Time-Varying Fund Manager Skill

Forthcoming Journal of Finance

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ABSTRACT

We propose a new definition of skill as a general cognitive ability to either pick stocks or time the market 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 measure of managerial ability that gives more weight to a fund's market timing in recessions and to a fund's stock picking in booms. The measure displays far more persistence than either market timing or stock picking alone and can predict fund performance.

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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 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 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 differs from the 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. This result not only holds for the standard NBER recession indicator, but also for measures of aggregate economic activity that are available in a more timely fashion.

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 of up to one year.

To measure skill, we construct estimates of stock picking (the product of a fund's portfolio weights in deviation from market weights with the firm-specific component of stock returns) and market timing (the product 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% 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 ability. Conversely, we can select the top 25% 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 50-80 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.

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 being 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 entertain the possibility that fund strategies change because the fund manager changes. Third, we analyze 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, we study whether this is a composition effect and find that it is not. 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 analyze 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 adjusting 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 defined as 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 factors exposures. 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* 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 studies that link fund performance to business-cycle variation (Ferson and Schadt (1996) Christopherson, Ferson, and Glassman (1998), and Moskowitz (2000)). Time variation in fund manager skill is a useful piece of evidence in the quest to understand fund behavior. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2011) find that this skill comes from managers' ability to choose portfolios that anticipate micro and macro fundamentals. Motivated by this additional evidence, they develop a new, information choice theory of fund management that can explain the time-varying skill facts and is supported by a host of other evidence. 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 portfolios to mutual funds–this work remains silent on what strategies investment managers pursue to achieve this differential performance. Similarly, Kosowski (2011) shows that fund performance varies over the business cycle but he does not distinguish between the sources of skill as we do here. Finally, de Souza and Lynch (2012) investigate cyclical performance by mutual fund style using a GMM technique. Our focus is on detecting the time-varying strategies that skilled funds employ that are behind the cyclical outperformance result.

The rest of the paper is organized as follows. Section I describes our data. Section II 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 III considers alternative explanations, not based on time-varying use of skill. Section IV proposes a real-time Skill Index and uses it to predict fund returns. Section V concludes.

I. 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.

A. 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 observations on funds that allocate less than 80% of their portfolio to stocks in the current quarter. 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 portfolio 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, and momentum. The aggregate stock market 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%). Section II.B considers alternative recession indicators.

B. *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 means 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, comove with the systematic component of the stock return:

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

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 $w_{i,t}^j$ is the fraction of a fund j's total assets held in risky asset i at the start of time t. The market weight $w_{i,t}^m$ 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 model of asset i's excess returns on market excess returns, using return data between month $t-11$ and month t. The return R_{t+1}^m 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, $Picking_t^j$ measures how a fund's holdings of each stock, relative to the market, comoves with the idiosyncratic component of the stock return:

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

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

In terms of interpretation, *Timing* and *Picking* are expressed in units of return per month. They are *hypothetical* portfolio returns based on the beginning-of-period portfolio weights $w_{it}^{j} - w_{it}^{m}$.[9] We also note that the summation is over all assets in fund j's portfolio (N^{j}).[10] Our results are robust to defining the measures as the sum over all stocks held by any of the funds in our sample.

Our *Picking* and *Timing* measures are variants 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 based on 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 available public information. We use unconditional measures instead. Conceptually, these measures differ: For example, in Ferson and Schadt (1996), skill means executing a trading strategy that outperforms a hypothetical investor who combined 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 and what allows the manager to construct a high-performance portfolio. We now show that the nature of that skill varies over time.

II. Skill Varies Over Time

A. Main results

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 comove more with the aggregate shock. Conversely, in expansions, their holdings comove 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 age (natural logarithm of age in years since inception, $\log(Age)$), size (natural logarithm of total net assets under management in millions of dollars, $\log(TNA)$), expense ratio (in % per year, *Expenses*), the turnover rate (in % 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 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.[11] To mitigate the impact of outliers on our estimates, we winsorize *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.

[Insert Table I about here]

Table I 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. Since *Timing* is expressed in units of monthly returns, columns (1) and (2) imply that our market timing measure is 14 basis points per month or 1.67% points per year higher in recessions than in expansions (and zero in expansions). Likewise, columns (3) and (4) show that stock-picking ability deteriorates substantially in recessions. *Picking* is 14 basis points per month or 1.75% per year lower in recessions than in expansions (and zero in expansions). In sum, we observe meaningful differences in average market timing and stock picking 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. 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 28 and 35 in absolute values. 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 of the NBER recession indicator are more significant, with t-statistics in excess of 100 in absolute values. Third, we cluster standard errors at the fund family level. In this estimation, the t-statistics are between 23 and 24 in absolute values. Table I in the Online Appendix provides the detailed results. All of these results reinforce the statistical significance of our findings.

The effects of *Recession* on *Timing* and *Picking* are also robust to including indicator variables for high aggregate volatility and high earnings dispersion. Changes in *Picking* and *Timing* skill are not statistically significantly related to stock return dispersion or volatility, once the effect of *Recession* is controlled for and do not diminish the effect of *Recession*. These results are omitted for brevity.

B. Real-time recession indicators

The previous result used the official NBER turning points to split the sample into boom and recession months. But how does a manager know when to use a market timing 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.

Nevertheless, we also investigate whether our results hold for two alternative recession indicators that are available in more timely fashion. They have an additional advantage over the NBER recession indicator variable in that they are continuous measures of the strength of the economy, rather than a coarser discrete measure. The first one, $RecRT$, is a real-time recession probability measure constructed by Chauvet and Piger (2008).[12] The second one, $RecCFNAI$, is the Chicago Fed National Activity Index multiplied by -1. $RecCFNAI$ is negative when economic activity is above average and is positive when economic activity is below average.[13] Table II reports results that are similar to those using NBER recessions. An increase in real-time recession probability $RecRT$ from 0 to 50% increases $Timing$ by

20 basis points per month or 2.46% per year and decreases *Picking* by 12 basis points per month or 1.41% per year. An increase in $RecCFNAI$ from its mean of 0 to a value of 0.7—CFNAI readings below −0.7 are typically considered as recessionary levels—increases *Timing* by 7 basis points per month or 79 basis points per year and decreases *Picking* by 4 basis points per month or 49 basis points per year. The effects are measured precisely and are of a similar magnitude as the effects of NBER recessions shown in Table I.

