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Holding Horizon: A New Measure of Active Investment Management

Chunhua Lan
University of New Brunswick Faculty of Management
clan@unb.ca

Fabio Moneta
University of Ottawa Telfer School of Management
fmoneta@uottawa.ca

Russ Wermers
University of Maryland at College Park Smith School of Business
wermers@umd.edu

Abstract

This article introduces a new holding horizon measure of active management and examines its relation to future risk-adjusted fund performance (alpha). Our measure reveals a wide cross-sectional dispersion in mutual fund investment horizons, and shows that long-horizon funds exhibit positive future long-term alphas by holding stocks with superior long-term fundamentals. Further, stocks largely held by long-horizon funds outperform stocks largely held by short-horizon funds by more than 3% annually, adjusted for risk, over the following 5-year period. We also find a clientele effect: to reduce liquidity costs, long-horizon funds attract more long-term investors through share classes that carry load fees.

I. Introduction

Both theory and empirical evidence suggest that the open-ended structure of mutual funds imposes binding constraints on implementing long-term arbitrage opportunities, as funds are exposed to the risk of investor outflows if they perform poorly over the short run.[1] As a large portion of investment capital in financial

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[1]See, for example, Chevalier and Ellison (1997) and Sirri and Tufano (1998) for evidence of the tendency of investors in mutual funds to sell following poor short-term returns. Also, see Shleifer and Vishny (1997) and Stein (2005) for theory models on the limits of arbitrage in capital markets.

markets, whether and how actively managed mutual funds engage in long-term investing is important, but has, to date, been left largely unexplored.

Theoretical models indicate that portfolio managers who pursue long-term investing opportunities are more likely to possess superior skills in forecasting long-term cash flows (e.g., Wang (1993)). Such skills require superior insights about the future prospects of a firm's major projects, the competitive position of the firm's products, and the strength of the firm's balance sheet.[2] Committing to long-term positions in response to these long-term forecasts can expose management companies and their fund managers to short-term risks due to the above-noted investment behavior of fund investors.[3] Therefore, it is reasonable to expect that only funds with a sufficient level of skills in generating long-run returns (high enough to offset such short-term concerns) will follow a long-holding strategy.

We should also expect that funds pursuing long-term opportunities are more likely to cater to "patient" investors who do not overly react to short-run returns. As Edelen (1999) shows, nondiscretionary trading due to mutual fund investor flows can reduce fund performance significantly; such trading is even more costly for funds relying on long-term strategies (Chordia (1996)). Accordingly, as Nanda, Narayanan, and Warther's (2000) theoretical model predicts, fund managers compete for investors with a low probability of liquidity needs; because such long-term investors are relatively scarce, fund managers with higher skills are better positioned to share economic rents with long-term investors, and to charge load fees to deter short-term investors.

In this article, we construct a unique and simple-to-measure point-in-time fund "holding horizon." In doing so, we find a wide cross-sectional dispersion in investment horizon among U.S.-domiciled, actively managed equity mutual funds. Importantly, we find that funds with a long investment horizon exhibit positive future long-term net alphas attributable to their superior skills in exploiting long-term firm fundamentals, and that they cater to a greater number of long-term investors by managing more AUM that charges load fees.

Key to our empirical design is our fund-level holding horizon (H–H) measure. Each quarter, we calculate the holding period of a stock held by a fund as the length of time from the initiation of a position in that stock to the current quarter, with nonzero holdings in the interim. A fund's H–H is then calculated as the portfolio-weighted holding period of all stocks held by the fund. This measure reflects the slow-trading motivation of Kyle, Obizhaeva, and Wang (2018) for an investor with long-term private information, who will optimally trade her portfolio slowly in

[2]Anecdotally, Warren Buffett, a student and follower of Benjamin Graham (who is considered, by many, to be the father of value investing) is widely known to focus on long-term growth, and to invest in quality firms with strong fundamentals. He famously stated that his "favorite holding period is forever."

[3]Froot, Scharfstein, and Stein (1992) provide a model where investment managers exploit the same signal when it may be socially optimal for them not to do so, due to short-term performance concerns. With short-term risk, such investment managers can be expected to follow, in common, lower-NPV signals that resolve more quickly relative to higher-NPV signals that resolve more slowly. Although Froot et al. (1992) is focused on the labor risk of individual portfolio managers, it can also be reasonably interpreted to apply to the labor risk of executives of investment management companies, who depend on short-term fee income for their compensation and employment, and who set compensation contracts for their portfolio managers.

financial markets, controlling for the price impact of trades, to exploit that the stock price has not fully reflected her private information. Our measure considers all trades of a given stock (from position initiation until liquidation) as being part of a unified strategy. In doing so, it recognizes that, should a manager update her belief about a stock—either following or beyond the pure price impact motivation outlined in Kyle et al. (2018)—the portfolio weight of the stock will change, which will affect the fund-level H–H measure. Our weighted-average holding horizon of stocks in a mutual fund is designed to be an ex ante proxy for a fund's intended holding period of its stocks.

When comparing the H–H measure of different funds, we control for fund investment objectives; funds with different investment objectives typically focus on different pools of stocks, which plausibly involve different "optimal" holding periods, even for the same management company. This design is motivated by Barberis and Shleifer (2003) and industry practice that compare a fund with its particular style benchmark. Following Hunter, Kandel, Kandel, and Wermers (2014), we assign the point-in-time "best-fit" index of Cremers and Petajisto (2009) to each fund as its benchmark. In doing so, we find that value (large-cap) funds have a longer investment horizon, on average, than growth (small- and mid-cap) funds. We then classify a fund as long- or short-horizon using a style-adjusted fund holding horizon, calculated as that fund's holding horizon, in excess of the (equal-weighted) average holding horizon of all funds with the same best-fit benchmark (i.e., the same investment style) as that fund.[4]

Using our style-adjusted H–H measure, we find a wide cross-sectional dispersion of fund-holding horizons. For example, funds in the shortest H–H quintile, on average, hold stocks for 1.1 years, whereas funds in the longest H–H quintile hold stocks for 4.8 years. Moreover, consistent with the prediction of Kyle et al. (2018), long-horizon funds take much longer, more than 1.5 years, on average, to build (or decrease) their positions in a particular stock, compared with short-horizon funds, which take only a few months.

