from a dynamic-factor markov-switching model applied to four monthly coincident variables: non-farm payroll employment, the index of industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales. An analysis of the performance of this model for dating business cycles in real time and more details are in Chauvet and Piger (2008).

Subsequently, we examine whether the *Skill Index* at time $t+1$ can predict fund performance, measured by the CAPM, three-factor, and four-factor fund alphas one month ahead, based on returns realized between time $t+1$ and time $t+2$, or one year ahead, based on returns realized between time $t+1$ and time $t+13$.[16] Since we now take the perspective of the investor, alphas are measured net of expenses. Table 7 shows that funds with a higher *Skill Index* have higher average net alphas. For example, when *Skill Index* is at its mean of zero, the net alpha is around -48bp per year. However, when the *Skill Index* is one standard deviation (0.96) above its mean, the one-month ahead CAPM alpha is 2.45 percentage points higher per year. The three- and four-factor alphas are respectively 1.27 and 1.17 percentage points higher per year. The three most right columns show similar predictive power of the *Skill Index* for one-year ahead alphas. A one-standard-deviation increase in the *Skill Index* is associated with a 2.31 percentage points higher CAPM alpha, 1.08 percentage points higher three-factor alphas, and 1.09 percentage points higher four-factor alpha.

The advantage of the above performance results are that they control for fund characteristics. The disadvantage, which we argued is modest in practice, is that overlapping return windows must be used to estimate the alphas. To further mitigate the concern that this affects our results, we consider the following portfolio formation exercise. Each month, we sort mutual funds into deciles based on their *Skill Index* in that month, and construct the

[16] One-month ahead alphas are obtained from time-series rolling-window regressions of fund returns on standard style benchmarks. For example, we estimate a CAPM regression from 12-month rolling window regressions of fund returns on the market return: $R^j_{t+2} = \alpha^j + \beta^j R^m_{t+2} + \epsilon^j_{t+2}$. The 12-month estimation window runs from $t-10$ until $t+2$, where time $t+1$ denotes the time at which the $Skill\,Index_{t+1}$ is constructed and known. We then define the one-month ahead alpha as the part of the return not explained by covariation with the market: $\alpha_{t+2} = \hat{\alpha}^j + \epsilon^j_{t+2} = R^j_{t+2} - \hat{\beta}^j R^m_{t+2}$. This is the analogue of an abnormal fund return except that it takes into account that the fund's beta with the market may not be unity. The inclusion of the idiosyncratic return piece ϵ^j_{t+2} is standard in the literature. While the constant α^j is estimated with return information that is partially known at time $t+1$, the ϵ^j_{t+2} term is not measurable with respect to time $t+1$ information. Practically, most of the variation in the one-month ahead alpha in the panel regression arises from the ϵ^j_{t+2} term. The one-year ahead alphas use return information from $t+1$ to $t+13$ to estimate $\hat{\alpha}^j$ and add ϵ^j_{t+13}. The one-year ahead results generate very similar point estimates than the one-month results, something that would be highly unlikely if the one-month ahead alphas were severely biased due to look-ahead issues or mechanical correlations.

value-weighted and equally weighted average portfolio returns over the next month.[17] This creates a portfolio return time series for each decile of the *Skill Index* distribution. We then estimate a time-series regression of decile excess returns on the aggregate market excess return (CAPM), size and value factor returns (three-factor model), and momentum factor returns (four-factor model). This time-series regression makes no use of overlapping data. We find that the value-weighted (equally weighted) CAPM alpha for the spread portfolio (decile ten minus decile one) is 38bp per month (40bp), net of fees. The spread portfolio has a three-factor alpha of 53bp (53bp) per month value-weighted (equally weighted), and a four-factor alpha of 27bp (28bp) per month. All spread returns are statistically different from zero. The strategy delivers economically significant spread returns, net of fees, between 3.2 and 6.4% per year.

4.2 Persistence of skill measures

To distinguish skill from luck it is important that skill be persistent. A fact that casts doubt on the existence of fund manager skill is the fact that stock picking and market timing do not exhibit much persistence.[18] To show this, we first sort funds in quintiles based on their $Timing$ scores in month zero and track their performance over the next 1 to 12 months. We then subtract the average $Timing$ measure of funds that were initially in quintile 1 (Q1) from that of funds that were initially in quintile 5 (Q5). We do the same for funds sorted by their stock picking scores. The top two panels of Figure 1 plot the Q5-Q1 differences in skill scores over these 12 months. If skill is persistent, we should see the top market timers (stock pickers) in month 0 to continue to outperform the worst month-zero market timers

[17] Consistent with equation (8), the $Skill\,Index_{t+1}$ depends on weights w_t, $Timing_t$, and $Picking_t$. The portfolio return for each decile is formed as the value-weighted (using assets under management at time t) or equally-weighted average of fund returns between $t+1$ and $t+2$ for all funds in that decile of the *Skill Index* distribution.

