# Stock-Selection Timing

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Abstract

We argue that mutual fund managers should trade actively only when the market presents opportunities to pick stocks with positive alpha. In this paper, we propose stock-selection opportunity measures and show that a significant portion of mutual funds time their active trading, i.e., they trade more when the market presents more stock-selection opportunities. We show that positive timers outperform negative timers by about 82 bps in annualized four-factor alpha over the subsequent six-month horizon and, more importantly, that stock-selection timing contributes significantly to fund performance even after controlling for fund managers' stock-picking ability. Finally, we present evidence that on average funds with very high portfolio turnover are actually poor timers, whereas younger funds and funds with larger family size exhibit better skills in timing stock-selection.

*Keywords*: Mutual funds; Active trading; Stock-selection opportunity; Stock-selection timing; Stock-picking ability

*JEL classifications*: G10, G11, G23

*Every season, millions of hunters take to the woods with renewed enthusiasm and vigor. Unfortunately, many come away empty handed, returning day after day to face similar results. The solution: hunting by the moon phase. Activity amongst all animals is greater when the moon is full and … hunting during periods of full moon can yield excellent results. If you know when the full moon occurs, you can be at the right spot, at the right time, and have the best chance for success …. Not only that, it can also help you figure out when not to hunt. (*http://www.moonconnection.com)

## I. Introduction

Stock-picking is a coveted skill of active mutual fund managers. The literature shows evidence that some managers of active mutual funds have the ability to pick stocks that outperform their benchmarks. Nevertheless, the literature documents mixed evidence on the relation between fund activeness and performance.[1] Exhibit A below shows the difference in performance between the top and bottom deciles of active funds over our sample period and illustrates that high-turnover funds often underperform low-turnover funds.[2] We argue and present evidence that this is because the market does not always present opportunities for active fund managers to pick winning stocks and the net gain of active trading is not always positive. For instance, when the market is driven predominantly by macroeconomic or systematic factors and individual stock returns are highly correlated with each other, it is hard for active fund managers to pick stocks with positive abnormal

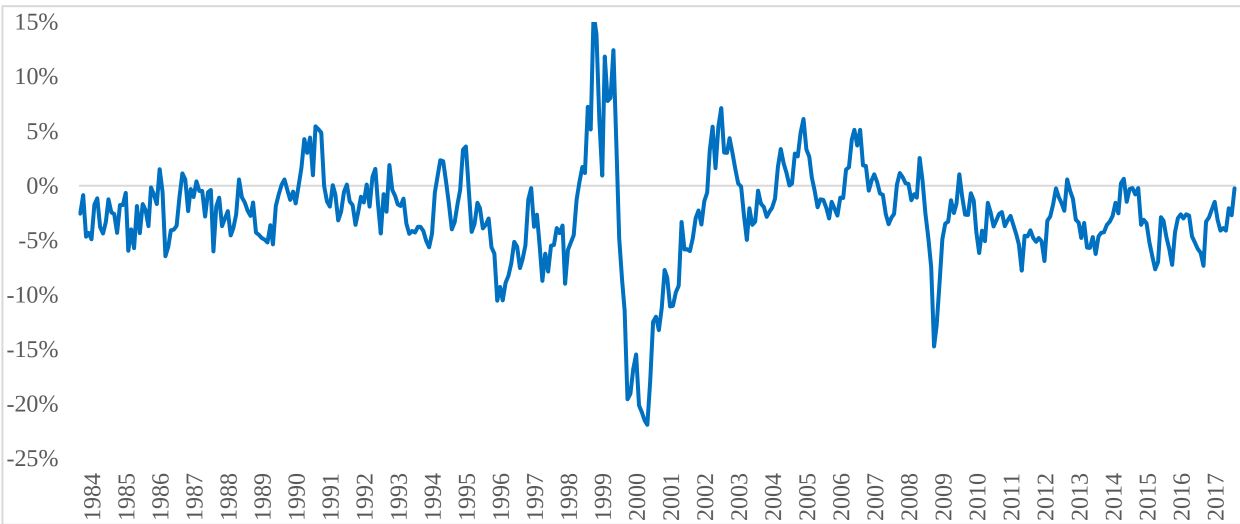
[1] Wermers (2000) finds that actively managed mutual funds hold stocks that outperform the market index by 130 bps per year, of which 71 bps is due to talent in picking stocks that beat their benchmarks. While Chen, Jegadeesh, and Wermers (2000), Cremers and Petajisto (2009), and Amihud and Goyenko (2013) find a positive relation between fund activeness and performance, Elton, Gruber, Das, and Hlavka (1993) and Carhart (1997) find a negative relation.

[2] We sort funds using stock-holding-based turnover. Fund net returns are collected from CRSP Mutual Fund Database. Wermers (2000) sorts funds based on the turnover ratio in CRSP database and fund returns are computed based on quarterly stock holdings. We replicated the sorting procedure in Wermers (2000) and confirm his findings.

returns.[3] Thus, prudent fund managers should possess both the abilities to pick the right stocks and also to trade at the right time.

**Exhibit A. Return Spread between High and Low Turnover Funds**

Each month from January 1984 to December 2018, we sort mutual funds into deciles based on fund portfolio turnover. We compute equal-weighted cumulative returns over the subsequent 12-month horizon for each fund decile. This figure plots the return spread between the highest and lowest turnover deciles.




In this study, we investigate whether mutual fund managers possess the ability to time stock-selection opportunities and, if so, whether funds with better timing skills deliver higher returns to investors. The main premise of our study is that in the absence of stock-selection opportunities, a prudent mutual fund manager should not engage in active trading. Fund managers should trade actively only when they anticipate high stock-selection opportunities. This is because active trading is costly, and transaction costs erode fund performance. Wermers (2000) shows that, despite stock-picking talent, mutual funds, on average, underperform market indices, and

[3] In an online article "Falling Correlations Good for Active Managers" by Sam Ro on January 12, 2014 (http://www.businessinsider.com), Nuveen Asset Management strategist Bob Doll is quoted as saying "Falling correlations means we'll see more active funds beat the funds that aim to track the benchmark indexes. With the reduction of correlations, the ability of active managers to outperform can increase..."

transaction costs alone contribute up to 80 bps of fund underperformance. Edelen, Evans, and Kadlec (2013) show that the "invisible" trading costs of mutual funds are typically higher than expense ratios and negatively affect performance. Cremers and Pareek (2016) suggest that among funds with high active shares, those funds that trade frequently tend to underperform. Busse, Chordia, Jiang and Tang (2020) document evidence that active funds tradeoff between transaction costs and stock allocation.

The stock-selection timing skill investigated in this work differs from other timing skills examined in the literature, namely market, volatility, and liquidity timing.[4] The stock-selection timing ability proposed in our study uncovers yet another novel dimension of active fund manager skill. Our research also differs from that of Pastor, Stambaugh, and Taylor (2017) who demonstrate that mutual funds that trade more actively subsequently earn higher returns. In our study, we examine whether fund managers possess the skill of timing future stock-selection opportunities. Appendix A presents a simple model to illustrate the importance of stock-selection timing. We show that given fund managers' stock-picking ability, abnormal returns from active trading are negatively related to trading costs and positively related to stock-selection opportunities.

To test the stock-selection timing skill of mutual funds, we construct measures for both fund activeness and stock-selection opportunity. To measure fund activeness, we employ the quarterly fund portfolio turnover proposed in Yan and Zhang (2009) in our main analysis. We use the active share proposed by Cremers and Petajisto (2009) as an alternative measure of fund activeness. To measure stock-selection opportunity, we employ the average positive four-factor alpha (Fama and

[4] Market timing focuses on whether mutual funds increase (decrease) the exposure of their portfolios to market portfolio when the expected market return is high (low) (see, e.g., Treynor and Mazuy,1966; Henriksson and Merton, 1981; and Bollen and Busse, 2001). Market volatility timing refers to funds' ability to decrease the level of fund systematic risk in anticipation of high future market volatility (Busse, 1999). Market liquidity timing refers to fund managers' ability to time market-wide liquidity (Cao, Simin, and Wang, 2013; Cao, Chen, Liang, and Lo, 2013; and Ferson and Mo, 2016).

French, 1993; and Carhart, 1997) in our main analysis. The alternative measures of stock-selection opportunity include the average idiosyncratic volatility (IVOL) from the four-factor model, average positive CAPM alpha, and cross-sectional dispersion of CAPM alpha.

Our results show that a significant portion of mutual funds have stock-selection timing ability. Specifically, more than 31% of the 4,239 mutual funds in our sample have Newey–West (1987) *t*-statistics of stock-selection timing coefficient estimates greater than 1.96. Yet, about 13% of funds incorrectly time stock selection opportunities with Newey–West *t*-statistics below -1.96. The results hold for subsamples of funds with different styles, with growth funds exhibiting better timing skills. To ensure that the evidence on mutual fund stock-selection timing ability is not due to pure luck, we employ a bootstrapping procedure for robust statistical inference (Efron, 1979). To further address the issues of downward bias and potential reverse causation, we follow the literature and perform the timing test based on the instrumental variable (IV) approach (Ferson and Harvey, 1991; and Bekaert, 1995). The results based on both approaches reach similar conclusions, i.e., a significant portion of mutual funds have the ability to time stock-selection opportunities.

We perform several robustness checks for our main analysis. The results are consistent when we use the aforementioned alternative measures of fund activeness and stock-selection opportunity. The results are robust to controlling for fund flows, fund performance, and other timing skills, namely market timing, volatility timing, and liquidity timing. We find that more mutual funds exhibit stock-selection timing skills during less volatile market conditions. In addition, we extend our timing tests and examine whether fund managers time the change of stock-selection opportunity. Our results show that a significant portion of mutual funds trade more when there is an increase in stock-selection opportunity.

More importantly, we find that funds with better stock-selection timing skills deliver significantly higher returns. Funds with positive timing skills outperform those with negative timing by about 82 bps ($t$ = 2.54) in annualized four-factor alpha over the subsequent six months. Given that fund managers with stock-selection timing skills are likely those with stock-picking ability, we further examine the economic significance of stock-selection timing by controlling for stock-picking. We divide funds into subgroups based on their stock-picking talent using measures proposed by Daniel, Grinblatt, Titman, and Wermers (1997) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014). We observe that positive stock-selection timers still outperform negative timers even after controlling for fund managers' stock-picking talent, suggesting that stock-selection timing contributes to fund performance beyond stock-picking.

Finally, we examine what information is used by mutual funds in stock-selection timing and what types of funds are better at stock-selection timing. The literature suggests that mutual funds may use macroeconomic information in their portfolio management (Ferson and Schadt, 1996; Christopherson, Ferson, and Glassman, 1998; and Ferson and Qian, 2004; Avramov and Wermers, 2006). Our results indicate that fund managers use information beyond macroeconomic variables in timing stock-selection. In addition, by regressing timing estimates on various lagged fund characteristics, our results show that younger funds and funds with larger family size exhibit stronger stock-selection timing skills. We also find a positive relation between fund flow and stock-selection timing ability. Interestingly, we observe a negative relation between stock-selection timing and high fund portfolio turnover, corroborating the evidence in Cremers and Pareek (2016) that funds that trade frequently generally underperform, including those with high active share.

The remainder of this paper is organized as follows. Section II motivates and presents the testable hypothesis for stock-selection timing. Section III describes the data and methodology. The main empirical results are presented in Section IV with further analyses in Section V. Section VI concludes.

**II. Motivation and Hypothesis**

As discussed in the introduction and illustrated in Exhibit A, active trading does not always generate higher returns. The simple model in Appendix A shows that abnormal return from active trading is positively related to the fund manager's stock-picking talent and, as expected, negatively related to transaction costs. More importantly, given a fund manager's stock-picking talent, fund return is positively related to expected stock-selection opportunity.

To test whether mutual fund managers have the ability to time stock-selection opportunities, we denote $E_t[SSO_{t+1}]$ as the expected stock-selection opportunity in time period *t*+1. If a fund manager can predict stock-selection opportunity in *t*+1 and adjust active trading accordingly in *t*, denoted by $ACT_{i,t}$, then we have the following relation:

$$ACT_{i,t} = c_i + g_i E_t[SSO_{t+1}] + u_t, \quad (1)$$

where $g_i$ measures fund *i*'s stock-selection timing ability. Using realized stock-selection opportunity measure $SSO_{t+1}$ as a proxy of $E_t[SSO_{t+1}]$ results in the following testable regression:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \varepsilon_{i,t+1} \quad (2)$$

The null hypothesis is that $H_0$: $g_i = 0$. A positive and significant estimate of $g_i$ indicates positive stock-selection timing ability, and no timing ability otherwise.

## III. Data and Methodology

### A. Data

The main data used in our empirical analyses are the CRSP Survivor-Bias-Free U.S. Mutual Fund Database, Thomson Reuters Mutual Fund Holdings Database, and CRSP monthly stock database. We merge the CRSP fund data with the holdings data using the MFLINK files developed by Russ Wermers through Wharton Research Data Services. We focus on open-end US domestic equity mutual funds and aggregate class-level shares, returns, and other characteristics to the fund level. Following the literature (e.g., Kacperczyk, Sialm, and Zheng, 2008), we exclude funds that hold, on average, less than 80% or greater than 105% of their portfolios in common stocks. We require each fund in our sample to have at least four quarters' holdings information. To mitigate the potential incubation (or back-filling) bias documented in Elton, Gruber, and Blake (2001) and Evans (2010), we exclude observations prior to the date the fund was first offered and observations where the names of funds are missing from the CRSP Mutual Fund Database. As pointed out by Kacperczyk, Sialm, and Zheng (2005), incubated funds tend to be small, thus we further exclude funds with TNA smaller than $5 million at the end of the previous month. Finally, we remove funds that hold fewer than 10 stocks. Our final sample consists of 4,239 unique funds and 606,316 fund-month observations over the period of January 1984 to December 2018.

Panel A in Table I reports the time series averages of cross-sectional mean and median of fund TNA, age, expense ratio, normalized fund flow, cash holdings, fund performance, and family TNA. Mutual funds in our sample, on average, have total net assets of $1,655 million and hold about 6% of their portfolios in cash. The average fund age in our sample is 14 years, and average expense ratio is 1.36%. Funds attract about 1% net flow each month. Average fund family size is $33.38 billion, and average fund return is 0.90% per month, or about 11% per year. The medians of fund TNA, age, cash holdings, normalized fund flow, and family TNA are smaller than the corresponding means, implying that these characteristics are highly right-skewed across funds.

We classify funds into one of four investment styles, namely small-growth, small-value, large-growth, and large-value, following a factor-model procedure proposed by Chan, Chen, and Lakonishok (2002). Brown and Goetzmann (1997) show that self-reported investment style performs poorly in forecasting variations in future performance of funds within each style. The classification is based on quarterly holdings and updated quarterly. Specifically, we calculate daily hypothetical fund returns based on quarter-end portfolio holdings following Wermers (2000). We then estimate the Fama and French (1993) three-factor model in each quarter based on daily hypothetical fund returns. Funds are classified into styles based on independent sorts using the median values of size and book-to-market betas. Panel A of Table I reports the fund characteristics for each category. Small-growth and small-value funds are relatively small and are younger with relatively high expense ratios. On the other hand, large-growth and large-value funds hold relatively small levels of cash and deliver relatively low returns.