To study the fund horizon-performance relation, we focus on fund abnormal returns—Carhart (1997) 4-factor net return alphas and DGTW-adjusted returns (prior to expenses and transaction costs) using Daniel, Grinblatt, Titman, and Wermers (1997) benchmarks—over various future return measurement horizons, ranging from 1 month to 5 years. We find that funds in the longest H–H decile achieve significantly positive 4-factor net alphas at a horizon of one quarter or longer, and significantly positive DGTW-adjusted returns at all future horizons. For example, risk-adjusted fund returns are 7% to 9% over a 5-year horizon, depending on the asset-pricing model; in addition, these risk-adjusted returns are 5% to 12% higher than those of funds in the shortest H–H decile. Notably, the outperformance of long H–H funds is higher among those having a larger asset-weighted proportion of share classes charging load fees, consistent with Nanda et al.'s (2000) equilibrium between loads and returns in the presence of heterogeneous investors in open-end funds. Moreover, long H–H funds exhibit significant long-term alphas, even after we control for other measures of fund activeness and various fund and stock characteristics.

[4]We reproduce our main results using an analogous H–H measure that is not style-adjusted; here we find results qualitatively similar to those using our style-adjusted H–H measure, albeit statistically weaker.

Further, we examine Berk and van Binsbergen's (2015) value-added measure, which accounts for fund scale in measuring manager skills. We find that the average fund in the longest H–H decile extracts value-added from financial markets of \$26 million and \$183 million over 1- and 5-year periods, respectively; both are statistically and economically significant. These extracted dollar values are \$25 million and \$181 million, respectively, higher than those extracted by the average fund in the shortest decile. This evidence further suggests that long-horizon funds are skillful.

We also address the possibility that long-horizon funds are merely "closet indexers," staying close to their benchmarks without trading for long periods of time. As evidence against this, we find that long- and short-horizon funds exhibit a similar level of "activeness," in terms of prior-documented measures, including Active Share (Cremers and Petajisto (2009)), R^2 (Amihud and Goyenko (2013)), and return gap (Kacperczyk, Sialm, and Zheng (2008)). Further, in a multivariate regression setting, we find that the variability of H–H cannot be explained by these prior measures, nor with other fund and stock characteristics. Thus, long-horizon funds are not simply passive funds that represent themselves as active funds, nor is H–H simply a proxy for these other measures of activeness. As further evidence, the strong fund horizon-performance relation that we find disappears in a sample of "closet indexers," identified using Active Share as in Cremers and Petajisto (2009).

At the stock level, after aggregating the consensus opinion of the value of a stock from long- and short- horizon funds separately, we find that stocks largely held by long-horizon funds, relative to short-horizon funds, exhibit superior future long-term buy-and-hold abnormal returns (either 4-factor or DGTW-adjusted); this finding yields a potential "quant signal" to exploit stock alphas. For instance, stocks held largely by long-horizon funds exhibit an 18.2% buy-and-hold 4-factor alpha over the following 5 years, 17.9% (3.6% per year) higher than that for stocks held largely by short-horizon funds; both are statistically and economically significant. Further, we find that long-horizon funds achieve their superior long-term performance mainly from their long-term equity positions, as opposed to their short-term positions, consistent with a long-term strategy for at least part of their portfolios.

We further explore the economic sources (stock fundamentals) of long-horizon funds' stock-selection skills. We measure information shocks to firm fundamentals using four different variables: cash-flow news (CF_NEWS), consensus analyst earnings forecast revisions (FRV), earnings-announcement-window returns (EAR), and market-adjusted EAR. We find that stocks held largely by long-horizon funds are associated with significantly positive long-term CF_NEWS, FRV, EAR, and adjusted EAR, much higher than those of stocks held largely by short-horizon funds. This finding indicates that long-horizon fund managers are better skilled in analyzing long-term firm fundamentals.

Finally, we explore the real-time efficacy of using H–H to predict long-term mutual fund alphas. To do so, we employ a recursive out-of-sample approach to evaluate the ex ante predictive ability of our H–H measure, along with eight other leading predictors proposed by prior research for mutual fund alpha forecasting. Here, we find that a real-time investor frequently picks H–H amid the set of eight other leading predictors available for fund selection, using carefully designed backtests. We also find that adding H–H to this list of eight other predictors improves out-of-sample fund performance, compared with the same set when H–H is excluded. These results suggest that our H–H measure is an important ex ante predictor, and that employing it, even among other strong fund return predictors, provides better out-of-sample mutual fund performance.

Our article makes three contributions to mutual fund studies. First, we introduce a new measure of a fund's holding horizon. Prior research has uncovered several metrics that can add value to managed assets, such as peer track records (Cohen, Coval, and Pástor (2005)), industry concentration and return gap (Kacperczyk, Sialm, and Zheng (2005), Kacperczyk et al. (2008)), network connections (Cohen, Frazzini, and Malloy (2008)), Active Share (Cremers and Petajisto (2009)), and R^2 from benchmark regressions (Amihud and Goyenko (2013)). Although this prior research examines the value added from actively managed mutual funds, its empirical evidence generally focuses on short-term investing strategies and performance. This short-term focus, usually over 1-year (or shorter) horizons, is consistent with the short-term incentives faced by active mutual funds. In contrast, our article is the first, to our knowledge, to provide empirical evidence focusing on long-term performance (up to 5 years) among actively managed equity mutual funds.

Second, our article provides empirical evidence that long-term investing is an important technique used by many mutual funds, and is rewarded. Our evidence indicates that these long-horizon funds use their insights about firms' future long-term fundamentals to forecast stock prices. Also, our finding that long-horizon funds are more skillful and are able to provide positive net alpha to attract more long-term investors lends empirical support to Nanda et al.'s (2000) theoretical prediction.

Third, this article shows that, despite being a simple statistic of trading activity, (the inverse of) reported fund turnover is a flawed and downward-biased proxy of a fund's investment horizon due to Jensen's inequality.[5] Because funds with high turnover have short investment horizons, in general, prior research uses fund turnover as a proxy for either trading activity (e.g., Grinblatt and Titman (1993), Carhart (1997), Wermers (2000), and Pástor, Stambaugh, and Taylor (2017)) or (inverse) investment horizon (e.g., Gaspar, Massa, and Matos (2005), Yan and Zhang (2009)). We find that the correlation of fund turnover and H–H, however, is relatively small, at about −45%. Using our H–H measure, we identify significant cross-sectional differences in fund performance, as opposed to the time-series variation in performance for a fund that is identified by Pástor et al. (2017) using reported fund turnover.