[18] Their first-order autocorrelation coefficients are not statistically different from zero. This lack of persistence also alleviates the concern that the results in Table 1 suffer from spurious regression bias. Formal tests of the null hypothesis that the errors from panel regressions (3) and (4) contain a unit root, due to Maddala and Wu (1999), are rejected at the 1% level.

(stock pickers) in months 1, 2, and beyond. Instead, what we see is that the difference in market-timing (top panel) and stock-picking (middle panel) skill disappears, even just one month post formation. On average, the previous month's worst market timers are no worse than the previous month's best market timers.

However, our skill index captures a more general cognitive ability that is more flexible: One that can be applied to picking stocks successfully one month and to timing the market in other months, or to doing some of each. If there are able managers but they employ different skills at different times, that could explain why neither picking nor timing is persistent. But then this more general skill should be. To test this, we perform the same sorting exercise on our *Skill Index* measure. The bottom panel of Figure 1 reveals that managers with high *Skill Index* in one month, on average still display higher skill, 12 months later. This difference is statistically significant for up to 6 months.

5 Conclusion

Do investment managers add value for their clients? The answer to this question matters for discussions ranging from market efficiency to what practical portfolio advice to give 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 type of 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 successfully pick stocks in booms and time the market well in recessions. Managers who exhibit this time-varying skill outperform the market by 70-90 basis points per year.

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.

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-specific and economy-wide shocks in a way that creates value.

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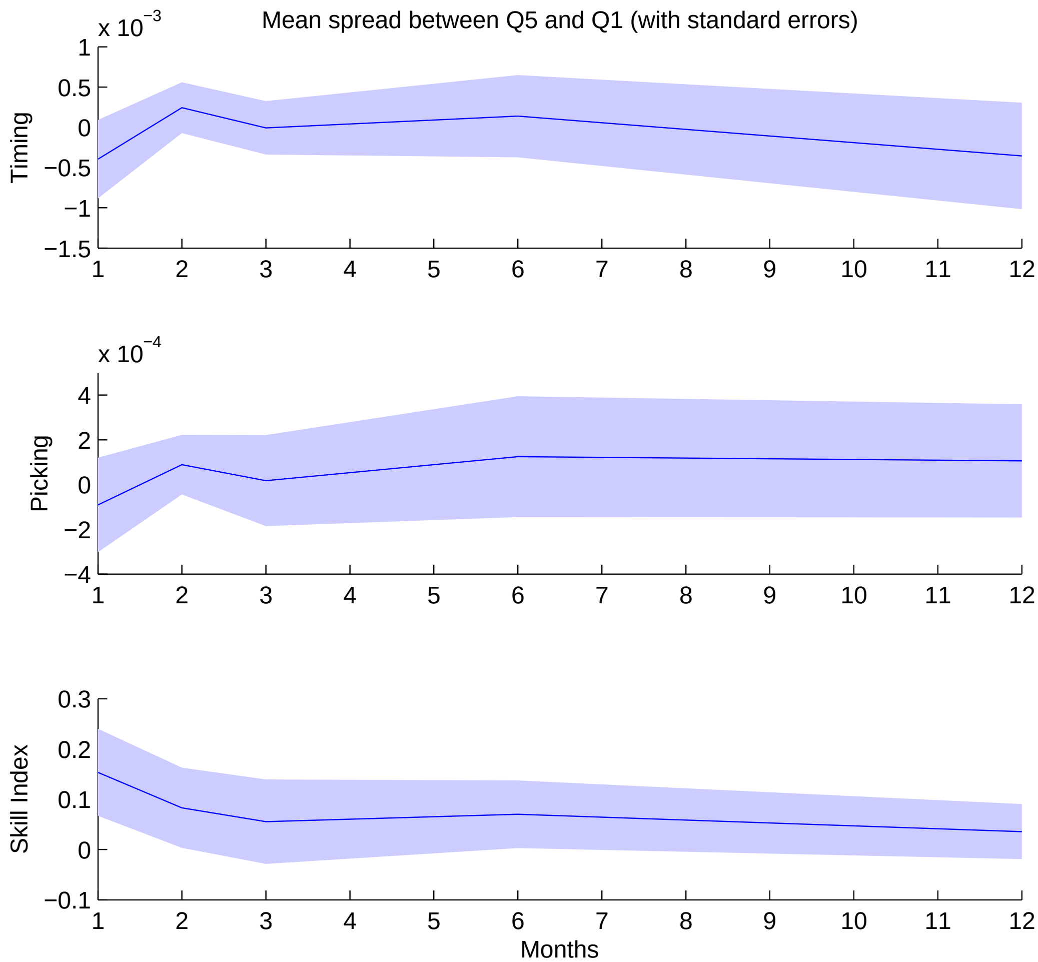

Figure 1: Persistence Of *Timing*, *Picking* and Skill Index.