## B. Measures of Fund Activeness

Previous studies propose several measures as proxies of mutual fund trading activeness. Following Yan and Zhang (2009), we define fund portfolio *turnover* ratio as follows:

$$Turnover_{i,t} = \frac{min(Buys_{i,t}, Sells_{i,t})}{\overline{TNA}_{i,[t-1,t]}}, \tag{3}$$

where $\overline{TNA}_{i,[t-1,t]}$ is fund *i*'s averaged quarter-end total net asset value over quarters *t* and *t*-1; $Buys_{i,t}$ and $Sells_{i,t}$ are fund *i*'s total purchases and sales of stocks through quarter *t*. In addition, we use *Active Share* (AS) proposed by Cremers and Petajisto (2009) as an alternative activeness measure for robustness checks.[5] Cremers and Petajisto (2009) define active share as the difference between fund portfolio holdings and the benchmark index holdings.

Panel A of Figure 1 plots the time series of average turnover across all funds and shows variation of fund activeness over time, in which monthly turnover is calculated by dividing the corresponding quarterly one by three. Over the sample period, fund activeness was low in the late 1980s and reached its lowest level in recent years after the financial crisis. Panel A.2 of Table I reports descriptive statistics of fund activeness measures. On average, fund activeness is 22% based on quarterly turnover. Panel A.2 also shows that trading activeness varies across fund categories. Consistent with fund average turnover, small-growth and small-value funds are relatively more active. Panel B of Table I reports the time-series average of cross-sectional correlation between the two measures of fund activeness, which is small and insignificant, and suggests that turnover and active share capture different aspects of fund activeness.

### C. Measures of Stock-Selection Opportunity and Macroeconomic Variables

The stock-selection opportunity measure in our main empirical analysis is the average positive alpha of individual stocks, where alpha for each stock is estimated from the single-factor CAPM:

$$R_{s,t} - R_{f,t} = \alpha_s + \beta_s\left(R_{m,t} - R_{f,t}\right) + \varepsilon_{s,t}, \tag{4}$$

and the Fama and French (1993) and Carhart (1997) four-factor model, respectively:

$$R_{s,t} - R_{f,t} = \alpha_s + \beta_{s1}\left(R_{m,t} - R_{f,t}\right) + \beta_{s2}SMB_t + \beta_{s3}HML_t + \beta_{s4}UMD_t + \varepsilon_{s,t}, \tag{5}$$

[5] The data on fund active share are available at Antti Petajisto's website over the sample period of June 1984 to June 2009. We follow Cremers and Petajisto (2009) and update the active share measure post June 2009 up to the end of our sample period December 2018.

where $R_{s,t}$ denotes the return of stock $s$, $R_{f,t}$ denotes the risk-free rate, $R_{m,t}$ denotes the value-weighted CRSP index return, and $SMB_t$, $HML_t$, and $UMD_t$ are returns on value-weighted zero-investment factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns, respectively. Returns of risk factors and the risk-free asset are obtained from Ken French's website. In our main analysis, we use the average positive four-factor alpha (FF4 alpha) estimated from daily returns during month $t$+1 as the measure of stock-selection opportunity. To incorporate the non-synchronous trading effect in daily returns, the Dimson (1979) approach with one lead and one lag of factor returns is used in the estimation. We confirm that the results are consistent when we estimate the factor model based on monthly stock returns over the past 36 months and obtain the alpha estimate in month $t$+1 as the difference between monthly stock return and the product of beta estimates and factor returns. Stocks with positive alphas present opportunities for active mutual funds since most funds hold only long positions in their portfolios. Since mutual funds generally shun microcaps, we exclude stocks smaller than the $20^{th}$ size percentile of all NYSE stocks. We confirm that the results are consistent when we define stock-selection opportunity as the average of positive FF4 alpha based on all CRSP stocks.

In addition to the average positive CAPM alpha, we consider alternative measures of stock-selection opportunity as robustness checks. One is the average idiosyncratic volatility (IVOL) based on the four-factor model, and the other is the cross-sectional dispersion or standard deviation of CAPM alpha. Pastor, Stambaugh, and Taylor (2017) use a similar measure as a proxy of the mispricing of individual stocks.

Panel B in Figure 1 plots the time series of stock-selection opportunity based on the average positive FF4 alpha of individual stocks. The plot shows substantial variation in stock-selection opportunity over time, with a clear spike during the dot-com bubble period and a drop after the recent financial crisis when the market is dominated by accommodative Fed monetary policy. Panel A of Table II report the descriptive statistics of the four stock-selection opportunity measures, and Panel B of Table II reports the time series correlation between alternative stock-selection opportunity measures. All measures are highly correlated.

Table II (Panel C) presents the summary statistics of macroeconomic and market variables. The macroeconomic variables include the short-term interest rate (*YLD*) defined as the annualized yield of three-month Treasury bills (Campbell, 1987; and Hodrick, 1992), term spread (*TERM*) defined as the difference in yields between ten-year Treasury notes and three-month Treasury bills (Chen, Roll, and Ross, 1986), default spread (*DEF*) defined as the differences in returns between Moody's BAA and AAA rated corporate bonds (Fama and French, 1989), and the aggregate dividend yield (*DIV*) of S&P 500 Index stocks (Campbell and Shiller, 1988a; 1988b).[6] Stock market variables include the value-weighted returns of all CRSP stocks, VIX index, and illiquidity index of Pastor and Stambaugh (2003). Since the VIX index is available only after 1990, we supplement the data before 1990 using the standard deviation of daily market returns each month.

## IV. Main Empirical Analysis

In this section, we first perform the stock-selection timing test using the base measures of fund activeness and stock-selection opportunity. We then perform bootstrapping analysis and instrumental variable analysis for formal statistical inference. Lastly, we perform robustness checks using alternative measures of fund activeness and stock-selection opportunity and further controlling for fund performance and flow as well as other potential timing skills.

[6] The data are obtained from the Board of Governors of the Federal Reserve System (http://www.federalreserve.gov).

### A. Stock-Selection Timing Test

We perform the stock-selection timing test in Eq. (2) for each fund and obtain estimates of timing coefficient ($g_i$) as well as the associated Newey–West (1987) *t*-statistics with four lags. The test is similar to that in Cao, Chen Liang and Lo (2013). Table III reports the cross-sectional distribution of the Newey–West *t*-statistics of the $\hat{g}_i$ estimates using the base measures of fund activeness and stock-selection opportunity. The table reports the percentages of funds with *t*-statistics exceeding various cutoffs. Overall, the results in Table III suggest that a significant portion of mutual funds have the ability to time stock-selection opportunities in the market. For the whole sample, about 31% of mutual funds have *t*-statistics of $\hat{g}_i$ estimates greater than or equal to 1.96, compared to the expected cutoff of 5%. On the other hand, about 13% of funds have *t*-statistics lower than -1.96, evidence that a substantial but smaller portion of funds incorrectly time stock-selection opportunities in the market. As shown in our subsequent analysis, some funds engage in active trading even in the absence of stock-selection opportunities. Figure 2 plots the kernel density of the cross-sectional distribution of the Newey–West *t*-statistics of $\hat{g}_i$ in Eq. (2) for all funds. Consistent with the results in Table III, the plot shows that the right tail of the *t*-statistics is thicker than the left tail. The results in Table III also show that among different categories of funds, large-growth and small-growth funds exhibit better timing ability.

One important question is whether mutual funds have stronger or weaker stock-selection timing ability during market crisis periods. We replicate our analysis during the market crisis periods of 2000-2002 and 2007-2009, and the cross-sectional distribution of the Newey–West *t*-statistics of $\hat{g}_i$ estimates are reported in Table A in the Internet Appendix. Overall, the results suggest that the percentage of funds with positive timing ability is slightly lower during market crisis periods than that over the whole sample period.

There are several concerns about the timing test in Eq. (2). One concern is that the underlying assumption of normal distribution of the $g_i$ estimates is likely violated due to several reasons. The first is that a fraction of funds out of a large number of funds may, by random chance, have significant *t*-statistics under the normality assumption even if none of the funds has true timing skill (Kosowski, Timmermann, Wermers, and White, 2006). The second is cross-sectional dependence of the timing measure, driven by the correlation among fund activeness when funds employ similar investment strategies over a given period (Cao, Chen, Liang, and Lo, 2013). Another major concern is that the error-in-variable (EIV) issue in the proxy of stock selection opportunity and potential reverse causation mean that the regression in Eq. (2) may not uncover the true coefficient $g_i$, as the coefficient estimate is likely inconsistent and biased downward. Following the literature, in the next two subsections, we implement the bootstrapping approach and instrumental variable approach for the timing test in Eq. (2) to address the above concerns.

**B. Bootstrapping Approach**

The bootstrapping analysis follows the procedure of Efron (1979), and the details are described in Appendix B. We focus on the *t*-statistic of the timing coefficients, because it is a pivotal and meaningful statistic of stock-selection timing and has favorable inference features (Horowitz, 2001; Cao, Chen, Liang, and Lo, 2013).[7] Figure 3 plots the kernel density of the 90$^{th}$ percentile of the Newey-west *t*-statistics (solid curve) from 10,000 bootstrapped pseudo datasets, as well as the corresponding 90$^{th}$ percentile of *t*-statistics from the actual sample (solid vertical line). It can be seen that the *t*-statistic of timing coefficients from the actual data is far to the right

[7] As stated by Efron and Hastie (2016), pivotal statistics is "one whose distribution does not depend upon the underlying probability distribution" (page 16). That is, the pivotal statistic incorporates information about the asymptotic distribution into the bootstrap procedure and has a better convergence property.

of the distribution of *t*-statistics from the pseudo-datasets. Also, in Figure 3, the bootstrapped *t*-statistics are clearly not normally distributed, implying that the inferences drawn from bootstrapped distributions can differ from conventional significance levels under normality assumption.

Table IV reports the bootstrapped *p*-values associated with the cross-sectional Newey–West *t*-statistics with four lags of stock-selection timing coefficient estimates in the bottom 25 percentiles and top 25 percentiles. The *t*-statistics for the 99$^{th}$, 97$^{th}$, 95$^{th}$, 90$^{th}$, and 75$^{th}$ percentile funds are as high as 7.63, 5.83, 5.21, 4.18, and 2.31, respectively, and the corresponding *p*-values are all close to zero. That is, the *t*-statistics of the $\hat{g}_i$estimates based on pseudo datasets under the assumption of no-timing skill are smaller than the corresponding *t*-statistics from the actual data. This is further evidence that mutual fund managers' stock-selection timing ability cannot be attributed to pure luck. The results also show that the bottom 25$^{th}$ percentile of funds with negative stock-selection timing cannot be attributed to pure randomness, but to the lack of skill, as the associated *p*-values are all close to zero. We also conduct bootstrapping analyses for funds in each category. The results are also reported in Table IV, which indicates that the timing coefficients of the top 25 percentiles are positive, and the corresponding *p*-values are all close to zero.

### C. Instrumental Variable Approach

We implement the instrumental variable (IV) analysis following existing studies (Ferson and Harvey, 1991; and Bekaert, 1995) and using lagged values of all measures of stock-selection opportunity as instruments. The IV analysis involves two stages. In the first stage, we estimate the $\widehat{SSO}_{t+1}$ based on the following regression over the whole sample period:

$$SSO_{t+1} = c + b * Instrument_t + \varepsilon_{t+1} \quad (6)$$

where $SSO_{t+1}$ is the base measure of average positive FF4 alpha; and $Instrument_t$ is a vector of four instrumental variables in $t$, including the average positive FF4 alpha, average FF4 idiosyncratic volatility, average positive CAPM alpha, and cross-sectional dispersion of CAPM alpha. In the second stage, we conduct the timing test for each fund using the estimated $\widehat{SSO}_{t+1}$ in the following regression:

$$ACT_{i,t} = c_i + g_i\widehat{SSO}_{t+1} + \varepsilon_{i,t+1} \tag{7}$$

Table V reports the percentages of funds with $t$-statistics of the timing coefficient $\widehat{g}_i$ in Eq. (7) exceeding various cutoffs. The results are similar to those reported in Table III and suggest that a significant portion of mutual funds have the ability to time stock-selection opportunities. For the whole sample, about 35% of 4,239 mutual funds have $t$-statistics of $\widehat{g}_i$ estimates greater than or equal to 1.96, compared to the expected cutoff of 5%. On the other hand, about 11% of funds have $t$-statistics lower than -1.96. Similar to the those reported in Table III, results based on subsample of funds in Table V also show that large-growth and small-growth funds exhibit better stock-selection timing skill.

**D. Robustness Check: Alternative Measures of Fund Activeness and Stock-Selection Opportunity**

In this section, we examine whether the findings on stock-selection timing documented in Section IV are robust to alternative measures of fund activeness and stock-selection opportunity. The alternative measure of fund activeness is active share proposed in Cremers and Petajisto (2009) as defined in Section III.B. We consider three alternative measures of stock-selection opportunity: average FF4 idiosyncratic volatility (%), average positive CAPM alpha, and the cross-sectional dispersion of CAPM alpha (%).

Table VI reports the cross-sectional distribution of the Newey–West *t*-statistics with four lags of the stock-selection timing coefficient estimates using active share as a proxy of fund activeness in Panel A and alternative measures of stock-selection opportunity in Panel B. Panel A shows that although the results based on active share measure are slightly weaker than the base case in Table III, they still suggest that mutual funds have the positive skill of timing stock-selection. Specifically, the percentage of funds with $t$-statistics of $\hat{g}_i$ estimates equal to or greater than 1.96 is 27.79%. The percentage of funds with $t$-statistics of $\hat{g}_i$ estimates equal to or lower than -1.96 is 16.31%. Similar results are observed for funds in each category. Panel B of Table VI indicates that the stock-selection timing skills documented in Table III are largely robust to alternative measures of stock-selection opportunity. For instance, the percentage of funds with timing *t*-statistics equal to or greater than 1.96 is 30.87% when the stock-selection opportunity is based on the average FF4 IVOL, 31.32% based on the average positive CAPM alpha, and 28.16% based on the CS dispersion of CAPM alpha. Again, the results are similar for funds in each category.

### E. Robustness Check: Controlling for Fund Performance and Flows

It is possible that fund activeness may be driven by fund flows or fund performance rather than a manager's ability in timing stock-selection opportunities. To address this concern, we control for fund flows and performance in our timing test:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \gamma_{1i} RET_{i,t} + \gamma_{2i} \sigma_{i,t}^{RET} + \theta_{1i} FLOW_{i,t} + \theta_{2i} \sigma_{i,t}^{FLOW} + \varepsilon_{i,t+1}, \tag{8}$$

where $RET_{i,t}$ and $FLOW_{i,t}$ denote fund *i*'s average return and normalized flow in months *t*-2 to *t*, respectively; and $\sigma_{i,t}^{RET}$ and $\sigma_{i,t}^{FLOW}$ are the fund return volatility and fund flow volatility, defined as the standard deviations of fund returns and normalized flows over months *t-5* to *t*, respectively.

If fund activeness is driven mainly by fund flows or fund performance, the stock-selection opportunity timing coefficient $g_i$ in Eq. (8) should be small and insignificant. Panel A of Table VII reports the distribution of cross-sectional Newey–West *t*-statistics with four lags of $g_i$ in Eq. (8). The results show that mutual funds' stock-selection timing skills cannot be explained by fund performance, performance volatility, fund flows, or flow volatility. The percentage of funds with timing *t*-statistics equal to or greater than 1.96 is 30.46% for the whole sample, 30.47% for small-growth funds, 29.33% for small-value funds, 33.90% for large-growth funds, and 28.11% for large-value funds. These numbers are similar to those in Table III. The bootstrapping results further confirm the findings.