We compare our H–H measure with the measures of Cremers and Pareek (2016). Cremers and Pareek find that investment managers with a high Active Share (Cremers and Petajisto (2009)) perform better if they implement "patient" strategies. Patient strategies are captured by either a low turnover ratio or a long portfolio-average "duration" of stockholdings. Their duration measure treats each buy of a fund (of the same stock) over time as having a different intended holding period, while our H–H measure treats all trades of the stock (until it is completely

[5]As we show in Section VI, the greater the dispersion in the holding period of stocks, across stocks within a fund portfolio, the greater the downward bias in the inverse of the turnover ratio as a proxy of holding horizon. This bias substantially affects the cross-section of funds, as different funds have very different levels of dispersion in the horizon over which they hold individual stocks in their portfolios.

liquidated) as being part of a unified strategy. As a result, when a manager increases a stock's position due to an updated belief, ceteris paribus, a fund's H–H measure, as expected, becomes longer, but its duration measure becomes shorter, as the holding duration of a newly added position of the stock is shortened, and so is the time-averaged period that the stock has been held across all transactions. As further evidence, when our H–H measure and duration both are included to explain future risk-adjusted fund returns, the duration measure loses its power, while the predictability of H–H remains strong. Further, Active Share exhibits style category biases, as argued by Frazzini, Friedman, and Pomorski (2016). We find that Active Share interacted with duration (or fund turnover) also exhibits such biases; its forecasting power disappears after conditioning on fund benchmark groups, while the predictability of our H–H measure is still strong.

II. Methodology

This section introduces our new holdings-based measure of investment horizon. It then discusses the approaches that we use to examine the relation of investment horizon with performance.

A. The Measure of Holding Horizon

Based on mutual fund holdings, we compute the fund holding horizon (H–H) measure as the value-weighted holding period of all stocks held by a fund at the end of a particular period, t. H–H calculates the holding horizon of a stock in a given fund portfolio as the time span with nonzero holdings of that stock; the length of time from the initiation of a position to the end of period t.[6] With our measure, as long as a manager holds a long position in a stock, we consider her outlook for the stock to be positive; the strength of this positive outlook is determined by the portfolio weight of the stock, as described below in equation (2).

Let θ_j be the date that is 5 years after the initiation date of fund j (or, if the fund existed at the beginning of our sample period, 5 years after that date). The use of this 5-year "warm-up" period allows us to observe the holding period of stocks in a fund portfolio through reported periodic portfolio holdings.[7] Let $h_{i,j,t}$ denote the holding horizon of stock i held by fund j at the end of period t, then

$$h_{i,j,t} = \begin{cases} t-k+1, & \text{for } k \le t \text{ and } t > \theta_j \\ 0, & \text{otherwise,} \end{cases} \tag{1}$$

where the stock is initially purchased during period k.

[6]Because mutual fund holdings are typically reported quarterly (or, at the beginning of our sample period, semi-annually), we do not observe the exact date of the purchase or sale of a stock. Following the mutual fund literature, we assume that such a trade occurs at the beginning of a period. However, our results do not rely on this assumption, and are robust to alternative assumptions that the purchase or sale of a stock occurs in the middle or the end (one day before a holdings report date) of a period.

[7]Constructing the H–H measure with a 2-, 3-, or 7-year warm-up period results in a measure that is highly correlated with the 5-year version we use; the correlation with each alternative measure equals 99%. Thus, we believe that a 5-year period is sufficiently long.

Our "first-buy-to-current-period" metric captures the empirical prediction of the smooth trading theory of Kyle et al. (KOW) (2018). In the KOW model, an investor with private information trades optimally to exploit her information while minimizing "telegraphing" her information to the market through trades. The KOW model predicts that a fund manager with longer-term private information will strategically trade slowly over time, in markets with limited depth, rather than implementing her trades quickly. The KOW theory is especially relevant in the case of equity mutual funds with large stock holdings, as their desired positions are often massive, compared to the daily trading volume of a stock. So, we can expect superior active managers to trade their large desired positions gradually over time as they exhibit care to minimize market impact.

This slower trading of large positions is also reflected in our measure of fund-level holding horizon, which is calculated as the value-weighted holding period of all stocks held by the fund. Specifically,

$$\text{(2)} \qquad \text{H–H}_{j,t} = \sum_{i=1}^{M_{j,t}} \omega_{i,j,t} h_{i,j,t},$$

where $M_{j,t}$ is the number of stocks held by fund j at the end of period t, and $\omega_{i,j,t}$ is the portfolio weight of stock i in fund j at the end of t. $\omega_{i,j,t}$ is computed as the number of shares of stock i held by fund j at the end of t multiplied by the stock price, then divided by the market value of the equity portfolio of fund j at that date.

Motivated by Barberis and Shleifer (2003) and industry practice that compare a fund with its benchmark, when comparing the holding horizon of different funds, we further account for fund investment objectives and styles. Funds with different investment objectives and styles typically focus on different pools of stocks. If their "best ideas" are selected from different pools, their optimal holding periods are likely to be different because of differential firm fundamentals and discount rates associated with these different style categories. As an example, we find that the median fund in the large-capitalization value category has an H–H of 2.5 years (averaged over all event quarters), while mid-capitalization growth funds have a median H–H of 1.6 years. These differences likely reflect the relative horizons over which funds in different categories generate their forecasts of future cashflows and discount rates.

Following Hunter et al. (2014), we consider nine style categories of funds, according to whether funds are of large-capitalization (with benchmark Russell 1000 Value, Russell 1000, or Russell 1000 Growth), mid-capitalization (with benchmark Russell Midcap Value, Russell Midcap, or Russell Midcap Growth), or small-capitalization (with benchmark Russell 2000 Value, Russell 2000, or Russell 2000 Growth). See Section A1 of the Supplementary Material for details. This classification of fund investment styles not only keeps a reasonably large number of funds in each category, which reduces noise in calculating the average investment horizon for each style, but also avoids the agency issues caused by the use of misleading self-claimed benchmarks (Sensoy (2009)). A fund's style-adjusted H–H measure is then calculated as that fund's holding horizon, in excess of the average holding horizon of all funds with the same investment style as that fund. For robustness, in Section VIII.E, we conduct our basic tests using

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an unadjusted version of the H–H measure; the results are similar, although slightly weaker.

As a robustness check, we also consider the duration measure implemented by Cremers and Pareek (CP) (2016). In CP, a fund's duration is the value-weighted stock-level duration across all stocks held by a fund; the duration of each stock held by a fund is calculated as the time-weighted buys and sells by the fund (of all buys and sells of that stock) over the past 5 years. This duration measure treats each buy of a fund (of the same stock) over time as having a different intended holding period, while our H–H measure treats all trades of the stock (until it is completely liquidated) as being part of a unified strategy. As a result, when a manager increases a stock's position because her signal updates positively, ceteris paribus, a fund's H–H measure, as expected, becomes longer, but its CP duration becomes shorter, as the holding duration of a newly added position of the stock is shortened and so is the time-averaged period that the stock has been held across all transactions (see equation (A-2) and discussions of the Supplementary Material). Simply put, the CP duration mechanically captures realized holding duration (of various trades over time),[8] whereas our H–H metric better measures the intended holding period through viewing all trades of a stock as part of a unified strategy.