[Insert Table II about here]

C. Do all managers have time-varying skills?

Since markets have to clear, not everyone can outperform the market. Sharpe (1991) and 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. Table I indeed bears out the average *Picking* is negative. The same is not true for market timing, since individual investors have negative timing ability because they systematically buy index funds when returns are low (Savov 2010). 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 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).

If there is a subset of skilled managers and they deploy different skills over the business cycle, then most of the time we should observe 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. Note that this is not a foregone conclusion: While the average *Timing* of the top group of funds sorted by *Timing* is by construction higher than that of the median fund, the effect of *Recession* on *Timing* need not be higher. We evaluate this hypothesis formally by estimating the models in equations (3) and (4) using quantile regressions. We consider three different quantiles: 50 (median, Q50), 75^{th} percentile (Q75), and 95^{th} percentile (Q95). In this regression, standard errors are calculated using block bootstrap (with 2000 repetitions), which takes into account cross-sectional dependence across funds (Luetkepohl 1993). Table III presents the results.

[Insert Table III about here]

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 and economically significant, both for stock picking and market timing. For example, the effect of *Recession* on *Timing* for extremely successful managers is about four times larger than that for the median manager: 25.1 vs. 5.9 basis points per month. The 19 basis point cross-sectional difference translates into 2.3% points per year. A similar comparison for *Picking* shows that the effect of *Recession* doubles at the 95th compared to the 50th percentile. While the economic magnitudes of the recession effect are stronger for higher quantiles, estimation error also increases. The t-statistic for *Timing* increase from 2.5 to 3.1 going from quantile 50 to quantile 95; at the same time, the respective t-statistics for *Picking* go from 4.0 to 2.6. 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.

D. 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 *Top* ($Top_j \in \{0, 1\}$) 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:

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

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 IV, column (3), we confirm that *Top* funds are significantly better at picking stocks in expansions, after controlling for fund characteristics. This is true by construction. Their measure of *Picking* in expansions is 5.9 basis points per month or 70 basis points per year higher than that of the remaining funds. The main point Table IV makes is that the same *Top* funds are on average also better at market timing in recessions. This result is evident from the positive coefficient of *Top* in column (2), which is statistically significant at the 5% level. Their *Timing* measure during recessions is 3.7 basis points per month or 45 basis points per year higher than that of all other funds. Finally, the *Top* funds do not exhibit superior market-timing ability in expansions (column 1) nor superior stock-picking ability in recessions (column 4). The fact that this group of funds is not simply better at either strategy all the time validates the point that *Top* funds switch strategies.

[Insert Table IV about here]

Table II of the Online Appendix shows that the fund manager need not know the NBER recession indicator to execute this switching strategy. The results in Table IV are robust to using the two real-time recession variables introduced in Section II.B.

A final note about Table IV is that the *Top* group has significantly lower value for *Picking* during recessions (column 4). In principle, poor stock picking performance in recessions could offset the benefits from superior market timing in recessions and stock picking in expansions. Studying the performance of the *Top* funds, to which we turn next, will be informative about whether the *Top* funds are indeed better managers.[14]

The existence of some 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 *Top* portfolio. Second, we confirm our results using Daniel, Grinblatt, Titman, and Wermers (1997)'s definitions of market timing (CT) and stock picking (CS). Third, 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.

E. 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 and across funds. Columns (1) and (2) of Table V 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* (16 basis points per month or 1.87% per year) and significantly lower *Picking* (19 basis points per month or 2.30% per year) 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. The results are also robust to using real-time recession measures (not reported).

We conclude that our results hold both at the fund and at the manager levels.

[Insert Table V about here]

F. 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 IV showed that there exists a set of *Top* funds that have both high stock-picking skills in booms and high market-timing skills in recessions. Table VI compares the *unconditional* performance of these *Top* 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, based on reported fund 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 4 to 7 basis points per month or 48 to 82 basis points per year higher for the *Top* portfolio, a difference that is statistically and economically significant. These results are the same order of magnitude as the difference in *Timing* and *Picking* between the *Top* funds and all other funds, which is consistent with the interpretation of *Timing* and *Picking* as (hypothetical) returns. The return measures in Table VI add additional evidence because they are based on observed fund returns, not hypothetical returns. Finally, given that the *Top* funds are no better at market timing in expansions and strictly worse at stock picking during recessions (recall Table IV), these unconditional outperformance results show that the *Top* funds are following market-timing strategies in recessions and stock-picking strategies in expansions.

[Insert Table VI about here]

Table III of the Online Appendix shows that the unconditional outperformance of the Top funds also holds when Top fund membership is defined based on real-time recession measures. The outperformance is between 5.0 and 7.2 basis points per month, very similar to the baseline results. This evidence bolsters the case for a robust link between various recession measures, including real-time measures, and fund outperformance. de Souza and Lynch (2012) find that the *average* fund outperformance in recessions is not robust to ex-ante measures of recession. Our results show that the unconditional outperformance of the *group* of skilled funds in Top is present, regardless of an ex-ante or ex-post definition of recession.

G. The characteristics of skilled funds and managers

In Panel A of Table VII, we compare the characteristics of the funds in the Top portfolio to those of funds not included in the portfolio. We note several differences. First, funds in Top 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 portfolio 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 skills. Sixth, the Top funds tend to hold portfolios with fewer stocks and higher stock-level and industry-level portfolio dispersion, measured as the Herfindahl index of portfolio weights in deviation from the market portfolio's weights. 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 *Top* (not reported). Including attributes that we could link to skilled funds' active investment behavior, such as stock and industry portfolio dispersion, and beta deviation, increases the R^2 to 19%.

[Insert Table VII about here]

Table VII, Panel B, examines *manager* characteristics. *Top* 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. Taken together, these findings paint a rough picture of what a typical skilled fund looks like.

H. 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: In recessions, they significantly increase their cash holdings, they reduce their holdings of high-beta stocks, and they tilt their portfolios away from cyclical and towards more defensive sectors.

To investigate changes in cash holdings, we measure cash either as *Reported Cash* from CRSP or as *Implied Cash*, backed out from fund size and its equity holdings. In expansions, funds hold about 5.25% of their portfolios in cash. In recessions, the fraction of their cash holdings rises by about 3 percentage points for *Implied Cash* and by 0.4 percentage points for *Reported Cash*. Both increases are statistically significant with t-statistics around 5, and each represents a change of about 10% of a standard deviation of the dependent variable. We also investigate the month-over-month change in the *Implied Cash* position. In recessions, cash holdings increase by 0.5 percentage points while in expansions they fall by 1.5 percentage points. The effect of *Recession* 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%).