### F. Robustness Check: Controlling for Other Potential Timing Skills

Previous studies document that mutual funds exhibit certain timing abilities, namely market timing skill (Jiang, Yao, and Yu, 2007), liquidity timing skill (Cao, Simin, and Wang, 2013), and volatility timing skill (Busse, 1999). Cao, Chen, Liang, and Lo (2013) provide evidence that timing skills may be correlated. As an additional robustness check, we perform stock-selection timing tests by controlling for the aforementioned timing skills documented in the literature:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \gamma_{1i} RET_{i,t} + \gamma_{2i} \sigma_{i,t}^{RET} + \theta_{1i} FLOW_{i,t} + \theta_{2i} \sigma_{i,t}^{FLOW} + \\ + \delta_{1i} R_{m,t+1} + \delta_{2i} VOL_{m,t+1} + \delta_{3i} IL_{m,t+1} + \varepsilon_{i,t+1}, \quad (9)$$

where $R_{m,t+1}$ denotes value-weighted returns of CRSP stocks, $VOL_{m,t+1}$ denotes the VIX index, and $IL_{m,t+1}$ denotes the Pastor and Stambaugh (2003) illiquidity index.

If mutual fund stock-selection timing skill is subsumed by other timing skills, the stock-selection timing coefficient $g_i$ in Eq. (9) will be small and insignificant. Panel B of Table VII reports the distribution of cross-sectional Newey–West *t*-statistics with four lags of $g_i$ in Eq. (9)

for all funds and for each fund category. The results show that mutual fund stock-selection timing skill cannot be explained by potential timing of market return, market volatility, or market illiquidity. While the percentage of funds with *t*-statistics of stock-selection timing coefficient estimates equal to or greater than 1.96 is 20.97%, lower than that the unconditional test, the percentage of funds with *t*-statistics of stock-selection timing coefficient estimate equal to or less than -1.96 remains at 12.86%, similar to that in Table III. We also perform the bootstrapping analysis and confirm the robustness of our findings.

We recognize that it may not be sufficient to simply include market variables in the regression to control for the effect of other timing skills. Below, we perform further analysis on stock-selection timing tests under different market conditions. Specifically, we replicate the stock-selection timing test during months with top 30% and bottom 30% market returns. The idea is that if stock-selection timing documented in our study is simply the manifestation of market timing, then narrowing down to periods with either very high or low market returns should eliminate or significantly diminish the evidence of stock-selection timing. The results presented in Table VIII show that the portion of positive stock-selection timing funds is noticeably lower than that over the whole sample period during months with either top or bottom 30% market returns. Comparatively, the portion of negative stock-selection timing funds is slightly higher than that over the whole sample period. Nonetheless, the portion of positive stock-selection timing funds is still higher than the portion of negative stock-selection timing funds.

We perform similar analyses to control for the effects of market liquidity timing and market volatility timing. The results reported in Internet Appendix Table B are similar to the results after controlling for the effect of market timing. Specifically, during months with top 30% and bottom 30% market liquidity, the portion of funds with positive stock-selection timing ability is lower than that over the whole sample period. These findings also exhibit an interesting pattern. While the proportion of funds with positive stock-selection timing ability during months with top 30% market volatility is lower than that over the whole sample period, the proportion of positive timing funds during months with bottom 30% market volatility is much higher. This seems to suggest that mutual funds exhibit a better skill of timing stock-selection during low volatility market conditions. The results are consistent with our findings on stock-selection timing over market crisis periods. Overall, while mutual fund's stock-selection timing ability varies during different market conditions, mutual fund's stock-selection timing skill cannot be explained by potential timing of market returns, market volatility, or market illiquidity.

### G. Stock-Selection Timing: Change of Stock-Selection Opportunity

Our stock-selection timing test so far has been based on the level of stock-selection opportunity.[8] Given the time-varying nature of stock-selection opportunity, we expect that funds should trade more (less) when the level of stock-selection opportunity increases (decreases). In this section, we examine the relation between fund activeness and the change of stock-selection opportunities.[9] Specifically, in each month for each stock, we subtract its FF four-factor alpha in the current month by its alpha in the previous month, and then aggregate the positive alpha differences as a proxy of stock selection opportunity change in current month. The timing test is specified as follows:

$$ACT_{i,t} = c_i + g_i \sum_{i=1}^{N_{t+1}} \Delta FF4\alpha_{i,t+1} \,|_{\Delta FF4\alpha_{i,t+1} > 0} + \varepsilon_{i,t+1}, \tag{10}$$

[8] By sorting stocks into quintiles based on current- and last-month FF4 alphas, we find that, on average, more than 70% of stocks changed their FF4 alpha quintiles, suggesting that stocks' FF4 alphas are not very persistent.

[9] We wish to thank the reviewer for suggesting this test.

where $\Delta FF4\alpha_{i,t+1}$ denotes the change of four-factor alpha of stock *i* between months *t*+1 and *t*, and $N_{t+1}$ denotes the number of stocks in month *t*+1 with positive changes of FF4 alpha.

Table IX reports the cross-sectional distribution of the Newey–West *t*-statistics with four lags of $\hat{g}_i$ based on the change of stock-selection opportunities. The estimates are close to those reported in Table III. Specifically, the percentage of funds with *t*-statistics equal to or greater than 1.96 is about 31%, while the percentage of funds with *t*-statistics equal to or lower than -1.96 is about 15%. The results suggest that mutual funds adjust active trading not only based on the level of stock-selection opportunity but also based on the change of stock-selection opportunities. Similar results are obtained for funds in each category.

## V. Further Analysis

In this section, we first examine whether funds with greater stock-selection timing skills deliver higher returns. We then control for mutual fund's stock-picking ability. Finally, we examine whether mutual funds use macroeconomic information in stock-selection timing and which funds possess stock-selection timing skills.

### A. Economic Significance of Stock-selection Timing

In this section, we examine whether funds with stock-selection timing skill outperform other funds. If stock-selection timing indeed reflects a unique skill of an active mutual fund manager, we expect positive timers to outperform negative timers subsequently. Following Cao, Chen, Liang and Lo (2013), we identify funds with skilled managers over a rolling window of time. Specifically, for each month, we obtain an estimate of $\hat{g}_i$ in Eq. (2) and its Newey–West *t*-statistic with four lags based on observations of fund activeness and stock-selection opportunity over the past 12 months. As robustness checks, we confirm that the results are similar when we use timing coefficients estimated over the past 18, 24, and 36 months. We then divide funds into three groups based on the cutoffs (±1.96 and ±1.65) of Newey–West *t*-statistics, namely positive timers, insignificant timers, and negative timers. Each month, we form portfolios of positive timers and negative timers and calculate the equal- and TNA-weighted cumulative returns of each portfolio over the subsequent three, six, and 12 months.

Panel A of Table X reports the equal-weighted raw returns and risk-adjusted returns of the positive and negative timers as well as the return spreads between the positive and negative timers and the associated Newey–West *t*-statistics with four lags. The results show that positive timers consistently outperform negative timers over the subsequent three, six, and 12-month horizons, and the differences in performance peak around the six-month horizon. For example, with *t*-statistic cutoffs of ±1.96, the positive timing funds have an average of 5.53% in raw returns, -0.095% in Fama–French three-factor alpha, and -0.152% in Carhart four-factor alpha over the subsequent six months, which are 0.24% ($t$ = 1.97), 0.31% ($t$ = 2.20), and 0.22% ($t$ = 2.05) higher than those for negative timers. The TNA-weighted results reported in Panel B of Table X further confirm that positive timers outperform negative timers. Specifically, with *t*-statistic cutoffs of ±1.96, positive timing funds outperform negative timing funds by 0.55% ($t$ = 3.31) in raw returns, 0.47% ($t$ = 2.83) in Fama–French 3-factor alpha, and 0.36% ($t$ = 1.99) in Carhart 4-factor alpha in the subsequent six months. Overall, the results in Table X show that stock-selection timing generates significant economic value for investors. We confirm that the results are quantitatively similar when we use timing estimates from Eqs. (8) and (9), controlling for fund performance, fund flow, and other potential timing skills. As a robustness check, we also replicate the analysis in Table X using average positive CAPM alpha as an alternative measure of stock-selection opportunity. The results are reported in Table C of the Internet Appendix and show similar patterns.

One interesting question is how much investors gain from investing in funds with stock-selection timing ability. To answer this question, we construct portfolios of positive and negative stock-selection timing funds and track their performance over time. In each month, funds are classified as positive and negative stock-selection timing funds based on Newey–West *t*-statistic cutoffs of ±1.96. Portfolio returns in the subsequent month are computed for positive and negative stock-selection timing funds, respectively. Figure 4 plots the cumulative returns of TNA-weighted positive and negative stock-selection timing fund portfolios from 1987 to 2018, where the starting value of each portfolio was $1 in January 1987. The plot indicates that the positive timing fund portfolio consistently outperforms the negative timing fund portfolio. With an investment of $1 in January 1987, the positive timing fund portfolio has an accumulated value of $11.26 at the end of December 2018, whereas the negative timing fund portfolio has an accumulated value of $8.26. However, during the financial crisis period, the positive timing fund portfolio slightly underperformed the negative timing fund portfolio. For instance, in August 2008, the average returns of positive and negative timing funds are -10.8%, and -9.7%, respectively.

Another important question is whether investors recognize funds with positive stock-selection ability. To address this question, we examine the relation between stock-selection ability and fund flows. We follow Evans and Fahlenbrach (2012) and Jiang and Yuksel (2017) to decompose fund flow into institutional and retail flows. Since fund flows are significantly related to fund performance (Chevalier and Ellison, 1997), we explicitly control for the impact of past performance on fund flows. Table D in the Internet Appendix reports performance-adjusted fund flows for positive and negative stock-selection timing funds. The results show that positive stock-selection timing funds attract more performance-adjusted flows than negative stock-selection timing funds. After decomposing fund flow into institutional and retail flows, we find that positive stock-selection timing funds attract more flows from both retail and institutional investors than negative stock-selection timing funds.

**B. Stock-Selection Timing vs. Stock-Picking**

As argued in Section II, stock-selection timing captures a different aspect of a fund manager's skill than the stock-picking talent examined in existing literature (e.g., Daniel, Grinblatt, Titman, and Wermers, 1997; Wermers, 2000; and Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2014). Nevertheless, fund managers with stock-picking talent are in a better position to time stock-selection. One natural question is to what extent the economic significance presented in the previous subsection is attributed to the stock-picking talent of fund managers. To address this question, we sequentially sort mutual funds into three stock-picking groups (high, medium, and low stock-picking ability funds) and three stock-selection timing groups (positive timing, no timing, and negative timing). We then test whether the positive stock-selection timers outperform negative timers after controlling for stock-picking talent. We follow Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) and define mutual funds' stock-picking ability as follows:

$$PICK_{i,t} = \sum_{s=1}^{N_i} (\omega_{i,s,t} - \omega_{m,s,t})\left(\tilde{R}_{s,t+1} - \beta_{s,t} R_{m,t+1}\right), \tag{11}$$

where $PICK_{i,t}$ denotes fund *i*'s picking ability, $\omega_{i,s,t}$ and $\omega_{m,s,t}$ denote the weight of stock *s* in fund *i*'s portfolio and market portfolio, $R_{s,t+1}$ denotes the return of stock *s*, $R_{m,t+1}$ denotes market return, and $\beta_{s,t}$ denotes the CAPM beta of stock *s* estimated with return data over [*t*-11, *t*]. In the Internet Appendix E, we report the results based on stock-picking ability measure proposed by Daniel, Grinblatt, Titman, and Wermers (1997). Both measures produce consistent results.

Table XI reports the equal-weighted performance of positive and negative timing fund portfolios within each stock-picking rank group over the subsequent three, six, and 12 months as well as the average performance across all stock-picking ranks. The results show that the economic significance of stock-selection timing is positively related to the stock-picking talent of fund managers. Within the low stock-picking ability group, the equal-weighted portfolio of positive timers outperforms the portfolio of negative timers by only 0.10% ($t$ = 0.55) over the subsequent 3 months. The differences in performance between positive timers and negative timers are higher for both the medium and high stock-picking ability groups. The positive timer portfolio outperforms the negative timer portfolio by 0.17% ($t$ = 1.72) for funds in the medium stock-picking ability group, and 0.16% ($t$ = 1.91) for funds in the high stock-picking ability group over the subsequent three months.

More importantly, the results in Table XI show that the economic value of stock-selection timing remains significant even after controlling for stock-picking talent. The average spreads between positive and negative timing funds across different ranks of stock-picking ability are positive and mostly significant. For example, after controlling for stock-picking talent, the positive timing portfolio outperforms the negative timing portfolio by 0.23% ($t$ = 2.41) in raw returns, 0.33% ($t$ = 2.52) in three-factor alpha, and 0.30% ($t$ = 1.97) in four–factor alpha over the subsequent six-month horizon. Overall, the results in Table XI show that the economic value of stock-selection timing goes beyond the effect of fund manager's stock-picking talent.

### C. Do Mutual Funds Use Macroeconomic Information in Stock-Selection Timing?

It is possible that the level of fund activeness is also related to fund managers' expectations on macroeconomic fundamentals. To address this question, we perform stock-selection timing tests by controlling for macroeconomic variables. Following the literature (Ferson and Schadt, 1996; Christopherson, Ferson, and Glassman, 1998; and Ferson and Qian, 2004), we include short-term interest rate (*YLD*), default spread (*DEF*), term spread (*TERM*), and the S&P 500 index dividend yield (*DIV*) as control variables in the following model:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \gamma_{1i} RET_{i,t} + \gamma_{2i}\sigma_{i,t}^{RET} + \theta_{1i} FLOW_{i,t} + \theta_{2i}\sigma_{i,t}^{FLOW} + \vartheta_{1i} YLD_t + \vartheta_{2i} DIV_t + \vartheta_{3i} TERM_t + \vartheta_{4i} DEF_t + \delta_{1i} R_{m,t+1} + \delta_{2i} VOL_{m,t+1} + \delta_{3i} IL_{m,t+1} + \varepsilon_{i,t+1}, \quad (12)$$

where all macroeconomic variables are defined in Section III.C. The coefficients ($\vartheta_{1,i}$, $\vartheta_{2,i}$, $\vartheta_{3,i}$ and $\vartheta_{4,i}$) capture the effect of macroeconomic information on fund active trading. Significant estimates of these coefficients are evidence that mutual funds use macroeconomic information in adjusting fund activeness. In addition to statistical inference on each individual coefficient, we perform the F-test for the joint hypothesis that all four coefficients are equal to zero ($H_0$: $\vartheta_{1,i} = \vartheta_{2,i} = \vartheta_{3,i} = \vartheta_{4,i} = 0$).

Table XII reports the distribution of cross-sectional Newey–West *t*-statistics with four lags of $\vartheta_{1,i}$, $\vartheta_{2,i}$, $\vartheta_{3,i}$, $\vartheta_{4,i}$ in Eq. (12) and the distribution of cross-sectional critical values of the *F*-test. The results show that mutual fund managers use macroeconomic information to adjust fund activeness. For instance, about 38% of mutual funds take advantage of the macroeconomic information in *YLD* to adjust their trading activity (with Newey–West *t*-statistics greater than 1.645). The joint tests also show that fund activeness is significantly related to macroeconomic information. Given that the critical value of the *F*-test is 4.51 at the 5% level, the results suggest that about three-quarters of funds use macroeconomic information in adjusting their level of active trading. The results also show that funds of all styles exploit information in macroeconomic variables when adjusting their trading activeness. Those findings are consistent with existing studies, which suggest that mutual fund managers incorporate macroeconomic information in their investment strategies (see Ferson and Schadt, 1996; Christopherson, Ferson, and Glassman, 1998; Jiang, Yao, and Yu, 2007; Lynch and Wachter, 2007). In particular, Avramov and Wermers (2006) document that macroeconomic state variables can be used to identify time-varying skills among U.S. equity mutual fund managers in different economic states.