We also note that, when both the H–H and CP duration measures are included to explain future risk-adjusted fund returns, the CP duration measure loses its explanatory power, while the predictability of H–H remains strong (see Table A1 in the Supplementary Material). Further comparisons of the predictive power of H–H versus CP proposed variables will be discussed in Section VIII.D.

B. Risk Models

We first use a sorted-portfolio approach to study the relation between fund H–H and performance. In our fund-level analysis, after sorting funds into deciles at the end of each month, we calculate buy-and-hold decile-portfolio returns over the next n periods, ranging from 1 month to 5 years. These portfolios are equal- or value-weighted in the formation month, then carried through the look-ahead return measurement horizon by following a buy-and-hold strategy; if funds drop out during the measurement horizon, we adjust the weights of the remaining funds in the decile by dividing each by one minus the weight of the disappearing funds.

Then, we average these buy-and-hold returns across all formation months for each decile and for each look-ahead return measurement horizon, n. To calculate standard errors, we apply a Newey–West approach with a lag of $n-1$ to account for autocorrelation and heteroskedasticity. This monthly portfolio formation strategy with the resultant overlapping windows improves the statistical power of our tests for multiperiod portfolio returns (Richardson and Smith (1991)).

We also calculate risk-adjusted abnormal returns using the CAPM (Jensen (1968)), the Carhart (1997) 4-factor model, and the holdings-based characteristic model of DGTW and Wermers (2004) to control for the exposures to market, size, value, and momentum factors. The alphas and DGTW-adjusted returns reflect

[8]The CP duration is also susceptible to informationless short-term trades, such as window dressing (Haugen and Lakonishok (1988), Ritter and Chopra (1989)), portfolio pumping (Carhart, Kaniel, Musto, and Reed (2002)), and flow-driven trades (Alexander, Cici, and Gibson (2007)).

investment returns after accounting for risk. Again, we employ Newey–West standard errors to account for autocorrelation and heteroskedasticity when inferring statistical significance of these abnormal returns.

To obtain alphas, we first follow Fama and French (1993) and the description of data construction from Kenneth French's website to construct four factors over a return measurement horizon of interest. For each component portfolio that is used to construct Carhart's four factors, we calculate its buy-and-hold return over a horizon of interest. Then, analogous to the construction of the monthly factors, we calculate 4-factor returns with different horizons ranging from 1 month to 5 years.

Specifically, we calculate market excess returns at horizon n as the difference between n-period compounded market returns and n-period compounded 1-month T-bill rates. Next, we compute n-period buy-and-hold returns for each of 2×3 size- and book-to-market (BM)-sorted portfolios.[9] Similar to Kamara, Korajczyk, Lou, and Sadka (2016), the size factor (SMB) at horizon n is the average of n-period compounded returns of small value portfolios, small medium portfolios, and small growth portfolios, minus the average of n-period compounded returns of big value portfolios, big medium portfolios, and big growth portfolios. The value factor (HML) at horizon n is the average of n-period compounded returns of small value portfolios and big value portfolios, minus the average of n-period compounded returns of small growth portfolios and big growth portfolios. Similarly, we compute n-period buy-and-hold returns for each of 2×3 portfolios sorted on size and cumulative returns over prior 2–12 months.[10] The momentum factor (MOM) at horizon n is then calculated as the average of n-period compounded returns of small winner portfolios and big winner portfolios, minus the average of n-period compounded returns of small loser portfolios and big loser portfolios. The CAPM and 4-factor alphas at horizon n are calculated as the intercepts of the regressions of n-period compounded fund net returns, in excess of n-period compounded 1-month T-bill rates, on the corresponding market excess returns and Carhart four factor returns, respectively, at horizon n.

Using n-period compounded returns in regressions has the advantage of obtaining unbiased estimates of n-period alphas because alphas and betas are likely to depend on return measurement horizon. As Levhari and Levy (1977) and Bessembinder, Cooper, and Zhang (2022) show, even under a simple assumption that returns conform to an IID process in the absence of estimation error, multi-period alphas and betas are nonlinear functions of 1-period alphas and betas for the CAPM. The complexity of actual return-generating processes, in addition to

[9]Following Fama and French (1993), size is computed as the market cap at the end of the most recent June of year t; the BM ratio is computed as the book value of equity for the fiscal year ending in year $t-1$ divided by the market cap in Dec. of $t-1$. Each June we sort common stocks into small and big according to the median NYSE size breakpoint, and, separately, sort stocks into growth, medium, and value according to the 30th and 70th NYSE BM percentiles. Note that we calculate buy-and-hold returns of these six portfolios over n periods starting from month m, where these portfolios are formed in the most recent June.

[10]Following the momentum construction at Kenneth French's website, each month, we sort common stocks into small and big according to their size using the median NYSE size breakpoint, where size is computed as the market cap at the end of the last month. Each month, we separately sort stocks into loser, medium, and winner according to their prior (2,12)-month cumulative returns using the 30th and 70th NYSE percentiles.

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estimation error, likely further complicates the nonlinear relations between multiperiod regression parameter estimates and 1-period estimates. Nevertheless, using overlapping n-period compounded returns encounters an issue of small sample sizes because there are fewer effective nonoverlapping observations for running a regression as return measurement horizon increases.[11] To address this issue, we also draw statistical inference for multiperiod alpha estimates based on empirical distributions via bootstrap simulations that attempt to capture the small-sample size issue and consider a possible nonlinear relation between multiperiod and 1-period alphas. We also adopt Jegadeesh and Titman's (1993) method to estimate n-period alphas by employing average monthly returns across H–H decile portfolios that are constructed over each of past n periods.[12] These alternative analyses and tests produce results in accordance with our baseline findings.

As robustness checks, we also control for risk exposure using three different models: the Pástor and Stambaugh (2003) liquidity factor or the De Bondt and Thaler (1985) long-term reversal factor in addition to the Carhart four factors, as well as Fama and French (2015) five factors (including the market, size, value, investment, and profitability factors) along with the momentum factor. Our results are robust to all these models used to control for risk.