Second, we examine 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 1.00 in recessions; the 0.11 difference has a t-statistic of 4. This means that funds hold different types of stocks in recessions, namely lower-beta stocks.[15]

Finally, we investigate whether funds rotate their portfolio allocations across different industries 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.[16] 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. Tables IV and V of the Online Appendix report the complete set of results for each of these exercises.

III. Alternative Explanations

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

A. 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.

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 IV) 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 V). 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.[17] 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.

B. 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. While this exercise does not consider every single alternative mechanical strategy, none of these strategies generates higher market-timing measures in recessions and higher stock-picking readings in expansions.

C. 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 17). 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:[18]

$$Portfolio\ Dispersion_t^j = \sum_{i=1}^{N^j} \left(w_{it}^j - w_{it}^m\right)^2 . \tag{6}$$

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.[19] Controlling for the fund characteristics listed in Table I changes this estimate by less than 1%. Thus, instead of finding more herding in recessions, we find less.[20]

While labor market considerations may be important to understand many aspects of the behavior of mutual fund managers, they do not account for the patterns we document.

IV. 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 construct an indicator of who the skilled managers are. 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.

A. 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:

$$Skill\,Index_{t+1}^j = w_t Timing_t^j + (1 - w_t) Picking_t^j \tag{7}$$

We normalize *Timing* and *Picking* so that each has a mean of zero and a standard deviation of 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). 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).

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.

B. Returns by Skill Index

In the first exercise, we sort each fund into one of five quintiles based on the *Skill Index* each month, ranked from low skill to high skill. For each quintile portfolio, we compute equal-weighted average portfolio returns. Since we now take the perspective of the investor, alphas are measured based on reported returns net of expenses.[21] This creates a portfolio return time series for each quintile of the *Skill Index* distribution. We then estimate a time-series regression of quintile excess returns on the aggregate market excess return (CAPM), size, and value factor returns (three-factor model), and momentum factor returns (four-factor model). The four panels of Table VIII show the average abnormal fund return, CAPM, three-factor, and four-factor alphas over the 1-, 3-, 6-, 9-, and 12-month periods post portfolio formation (not cumulative returns).

Performance measures increase monotonically with the *Skill Index* (from Q1 to Q5). While the *average* fund does not outperform (last row of each panel), the average fund in the top quintile of the *Skill Index* performs substantially better than the average fund in the bottom quintile. The annual return difference is 3-6%, depending on the measure of performance, one-to-six months after portfolio formation, and 0.6 to 2.1% 12 months after portfolio formation. In sum, the strategy delivers economically significant spread returns, net of fees.

[Insert Table VIII about here]

The advantage of these portfolio sorting results is that they are based on time-series regressions, which make no use of overlapping data. The disadvantage is that they do not control for fund characteristics. In a second exercise, we control for fund characteristics but use overlapping data. In particular, 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 $t+13$.[22] Table IX 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 -0.5% per year. However, when the *Skill Index* is one standard deviation (0.96) above its mean, the one-month ahead CAPM alpha is 2.4% higher per year. The three- and four-factor alphas are respectively 1.2% and 1.1% points higher per year for a one-standard-deviation increase in the *Skill Index*. 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 2.2% per year higher CAPM alpha and 1.0% higher three-factor and four-factor alphas.

[Insert Table IX about here]

Table VI in the Online Appendix shows that these results are robust to using different definitions for the Skill Index. In particular, they explore a different weighting scheme for w_t in equation (7). Both measures set w_t equal to 0.8 in recessions and 0.2 in expansions. But the first measure defines recessions as months with real-time recession probabilities above 20% while the second measure defines recessions as months in which CFNAI is below -0.7. Both results are qualitatively and quantitatively similar to the benchmark results.

C. Persistence of skill measures

Skill is persistent, luck is not. The fact that stock picking and market timing do not exhibit much persistence casts doubt on the existence of fund manager skill.[23] To show this, we first sort funds into 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 (stock pickers) in months 1, 2, and beyond. Instead, 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 *Skill Index*. 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.

[Insert Figure 1 about here]

V. 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. Most 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 50-90 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) explore 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. 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.

Our findings leave several interesting questions for future research. One important one is why the group of funds that we associated with superior performance does not raise fees or attract inflows until outperformance disappears. We do observe higher fees, smaller size, and higher inflows for this group of funds, suggesting that the equalizing forces operate. Their strength is likely mitigated by the presence of trading costs, including the inability to short poorly performing mutual funds, partial investor unawareness of our findings and uncertainty in the economic environment. Given the volatility of stock and fund returns, it takes time for investors to learn who the best funds are and for fund managers to learn about their own ability. Future work could fruitfully incorporate such considerations.

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Notes

[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).

[4]See e.g., Graham and Harvey (1996), Ferson and Schadt (1996), Daniel, Grinblatt, Titman, and Wermers (1997), Becker, Ferson, Myers, and Schill (1999) and Kacperczyk and Seru (2007)). Notable exceptions are Mamaysky, Spiegel, and Zhang (2008) who find evidence for market timing using Kalman filtering techniques, Bollen and Busse (2001) and Elton, Gruber, and Blake (2011) who find evidence of market timing using higher frequency holdings data, and Ferson and Qian (2004) who look at market timing in different economic conditions.

[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.

[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.

[9]We thank the referee for pointing this out. For a related measure of hypothetical portfolio returns, see Jiang, Yao, and Yu (2007).

[10]We note that the market weights of all stocks in fund j's portfolio do not sum to one. Rather, it is the product of two variables with different means. This implies that Timing does not have a cross-sectional mean of zero.

[11]The size style of a fund is the value-weighted score of its stock holdings' quintile scores calculated based on the stocks' market capitalizations (1 denotes the smallest size quintile; 5 denotes the largest size quintile). The value style is the value-weighted score of its stock holdings' quintile scores calculated based on the stocks' book-to-market ratios (1 denotes the smallest B/M quintile; 5 denotes the largest B/M quimtile). The momentum style is

the value-weighted score of a fund's stock holdings' percentile scores calculated based on the stocks' past twelve-month returns (1 denotes the smallest return quintile; 5 denotes the largest return percentile). These style measures are similar in spirit to those defined in Kacperczyk, Sialm, and Zheng (2005).