**D. What Types of Funds Have Stronger Stock-selection Timing Skills?**

In previous sections, we present evidence that most mutual fund managers time stock-selection opportunities. In this section, we examine which funds have better skills in timing stock-selection opportunity. We examine the relation between stock-selection timing ability and various fund characteristics, including expense ratio, turnover, cash holdings, fund TNA, fund family TNA, fund age, historical performance, fund return volatility, fund flow, and fund flow volatility. All these variables are shown in existing studies as proxies of fund manager skill or determinants of fund performance.[10] Fund return, return volatility, fund flow, and flow volatility are defined in Section IV.F, and all other variables are defined in Section III. Following conventions in the literature (e.g., Kacperczyk, Sialm, and Zheng, 2008), we use log values for fund TNA, age, and family TNA.

We perform the following Fama–MacBeth regressions to examine the relation between stock-selection timing skill and various fund characteristics:

$$\hat{t}_{i,t} = c + \sum_{k=1}^{K} \delta_k * X_{i,k,t-1} + \varepsilon_{i,t}, \tag{13}$$

[10] Ferson and Schadt (1996), Edelen (1999), and Chen, Hong, Huang, and Kubik (2004) present evidence that fund flow is related to manager skill. Hendricks, Patel, and Zeckhauser (1993), Malkiel (1995), and Bollen and Busse (2005) document evidence of performance persistence ("hot hands"). Chen, Hong, Huang, and Kubik (2004), and Pastor and Stambaugh (2012) provide evidence that fund size is negatively related to fund performance. Malkiel (1995), Wermers (2000), and Edelen, Evans, and Kadlec (2013) show that fund expenses and transaction costs significantly impact fund performance. Chen, Hong, Huang, and Kubik (2004), Nanda, Wang, and Zheng (2004), Elton, Gruber, and Green (2007), and Pollet and Wilson (2008) show that fund family size can improve individual fund performance due to spillover effects among individual funds.

where $\hat{t}_{i,t}$ denotes fund $i$'s Newey–West $t$-statistics with four lags of the timing coefficient $g_i$ in Eq. (2) over a rolling window $[t, t+23]$; and $X_{i,k,t-1}$ denotes fund $i$'s characteristics. All fund characteristics are lagged by at least one month.

Table XIII reports the results of the regressions in Eq. (13) with different specifications. As shown in all specifications, stock-selection timing ability has no significant relation with expense ratio, cash holdings, past fund return, or past fund return volatility. The coefficients of fund TNA are positive, although they are not significant in any of the specifications. That is, large funds are not necessarily at a disadvantage in timing stock-selection opportunities, although are often constrained by investment opportunities when picking stocks (Chen, Hong, Huang, and Kubik, 2004). The results also show that the coefficient of fund age is negative and significant in all specifications, meaning younger funds have better skills in timing stock-selection. This is consistent with Chevalier and Ellison (1999) who argue that younger managers may work harder because of career concerns. The coefficient of fund family TNA is also positive and significant in all specifications. This suggests that funds, as part of a larger family, have stronger skills in timing stock-selection.

The results in Table XIII also demonstrate that the coefficient of turnover is negative, suggesting that high-turnover funds do not necessarily have better stock-selection timing ability. To further understand whether this negative relation is driven mainly by high- or low-turnover funds, we construct a dummy variable, $d^{HTO}$, which equals 1 if fund turnover is greater than the median in a given month and is 0 otherwise. The results show that the coefficient of the interaction term between high-turnover dummy and turnover is significantly negative, whereas the coefficient of turnover itself remains insignificant. That is, the negative relation between turnover and stock-selection timing is driven mainly by high-turnover funds, which implies that some funds trade actively even during periods with low stock-selection opportunities. The findings are consistent with those of Busse, Tong, Tong, and Zhang (2019) who document that mutual funds that trade regularly earn greater abnormal returns from their trades than funds that trade less regularly. However, among those who trade most regularly, larger funds perform relatively worse because they incur higher transaction costs associated with their larger trades. This finding also corroborates evidence documented by Cremers and Pareek (2016) that frequently trading funds generally underperform. Finally, the results show that the coefficient of lagged fund flow is negative but insignificant. However, institutional fund flow is positively related to stock-selection timing ability. The negative and significant coefficient of fund flow volatility suggests that volatility in net fund flows has a negative effect on fund stock-selection ability. This is consistent with evidence reported by Edelen (1999), i.e., fund managers may not be able to pick stocks with positive alphas when trades are driven by investor liquidity demand.

## VI. Conclusion

In this study, we propose measures of stock-selection opportunity and provide evidence that a significant portion of mutual funds have the ability to time stock-selection. That is, they trade more to capture positive alpha opportunities and less in the absence of such opportunities. The results are robust to using alternative measures of fund activeness and stock-selection opportunity, controlling for fund flows, fund performance, and other potential timing skills of mutual funds. In addition, we perform bootstrapping analysis and instrumental variable analysis to address various statistical issues and show that mutual fund stock-selection timing skill cannot be attributed to pure luck and our findings are robust to potential estimation biases. We further show that funds with positive timing skills deliver higher returns than funds with negative timing skills. Moreover, the value generated by stock-selection timing goes beyond the effect of stock-picking talent. Finally, we show that younger funds and funds with larger family size exhibit stronger stock-selection timing skills, whereas those with high flow volatility and high turnover are worse stock-selection timers. Overall, our study introduces to the literature a novel measure of active mutual fund managers skills, namely the stock-selection timing ability.

**Appendix A.**

**A Simple Model: Stock-Selection Opportunity and Active Trading**

This section presents a simple model to illustrate the importance of stock-selection timing for active fund managers. Let $A$ be a stock in the fund portfolio with expected abnormal return of $\alpha_A$; the fund manager decides to replace stock $A$ with stock $B$ of similar characteristics but expected abnormal return of $\alpha_B$. If the fund manager has stock-picking ability, $p$, then we have:

$$\alpha_B - \alpha_A \begin{cases} > 0 & with\, p\ (> \frac{1}{2}) \\ \leq 0 & with\ 1 - p. \end{cases} \tag{A.1}$$

For simplicity, we assume that $\alpha_B = -\alpha_A = \alpha > 0$. The expected return of the trade is then given by $(2p - 1)\alpha$. Note that in the case of net fund inflow, we can think of stock $A$ as the fund style benchmark portfolio. That is, the fund manager's job is to pick a stock that beats the style benchmark. In the case of net fund outflow, we can think of stock $B$ as the fund style benchmark portfolio. Further, let $c$ be the cost of the trade, defined as a percentage of current stock price. The expected return net of trading cost is given by $(2p - 1)\alpha - c$.

Suppose there are $2N$ stocks with a symmetric distribution of expected abnormal returns. That is, half the stocks have positive expected abnormal returns $\{\alpha_i > 0, i = 1,2, \dots, N\}$. For simplicity, we assume that $\alpha_i$ follows a uniform distribution with:

$$\alpha_i = \frac{N-i+1}{N}\sigma, \ \ i = 1,2, \dots, N, \tag{A.2}$$

where $\sigma (> 0)$ is the cross-sectional stock return dispersion $(\alpha_1 - \alpha_N = \frac{N-1}{N}\sigma)$.

Finally, let $K$ be the number of stocks traded by the fund manager in a given period. Under the best scenario (i.e., these $K$ stocks have the highest possible abnormal returns among all stocks, or the fund manager has perfect stock-picking ability), the expected return of trading, or net of trading costs, is given by:

$$\mu = \sum_{k=1}^{K}(2p - 1)\alpha_k - Kc = (\mathrm{N} + \frac{1}{2} - \frac{\mathrm{K}}{2})\ (2p - 1)\ \sigma - Kc. \tag{A.3}$$

We summarize our results in the following proposition.

*Proposition*. The number of stocks traded $(K)$ to generate positive returns under the best scenario is (i) positively related to a fund manager's stock-picking talent $(p)$, (ii) negatively related to transaction costs $(c)$, and (iii) positively related to cross-sectional return dispersion or stock-selection opportunity $(\sigma)$.

The proposition implies that given fund managers' stock-picking talent and transaction costs, trading activeness should be positively related to stock return dispersion, or stock-selection opportunity.

## Appendix B.

### Procedure for Bootstrapping Analysis

Our bootstrapping procedure is based on Efron (1979) and is similar to that by Kosowski, Timmerman, Wermers, and White (2006), Chen and Liang (2007), Jiang, Yao, and Yu (2007), Kosowski, Naik, and Teo (2007), Fama and French (2010), Cao, Simin, and Wang (2013), and Cao, Chen, Liang, and Lo (2013). Specifically, the procedure entails the following five steps:

Step 1. Run the stock-selection timing test specified in Eq. (B1) (same as in Eq. (2)) across individual funds, and collect the estimates, fitted values, and residuals for each fund in each period:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \varepsilon_{i,t+1}. \tag{B.1}$$

Step 2. Randomly resample residuals for each fund with a replacement and obtain a hypothetical time series of residuals for each fund.

Step 3. Construct a time series of pseudo-monthly activeness for each fund under a no-timing-ability assumption, i.e., set timing coefficient to zero:

$$ACT_{i,t}^{bs} = \hat{c}_i + \hat{\varepsilon}_{i,t+1} \tag{B.2}$$

Step 4. Conduct the stock-selection timing tests using the pseudo-data and record timing coefficients and the associated *t*-statistics for each pseudo-fund:

$$ACT_{i,t}^{bs} = c_i + g_i SSO_{t+1} + \mu_{i,t+1} \tag{B.3}$$

Step 5. Repeat the above four steps 10,000 times and obtain distributions of timing coefficients and associated *t*-statistics.

We calculate *p*-value as the fraction of bootstrapping statistics greater than the sample estimated statistics over the 10,000 bootstraps for each cross-sectional statistic (for example, the top 10th percentile). Small *p*-values reflect timing skill rather than pure luck.

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## Table I. Summary Statistics of Fund Characteristics and Fund Activeness Measures

This table reports the summary statistics of fund characteristics and fund activeness measures in Panel A and the time series averages of cross-sectional correlations of fund activeness measures in Panel B. Fund characteristics include fund TNA, age, expense ratio, fund flow, cash holdings, monthly return, and family TNA. Fund TNA is the total net asset of a fund at the beginning of the month. Fund Age is defined as the time (years) during which a fund is in the CRSP Mutual Fund Database. Expense Ratio is the percentage of total investment that shareholders pay for the fund's expenses, including 12b-1 fees. Normalized Fund Flow is defined as fund flow in a month divided by fund TNA at the beginning of the month. Cash Holdings is the percentage of a fund portfolio in cash. Return is the monthly fund return. Fund Family TNA is the sum of TNAs for all funds under the same management company. Fund activeness measures include quarterly fund portfolio turnover (Turnover) defined in Eq. (3) (Yan and Zhang, 2009) and active share proposed by Cremers and Petajisto (2009). Panel A reports the time series averages of monthly cross-sectional mean and median of each variable for the whole sample of funds and subsamples of funds. Funds are divided into four categories based on double sorts of size and book-to-market loadings of Fama and French's (1993) three-factor model, which is estimated from the past 3-month hypothetical daily fund returns implied from quarter-end portfolio holdings. The average number of funds is also reported. The sample period was from January 1984 to December 2018.

Panel A. Fund Characteristics and Activeness Measures

| | All Funds | | Small-Growth | | Small-Value | | Large-Growth | | Large-Value | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Mean | Median | Mean | Median | Mean | Median |
| A.1. Fund Characteristics | | | | | | | | | | |
| No. of Funds | 4,239 | | 1,130 | | 1,022 | | 1,169 | | 1,018 | |
| Fund TNA ($mil) | 1,655 | 288 | 900 | 265 | 627 | 172 | 2,245 | 326 | 1,901 | 355 |
| Fund Age | 13.89 | 9.95 | 14.05 | 10.13 | 10.54 | 8.34 | 14.62 | 9.59 | 15.33 | 9.75 |
| Expense Ratio (%) | 1.36 | 1.30 | 1.48 | 1.46 | 1.46 | 1.43 | 1.23 | 1.18 | 1.28 | 1.20 |
| Normalized Fund Flow (%) | 0.97 | -0.30 | 0.71 | -0.34 | 1.18 | -0.22 | 1.14 | -0.33 | 0.87 | -0.28 |
| Cash Holdings (%) | 6.06 | 3.61 | 6.54 | 4.42 | 6.59 | 3.92 | 5.40 | 3.00 | 5.82 | 3.37 |
| Return (%) | 0.90 | 0.87 | 0.98 | 0.97 | 0.90 | 0.88 | 0.88 | 0.88 | 0.86 | 0.85 |
| Family TNA ($mil) | 33,380 | 6,090 | 25,456 | 5,743 | 27,614 | 4,579 | 44,325 | 6,565 | 33,787 | 8,472 |
| A.2. Fund Activeness Measures | | | | | | | | | | |
| Turnover | 0.22 | 0.24 | 0.23 | 0.19 | 0.21 | 0.16 | 0.26 | 0.16 | 0.20 | 0.15 |
| Active Share | 0.77 | 0.79 | 0.84 | 0.86 | 0.85 | 0.89 | 0.66 | 0.69 | 0.75 | 0.75 |

Panel B. Correlations between Fund Activeness Measures

| | Turnover | Active share |
|---|---|---|
| Turnover | 1 | 0.01 |
| Active Share | | 1 |

## Table II. Summary Statistics of Stock-Selection Opportunity Measures and Macroeconomic and Stock Market Variables

This table reports the summary statistics of monthly stock-selection opportunity measures in Panel A, the time series correlation between stock-selection opportunity measures in Panel B, and macroeconomic variables and stock market variables in Panel C. Stock-selection opportunity measures include average positive Fama and French (1993) and Carhart (1997) four-factor alpha (FF4 alpha) across stocks, average idiosyncratic volatility (IVOL) from the four-factor model across stocks, average positive CAPM alpha across stocks, and cross-sectional (CS) dispersion of CAPM alpha. Stocks smaller than the 20$^{th}$ size percentile of all NYSE stocks are excluded from the calculation of stock-selection opportunity measures. Macroeconomic variables include annualized short-term interest rate, defined as the annualized yield of three-month Treasury bills, term spread (defined as the difference in yields between ten-year Treasury notes and three-month Treasury bills), default spread (defined as the difference in returns between Moody's BAA and AAA rated corporate bonds), and the aggregated dividend yield of S&P 500 Index stocks. Stock market variables include return of the value-weighted CRSP index, VIX index, and market liquidity based on the market illiquidity index introduced by Pastor and Stambaugh (2003). For each variable, we report time series mean, median, standard deviation, and 5$^{th}$ and 95$^{th}$ percentile values. In Panel B, ** denotes significance at the 1% level. The sample period was from January 1984 to December 2018 for all variables. The VIX index began January 1990 and was augmented by the monthly standard deviation of daily return of the CRSP value-weighted portfolio.