To obtain DGTW-adjusted returns, we first calculate a stock's DGTW benchmark return.[13] In doing so, we reconstitute DGTW benchmark portfolios every quarter instead of every June to better control for changing stock characteristics (Wermers (2004)). We calculate a fund's holdings-based return as value-weighted stock returns across all stocks held by the fund using the fund's portfolio weight at the beginning of a month; similarly, we calculate a fund's DGTW benchmark return by replacing its constituent stocks' returns with the stocks' DGTW benchmark returns. To obtain DGTW-adjusted returns over n periods for a portfolio, we compound n-period DGTW benchmark returns for the portfolio, then subtract them from n-period compounded returns of the portfolio.

Finally, to measure managerial skill we compute the "value-added" measure of Berk and van Binsbergen (2015). It is computed as the benchmark-adjusted gross return times the last-month-end inflation-adjusted total net asset, where a fund's gross return is equal to its net return plus a monthly estimate of the fees charged by the fund, and its benchmark return is constructed from a set of Vanguard index funds by following the procedure proposed by Berk and van Binsbergen. The value-added measure represents the value a fund manager obtained from financial markets and

[11]Boudoukh, Israel, and Richardson (2019) show that using overlapping compounded returns over a long horizon helps improve the statistical power of tests but its efficiency gain is quite limited.

[12]Although Jegadeesh and Titman's (1993) method helps mitigate the small-sample size issue, multiperiod alphas estimated using this method may not capture the nonlinearity of multiperiod alphas and betas inherited from dynamics of compounded returns, in which a buy-and-hold investor is interested, with respect to 1-period alphas and betas.

[13]Specifically, we sort, at the end of each quarter, all common stocks into 125 $(5 \times 5 \times 5)$ benchmark portfolios using a sequential triple-sorting procedure based on size, BM ratio, and momentum. Size is the market cap at the end of the quarter (using NYSE breakpoints when sorting). BM is computed as the book value of equity for the most recently reported fiscal year divided by the quarter-end market cap. Momentum is the 12-month return ending 1 month prior to the quarter-end. The DGTW benchmark return for a stock is the value-weighted average return of one of 125 DGTW portfolios to which the stock belongs.

added to her fund portfolio. One of the advantages of this measure is to account for the scale of the assets under management. We note that value-weighted fund-level alphas are more related with the notion of value-added than equal-weighted alphas. That is, the value-weighted fund-level alphas represent the alpha for an investor who splits $1 into each fund in proportion to that fund's AUM. Since both alphas produce similar results, we report those using value-weighted fund-level alphas in most of our various tests and those using equal-weighted alphas in only a few tests for comparison.

III. Data and Summary Statistics

Our data for U.S. actively managed equity mutual funds come from the intersection of the Thomson Reuters mutual fund holdings database (s12) and the CRSP mutual fund database. These two databases are linked using MFLINKS from Wharton Research Data Services (WRDS). Thomson Reuters provides reliable information on equity mutual fund holdings of common stocks at a quarterly or semiannual frequency. CRSP provides information on mutual fund net returns, total net assets (TNA), and several fund characteristics such as expense ratio and turnover ratio. The information provided by CRSP is at the share class level. We therefore calculate value-weighted fund net returns and fund characteristics across multiple share classes within a fund using the latest share class TNA as weights, except that fund age is calculated based on the oldest share class and TNA as the sum of net assets across all share classes pertaining to the same fund. For the sample selection, we follow the procedure of Kacperczyk et al. (2008). In particular, we exclude funds that do not invest primarily in equity securities, funds that hold fewer than 10 stocks, and those that, in the previous month, manage assets of less than $20 million. Finally, we exclude index funds using fund names, index flag, as well as the sample of index funds identified by Cremers and Petajisto (2009). See more details in Section A3 of the Supplementary Material.

Our final sample includes 2,918 unique equity funds with valid H–H measure. Return data end in Dec. 2020; the H–H measure starts in Dec. 1984 and ends in Dec. 2015 given that we examine up to 5-year-ahead performance.[14] Stock returns, prices, and shares outstanding are obtained from CRSP. Accounting data, such as earnings, come from Compustat. Analyst earnings forecasts come from the Institutional Broker's Estimate System (IBES) summary unadjusted file.

A. Summary Statistics

Panel A of Table 1 reports summary statistics for our mutual fund sample. On average, equity mutual funds hold stocks with total net assets of $1.5 billion, with a median (average) H–H of 2.18 (2.52) years.[15]

[14]Our fund holdings data starts in 1980. Because of the 5-year warm-up period needed for the construction of H–H, the H–H measure actually starts in Dec. 1984.

[15]We have also computed a version of the H–H measure that uses the entire history of a fund's holdings that is available to us to estimate the H–H of that fund, rather than the ex ante version that we prefer. While this "ex post H–H" has a longer median (average) of 3.57 (4.05) years, the cross-sectional correlation between our H–H measure and its "ex post" counterpart is 0.89.

The median (mean) CRSP reported turnover ratio (also available from other mutual fund databases, such as Morningstar, or from SEC filings) is 62% (80%), which is defined as

$$\text{CRSP\_TR} = \frac{\min(\$\text{buys}, \$\text{sells})}{\text{Average TNA}}$$

during a fund's fiscal year.

To examine the investment preferences of funds, we first calculate the value-weighted quintile rankings of stocks held in a fund portfolio at the end of a given calendar quarter, where stocks are sorted separately on size, book-to-market ratio,

TABLE 1

Summary Statistics

Table 1 reports summary statistics of fund holding horizon (H–H), fund characteristics, stock characteristics of fund holdings, and other measures of fund activeness. The H–H measure is described in Section II.A. Style-adjusted H–H measure is calculated as a fund's holding horizon in excess of the average holding horizon of its peers with the same investment style. Investment styles include Russell 1000 (R1), Russell 1000 Growth (R1G), Russell 1000 Value (R1V), Russell Midcap (RM), Russell Midcap Growth (RMG), Russell Midcap Value (RMV), Russell 2000 (R2), Russell 2000 Growth (R2G), and Russell 2000 Value (R2V). Other measures of fund activeness include CRSP fund turnover ratio (CRSP_TR), Active Share of Cremers and Petajisto (2009), R^2 of Amihud and Goyenko (2013), and return gap of Kacperczyk et al. (2008). The size, book-to-market, momentum, and Amihud's (2002) illiquidity ranks for a given fund are the value-weighted average quintile rankings of stocks across all stocks held by the fund, with 1 being the lowest and 5 being the highest quintile. The proportion of TNA in front-load (rear-load) class is computed for funds having nonmissing front-end (rear-end) load data. For the proportion of TNA in share class with 12b-1 fees we only consider those with 12b-1 fees greater than or equal to 25 basis points. Cash position is the percentage of total net assets held in cash. Factor-related return (FRR) is calculated as in Song (2020) and is the sum of the return components over the past 4 years that are traced to size, value, momentum, and three industry factors of Pástor and Stambaugh (2002) after these factors are orthogonalized to the market factor. Flow volatility is the standard deviation of monthly fund flows over the past 12 months. We define monthly fund flows as the change in monthly TNA adjusted for the fund's net return of the month, then divided by the lagged TNA. Fund flows are cumulated monthly fund flows over the past 12 months. Panel A reports statistics for the full sample, Panel B presents the mean, median, and standard deviation of the H–H measure for each fund investment style, and Panel C reports the means of various variables across funds in each quintile portfolio that is sorted on the style-adjusted H–H measure, with Q1 (Q5) consisting of funds with the shortest (longest) investment horizons. The last column of Panel C presents the difference of statistics between Q5 and Q1, with *** representing significance at the 1% confidence interval.