[12]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). Results are similar for the real-time recession probability measure from the Survey of Professional Forecaster and are omitted for brevity.

[13]The CFNAI is a coincident indicator of national economic activity comprising 85 existing macroeconomic time series. It is constructed to have an average value of zero and a standard deviation of one. We use the headline three-month moving average. The CFNAI is released in the third week of the month following the month to which it pertains.

[14]An alternative interpretation of the negative sign of *Recession* in column 4 is that it may be due in part to measurement error. Because measurement error can make slope and intercept estimates negatively correlated, the estimated good market timers in recessions may bias downward stock picking for the *Top* group. We thank our Referee for pointing this out. However, such an argument cannot explain our main result, that good stock pickers in expansions are good market timers in recessions, because that result is based on two different regressions, one for the subsample of recession months and a separate one for expansion months.

[15]The results on cash holdings and equity betas are robust to using real-time recession

measures; results are omitted for brevity.

[16]While the sector weights are persistent over time, we can reject the null hypothesis of a unit root in the regression residuals for each of the sectors using the test developed by Maddala and Wu (1999). Hence, persistent regressor bias is unlikely to explain these results.

[17]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, but 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.

[18]We have explored the robustness of our results using the specification that does not include market-weight adjustment. The results from estimating this alternative specification are very similar.

[19]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).

[20]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 younger managers should hold portfolios with lower dispersion in booms. 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 of 0.40 with a standard error of 0.08.

[21]Consistent with equation (7), the $Skill\,Index_{t+1}$ depends on weights w_t, $Timing_t$, and $Picking_t$. The portfolio return for each quintile is formed as the equal-weighted average of fund returns between $t+1$ and $t+2$ for all funds in that quintile of the *Skill Index* distribution.

[22]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.

[23]Their first-order autocorrelation coefficients are not statistically different from zero. This lack of persistence also alleviates the concern that the results in Table I 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.

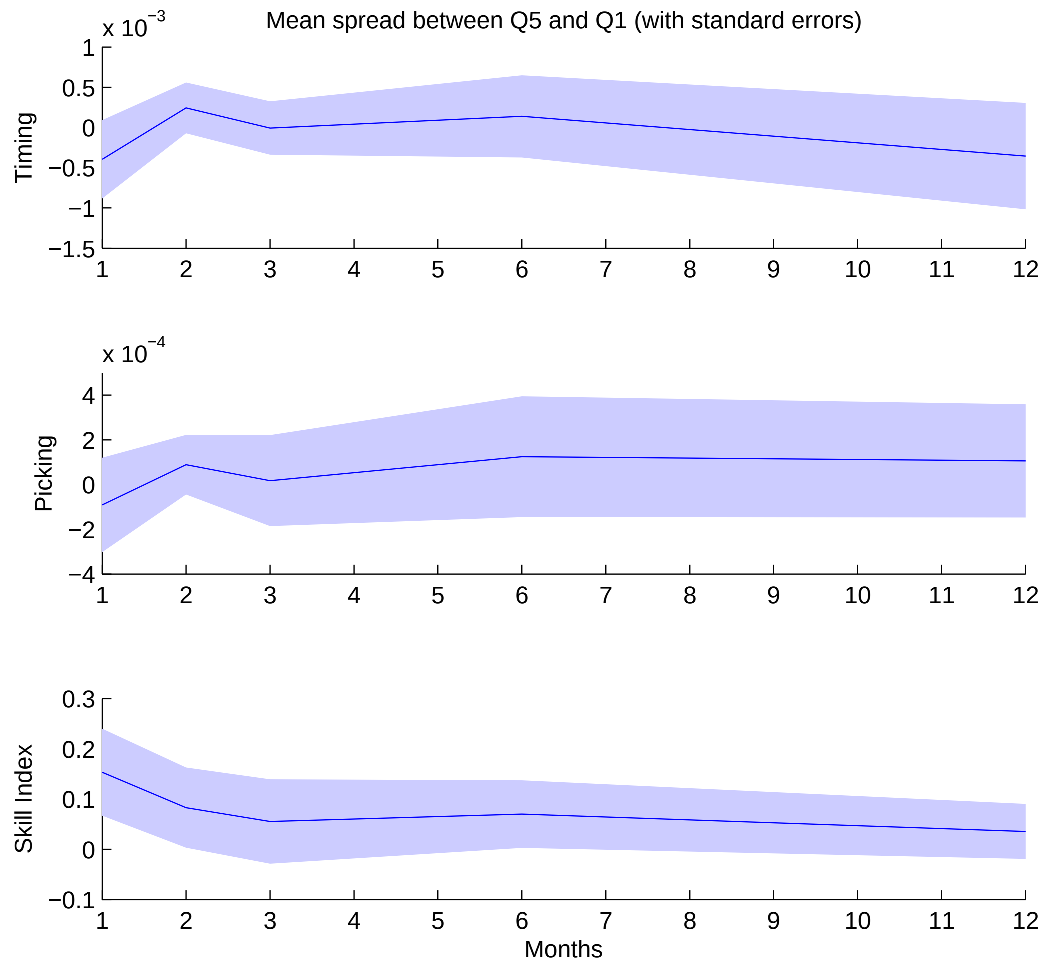

Figure 1: Persistence Of *Timing*, *Picking* and Skill Index.

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 I: **Timing and Picking Skills are Cyclical**

The dependent variables are *Timing* and *Picking*, defined in equations (1) and (2), where each stock's β is measured over a twelve-month rolling window. *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, based on the average scores of stocks in the fund's portfolio in that month sorted into quintiles along each respective characteristic. 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
		(0.003)		(0.003)
Expenses		0.677		-0.636
		(1.150)		(0.537)
Turnover		0.008		0.012
		(0.011)		(0.007)
Flow		0.003		0.044
		(0.077)		(0.078)
Load		0.066		0.142
		(0.178)		(0.106)
Size		-0.009		0.005
		(0.009)		(0.007)
Value		-0.015		0.030
		(0.013)		(0.010)
Momentum		-0.015		0.034
		(0.034)		(0.034)
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 II: **Timing and Picking with Real-Time Recession Indicators**

The dependent variables are *Timing* and *Picking*. *RecRT* is a recession measure based on the Chauvet and Piger real-time recession probability. *RecRT* is a continuous variable and is expressed in %, its mean is 7.52 and its standard deviation is 17. *RecCFNAI* is the Chicago Fed National Activity Index, multiplied by -1. *RecCFNAI* is a continuous variable and has mean of 0.08 and standard deviation of 0.54. All other controls are defined in Table 1. All independent variables, including *RecRT* and *RecCFNAI*, are demeaned in the regression. The data are monthly and cover the period 1980 to 2005. Standard errors (in parentheses) are clustered by fund and time.