Panel A. Stock-selection Opportunity Measures

| | Mean | Median | St. Dev. | 5% | 95% |
|---|---|---|---|---|---|
| Average Positive FF4 Alpha (%) | 0.49 | 0.44 | 0.16 | 0.32 | 0.80 |
| Average FF4 IVOL (%) | 1.90 | 1.80 | 0.56 | 1.28 | 3.09 |
| Average Positive CAPM Alpha (%) | 1.75 | 1.59 | 0.54 | 1.24 | 3.24 |
| CS Dispersion of CAPM Alpha (%) | 0.64 | 0.61 | 0.16 | 0.44 | 0.97 |

Panel B. Correlations between Stock-selection Opportunity Measures

| | FF4-Alpha | FF4-IVOL | CAPM-Alpha | CS Dispersion |
|---|---|---|---|---|
| Average Positive FF4 Alpha (%) | 1.00 | 0.79** | 0.53** | 0.82** |
| Average FF4 IVOL (%) | | 1.00 | 0.63** | 0.85** |
| Average Positive CAPM Alpha (%) | | | 1.00 | 0.87** |
| CS Dispersion of CAPM Alpha (%) | | | | 1.00 |

Panel C. Macroeconomic and Stock Market Variables

| | Mean | Median | St. Dev. | 5% | 95% |
|---|---|---|---|---|---|
| Short-Term Interest Rate (%) | 3.50 | 3.67 | 2.73 | 0.03 | 8.01 |
| Term Spread (%) | 2.38 | 2.44 | 1.23 | 0.36 | 4.16 |
| Default Spread (%) | 1.00 | 0.92 | 0.38 | 0.61 | 1.49 |
| S&P 500 Index Dividend Yield (%) | 2.36 | 2.06 | 0.84 | 1.26 | 4.09 |
| Monthly Market Return (%) | 0.91 | 1.34 | 4.35 | -7.03 | 7.37 |
| VIX Index | 19.30 | 17.28 | 8.92 | 11.47 | 33.73 |
| Pastor and Stambaugh Illiquidity (%) | -2.07 | -0.01 | 6.35 | -13.69 | 6.34 |

### Table III. Stock-Selection Timing Test

This table reports the cross-sectional distribution of the Newey–West $t$-statistics of the stock-selection timing coefficient estimates in the following regression for all funds and funds in each category:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \varepsilon_{i,t+1},$$

where $ACT_{i,t}$ denotes fund $i$'s activeness in month $t$, and $SSO_{t+1}$ denotes stock-selection opportunity in month $t$+1. The model is estimated for each fund based on monthly observations of fund activeness and stock-selection opportunity measures. Fund activeness is turnover, as defined in Table I, and stock-selection opportunity is the average positive FF4 alpha, as defined in Table II. For details on fund classifications, please refer to Table I. The sample period was from January 1984 to December 2018.

| | No. of Funds | Percentage of Funds in Each $t$-stat Cutoff (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | t≤-2.326 | t≤-1.960 | t≤-1.645 | t≤-1.282 | t≥1.282 | t≥1.645 | t≥1.960 | t≥2.326 |
| All Funds | 4,239 | 10.50 | 12.88 | 15.52 | 19.34 | 40.55 | 35.53 | 31.14 | 27.01 |
| Small-Growth | 1,169 | 9.23 | 11.11 | 13.93 | 17.44 | 41.79 | 36.41 | 31.28 | 27.61 |
| Small-Value | 1,018 | 12.18 | 14.73 | 17.19 | 21.71 | 38.80 | 34.09 | 30.75 | 26.72 |
| Large-Growth | 1,130 | 8.93 | 11.46 | 13.69 | 16.99 | 44.95 | 38.93 | 33.40 | 28.73 |
| Large-Value | 1,022 | 11.85 | 14.50 | 17.53 | 21.55 | 36.43 | 32.52 | 29.09 | 24.88 |

## Table IV. Stock-Selection Timing Test – Bootstrapping Approach

This table reports the bootstrapped $p$-values associated with the cross-sectional Newey–West $t$-statistics of the stock-selection timing coefficient estimates in the bottom and top 25th percentiles, respectively. The Newey–West $t$-statistics of the stock-selection timing coefficient are based on the following regression:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \varepsilon_{i,t+1},$$

where $ACT_{i,t}$ denotes fund $i$'s activeness in month $t$, and $SSO_{t+1}$ denotes stock-selection opportunity in month $t$+1. The model is estimated for each fund based on monthly observations of fund activeness and stock-selection opportunity measures. Fund activeness is turnover, as defined in Table I, and stock-selection opportunity is the average positive FF4 alpha, as defined in Table II. $p$-value is defined as the frequency that the values of the bootstrapped cross-sectional $t$-statistics (for example, the top-5th percentile) for the pseudo-funds from 10,000 simulations exceed the actual estimated value of the cross-sectional statistics. The sample period was from January 1984 to December 2018.

| | | Bottom $t$-statistics of $\hat{g}_i$ | | | | | Top $t$-statistics of $\hat{g}_i$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1% | 3% | 5% | 10% | 25% | 75% | 90% | 95% | 97% | 99% |
| All Funds | $t$ | -5.58 | -4.20 | -3.48 | -2.52 | -1.00 | 2.31 | 4.18 | 5.21 | 5.83 | 7.63 |
| | $p$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Small-Growth | $t$ | -5.33 | -4.02 | -3.50 | -2.41 | -0.95 | 2.29 | 4.19 | 5.02 | 5.62 | 7.18 |
| | $p$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Small-Value | $t$ | -5.99 | -4.68 | -3.90 | -2.69 | -1.19 | 2.39 | 4.22 | 5.51 | 6.43 | 7.69 |
| | $p$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Large-Growth | $t$ | -5.36 | -3.76 | -3.07 | -2.18 | -0.73 | 2.41 | 4.29 | 5.34 | 6.01 | 7.96 |
| | $p$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Large-Value | $t$ | -5.56 | -4.58 | -3.46 | -2.70 | -1.17 | 2.15 | 4.04 | 4.92 | 5.81 | 7.08 |
| | $p$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

## Table V. Stock-Selection Timing Test – Instrumental Variable Approach

This table reports the cross-sectional distribution of the Newey–West $t$-statistics of the stock-selection timing coefficient estimates in the following regression for all funds and funds in each category:

$$ACT_{i,t} = c_i + g_i \widehat{SSO}_{t+1} + \varepsilon_{i,t+1},$$

where $ACT_{i,t}$ denotes fund $i$'s activeness in month $t$, and $\widehat{SSO}_{t+1}$ denotes estimated stock-selection opportunity in month $t$+1 from the regression of $SSO_{t+1} = c + d * Instrument_t + \varepsilon_{t+1}$, where $SSO_{t+1}$ is the average positive FF4 alpha; and $Instrument_t$ is a vector of instruments, including the average positive FF4 alpha, average FF4 IVOL, average positive CAPM alpha, and cross-sectional dispersion of CAPM alpha, as defined in Table II. The model is estimated for each fund based on monthly observations of fund activeness and stock-selection opportunity measures. Fund activeness is turnover, as defined in Table I. For details on fund classifications, please refer to Table I. The sample period was from January 1984 to December 2018.

| | No. of Funds | Percentage of Funds in each t-stat Cutoff (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | t≤-2.326 | t≤-1.960 | t≤-1.645 | t≤-1.282 | t≥1.282 | t≥1.645 | t≥1.960 | t≥2.326 |
| All Funds | 4,239 | 8.23 | 10.86 | 13.01 | 17.09 | 45.58 | 39.97 | 35.12 | 30.21 |
| Small-Growth | 1,169 | 7.37 | 9.79 | 11.75 | 15.49 | 47.95 | 41.04 | 36.19 | 30.32 |
| Small-Value | 1,108 | 9.86 | 12.46 | 15.28 | 18.96 | 43.55 | 38.35 | 33.80 | 30.34 |
| Large-Growth | 1,130 | 6.84 | 9.63 | 11.34 | 14.87 | 48.66 | 43.64 | 37.86 | 31.87 |
| Large-Value | 1,022 | 9.02 | 11.74 | 13.91 | 19.35 | 41.74 | 36.63 | 32.39 | 28.26 |

## Table VI. Robustness Check: Alternative Measures of Fund Activeness and Stock-Selection Opportunity

This table reports the cross-sectional distribution of Newey–West *t*-statistics of the stock-selection timing coefficient estimates of the regression in Table III for all funds and funds in each category using alternative measures of fund activeness or stock-selection opportunity. Panel A reports results based on the stock-selection opportunity measure used in Table III, namely the average positive FF4 alpha, as defined in Table I, and an alternative fund activeness measure, namely active share, as defined in Table I. Panel B reports results based on the fund activeness measure used in Table III, namely turnover, as defined in Table I, and three alternative measures of stock-selection opportunity: average FF4 IVOL, average positive CAPM alpha, and CS dispersion of CAPM alpha, as defined in Table II. The sample period was from January 1984 to December 2018.

| | No. of Funds | Percentage of Funds in each t-stat Cutoff (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | t≤-2.326 | t≤-1.960 | t≤-1.645 | t≤-1.282 | t≥1.282 | t≥1.645 | t≥1.960 | t≥2.326 |
| **Panel A. Alternative Measure of Fund Activeness: Active Share** | | | | | | | | | |
| All Funds | 2,998 | 13.64 | 16.31 | 18.85 | 21.88 | 39.93 | 32.99 | 27.79 | 22.72 |
| Small-Growth | 834 | 16.79 | 20.13 | 21.64 | 26.18 | 34.05 | 27.74 | 21.45 | 18.14 |
| Small-Value | 718 | 12.58 | 15.21 | 17.41 | 19.02 | 44.71 | 37.46 | 31.34 | 26.88 |
| Large-Growth | 713 | 12.34 | 14.03 | 16.27 | 18.93 | 43.06 | 35.34 | 29.17 | 22.72 |
| Large-Value | 733 | 10.91 | 12.28 | 15.29 | 18.01 | 43.41 | 35.27 | 28.71 | 23.64 |
| **Panel B. Alternative Measures of Stock-selection Opportunity** | | | | | | | | | |
| | | | | Average FF4 IVOL | | | | | |
| All Funds | 4,239 | 13.51 | 16.75 | 20.17 | 24.93 | 39.95 | 34.58 | 30.87 | 26.01 |
| Small-Growth | 1,169 | 13.50 | 16.41 | 19.66 | 24.10 | 41.11 | 34.10 | 30.59 | 24.79 |
| Small-Value | 1,018 | 16.11 | 19.45 | 23.28 | 27.41 | 37.33 | 32.81 | 29.96 | 25.10 |
| Large-Growth | 1,130 | 10.58 | 13.11 | 15.63 | 20.48 | 43.59 | 38.06 | 33.59 | 29.13 |
| Large-Value | 1,022 | 13.89 | 18.10 | 22.21 | 27.89 | 37.57 | 33.66 | 29.35 | 24.95 |
| | | | | Average Positive CAPM Alpha | | | | | |
| All Funds | 4,239 | 16.32 | 19.63 | 22.28 | 26.56 | 40.97 | 35.52 | 31.32 | 26.49 |
| Small-Growth | 1,169 | 17.26 | 20.77 | 24.70 | 29.06 | 37.86 | 32.48 | 29.15 | 23.85 |
| Small-Value | 1,018 | 18.96 | 22.20 | 24.46 | 28.98 | 39.29 | 22.69 | 29.17 | 24.56 |
| Large-Growth | 1,130 | 13.20 | 16.70 | 18.54 | 21.65 | 46.80 | 42.33 | 38.64 | 33.30 |
| Large-Value | 1,022 | 15.75 | 18.69 | 21.35 | 26.22 | 40.31 | 33.95 | 28.57 | 24.56 |
| | | | | CS Dispersion of CAPM Alpha | | | | | |
| All Funds | 4,239 | 10.68 | 13.98 | 17.47 | 22.87 | 38.37 | 32.50 | 28.16 | 24.76 |
| Small-Growth | 1,169 | 10.40 | 13.83 | 16.48 | 21.76 | 37.80 | 31.54 | 27.40 | 24.08 |
| Small-Value | 1,018 | 11.44 | 15.26 | 19.38 | 25.15 | 34.53 | 30.72 | 27.22 | 24.30 |
| Large-Growth | 1,130 | 9.28 | 12.51 | 15.84 | 20.38 | 40.26 | 35.82 | 31.28 | 26.93 |
| Large-Value | 1,022 | 11.70 | 14.39 | 18.43 | 24.43 | 36.75 | 31.99 | 26.82 | 23.77 |

## Table VII. Robustness Checks: Controlling for Fund Performance, Flow, and Other Timing Skills

Panel A of this table reports results of the stock-selection timing test after controlling for fund performance and flows. The timing test is based on the following regression:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \gamma_{1i} RET_{i,t} + \gamma_{2i}\sigma_{i,t}^{RET} + \theta_{1i} FLOW_{i,t} + \theta_{2i}\sigma_{i,t}^{FLOW} + \varepsilon_{i,t+1},$$

where $RET_{i,t}$ and $FLOW_{i,t}$ denote, respectively, fund *i*'s average return and normalized flows over months *t*-2 to *t*, $\sigma_{i,t}^{RET}$ and $\sigma_{i,t}^{FLOW}$ denote fund return volatility and flow volatility, respectively, which are defined as the standard deviations of fund return and normalized flows over months *t*-5 to *t*. All other variables are defined in Table III. Panel B reports the results of the stock-selection timing test after controlling for fund performance, flow, and other potential timing skills. The timing test is based on the following regression:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \gamma_{1i} RET_{i,t} + \gamma_{2i}\sigma_{i,t}^{RET} + \theta_{1i} FLOW_{i,t} + \theta_{2i}\sigma_{i,t}^{FLOW} + \delta_{1i} R_{m,t+1} + \delta_{2i} Vol_{m,t+1} + \delta_{3i} IL_{m,t+1} + \varepsilon_{i,t+1},$$

where $R_{m,t+1}$ denotes value-weighted returns of CRSP stocks in month *t*+1, $Vol_{m,t+1}$ denotes market volatility based on the VIX index in month *t*+1 and supplemented by the standard deviation of daily returns of the value-weighted CRSP index over a month, and $IL_{m,t+1}$ denotes the Pastor-Stambaugh market illiquidity index. Each panel reports the cross-sectional distribution of the Newey–West *t*-statistics of the stock-selection timing coefficient estimates. The sample period was from January 1984 to December 2018.

| | No. of funds | Percentage of Funds in each t-stat Cutoff (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | t≤-2.326 | t≤-1.960 | t≤-1.645 | t≤-1.282 | t≥1.282 | t≥1.645 | t≥1.960 | t≥2.326 |
| Panel A. Controlling for Fund Performance and Flows | | | | | | | | | |
| All Funds | 3,864 | 12.06 | 14.75 | 17.62 | 21.87 | 40.17 | 34.67 | 30.46 | 25.31 |
| Small-Growth | 1,047 | 10.79 | 13.79 | 16.23 | 20.82 | 41.36 | 34.39 | 30.47 | 25.02 |
| Small-Value | 941 | 13.50 | 17.00 | 19.66 | 23.38 | 37.94 | 33.05 | 29.33 | 25.29 |
| Large-Growth | 944 | 9.96 | 12.50 | 14.94 | 18.43 | 44.81 | 37.82 | 33.90 | 28.07 |
| Large-Value | 932 | 14.16 | 16.63 | 19.85 | 25.00 | 36.37 | 32.19 | 28.11 | 22.85 |
| Panel B. Further Controlling for Other Timing Skills | | | | | | | | | |
| All Funds | 3,624 | 9.49 | 12.86 | 16.06 | 20.34 | 31.54 | 25.25 | 20.97 | 16.25 |
| Small-Growth | 986 | 7.61 | 10.45 | 13.79 | 17.75 | 32.35 | 25.86 | 21.20 | 17.34 |
| Small-Value | 887 | 10.15 | 14.54 | 17.93 | 22.77 | 29.76 | 24.80 | 20.18 | 14.99 |
| Large-Growth | 891 | 8.75 | 11.90 | 14.03 | 17.73 | 34.23 | 26.26 | 22.78 | 17.96 |
| Large-Value | 860 | 11.74 | 14.88 | 18.84 | 23.49 | 29.65 | 23.95 | 19.65 | 14.53 |