Panel A. The Full Sample

	Mean	Median	Std. Dev.
TNA ($ millions)	1,488.14	372.66	4,456.64
EXPENSE_RATIO (%)	1.15	1.12	0.39
FUND_AGE (years)	20.65	16.03	14.26
H–H (years)	2.52	2.18	1.51
STYLE-ADJUSTED_H–H (years)	0.07	−0.23	1.45
CRSP_TR (%/year)	80.12	61.92	73.74
ACTIVE_SHARE	0.81	0.84	0.13
R^2	0.90	0.93	0.09
RETURN_GAP (%)	−0.05	−0.05	1.28
SIZE_RANK	4.15	4.49	0.85
BOOK_TO_MARKET_RANK	2.68	2.66	0.66
MOMENTUM_RANK	3.10	3.08	0.45
AMIHUD_ILLIQUIDITY_RANK	1.23	1.07	0.36

Panel B. Fund H–H Measure Conditional on Styles

Investment Styles	Mean	Median	Std. Dev.
R1	2.94	2.58	1.65
R1G	2.54	2.17	1.52
R1V	2.81	2.54	1.50
RM	1.96	1.77	0.86
RMG	1.87	1.61	1.05
RMV	2.35	2.07	1.37
R2	2.19	1.96	1.10
R2G	1.79	1.61	0.89
R2V	2.47	2.23	1.29

(continued on next page)

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TABLE 1 (continued)

Summary Statistics

Panel C. Sorting Based on the Style-Adjusted H–H Measure

	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1
TNA (total in $ millions)	825.21	940.90	1,255.97	1,580.91	2,833.31	2,008.10***
TNA (median in $ millions)	276.21	329.70	384.05	435.15	527.78	251.57***
EXPENSE_RATIO (%)	1.21	1.21	1.19	1.13	1.00	−0.22***
FUND_AGE (years)	19.73	19.41	19.34	20.21	24.51	4.78***
H–H (years)	1.09	1.61	2.14	2.92	4.83	3.74***
Within-fund stock holding-period STD_DEV (years)	1.06	1.37	1.73	2.22	3.29	2.23***
STYLE-ADJUSTED_H–H (years)	−1.50	−0.78	−0.22	0.52	2.32	3.82***
CRSP_TR, mean (%/year)	137.94	101.74	75.42	52.25	32.37	−105.57***
CRSP_TR, median (%/year)	118.72	88.73	65.19	43.94	22.15	−96.56***
ACTIVE_SHARE	0.82	0.82	0.82	0.81	0.80	−0.02***
R^2	0.90	0.91	0.91	0.91	0.89	−0.01***
RETURN_GAP (%)	−0.06	−0.06	−0.04	−0.05	−0.06	0.00
CASH_ALLOCATION (%)	4.30	4.51	4.60	5.69	4.41	0.43
SIZE_RANK	4.22	4.08	4.06	4.12	4.28	0.06***
BOOK_TO_MARKET_RANK	2.69	2.59	2.61	2.69	2.80	0.11***
MOMENTUM_RANK	3.24	3.20	3.11	3.01	2.94	−0.30***
AMIHUD_ILLIQUIDITY_RANK	1.19	1.24	1.25	1.26	1.23	0.04***
Proportion of TNA in front-load class (class A) (%)	51.22	50.52	54.31	58.43	62.15	10.93***
Proportion of TNA in rear-load class (%)	36.72	36.98	37.66	36.90	41.13	4.41***
Proportion of TNA in share class with 12b-1 fees (%)	38.14	37.94	36.75	34.65	27.39	−10.75***
FRR (past 4 years, % and annualized)	0.37	0.27	0.03	−0.12	0.03	−0.34***
FUND_FLOWS (past 12 months, %)	8.94	7.46	7.14	5.23	2.34	−6.60***
FLOW_VOLATILITY (past 12 months)	0.03	0.03	0.03	0.03	0.02	−0.01***
FAMILY_TNA (mean, $ millions)	31,739.18	28,836.76	30,339.48	35,570.03	51,573.98	19,834.80***

momentum, or illiquidity, as measured by Amihud's (2002) measure, with one being the lowest and five being the highest quintile score for each metric. We average each of these quintile rankings across funds, and then over time. Consistent with previous studies (e.g., Falkenstein (1996), Chan, Chen, and Lakonishok (2002)), equity mutual funds, on average, tend to prefer larger growth companies, past winners, and more liquid stocks.

Panel B of Table 1 shows that the average fund H–H varies considerably across investment styles. Because equity mutual funds with the same investment style typically focus on a similar subcategory of stocks, it is likely that being in a particular style affects the investment horizon of a given fund. The results in Panel B support this conjecture: large-cap funds hold stocks, on average, longer than mid- and small-cap funds, and value funds hold stocks on average longer than growth funds. It is clear that funds in different investment objective categories routinely hold stocks for different lengths of time. We reject the null hypothesis that the mean values of H–H across different styles are equal at the significance level of 1%. These differences motivate us to adjust a fund's horizon measure by that of the average fund within its style category when analyzing the fund horizon-performance relation. Nevertheless, fund style explains only about 9% of variance of unadjusted H–H in a regression of H–H on fund-style dummies. Hence, our results do not depend on the style adjustment of our H–H measure (see Section VIII.E for more details).