	(1) Timing	(2) Timing	(3) Picking	(4) Picking
RecRT	0.004		-0.002	
	(0.002)		(0.001)	
RecCFNAI		0.094		-0.059
		(0.058)		(0.029)
Log(Age)	0.008	0.007	0.004	0.004
	(0.007)	(0.007)	(0.004)	(0.004)
Log(TNA)	-0.001	-0.001	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Expenses	0.552	0.524	-0.607	-0.358
	(1.186)	(1.069)	(0.543)	(0.550)
Turnover	0.010	0.009	0.012	0.012
	(0.011)	(0.010)	(0.007)	(0.007)
Flow	-0.002	-0.002	0.042	0.051
	(0.078)	(0.077)	(0.078)	(0.079)
Load	0.092	0.093	0.136	0.111
	(0.188)	(0.176)	(0.108)	(0.108)
Size	-0.008	-0.009	0.006	0.005
	(0.008)	(0.009)	(0.007)	(0.007)
Value	-0.019	-0.017	0.029	0.028
	(0.013)	(0.012)	(0.010)	(0.010)
Momentum	-0.019	-0.018	0.036	0.032
	(0.035)	(0.036)	(0.034)	(0.033)
Constant	0.019	0.019	-0.022	-0.022
	(0.024)	(0.024)	(0.017)	(0.017)
Observations	221,292	221,292	221,292	221,292

Table III: **Cyclical Variation in Timing and Picking in the Cross-Section of Funds**

The dependent variables are *Timing* and *Picking* defined in equations (1) and (2). The independent variables are the same as in Table I. This table shows results from estimating quantile regression models at the median (columns 1 and 4, Q50), seventy-fifth percentile (columns 2 and 5, Q75), and ninety-fifth percentile (columns 3 and 6, Q95) of the cross-sectional distribution (across funds) of *Timing* and *Picking*. Standard errors are computed using block bootstrap, where the block is a cluster of analysis as in Luetkepohl (1993).

	(1) Q50	(2) Q75	(3) Q95	(4) Q50	(5) Q75	(6) Q95
		Timing			Picking	
Recession	0.059	0.114	0.251	-0.084	-0.091	-0.173
	(0.023)	(0.041)	(0.082)	(0.021)	(0.022)	(0.067)
Log(Age)	0.000	-0.003	-0.020	0.003	-0.005	-0.057
	(0.001)	(0.004)	(0.017)	(0.002)	(0.003)	(0.010)
Log(TNA)	0.000	0.004	-0.004	-0.001	0.001	0.005
	(0.001)	(0.003)	(0.010)	(0.001)	(0.002)	(0.007)
Expenses	0.162	4.015	21.046	-0.588	3.096	18.869
	(0.258)	(1.036)	(3.464)	(0.277)	(0.597)	(1.842)
Turnover	0.001	0.053	0.404	0.001	0.042	0.305
	(0.001)	(0.012)	(0.042)	(0.001)	(0.006)	(0.031)
Flow	0.004	0.036	0.228	0.035	0.099	0.192
	(0.011)	(0.048)	(0.218)	(0.021)	(0.041)	(0.140)
Load	-0.013	-0.327	-1.404	0.108	-0.129	-1.213
	(0.028)	(0.110)	(0.475)	(0.036)	(0.078)	(0.249)
Size	0.000	-0.015	-0.071	0.005	-0.026	-0.130
	(0.001)	(0.005)	(0.026)	(0.003)	(0.005)	(0.019)
Value	-0.001	-0.031	-0.172	0.015	-0.006	-0.046
	(0.002)	(0.010)	(0.044)	(0.004)	(0.006)	(0.021)
Momentum	-0.001	0.037	0.196	0.013	0.071	0.278
	(0.005)	(0.019)	(0.072)	(0.009)	(0.013)	(0.047)
Constant	0.000	0.108	0.765	-0.015	0.126	0.722
	(0.004)	(0.020)	(0.061)	(0.005)	(0.013)	(0.053)
Observations	221,306	221,306	221,306	221,306	221,306	221,306

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

We divide all fund-month observations into Recession and Expansion subsamples. $Expansion \equiv 1 - Recession$. *Top* 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 I.

	(1)	(2)	(3)	(4)
	Timing		Picking	
	Expansion	Recession	Expansion	Recession
Top	-0.001	0.037	0.059	-0.054
	(0.004)	(0.013)	(0.005)	(0.017)
Log(Age)	0.009	-0.015	-0.001	0.027
	(0.002)	(0.006)	(0.002)	(0.007)
Log(TNA)	-0.001	0.004	-0.001	-0.024
	(0.001)	(0.003)	(0.001)	(0.003)
Expenses	0.571	0.981	-0.985	-3.491
	(0.322)	(1.085)	(0.366)	(1.355)
Turnover	0.010	0.009	0.013	-0.005
	(0.003)	(0.008)	(0.004)	(0.012)
Flow	0.058	-0.852	0.127	-0.054
	(0.024)	(0.112)	(0.036)	(0.092)
Load	0.124	0.156	0.104	0.504
	(0.050)	(0.162)	(0.054)	(0.197)
Size	-0.009	-0.057	0.011	0.023
	(0.002)	(0.006)	(0.002)	(0.007)
Value	-0.018	-0.057	0.027	0.107
	(0.003)	(0.010)	(0.003)	(0.011)
Momentum	-0.007	-0.148	0.031	-0.007
	(0.003)	(0.010)	(0.004)	(0.011)
Constant	0.018	0.055	-0.022	-0.159
	(0.001)	(0.005)	(0.002)	(0.006)
Observations	204,311	18,354	204,311	18,354

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

The dependent variables are *Timing* and *Picking*, defined in equations (1) and (2), both tracked at the manager level. In columns 3 and 4, we include manager-fixed effects. Control variables, sample period, and standard errors are described in Table I.