We rank funds into quintiles based on their *Timing*, *Picking*, or Skill Index score at time 0. Next, we subtract the average score in quintile 5 (Q5) from that in quintile 1 (Q1) in each of the following 12 months. We report that difference in the post-formation period. A positive difference indicates persistent skill. The shading shows 2 standard errors on either side of the point estimate (solid line).

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

Dependent variables: $Timing_t^j$ 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: $Timing_t^j$ 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. To compute the standard errors we use block bootstrap, where the block is a cluster of analysis as in Luetkepohl (1993).

	(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
	(0.026)	(0.039)	(0.083)	(0.023)	(0.022)	(0.053)
Log(Age)	0.000	-0.003	-0.020	0.003	-0.005	-0.057
	(0.001)	(0.004)	(0.017)	(0.002)	(0.003)	(0.011)
Log(TNA)	0.000	0.004	-0.004	-0.001	0.001	0.005
	(0.001)	(0.002)	(0.010)	(0.001)	(0.002)	(0.007)
Expenses	0.162	4.015	21.046	-0.588	3.096	18.869
	(0.201)	(1.075)	(3.590)	(0.291)	(0.526)	(2.226)
Turnover	0.001	0.053	0.404	0.001	0.042	0.305
	(0.001)	(0.012)	(0.042)	(0.001)	(0.006)	(0.035)
Flow	0.004	0.036	0.228	0.035	0.099	0.192
	(0.012)	(0.055)	(0.193)	(0.024)	(0.039)	(0.147)
Load	-0.013	-0.327	-1.404	0.108	-0.129	-1.213
	(0.026)	(0.117)	(0.465)	(0.039)	(0.072)	(0.306)
Constant	0.000	0.108	0.765	-0.015	0.126	0.722
	(0.003)	(0.020)	(0.067)	(0.006)	(0.011)	(0.053)
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: **Managers as the Unit of Observation**

$Timing_t^j$ and $Picking_t^j$ are defined in equations (1) and (2), 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.

	Timing	Picking	Timing	Picking
Recession	0.156	-0.192	0.160	-0.187
	(0.074)	(0.055)	(0.074)	(0.057)
Log(Age)	0.004	0.002	0.004	-0.005
	(0.006)	(0.005)	(0.010)	(0.008)
Log(TNA)	0.001	-0.000	0.002	0.003
	(0.003)	(0.005)	(0.006)	(0.009)
Expenses	0.772	-0.938	1.238	-0.760
	(1.396)	(1.107)	(1.235)	(0.867)
Turnover	0.006	0.017	0.002	0.014
	(0.016)	(0.014)	(0.011)	(0.011)
Flow	0.002	0.201	0.007	0.183
	(0.092)	(0.194)	(0.094)	(0.202)
Load	0.118	0.081	0.162	-0.015
	(0.206)	(0.170)	(0.187)	(0.237)
Constant	0.012	-0.009	0.012	-0.009
	(0.026)	(0.022)	(0.027)	(0.022)
Manager Fixed Effect	N	N	Y	Y
Observations	333,612	333,612	333,612	333,612

Table 5: **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. Recession is measured as the NBER indicator variable.

	(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 6: **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, $Expenses$, $Turnover$ and $Flow$ are defined in Table 1. RSI comes from Kacperczyk, Sialm, and Zheng (2008). $Portfolio\ dispersion$ 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
RSI	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 7: **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 window regression. The regression window is $t-10$ to $t+2$ for one month ahead and $t+1$ to $t+13$ for one year ahead. For each fund, we form the skill index in equation (8). *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	0.212	0.110	0.101	0.200	0.093	0.094
	(0.039)	(0.020)	(0.018)	(0.027)	(0.023)	(0.013)
Loga(Age)	-0.035	-0.025	-0.036	-0.020	-0.010	-0.025
	(0.008)	(0.006)	(0.006)	(0.008)	(0.005)	(0.006)
Log(TNA)	0.027	0.010	0.012	-0.016	-0.018	-0.011
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Expenses	-2.871	-7.028	-7.314	-5.702	-9.049	-9.264
	(1.623)	(1.007)	(0.960)	(1.562)	(0.921)	(0.892)
Turnover	-0.011	-0.048	-0.040	-0.001	-0.041	-0.036
	(0.016)	(0.014)	(0.010)	(0.016)	(0.014)	(0.010)
Flow	2.358	1.635	1.492	0.189	0.188	0.205
	(0.157)	(0.099)	(0.095)	(0.114)	(0.085)	(0.071)
Load	-0.782	-0.101	-0.320	-0.699	0.205	-0.052
	(0.232)	(0.143)	(0.156)	(0.224)	(0.129)	(0.149)
Constant	-0.031	-0.055	-0.041	-0.044	-0.070	-0.056
	(0.023)	(0.018)	(0.021)	(0.024)	(0.019)	(0.022)
Observations	219,339	219,339	219,339	187,668	187,668	187,668