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Panel C of Table 1 presents the average values of fund characteristics and stock characteristics in each fund quintile, where funds are sorted on their style-adjusted H–H measure. Notice that funds in the shortest, middle, and longest H–H quintiles, on average, hold stocks for 1.09, 2.14, and 4.83 years, respectively. After style adjustment, H–H in these three quintiles becomes −1.50, −0.22, and 2.32 years. For simplicity, we will use style-adjusted H–H without explicitly mentioning "style-adjusted" throughout the remainder of our article, unless necessary for clarification. Long-horizon funds, on average, exhibit a standard deviation of stock-level holding period of 3.29 years, while the average for short-horizon funds is 1.06 years. The reason is that the former hold stocks for a wide variety of long periods, while holdings of the latter concentrate on short periods. Long-term funds are also large and long-established funds with a lower expense ratio and a lower turnover ratio. Long- and short-horizon funds, on average, hold stocks with similar capitalization and liquidity, although short-term funds prefer more past winners as well as growth stocks.

One may wonder whether funds with a long H–H are simply "closet indexers." To address this issue, we examine differences in activeness as measured by prior "activeness" measures, which include Active Share (Cremers and Petajisto (2009)), R^2 (Amihud and Goyenko (2013)), and return gap (Kacperczyk et al. (2008)).[16] There is no significant difference in the level of activeness between long- and short-horizon funds in terms of return gap, and the differences in Active Share and R^2 are relatively small. Clearly, long H–H funds are not merely passive funds that represent themselves as active funds (Cremers and Petajisto consider a fund as a closet indexer if Active Share is less than 0.6); our H–H measure captures a characteristic of active management that is not captured by prior measures of activeness of asset managers.

We also find evidence that long H–H funds cater to long-term investors. Starting in the 1990s, many funds, to cater to different types of investors, offer multiple share classes representing ownership interests in the same portfolio, but using different fee structures. Nanda, Wang, and Zheng (2009) suggest that funds in class A and B tend to attract investors that are more long-term oriented.[17] Panel C of Table 1 shows that long H–H funds have a significantly greater proportion of TNA invested in the A share class than short H–H funds (62% vs. 51%). The 11% difference is both statistically and economically significant, given that long H–H funds have large fund size and, on average, manage $1.3 billion more assets charging front-load fees. This finding is consistent with the clientele of long H–H fund investors being more patient, as more of them have made a significant (front-end)

[16]Active Share is downloaded from Petajisto's website https://www.petajisto.net/data.html, see also Petajisto (2013); R^2 is obtained by running regressions of fund excess net returns on the Carhart four factors using a 24-month rolling window; return gap is defined, following Kacperczyk et al. (2008), as the monthly difference between the reported fund net return, plus 1/12 the most recent fund annual expense ratio, and the return of a hypothetical portfolio that invests in the most recently disclosed portfolio holdings.

[17]The A class is characterized by high front-end loads and low annual 12b-1 fees. The B class is characterized by a back-end load that is at its highest in the first year after an investment, then drops to zero within 5–10 years. Given the absence of an identifier for an A share class, motivated by Nanda et al. (2009), we classify a share class as an A class if it charges a front-end load.

commitment to holding fund shares for a long period of time. Further, we find that long H–H funds have a significantly greater proportion of TNA invested in share classes with back-end loads (41% vs. 37%). This is another indication that they cater to long-term investors given that, typically, this fee is at its highest in the first year after an investment, then drops to zero within 5–10 years.

Also noteworthy is the pattern that short-horizon funds have a greater proportion of TNA charging 12b-1 fees more than 25 basis points than long-horizon funds (38% vs. 27%).[18] This pattern is consistent with investors of short-horizon funds being short-term and better off paying higher 12b-1 fees annually instead of paying front- or back-load, which, though paid once, is a few times higher than annual 12b-1 fees.

If long-horizon fund managers are able to exploit information that is reflected in stock prices over the long run, KOW's model predicts that these managers accumulate or liquidate a position slowly to reduce the market impact of their trades. To capture these dynamics, we calculate the value-weighted average of the time span of consecutive purchases (sales) of a given stock for all stocks held in a fund portfolio, in the same way as we calculate fund investment horizon specified in (2) by replacing a stock's holding horizon with a stock's time span of consecutive purchases (sales). The time span of consecutive purchases (sales) of a stock by a fund is defined as the longest time interval that starts with a purchase (sale) of the stock by the fund and ends with another purchase (sale) of the same stock, without a sale (purchase) of the stock in the interim. In untabulated analysis, we find that long-horizon funds take much longer to either increase or decrease their positions than short-horizon funds, consistent with KOW's prediction. Long-horizon funds, defined as the top H–H tercile, take almost 19 (25) months, on average, to accumulate (reduce) a position, compared with approximately 5 (10) months for short-horizon funds. The top 10% of long-horizon funds even take roughly 3–5 years to accumulate or liquidate a position.

B. The Persistence of Fund Holding Horizon

An important question in testing the predictive power of H–H for future fund performance is whether funds have persistent levels of H–H over long time (i.e., whether their particular strategies and, potentially, skills are durable). To check this persistence, each month, we sort funds into deciles according to the H–H measure. D1 consists of funds with the shortest holding horizons within their investment styles, while D10 consists of funds with the longest holding horizons. Figure 1 depicts the average style-adjusted fund holding horizons of each decile at the formation period and during the subsequent 20 quarters.

Fund investment horizon exhibits long-term stability. The ranking of the decile portfolios remains stable as far out as the 20th quarter after the formation period. For example, fund investment periods in excess of their style average are −1.84, −1.25, −0.33, −0.02, 1.53, and 3.39 years, on average, for funds in deciles 1, 2, 5, 6, 9,

[18]SEC prohibits registered broker-dealers from describing funds as "no-load" funds if the funds charge 12b-1 fees greater than 25 basis points.