	(1) Timing	(2) Picking	(3) Timing	(4) Picking
Recession	0.156	-0.192	0.160	-0.187
	(0.074)	(0.053)	(0.074)	(0.054)
Log(Age)	0.005	0.002	0.004	-0.003
	(0.005)	(0.004)	(0.009)	(0.007)
Log(TNA)	0.001	-0.001	0.004	0.002
	(0.003)	(0.004)	(0.005)	(0.008)
Expenses	0.194	-0.586	0.569	-0.491
	(1.205)	(0.596)	(1.206)	(0.803)
Turnover	0.008	0.012	0.004	0.011
	(0.013)	(0.008)	(0.010)	(0.008)
Flow	0.014	0.181	0.019	0.166
	(0.094)	(0.177)	(0.095)	(0.184)
Load	0.170	0.051	0.223	-0.016
	(0.209)	(0.121)	(0.191)	(0.185)
Size	-0.009	0.007	-0.015	0.005
	(0.010)	(0.008)	(0.019)	(0.011)
Value	-0.029	0.030	-0.033	0.021
	(0.016)	(0.010)	(0.019)	(0.014)
Momentum	-0.022	0.036	-0.026	0.037
	(0.039)	(0.042)	(0.048)	(0.048)
Constant	0.012	-0.009	0.012	-0.010
	(0.026)	(0.021)	(0.027)	(0.022)
Manager Fixed Effect	N	N	Y	Y
Observations	333,582	333,582	333,582	333,582

Table VI: **Strategy Switchers Outperform**

The dependent variables CAPM alpha, 3-factor alpha, and 4-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. *Top* 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 I. *Expansion* equals one every month the economy is not in recession according to the NBER, and zero otherwise.

	(1)	(2)	(3)
	CAPM alpha	3-factor alpha	4-factor alpha
Top	0.068	0.040	0.058
	(0.028)	(0.018)	(0.016)
Log(Age)	-0.035	-0.029	-0.038
	(0.008)	(0.006)	(0.006)
Log(TNA)	0.036	0.013	0.014
	(0.005)	(0.004)	(0.003)
Expenses	4.972	0.187	0.070
	(0.942)	(0.777)	(0.716)
Turnover	-0.002	-0.049	-0.042
	(0.012)	(0.011)	(0.008)
Flow	2.543	1.765	1.608
	(0.181)	(0.101)	(0.101)
Load	-0.649	-0.067	-0.282
	(0.186)	(0.138)	(0.146)
Size	-0.057	0.001	-0.000
	(0.025)	(0.008)	(0.009)
Value	0.125	-0.061	-0.020
	(0.044)	(0.025)	(0.017)
Momentum	0.296	0.184	0.177
	(0.038)	(0.028)	(0.023)
Constant	0.058	0.041	0.050
	(0.020)	(0.016)	(0.019)
Observations	226,769	226,769	226,769

Table VII: **Comparing Top 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. Top is one for any fund with a *Picking* measure (defined in Table I) 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 I. 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. *Top1-Top0* is the difference between the mean values of the groups for which Top equals one and zero, respectively. p-values measure statistical significance of the difference. The data are monthly from 1980 to 2005.

	Top = 1			Top = 0			Difference	
	Mean	Stdev.	Median	Mean	Stdev.	Median	Top1-Top0	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 VIII: **Skill Index Portfolio Sorts**

Each month we sort mutual funds into five quintiles based on their *Skill Index*, defined in equation (7), from lowest values (Q1) to highest values (Q5). We report equal-weighted average abnormal returns (Panel A), CAPM alphas (Panel B), Fama-French 3-factor alphas (Panel C), and Fama-French-Carhart 4-factor alphas (Panel D) of each quintile portfolio 1, 3, 6, 9, or 12 months after portfolio formation. The last row of each table (average) reports the average abnormal return or alpha across all funds. All numbers represent monthly returns (in %).

	Panel A: Abnormal Returns						Panel C: FF 3F Alpha				
	1mo	3mo	6mo	9mo	12mo		1mo	3mo	6mo	9mo	12mo
Q1	-0.262	-0.076	-0.240	-0.049	-0.017	Q1	-0.176	-0.180	-0.193	-0.198	-0.088
Q2	-0.121	-0.059	-0.199	-0.094	-0.041	Q2	-0.101	-0.101	-0.104	-0.110	-0.070
Q3	-0.052	-0.047	-0.065	-0.094	-0.064	Q3	-0.067	-0.065	-0.062	-0.065	-0.065
Q4	0.033	-0.015	0.074	-0.006	-0.032	Q4	-0.019	-0.018	-0.020	-0.018	-0.059
Q5	0.250	0.037	0.263	0.081	-0.007	Q5	0.117	0.108	0.101	0.095	-0.025
Q5-Q1	0.512	0.113	0.502	0.130	0.009	Q5-Q1	0.293	0.288	0.294	0.293	0.064
Average	-0.030	-0.032	-0.033	-0.032	-0.032	Average	-0.049	-0.051	-0.055	-0.059	-0.061
	Panel B: CAPM Alpha						Panel D: Carhart 4F Alpha				
	1mo	3mo	6mo	9mo	12mo		1mo	3mo	6mo	9mo	12mo
Q1	-0.271	-0.289	-0.283	-0.304	-0.107	Q1	-0.144	-0.146	-0.152	-0.164	-0.067
Q2	-0.138	-0.146	-0.146	-0.161	-0.086	Q2	-0.083	-0.085	-0.086	-0.086	-0.053
Q3	-0.052	-0.050	-0.054	-0.061	-0.061	Q3	-0.055	-0.054	-0.051	-0.054	-0.053
Q4	0.064	0.071	0.063	0.068	-0.014	Q4	-0.010	-0.009	-0.014	-0.015	-0.047
Q5	0.249	0.253	0.242	0.262	0.065	Q5	0.113	0.106	0.096	0.091	-0.016
Q5-Q1	0.519	0.541	0.526	0.566	0.172	Q5-Q1	0.257	0.252	0.248	0.255	0.051
Average	-0.029	-0.032	-0.035	-0.039	-0.041	Average	-0.036	-0.037	-0.041	-0.045	-0.047

Table IX: **Skill Index Predicts Performance**

The dependent variables are respectively the fund's cumulative CAPM, 3-factor, or 4-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* defined in equation (7). *Picking* and *Timing* are defined in Table I, except that they are normalized so that they are mean zero and have a standard deviation of one over the full sample. The other control variables, the sample period, and the standard error calculation are the same as in Table I.