## Table VIII. Robustness Check: Stock-Selection Timing under Different Market Conditions

This table reports results of the stock-selection timing test during months with top 30% and bottom 30% market returns. The timing test is based on the following regression:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \varepsilon_{i,t+1}.$$

The table reports the cross-sectional distribution of the Newey–West *t*-statistics of the stock-selection timing coefficient estimates. Fund activeness measure and stock-selection opportunity measure are the same as those used in Table III and defined in Tables I and II, respectively. The sample period was from January 1984 to December 2018.

| | No. of Funds | Percentage of Funds in each t-stat Cutoff (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | t≤-2.326 | t≤-1.960 | t≤-1.645 | t≤-1.282 | t≥1.282 | t≥1.645 | t≥1.960 | t≥2.326 |
| | | Months of top 30% market returns | | | | | | | |
| All Funds | 3,577 | 11.13 | 15.07 | 18.00 | 23.62 | 32.71 | 27.51 | 23.01 | 19.04 |
| Small-Growth | 967 | 10.86 | 14.47 | 17.17 | 21.72 | 32.06 | 25.85 | 21.41 | 16.96 |
| Small-Value | 875 | 10.06 | 15.09 | 17.83 | 25.03 | 32.57 | 27.77 | 23.31 | 19.89 |
| Large-Growth | 883 | 9.74 | 13.48 | 16.76 | 21.06 | 34.65 | 31.03 | 25.59 | 21.97 |
| Large-Value | 852 | 13.97 | 17.37 | 20.42 | 26.70 | 31.57 | 25.47 | 21.83 | 17.49 |
| | | Months of bottom 30% market returns | | | | | | | |
| All Funds | 3,676 | 10.58 | 13.41 | 16.29 | 20.84 | 34.12 | 29.54 | 25.08 | 20.87 |
| Small-Growth | 997 | 9.03 | 11.84 | 15.05 | 20.46 | 34.01 | 28.89 | 24.47 | 20.26 |
| Small-Value | 894 | 10.96 | 13.76 | 16.11 | 19.91 | 34.79 | 29.74 | 24.94 | 21.14 |
| Large-Growth | 907 | 10.03 | 12.68 | 15.88 | 21.06 | 36.49 | 31.64 | 27.01 | 22.05 |
| Large-Value | 878 | 12.53 | 15.60 | 18.34 | 21.98 | 34.17 | 27.90 | 23.92 | 20.05 |

## Table IX. Stock-Selection Timing Based on Change of Stock-Selection Opportunity

This table reports the cross-sectional distribution of the Newey–West *t*-statistics of the stock-selection timing coefficient estimates in the following regression for all funds and funds in each category:

$$ACT_{i,t} = c_i + g_i \sum_{i=1}^{N_{t+1}} \Delta FF4\alpha_{i,t+1} |_{\Delta FF4\alpha_{i,t+1}>0} + \varepsilon_{i,t+1,}$$

where $ACT_{i,t}$ denotes fund $i$'s activeness in month $t$, and $\Delta SSO_{t+1}$ denotes stock-selection opportunity change from month t to $t$+1. The model is estimated for each fund based on monthly observations of fund activeness and stock-selection opportunity measures. Stock-selection opportunity change is defined as the change in average positive FF4 alphas between two consecutive periods. Fund activeness is turnover, as defined in Table I. For details on fund classifications, please refer to Table I. The sample period was from January 1984 to December 2018.

| | No. of Funds | Percentage of Funds in each t-stat Cutoff (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | t≤-2.326 | t≤-1.960 | t≤-1.645 | t≤-1.282 | t≥1.282 | t≥1.645 | t≥1.960 | t≥2.326 |
| All Funds | 4,239 | 11.64 | 14.98 | 18.73 | 23.54 | 39.10 | 34.55 | 30.80 | 26.76 |
| Small-Growth | 1,169 | 10.46 | 13.88 | 17.84 | 22.50 | 41.83 | 36.56 | 32.69 | 28.38 |
| Small-Value | 1,108 | 12.89 | 16.14 | 20.00 | 24.77 | 37.56 | 33.91 | 30.15 | 26.50 |
| Large-Growth | 1,130 | 10.65 | 14.20 | 17.75 | 21.60 | 40.83 | 36.09 | 32.45 | 27.51 |
| Large-Value | 1,022 | 12.75 | 15.86 | 19.48 | 25.50 | 35.74 | 31.33 | 27.61 | 24.40 |

## Table X. Economic Significance of Stock-Selection Timing

This table reports the average performance of positive and negative stock-selection timing funds over the subsequent 3 to 12 months. At the end of each month, funds are classified as negative or positive timers based on the rolling Newey–West *t*-statistics of the stock-selection timing coefficients estimated over the most recent 12 months. The timing test is based on the regression in Eq. (2). The stock-selection opportunity and fund activeness measures are the same as those used in Table III. Cutoff values of ±1.96 and ±1.65 for *t*-statistics are used. The table reports equal-weighted (Panel A) and TNA-weighted (Panel B) raw returns, and Fama-French three- and four-factor alphas (in percent) of each portfolio over the subsequent three, six, and 12 months, respectively. The differences between positive and negative timers as well as their Newey–West *t*-statistics are also reported. The sample period was from January 1984 to December 2018.

| | Raw Return | | | FF3 Alpha | | | FF4 Alpha | | |
|---|---|---|---|---|---|---|---|---|---|
| | 3M | 6M | 12M | 3M | 6M | 12M | 3M | 6M | 12M |
| Panel A. Equal-weighted Portfolio Returns | | | | | | | | | |
| Cutoff t = ±1.96 | | | | | | | | | |
| Negative Timer | 2.670 | 5.287 | 11.243 | -0.233 | -0.405 | -0.577 | -0.165 | -0.377 | -0.718 |
| Positive Timer | 2.841 | 5.530 | 11.493 | -0.053 | -0.095 | -0.275 | -0.050 | -0.152 | -0.495 |
| Positive-Negative | 0.171 | 0.244 | 0.249 | 0.180 | 0.310 | 0.302 | 0.114 | 0.226 | 0.223 |
| (t-stat) | (1.94) | (1.97) | (1.67) | (1.85) | (2.20) | (1.69) | (1.72) | (2.05) | (1.65) |
| Cutoff t = ±1.65 | | | | | | | | | |
| Negative Timer | 2.447 | 4.950 | 10.734 | -0.252 | -0.440 | -0.770 | -0.182 | -0.372 | -0.730 |
| Positive Timer | 2.600 | 4.784 | 11.079 | -0.095 | -0.113 | -0.430 | -0.089 | -0.145 | -0.539 |
| Positive-Negative | 0.153 | 0.280 | 0.345 | 0.157 | 0.326 | 0.350 | 0.093 | 0.227 | 0.191 |
| (t-stat) | (1.95) | (2.37) | (1.87) | (1.87) | (2.69) | (2.11) | (0.93) | (1.85) | (1.65) |
| Panel B. TNA-weighted Portfolio Returns | | | | | | | | | |
| Cutoff t = ±1.96 | | | | | | | | | |
| Negative Timer | 2.445 | 4.848 | 10.735 | -0.352 | -0.643 | -1.021 | -0.281 | -0.553 | -1.055 |
| Positive Timer | 2.740 | 5.400 | 11.410 | -0.089 | -0.175 | -0.425 | -0.090 | -0.194 | -0.442 |
| Positive-Negative | 0.295 | 0.553 | 0.675 | 0.264 | 0.468 | 0.596 | 0.191 | 0.358 | 0.613 |
| (t-stat) | (2.36) | (3.31) | (3.07) | (2.13) | (2.83) | (2.35) | (1.84) | (1.99) | (2.46) |
| Cutoff t = ±1.65 | | | | | | | | | |
| Negative Timer | 2.202 | 4.494 | 10.089 | -0.384 | -0.725 | -1.208 | -0.295 | -0.601 | -1.196 |
| Positive Timer | 2.483 | 4.725 | 10.885 | -0.157 | -0.196 | -0.508 | -0.150 | -0.193 | -0.532 |
| Positive-Negative | 0.280 | 0.583 | 0.795 | 0.227 | 0.529 | 0.740 | 0.144 | 0.408 | 0.664 |
| (t-stat) | (2.55) | (3.90) | (3.57) | (2.15) | (3.39) | (2.92) | (1.78) | (2.54) | (2.63) |

## Table XI. Stock-Selection Timing versus Stock-Picking Ability

This table reports the economic significance of stock-selection timing after controlling for stock-picking ability. Each month, we sort mutual funds based on stock-picking ability into low, medium, and high stock-picking groups. Within each stock-picking group, we further identify negative and positive stock-selection timers based on the Newey–West *t*-statistic cutoff of ±1.96. The table reports equal-weighted raw returns, three- and four-factor alphas (in percent) of each portfolio and the average returns and alphas of negative and positive stock-selection timers across different stock-picking groups over the subsequent three, six, and 12 months. The differences between positive and negative timers as well as their Newey–West *t*-statistics are also reported. A fund's stock-picking ability measure is defined according to Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014). The sample period was from January 1984 to December 2018.

| Stock-Picking | Raw Return | | | 3-Factor Alpha | | | 4-Factor Alpha | | |
|---|---|---|---|---|---|---|---|---|---|
| | Negative Timers | Positive Timers | Positive-Negative | Negative Timers | Positive Timers | Positive-Negative | Negative Timers | Positive Timers | Positive-Negative |
| Three-month Horizon | | | | | | | | | |
| Low | 2.437 | 2.541 | 0.104 (0.55) | -0.522 | -0.433 | 0.089 (0.80) | -0.340 | -0.274 | 0.066 (0.64) |
| Medium | 2.655 | 2.820 | 0.165 (1.72) | -0.264 | -0.100 | 0.164 (1.72) | -0.259 | -0.068 | 0.191 (1.87) |
| High | 3.002 | 3.158 | 0.156 (1.91) | -0.110 | 0.066 | 0.176 (1.64) | -0.199 | -0.035 | 0.164 (1.91) |
| Average | 2.716 | 2.825 | 0.109 (1.51) | -0.309 | -0.143 | 0.166 (1.97) | -0.264 | -0.105 | 0.159 (1.72) |
| Six-month Horizon | | | | | | | | | |
| Low | 5.145 | 5.293 | 0.148 (1.21) | -0.762 | -0.575 | 0.187 (1.43) | -0.457 | -0.417 | 0.040 (0.22) |
| Medium | 5.243 | 5.743 | 0.500 (2.52) | -0.666 | -0.179 | 0.487 (3.20) | -0.584 | -0.117 | 0.467 (3.00) |
| High | 5.901 | 6.136 | 0.235 (1.96) | -0.314 | -0.019 | 0.295 (2.36) | -0.580 | -0.346 | 0.264 (1.93) |
| Average | 5.494 | 5.721 | 0.227 (2.41) | -0.620 | -0.291 | 0.328 (2.52) | -0.590 | -0.288 | 0.302 (1.97) |
| 12-month Horizon | | | | | | | | | |
| Low | 10.527 | 10.664 | 0.137 (0.46) | -1.241 | -1.103 | 0.138 (0.48) | -1.057 | -0.976 | 0.081 (0.25) |
| Medium | 10.785 | 11.418 | 0.633 (2.39) | -0.884 | -0.369 | 0.515 (1.99) | -0.836 | -0.449 | 0.387 (2.08) |
| High | 11.601 | 12.091 | 0.490 (2.19) | -0.298 | 0.018 | 0.316 (1.98) | -0.579 | -0.283 | 0.296 (2.31) |
| Average | 11.006 | 11.471 | 0.465 (1.99) | -0.881 | -0.454 | 0.427 (2.04) | -0.961 | -0.697 | 0.264 (2.05) |

## Table XII. Do Fund Managers Use Macroeconomic Information in Stock-Selection Timing?

This table reports the cross-sectional distribution of the Newey–West *t*-statistics of the coefficient estimates of macroeconomic variables in the following regression:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \gamma_{1i} RET_{i,t} + \gamma_{2i}\sigma_{i,t}^{RET} + \theta_{1i} FLOW_{i,t} + \theta_{2i}\sigma_{i,t}^{FLOW} + \vartheta_{1i} YLD_t + \vartheta_{2i} DIV_t + \vartheta_{3i} TERM_t + \vartheta_{4i} DEF_t + \delta_{1i} R_{m,t+1} + \delta_{2i} Vol_{m,t+1} + \delta_{3i} IL_{m,t+1} + \varepsilon_{i,t+1},$$

where $YLD_t$ denotes the annualized yield of three-month Treasury bills, $DIV_t$ denotes the aggregated dividend yield of S&P 500 Index stocks, $TERM_t$ denotes the average yield spread between ten-year Treasury notes and three-month Treasury bills, and $DEF_t$ denotes average yield spread between Moody's rated BAA and AAA corporate bonds. All other variables are defined in Tables III and VII. This table also reports results of an $F$-test for the null hypothesis that the coefficients of all four macroeconomic variables are jointly zero. The $F$-tests for each subsample are also reported. The sample period was from January 1984 to December 2018.

| | Percentage of Funds in Each t-stat Cutoff | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | t≤-2.326 | t≤-1.960 | t≤-1.645 | t≤-1.282 | t≥1.282 | t≥1.645 | t≥1.960 | t≥2.326 |
| | All Funds | | | | | | | |
| $\vartheta_{1,i}$ | 14.67 | 17.51 | 21.10 | 25.19 | 42.10 | 37.57 | 32.98 | 28.65 |
| $\vartheta_{2,i}$ | 17.18 | 21.93 | 25.64 | 30.86 | 28.59 | 23.98 | 19.97 | 16.44 |
| $\vartheta_{3,i}$ | 8.37 | 10.55 | 13.18 | 16.71 | 47.04 | 41.13 | 36.30 | 31.13 |
| $\vartheta_{4,i}$ | 10.06 | 13.51 | 17.21 | 22.07 | 31.99 | 25.86 | 20.75 | 16.08 |
| *Joint test* | 1% | 5% | 10% | 25% | 75% | 90% | 95% | 99% |
| *F-values* | 0.58 | 1.41 | 2.24 | 4.67 | 18.36 | 29.23 | 40.05 | 65.87 |
| | Small-Growth | | | | | | | |
| *Join test* | 1% | 5% | 10% | 25% | 75% | 90% | 95% | 99% |
| *F-values* | 0.63 | 1.33 | 1.99 | 3.76 | 16.93 | 28.61 | 39.15 | 70.56 |
| | Small-Value | | | | | | | |
| *Joint test* | 1% | 5% | 10% | 25% | 75% | 90% | 95% | 99% |
| *F-values* | 0.52 | 1.35 | 2.09 | 4.72 | 17.06 | 28.89 | 36.99 | 58.17 |
| | Large-Growth | | | | | | | |
| *Joint test* | 1% | 5% | 10% | 25% | 75% | 90% | 95% | 99% |
| *F-values* | 0.61 | 1.62 | 2.23 | 4.80 | 20.22 | 30.07 | 41.59 | 66.31 |
| | Large-Value | | | | | | | |
| *Joint test* | 1% | 5% | 10% | 25% | 75% | 90% | 95% | 99% |
| *F-values* | 0.57 | 1.48 | 2.20 | 4.59 | 18.74 | 32.69 | 41.76 | 68.08 |