	(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	0.202	0.103	0.094	0.197	0.090	0.091
	(0.038)	(0.019)	(0.017)	(0.028)	(0.023)	(0.013)
Log(Age)	-0.027	-0.022	-0.033	-0.014	-0.008	-0.023
	(0.007)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)
Log(TNA)	0.025	0.005	0.008	-0.012	-0.018	-0.012
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Expenses	-3.347	-8.139	-8.040	-5.571	-9.423	-9.475
	(1.026)	(0.797)	(0.755)	(0.983)	(0.748)	(0.660)
Turnover	-0.041	-0.075	-0.065	-0.007	-0.050	-0.048
	(0.010)	(0.010)	(0.008)	(0.012)	(0.011)	(0.009)
Flow	2.226	1.585	1.436	0.106	0.163	0.164
	(0.156)	(0.095)	(0.091)	(0.114)	(0.084)	(0.071)
Load	-0.655	-0.037	-0.271	-0.576	0.250	-0.009
	(0.189)	(0.134)	(0.143)	(0.174)	(0.122)	(0.132)
Size	-0.031	0.016	0.012	-0.061	-0.005	-0.005
	(0.024)	(0.008)	(0.009)	(0.028)	(0.010)	(0.010)
Value	0.237	0.010	0.045	0.235	0.034	0.074
	(0.030)	(0.019)	(0.017)	(0.036)	(0.025)	(0.021)
Momentum	0.246	0.158	0.157	0.098	0.056	0.088
	(0.042)	(0.031)	(0.025)	(0.031)	(0.030)	(0.025)
Constant	-0.032	-0.056	-0.042	-0.044	-0.071	-0.058
	(0.023)	(0.017)	(0.020)	(0.024)	(0.018)	(0.021)
Observations	219,321	219,321	219,321	187,659	187,659	187,659

Internet Appendix for "Time-Varying Skill" *

List of Tables

*Please cite this supplement document as: Kacperczyk, Marcin, Van Nieuwerburgh, Stijn and Laura Veldkamp, 2013, Internet Appendix for "Time-Varying Skill," *Journal of Finance* XX, YYYY-ZZZZ, http://www.afajof.org/IA/2013.asp. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

Table I: **Different Assumptions on Clustering for Standard Errors**

We re-estimate our main results in Table 1 of the main text but cluster standard errors in three different ways from our baseline result, which clusters standard errors by time and by fund. First, we only cluster at the fund level and not at the time dimension (Columns 1 and 2). 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 (Columns 3 and 4). Third, we cluster standard errors at the fund family level (Columns 5 and 6).

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Timing	Picking	Timing	Picking	Timing	Picking
Clustering by	Fund Only		Fund Style		Fund Family	
Recession	0.138	-0.142	0.138	-0.142	0.140	-0.145
	(0.004)	(0.005)	(0.000)	(0.000)	(0.006)	(0.006)
Log(Age)	0.006	0.004	0.006	0.004	0.006	0.004
	(0.002)	(0.002)	(0.000)	(0.000)	(0.002)	(0.002)
Log(TNA)	0.000	-0.003	0.000	-0.003	0.001	-0.003
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Expenses	0.677	-0.636	0.677	-0.636	0.724	-0.736
	(0.298)	(0.355)	(0.001)	(0.018)	(0.343)	(0.410)
Turnover	0.008	0.012	0.008	0.012	0.007	0.012
	(0.003)	(0.004)	(0.000)	(0.000)	(0.003)	(0.004)
Flow	0.003	0.044	0.003	0.044	0.009	0.047
	(0.023)	(0.029)	(0.000)	(0.001)	(0.026)	(0.034)
Load	0.066	0.142	0.066	0.142	0.059	0.137
	(0.047)	(0.054)	(0.000)	(0.001)	(0.055)	(0.063)
Size	-0.009	0.005	-0.009	0.005	-0.010	0.005
	(0.002)	(0.002)	(0.000)	(0.000)	(0.002)	(0.002)
Value	-0.015	0.030	-0.015	0.030	-0.015	0.030
	(0.003)	(0.003)	(0.000)	(0.001)	(0.003)	(0.004)
Momentum	-0.015	0.034	-0.015	0.034	-0.015	0.034
	(0.003)	(0.004)	(0.000)	(0.000)	(0.005)	(0.005)
Constant	0.007	-0.010	0.007	-0.010	0.007	-0.010
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)
Observations	221,292	221,292	221,292	221,292	216,948	216,948

Table II: **Same Funds Switch Strategies with Alternative Recession Indicators**

This table repeats the analysis of Table 4 in the main text for two different groups of skilled funds, funds for which the indicator variable $SPRT$ and $SPCFNAI$ is one, respectively. SP is an indicator variable equal to one for all funds whose $Picking$ measure during expansions is in the highest 25th percentile of the distribution, and zero otherwise. The results in the two panels differ by which months constitute expansions. In the first panel, we define expansions as the observations for which the real-time recession probability $RecRT$ is below 20% (13.5% of months are recessions). In the second panel, we define expansions as the months for which the $RecCFNAI$ is below 0.7, i.e., CFNAI economic activity level is above -0.7. (15.4% of months are recessions). Each set of regressions has the same controls as in Table 4 of the main paper. The coefficient estimates on these controls are omitted for brevity. All control variables are demeaned.

	(1)	(2)	(3)	(4)
	Expansion	Recession	Expansion	Recession
	Timing		Picking	
SPRT	-0.002	0.063	0.055	-0.015
	(0.004)	(0.014)	(0.005)	(0.014)
Constant	0.026	-0.009	-0.022	-0.110
	(0.001)	(0.005)	(0.002)	(0.005)
Controls	Y	Y	Y	Y
Observations	196,620	26,045	196,620	26,045
SPCFNAI	-0.001	0.044	0.056	-0.009
	(0.004)	(0.012)	(0.005)	(0.012)
Constant	0.029	-0.012	-0.023	-0.094
	(0.001)	(0.005)	(0.002)	(0.004)
Controls	Y	Y	Y	Y
Observations	191,820	30,845	191,820	30,845

Table III: **Strategy Switchers Outperform with Alternative Recession Indicators**

This table repeats the analysis of Table 6 in the main text for two different groups of skilled funds, funds for which the indicator variable $SPRT$ and $SPCFNAI$ is one, respectively. SP is an indicator variable equal to one for all funds whose *Picking* measure during expansions is in the highest 25th percentile of the distribution, and zero otherwise. The results in the two panels differ by which months constitute expansions. In the first panel, we define expansions as the observations for which the real-time recession probability $RecRT$ is below 20% (13.5% of months are recessions). In the second panel, we define expansions as the months for which the $RecCFNAI$ is below 0.7, i.e., CFNAI economic activity level is above -0.7. (15.4% of months are recessions). Each set of regressions has the same controls as in Table 6 of the main paper. The coefficient estimates on these controls are omitted for brevity. All control variables are demeaned. The alphas that are reported are one-Factor CAPM alphas, 3-Factor Fama-French alphas, and 4-Factor Carhart alphas.