## Table XIII. Determinants of Stock-Selection Timing

This table reports the results of Fama–MacBeth regression of stock-selection timing on fund characteristics:

$$\hat{t}_{i,t} = c + \sum_{k=1}^{K} \delta_k X_{i,k,t-1} + \varepsilon_{i,t},$$

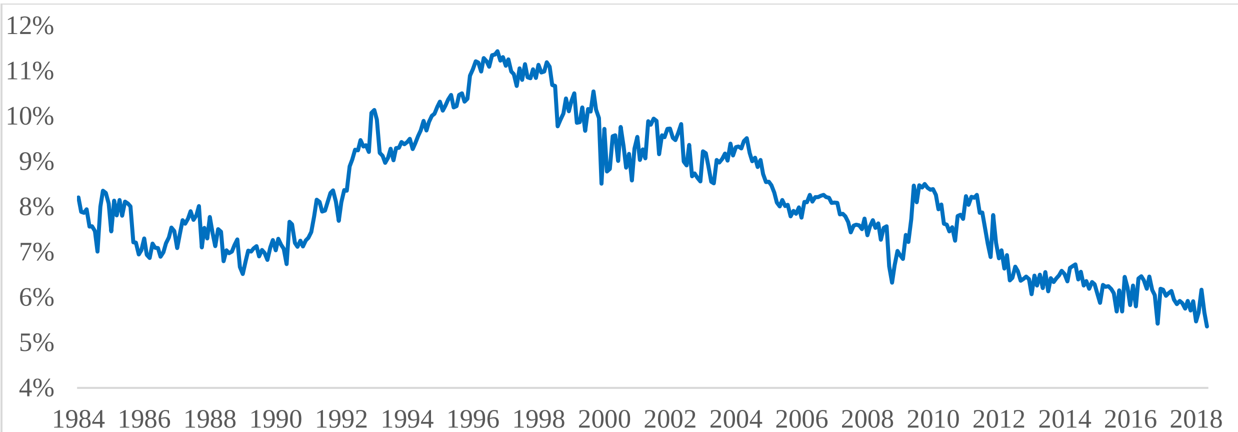
where $\hat{t}_{i,t}$ denotes the Newey–West *t*-statistic of fund $i$'s stock-selection timing coefficient $g_i$ from the regression in Table III estimated over the rolling [$t$, $t$+23] months. Fund activeness and stock-selection opportunity measures are the same as those used in Table III. $X_{i,k,t-1}$ includes the expense ratio, turnover, cash holding, fund size (log fund TNA), fund family size (log family TNA), fund age, fund return, fund return volatility, normalized fund flow, and normalized fund flow volatility. $d^{HTO}$ is a dummy variable equal to 1 if fund turnover is above the median of the whole sample and is 0 otherwise. In column 7, the normalized fund flow is further decomposed into retail flow and institutional flow. All variables are lagged by at least one month. Newey–West *t*-statistics are in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period was from January 1984 to December 2018.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| Expense Ratio | 0.018 | | 0.010 | 0.005 | 0.006 | 0.005 | 0.011 |
| | (0.82) | | (0.53) | (0.23) | (0.36) | (0.23) | (0.19) |
| Turnover | -0.004 | | -0.005 | -0.001 | -0.001 | -0.002 | 0.003 |
| | (-1.03) | | (-0.15) | (-0.11) | (-0.06) | (-0.15) | (0.19) |
| $d^{HTO}$*Turnover | | | | | | -0.066* | -0.047* |
| | | | | | | (-1.90) | (-1.82) |
| Cash Holdings | 0.328 | | 0.147 | 0.116 | 0.060 | 0.190 | 0.283 |
| | (0.71) | | (0.47) | (0.38) | (0.20) | (0.64) | (0.97) |
| Log Fund TNA | | 0.005 | 0.010 | 0.007 | 0.006 | 0.007 | 0.009 |
| | | (0.65) | (1.37) | (0.97) | (0.84) | (1.00) | (1.39) |
| Log Family TNA | | 0.008** | 0.006** | 0.007** | 0.006** | 0.006** | 0.005** |
| | | (2.55) | (2.37) | (2.36) | (2.34) | (2.34) | (2.37) |
| Log Age | | | -0.035*** | -0.034*** | -0.034*** | -0.035*** | -0.035*** |
| | | | (-2.86) | (-2.83) | (-2.92) | (-2.92) | (-3.01) |
| Fund Ret | | | | -1.376 | -1.153 | -1.287 | -1.521 |
| | | | | (-1.22) | (-1.01) | (-1.14) | (-1.29) |
| Fund Ret VOL | | | | 0.173 | 0.058 | 0.141 | 0.440 |
| | | | | (0.15) | (0.25) | (0.23) | (0.37) |
| Fund Flow | | | | | -0.385 | -0.537 | |
| | | | | | (-0.62) | (-0.90) | |
| Retail Flow | | | | | | | -0.194 |
| | | | | | | | (-1.02) |
| Institutional Flow | | | | | | | 5.278*** |
| | | | | | | | (3.38) |
| Flow VOL | | | | | -0.498* | -0.495* | -0.259* |
| | | | | | (-1.79) | (-1.71) | （-1.85） |
| Intercept | 0.060 | -0.019 | 0.063 | 0.070 | -0.107 | 0.067 | 0.075 |
| | (1.43) | (-0.59) | (1.59) | (1.26) | (-0.20) | (1.27) | (1.49) |
| N | 364,737 | 364,737 | 364,737 | 364,737 | 364,737 | 364,737 | 364,737 |
| Adjusted $R^2$ (%) | 2.07 | 1.14 | 3.19 | 3.83 | 4.95 | 5.07 | 5.37 |

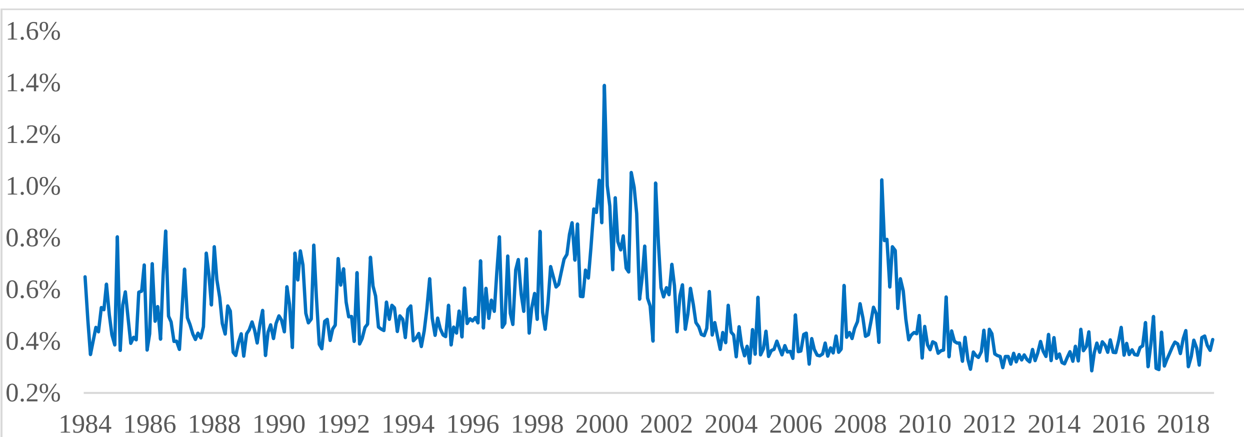
**Figure 1. Time Series of Fund Activeness and Stock-Selection Opportunity Measures**

Panel A plots the time series of average monthly activeness measure of all funds, namely turnover, as defined in Table I. Panel B plots the time series of stock-selection opportunity measure, namely average positive FF4 alpha, as defined in Table II. The sample period was from January 1984 to December 2018.

Panel A. Time Series of Average Turnover of All Funds




Panel B. Time Series of Stock-selection Opportunity: Average Positive FF4 Alpha

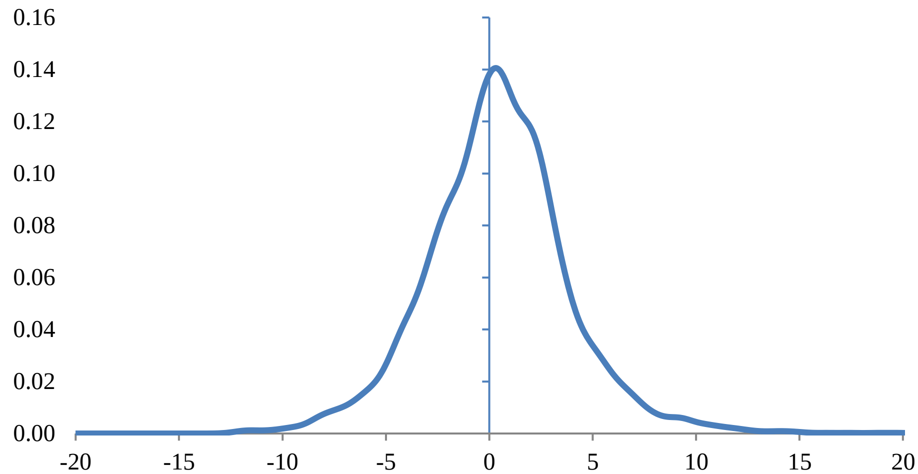


### Figure 2. Kernel Density of $t$-statistics of Stock-Selection Timing Coefficients

This figure plots the kernel density of the cross-sectional distribution of the Newey–West $t$-statistics of the stock-selection timing coefficient estimates from the following regression:

$$ACT_{i,t} = c_i + g_i SSO_{t+1} + \varepsilon_{i,t+1},$$

where fund activeness is turnover, as defined in Table I; and stock-selection opportunity is the average positive FF4 alpha, as defined in Table II. The sample period was from January 1984 to December 2018.




### Figure 3. Kernel Density of Bootstrapped 90th Percentile $t$-statistics of Stock-Selection Timing Coefficients

This figure plots the kernel density of the bootstrapped 90th percentile $t$-statistics of the timing coefficient estimates based on 10,000 pseudo-samples (under the assumption of no stock-selection timing ability). The corresponding $t$-statistic estimated from mutual fund data is also plotted (vertical bar).

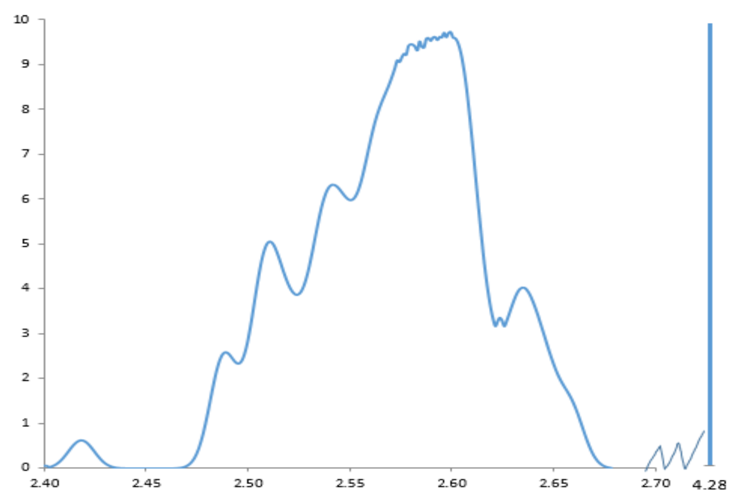
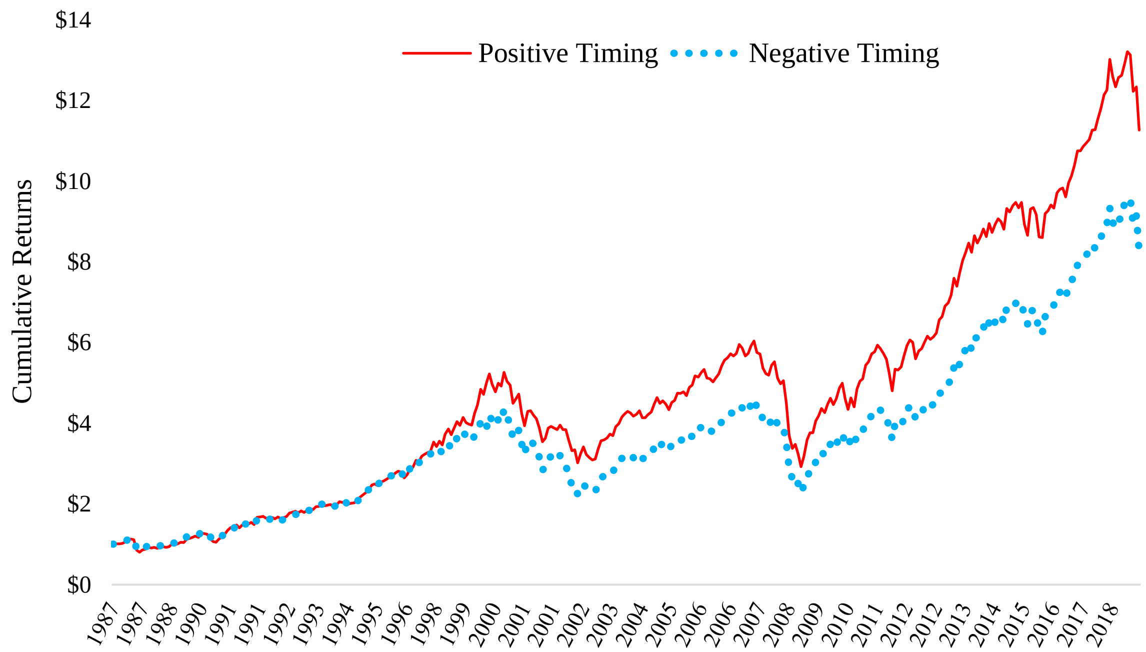


**Figure 4. Cumulative Returns of Positive and Negative Stock-Selection Timing Funds**

This figure plots the cumulative returns of TNA-weighted positive and negative stock-selection timing fund portfolios from 1987 through 2018. Each month, starting in January 1987, funds were classified as positive and negative stock-selection timing funds based on the Newey–West *t*-statistic cutoff of ±1.96. Portfolio returns in subsequent month are computed for positive and negative stock-selection timing funds, respectively. The starting value of each portfolio was $1 in January 1987.



# Internet Appendix

## A. Robustness Check: Effect of Market Crises

To examine the effect of market crises on stock-selection timing, we replicate the stock-selection timing test in Table III by focusing on market crisis periods: 2000-2002 and 2007-2009. The results are reported below in Table A.

### Table A. Stock-Selection Timing Test: Market Crisis Periods

This table reports the cross-sectional distribution of the Newey–West *t*-statistics of the stock-selection timing coefficient estimates of the regression in Table III for all funds and funds in each category. Fund activeness measure and stock-selection opportunity measure are the same as those used in Table III and defined in Tables I and II, respectively. For details on fund classifications, please refer to Table I. The periods include 2000-2002 and 2007-2009.

| | No. of Funds | Percentage of Funds in Each t-stat Cutoff (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $t \leq -2.326$ | $t \leq -1.960$ | $t \leq -1.645$ | $t \leq -1.282$ | $t \geq 1.282$ | $t \geq 1.645$ | $t \geq 1.960$ | $t \geq 2.326$ |
| All Funds | 3,330 | 12.58 | 16.79 | 20.87 | 25.29 | 38.77 | 33.48 | 28.89 | 24.29 |
| Small-Growth | 914 | 10.94 | 15.21 | 18.82 | 22.98 | 42.01 | 36.65 | 32.06 | 27.13 |
| Small-Value | 812 | 15.52 | 19.83 | 24.14 | 28.33 | 37.07 | 31.90 | 28.20 | 22.66 |
| Large-Growth | 828 | 8.45 | 11.84 | 16.91 | 21.39 | 42.03 | 35.50 | 30.80 | 25.97 |
| Large-Value | 776 | 15.85 | 20.75 | 24.09 | 28.99 | 33.25 | 29.25 | 23.84 | 20.88 |

## B. Robustness Check: Stock-Selection Timing under Different Market Conditions

As a robustness check, we replicate the analysis in Table VIII for different market conditions: extreme market liquidity and market volatility. The results are reported below in Table B.