	(1) 1F α	(2) 3F α	(3) 4F α	(4) 1F α	(5) 3F α	(6) 4F α
SPRT	0.072	0.055	0.062			
	(0.040)	(0.022)	(0.018)			
SPCFNAI				0.069	0.050	0.058
				(0.040)	(0.022)	(0.018)
Log(Age)	-0.039	-0.029	-0.039	-0.039	-0.029	-0.039
	(0.008)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)
Log(TNA)	0.032	0.013	0.015	0.032	0.013	0.014
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Expenses	5.014	0.700	0.274	5.126	0.814	0.390
	(1.073)	(0.801)	(0.742)	(1.094)	(0.807)	(0.746)
Turnover	-0.008	-0.047	-0.041	-0.007	-0.046	-0.040
	(0.014)	(0.012)	(0.009)	(0.014)	(0.012)	(0.009)
Flow	2.586	1.757	1.606	2.586	1.757	1.606
	(0.174)	(0.102)	(0.102)	(0.174)	(0.102)	(0.102)
Load	-0.749	-0.088	-0.289	-0.767	-0.104	-0.306
	(0.214)	(0.137)	(0.145)	(0.218)	(0.138)	(0.146)
Size	-0.029	0.018	0.017	-0.029	0.018	0.016
	(0.025)	(0.009)	(0.009)	(0.025)	(0.009)	(0.009)
Value	0.246	0.014	0.052	0.246	0.014	0.052
	(0.031)	(0.019)	(0.017)	(0.031)	(0.019)	(0.017)
Momentum	0.297	0.184	0.177	0.297	0.185	0.177
	(0.038)	(0.028)	(0.023)	(0.038)	(0.028)	(0.023)
Constant	0.057	0.038	0.049	0.058	0.039	0.050
	(0.017)	(0.015)	(0.018)	(0.017)	(0.016)	(0.018)
Observations	226,769	226,769	226,769	226,769	226,769	226,769

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

The dependent variables are three measures of funds' cash holdings. *Reported Cash* 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). *Implied Cash* 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. *%Change Cash* 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 the same as and described in Table 1 of the main text.

	(1) Implied Cash	(2) Reported Cash	(3) % Change Cash	(4) Equity Beta
Recession	3.278	0.362	0.545	-0.106
	(0.535)	(0.087)	(0.050)	(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)
Size	2.803	0.493	-0.516	-0.179
	(0.997)	(0.123)	(0.057)	(0.012)
Value	-2.113	-0.557	0.327	-0.054
	(0.432)	(0.067)	(0.041)	(0.007)
Momentum	-0.597	0.566	-0.147	0.137
	(0.522)	(0.082)	(0.041)	(0.012)
Constant	5.252	4.656	-1.495	1.111
	(0.479)	(0.062)	(0.031)	(0.008)
Observations	230,185	209,516	225,374	226,094

Table V: **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: $w_{lt}^{j} - w_{lt}^{m}$. Weights are mulitplied by 100 so that they are expressed as percentages. 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) NDRBL	(2) DRBL	(3) HLTH	(4) MFCT	(5) ENER	(6) UTIL	(7) TEL	(8) BUSEQ	(9) WHLS	(10) 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)
Size	0.128	0.918	1.124	-2.488	0.444	0.425	0.803	-1.997	-1.808	2.318
	(0.038)	(0.065)	(0.053)	(0.061)	(0.035)	(0.030)	(0.043)	(0.074)	(0.049)	(0.090)
Value	0.950	1.491	-4.508	4.887	2.644	2.914	-0.577	-11.869	-2.633	6.569
	(0.065)	(0.082)	(0.126)	(0.100)	(0.083)	(0.048)	(0.054)	(0.233)	(0.084)	(0.127)
Momentum	-0.856	-0.526	0.420	-0.869	-0.191	-0.176	-0.255	2.116	0.794	-0.454
	(0.091)	(0.071)	(0.129)	(0.128)	(0.127)	(0.088)	(0.105)	(0.250)	(0.131)	(0.143)
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	207,394	207,382	207,382	207,373	207,352	207,322	207,314	207,294	206,741	202,107

Table VI: **Skill Index Predictability with Alternative Recession Indicators**

The table reports results with alternative ways of defining the Skill Index, and is otherwise similar to Table 9 in the main text. Each set of regressions has the same controls as in Table 9 of the paper. The coefficient estimates on these controls are omitted for brevity. All control variables are demeaned. The first alternative Skill Index measure (Skill Index RT alt) sets the weight on $Timing$, w_t, in the Skill Index definition equal to 0.8 in recessions and 0.2 in expansions, where recessions are defined as the real-time recession probabilities above 20%. A second alternative measure (Skill Index CFNAI) sets w_t equal to 0.8 in recessions and 0.2 in expansions, where recessions are defined as months in which CFNAI is below -0.7. The alphas that are reported are one-Factor CAPM alphas, 3-Factor Fama-French alphas, and 4-Factor Carhart alphas.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	1F α	3F α	4F α	1F α	3F α	4F α
	One Month Ahead			One Year Ahead		
Skill Index RT alt	0.191	0.099	0.083	0.197	0.098	0.098
	(0.046)	(0.020)	(0.021)	(0.032)	(0.025)	(0.014)
Constant	-0.028	-0.054	-0.040	-0.040	-0.069	-0.056
	(0.024)	(0.017)	(0.020)	(0.025)	(0.018)	(0.021)
Controls	Y	Y	Y	Y	Y	Y
Observations	219,321	219,321	219,321	187,659	187,659	187,659
Skill Index CFNAI	0.186	0.095	0.078	0.195	0.094	0.097
	(0.046)	(0.020)	(0.020)	(0.031)	(0.025)	(0.015)
Constant	-0.030	-0.055	-0.041	-0.042	-0.070	-0.057
	(0.024)	(0.017)	(0.020)	(0.025)	(0.018)	(0.021)
Controls	Y	Y	Y	Y	Y	Y
Observations	219,321	219,321	219,321	187,659	187,659	187,659