## Table B. Stock-Selection Timing under Different Market Conditions (Liquidity and Volatility)

This table reports the cross-sectional distribution of the Newey–West *t*-statistics of the stock-selection timing coefficient estimates of the regression in Table III for all funds and funds in each category during months with top 30% and bottom 30% market liquidity in Panel A and during months with top 30% and bottom 30% market volatility in Panel B.

Panel A. Results for Months with Top 30% and Bottom 30% Market Liquidity

| | No. of Funds | Percentage of Funds in each t-stat Cutoff (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | t≤-2.326 | t≤-1.960 | t≤-1.645 | t≤-1.282 | t≥1.282 | t≥1.645 | t≥1.960 | t≥2.326 |
| | | Months with top 30% market liquidity | | | | | | | |
| All Funds | 3,734 | 12.05 | 14.70 | 17.89 | 21.48 | 35.35 | 28.28 | 22.92 | 17.60 |
| Small-Growth | 1,010 | 10.69 | 12.77 | 15.94 | 19.80 | 36.34 | 28.41 | 23.17 | 17.33 |
| Small-Value | 913 | 12.71 | 15.33 | 19.28 | 23.33 | 35.05 | 28.04 | 23.66 | 17.74 |
| Large-Growth | 919 | 11.10 | 13.93 | 16.43 | 19.47 | 37.21 | 30.36 | 25.24 | 20.67 |
| Large-Value | 892 | 13.90 | 17.04 | 20.18 | 23.54 | 32.62 | 26.23 | 19.51 | 14.58 |
| | | Months with bottom 30% market liquidity | | | | | | | |
| All Funds | 3,709 | 10.03 | 12.94 | 15.91 | 20.63 | 34.51 | 28.50 | 23.78 | 19.47 |
| Small-Growth | 1,005 | 8.26 | 10.95 | 14.03 | 19.20 | 33.33 | 27.86 | 23.18 | 18.01 |
| Small-Value | 904 | 11.95 | 15.15 | 17.59 | 21.90 | 34.40 | 27.99 | 22.90 | 19.47 |
| Large-Growth | 914 | 8.42 | 10.39 | 13.24 | 18.16 | 36.76 | 30.31 | 25.16 | 20.79 |
| Large-Value | 886 | 11.74 | 15.58 | 19.07 | 23.48 | 33.63 | 27.88 | 23.93 | 19.75 |

Panel B. Results for Months with Top 30% and Bottom 30% Market Volatility

| | No. of Funds | Percentage of Funds in each t-stat Cutoff (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | t≤-2.326 | t≤-1.960 | t≤-1.645 | t≤-1.282 | t≥1.282 | t≥1.645 | t≥1.960 | t≥2.326 |
| | | Months with top 30% market volatility | | | | | | | |
| All Funds | 3,489 | 14.33 | 17.68 | 21.07 | 25.77 | 33.39 | 26.91 | 22.76 | 18.43 |
| Small-Growth | 934 | 13.38 | 17.02 | 20.34 | 25.26 | 33.73 | 26.23 | 22.06 | 17.67 |
| Small-Value | 854 | 13.00 | 15.81 | 19.20 | 23.65 | 35.36 | 28.57 | 23.54 | 19.67 |
| Large-Growth | 862 | 15.78 | 18.79 | 21.58 | 26.91 | 32.02 | 26.91 | 22.51 | 17.05 |
| Large-Value | 839 | 15.26 | 19.19 | 23.24 | 27.29 | 32.42 | 25.98 | 23.00 | 19.43 |
| | | Months with bottom 30% market volatility | | | | | | | |
| All Funds | 3,604 | 13.12 | 16.59 | 19.92 | 24.22 | 45.31 | 39.51 | 34.87 | 30.58 |
| Small-Growth | 977 | 13.00 | 16.58 | 19.34 | 24.67 | 45.86 | 40.12 | 35.72 | 30.91 |
| Small-Value | 887 | 15.22 | 18.71 | 21.98 | 26.16 | 44.42 | 39.57 | 22.71 | 29.99 |
| Large-Growth | 884 | 11.31 | 14.71 | 17.54 | 21.04 | 47.05 | 40.61 | 36.99 | 31.13 |
| Large-Value | 856 | 12.97 | 16.36 | 20.91 | 25.00 | 43.81 | 37.62 | 32.94 | 29.21 |

## C. Robustness Check: Economic Significance of Stock-Selection Timing

As a robustness check, we use the average positive CAPM alpha as an alternative measure of stock-selection opportunity and replicate the analysis in Table X. The results are reported below in Table C.

### Table C. Economic Significance of Stock-Selection Timing Based on Average Positive CAPM alpha

At the end of each month, funds are classified as negative or positive timers based on the Newey–West *t*-statistics of the stock-selection timing coefficients estimated over the most recent 12 months. The timing test is based on the regression in Eq. (2). Stock-selection opportunity measure is average positive CAPM alpha, as defined in Table II, and fund activeness measure is turnover, as defined in Table I. The table reports equal-weighted (Panel A) and TNA-weighted (Panel B) raw returns, and three- and four-factor alphas (in percent) of each portfolio over the subsequent three, six, and 12 months, respectively. The sample period was from January 1984 to December 2018.

| | Raw Return | | | FF3 Alpha | | | FF4 Alpha | | |
|---|---|---|---|---|---|---|---|---|---|
| | 3M | 6M | 12M | 3M | 6M | 12M | 3M | 6M | 12M |
| Panel A. Equal-weighted Portfolio Returns | | | | | | | | | |
| Cutoff t = ±1.96 | | | | | | | | | |
| Negative Timer | 2.617 | 5.450 | 11.787 | -0.210 | -0.466 | -0.776 | -0.169 | -0.398 | -0.827 |
| Positive Timer | 2.752 | 5.685 | 12.150 | -0.100 | -0.193 | -0.432 | -0.076 | -0.204 | -0.551 |
| Positive-Negative | 0.136 | 0.235 | 0.364 | 0.110 | 0.274 | 0.344 | 0.093 | 0.194 | 0.276 |
| (t-stat) | (2.15) | (2.78) | (1.99) | (1.97) | (2.58) | (1.98) | (1.95) | (2.42) | (2.09) |
| Cutoff t = ±1.65 | | | | | | | | | |
| Negative Timer | 2.638 | 5.491 | 11.921 | -0.223 | -0.505 | -0.761 | -0.186 | -0.408 | -0.754 |
| Positive Timer | 2.772 | 5.755 | 12.237 | -0.083 | -0.186 | -0.310 | -0.063 | -0.190 | -0.405 |
| Positive-Negative | 0.134 | 0.264 | 0.316 | 0.141 | 0.319 | 0.452 | 0.123 | 0.217 | 0.349 |
| (t-stat) | (2.14) | (2.83) | (2.41) | (2.13) | (3.42) | (2.13) | (2.10) | (2.16) | (1.97) |
| Panel B. TNA-weighted Portfolio Returns | | | | | | | | | |
| Cutoff t = ±1.96 | | | | | | | | | |
| Negative Timer | 2.453 | 5.195 | 11.410 | -0.351 | -0.689 | -1.088 | -0.300 | -0.664 | -1.066 |
| Positive Timer | 2.687 | 5.663 | 11.986 | -0.103 | -0.162 | -0.498 | -0.097 | -0.180 | -0.549 |
| Positive-Negative | 0.234 | 0.468 | 0.576 | 0.248 | 0.527 | 0.590 | 0.203 | 0.483 | 0.517 |
| (t-stat) | (2.88) | (4.05) | (2.98) | (2.76) | (4.17) | (2.52) | (2.10) | (3.67) | (1.97) |
| Cutoff t = ±1.65 | | | | | | | | | |
| Negative Timer | 2.485 | 5.271 | 11.424 | -0.343 | -0.670 | -1.161 | -0.291 | -0.635 | -1.101 |
| Positive Timer | 2.718 | 5.687 | 11.928 | -0.094 | -0.183 | -0.529 | -0.080 | -0.170 | -0.538 |
| Positive-Negative | 0.233 | 0.417 | 0.504 | 0.249 | 0.489 | 0.632 | 0.211 | 0.465 | 0.563 |
| (t-stat) | (3.25) | (3.91) | (2.94) | (3.17) | (4.21) | (2.95) | (2.50) | (3.92) | (2.32) |

### D. Stock-Selection Timing and Fund Flow

For each fund, we follow the literature (Evans and Fahlenbrach, 2012; Jiang and Yuksel, 2017) to identify retail and institutional funds and compute retail flow and institutional flow separately. We first use the CRSP Mutual Fund Database investor classifications (*retail_fund*, *inst_fund*) to classify funds into either institutional or retail funds. Since the CRSP investor classifications are only available after December 1999, we then backfill the CRSP investor classifications for funds that are in the database after December 1999. Finally, we complement our backfill procedure by implementing a text algorithm to further identify fund types based on fund names. Examples of keywords include "institutional class," "/instl," "/inst," "retail share," "/retail," "consumer," "b shares," "class c," "class a," etc. We examine fund flows for positive and negative stock-selection timers. The results are reported in Table D.

### Table D. Stock-Selection Timing and Fund Flow

At the end of each month, funds are classified as negative or positive timers based on the Newey–West *t*-statistics of the stock-selection timing coefficients estimated over the most recent 12 months. The cutoff of *t*-statistics is ±1.65. The timing test is based on the regression as well as the stock-selection opportunity and fund activeness measures used in Table III. This table reports equal-weighted fund flows over months *t*, *t*-1, *t*+1, [*t*-3, *t*-1], and [*t*+1, *t*+3]. The normalized fund flow is also decomposed into institutional flow and retail flow. The differences between positive and negative timers as well as their Newey–West *t*-statistics are also reported. Fund flows are performance-adjusted. The sample period was from January 1984 to December 2018.

| | Last quarter | Last month | Current month | Next month | Next quarter |
|---|---|---|---|---|---|
| | | | Fund flow | | |
| Negative Timer | -0.17 | -0.10 | -0.18 | -0.23 | -0.61 |
| Positive Timer | 0.07 | 0.00 | 0.06 | -0.08 | -0.18 |
| Positive-Negative | 0.24 | 0.10 | 0.24 | 0.15 | 0.43 |
| (t-stat) | (1.12) | (0.93) | (2.26) | (1.67) | (2.36) |
| | | | Retail Flow | | |
| Negative Timer | -0.60 | -0.21 | -0.29 | -0.28 | -0.84 |
| Positive Timer | -0.46 | -0.16 | -0.15 | -0.23 | -0.63 |
| Positive-Negative | 0.14 | 0.05 | 0.14 | 0.06 | 0.22 |
| (t-stat) | (0.89) | (0.75) | (2.14) | (0.87) | (1.71) |
| | | | Institution Flow | | |
| Negative Timer | 0.43 | 0.12 | 0.11 | 0.05 | 0.23 |
| Positive Timer | 0.53 | 0.17 | 0.21 | 0.14 | 0.45 |
| Positive-Negative | 0.10 | 0.05 | 0.10 | 0.09 | 0.22 |
| (t-stat) | (1.55) | (0.68) | (1.66) | (1.80) | (2.07) |

## E. Robustness Check: Stock-selection Timing versus Stock-picking

As a robustness check, we use the managerial ability measure developed by Daniel, Grinblatt, Titman, and Wermers (1997) as an alternative measure of stock-picking ability and replicate the analysis in Table XI. A fund's stock-picking ability, namely the Characteristic Selectivity (CS) measure, is defined as follows:

$$CS_t = \sum_{j=1}^{N} \widetilde{\omega}_{j,t-1} \left( \tilde{R}_{j,t+1} - \tilde{R}_t^{b_{j,t-1}} \right),$$

where $\widetilde{\omega}_{j,t-1}$ is the portfolio weight on stock *j* at the end of month *t*-1; $\tilde{R}_{j,t}$ is the month *t* buy-and-hold return of stock *j*; and $\tilde{R}_t^{b_{j,t-1}}$ is the month *t* buy-and-hold return of the value-weighted matching benchmark portfolio. The matching benchmark portfolios are defined per Daniel, Grinblatt, Titman, and Wermers (1997). The results are reported below in Table E.

## Table E. Stock-Selection Timing versus Stock-Picking Ability: Alternative Measure of Stock-Picking

This table reports the economic significance of stock-selection timing after controlling for stock-picking ability. Each month, we sort funds based on stock-picking ability into low, medium, and high stock-picking groups. Within each stock-picking group, we further identify negative and positive stock-selection timers based on the Newey–West *t*-statistic cutoff of ±1.96. The table reports equal-weighted raw returns, three- and four-factor alphas (in percent) of each portfolio and the average returns and alphas of negative and positive stock-selection timers across different stock-picking groups over the subsequent three, six, and 12 months. The differences between positive and negative timers as well as their Newey–West *t*-statistics are also reported. A fund's stock-picking ability is defined as the Characteristic Selectivity (CS) measure according to Daniel, Grinblatt, Titman, and Wermers (1997). The sample period was from January 1984 to December 2018.

| Stock-Picking | Raw Return | | | 3-Factor Alpha | | | 4-Factor Alpha | | |
|---|---|---|---|---|---|---|---|---|---|
| | Negative Timers | Positive Timers | Positive-Negative | Negative Timers | Positive Timers | Positive-Negative | Negative Timers | Positive Timers | Positive-Negative |
| | | | | Three-month Horizon | | | | | |
| Low | 1.347 | 1.466 | 0.119 (1.78) | -1.305 | -1.191 | 0.114 (1.59) | -1.282 | -1.229 | 0.054 (1.34) |
| Medium | 2.322 | 2.388 | 0.065 (1.38) | -0.199 | -0.081 | 0.118 (1.75) | -0.141 | -0.025 | 0.116 (1.65) |
| High | 3.318 | 3.376 | 0.058 (1.21) | 0.820 | 0.904 | 0.084 (1.02) | 0.855 | 0.936 | 0.080 (0.88) |
| Average | 2.410 | 2.812 | 0.081 (1.60) | -0.228 | -0.122 | 0.105 (1.31) | -0.190 | -0.106 | 0.084 (0.95) |
| | | | | Six-month Horizon | | | | | |
| Low | 3.428 | 3.731 | 0.305 (2.05) | -1.990 | -1.683 | 0.308 (2.11) | -1.911 | -1.747 | 0.164 (1.88) |
| Medium | 4.437 | 4.680 | 0.244 (1.97) | -0.772 | -0.471 | 0.301 (2.33) | -0.642 | -0.430 | 0.213 (1.92) |
| High | 5.616 | 5.779 | 0.163 (1.76) | 0.394 | 0.589 | 0.195 (1.73) | 0.515 | 0.591 | 0.076 (1.52) |
| Average | 4.493 | 4.730 | 0.237 (1.96) | -0.790 | -0.522 | 0.268 (2.35) | -0.679 | -0.528 | 0.151 (1.61) |
| | | | | 12-month Horizon | | | | | |
| Low | 8.296 | 8.306 | 0.011 (0.94) | -3.374 | -3.382 | -0.008 (-0.53) | -3.294 | -3.578 | -0.283 (-1.20) |
| Medium | 9.231 | 9.466 | 0.235 (1.76) | -2.136 | -1.898 | 0.239 (1.88) | -1.984 | -1.857 | 0.127 (1.54) |
| High | 10.423 | 10.768 | 0.345 (2.05) | -1.027 | -0.554 | 0.474 (2.29) | -0.876 | -0.541 | 0.335 (1.94) |
| Average | 9.312 | 9.513 | 0.197 (1.69) | -2.179 | -1.944 | 0.235 (2.16) | -2.038 | -2.025 | 0.129 (0.76) |