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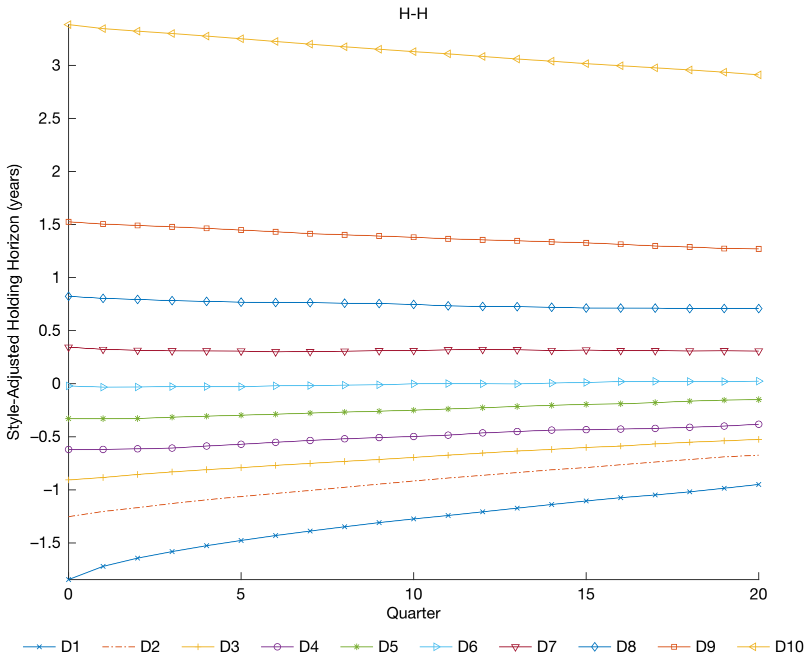
FIGURE 1

Persistence of the Style-Adjusted Fund Holding Horizon

Figure 1 plots the average style-adjusted fund holding horizon (H–H) for each fund decile at the formation period, and the first to the 20th quarter into the future after the formation period. Each month funds are sorted into deciles according to the style-adjusted H–H measure, with D1 consisting of funds with short H–H and D10 consisting of funds with long H–H.



and 10 at the formation period, while these average investment periods become −0.95, −0.67, −0.15, 0.03, 1.27, and 2.91 years after 20 quarters.

IV. Empirical Results on Fund Performance

In this section, we examine the fund horizon-performance relation, using both a sorted fund portfolio approach and Fama–MacBeth regressions that control for fund characteristics, as well as other measures of active fund management that, according to prior studies, predict future fund performance.

A. Fund Performance Using a Sorted Portfolio Approach

We use both fund net returns available from CRSP and holdings-based returns (gross of fees and trading costs), calculated as the value-weighted returns on stocks held by a given fund, to measure fund performance. In this sorted portfolio approach, each month, we group funds into deciles according to the H–H measure that we have described in Section II.A. For each decile and each look-ahead return measurement horizon from the next month up to the next 5 years, we calculate buy-and-hold cumulative net returns and risk-adjusted abnormal returns (CAPM alphas and 4-factor alphas computed from fund net returns and DGTW abnormal returns based on holdings-based returns) as described in Section II.B.[19] Note that net alphas are the benefits fund investors receive per dollar investment, after controlling for common factor exposures, while DGTW abnormal returns are the benefits that fund investors and fund managers collectively receive per dollar investment, gross of fees, and trading costs.

Table 2 summarizes the results using value-weighted portfolios of funds on the left, and equal-weighted portfolios on the right. D1 (D10) consists of short-horizon (long-horizon) funds. Value-weighted alphas represent the alphas of a dollar investment split among funds in proportion to their AUM at the portfolio formation date, while equal-weighted alphas represent the alphas for an equal investment in each fund at that date.

Note that long H–H funds (D10) achieve significantly positive 4-factor net alphas at horizons of a quarter and longer,[20] and significantly positive DGTW abnormal returns over all horizons. Take the 5-year horizon as an example. The 5-year 4-factor net alpha is 8.99% (1.8% per year) for value-weighted D10 fund portfolios, and 7.94% (1.59% per year) for equal-weighted D10 fund portfolios, while 5-year DGTW abnormal returns are 8.47% (1.69% per year) and 7.43% (1.49% per year), respectively. By contrast, short H–H funds (D1) essentially exhibit no abnormal returns. The pattern of CAPM net alphas is similar to that of 4-factor net alphas.

The spread of 4-factor net alphas between the two extreme deciles is 0.16% at the 1-month horizon (1.92% per year) for value-weighted fund portfolios, and 0.11% (1.32% per year) for equal-weighted fund portfolios. Both are statistically significant. Results for the spread between the top and bottom quintile portfolios (D10 + D9 − D1 − D2)/2 are similar, and only modestly reduced in magnitude from the decile spreads. The results at longer investment horizons exhibit the same qualitative patterns. For instance, the spread of the 5-year cumulative 4-factor net alpha between top and bottom decile portfolios is 11.96% for value-weighted portfolios, and 10.24% for equal-weighted portfolios. The pattern of spreads in CAPM alphas and DGTW-adjusted returns is generally consistent with that of 4-factor alphas; long H–H funds outperform short H–H funds using both alternative risk models.

We have discussed, in Section III.A, that long H–H funds appear to cater to long-term investors by managing a larger portion of AUM charging load fees. This clientele effect leads long H–H funds to experience a lower flow sensitivity to their past short-term performance, as opposed to short H–H funds; we will discuss this further in Section VII. Nondiscretionary trading due to mutual fund investor flows

[19]The extant mutual fund literature, with few exceptions, focuses on predicting short-term performance of up to 1 year; our study provides a view of the longer-term outperformance of long-horizon funds.

[20]As Tables A2 and A3 in the Supplementary Material show, long H–H funds' positive 4-factor net alphas at return measurement horizons of one quarter and longer remain statistically significant based on bootstrapped p-values calculated under empirical distributions that account for the potential small-sample size bias (Boudoukh et al. (2019)). See Section A4 of the Supplementary Material for detail. In addition, we follow Jegadeesh and Titman (1993) and employ monthly returns for H–H decile portfolios that are formed over each of the past (overlapping) n periods, along with monthly factor returns, to compute n-period 4-factor net alphas. The results, shown in Table A4 in the Supplementary Material, are comparable to our baseline results reported in Table 2.

TABLE 2

Informativeness of Fund Holdings: Fund Portfolio Performance

In Table 2, funds are sorted into deciles each month according to the style-adjusted H–H measure, with D1 consisting of short-horizon funds and D10 consisting of long-horizon funds. Table 2 reports buy-and-hold fund portfolio net returns (NET_RET) and abnormal returns over the next month, next quarter, and next 1–5 years after portfolio formation. As explained in Section II.B, the abnormal returns are the CAPM net alphas (NET_CAPM α) and Carhart 4-factor net alphas (NET_4-F α), which are computed from buy-and-hold net returns, as well as DGTW-adjusted returns (DGTW), which are computed from holdings-based returns. Portfolio weights are either value or equally weighted at the formation month and are then updated following a buy-and-hold strategy. If funds drop out of a decile portfolio during a return measurement horizon, we distribute the value of the disappearing funds to the remaining funds in the decile in proportion to the portfolio values of the remaining funds. The table also reports the average number of funds in each decile, the return spreads between the D10 and D1 portfolios, and the spreads between the top two decile portfolios and the bottom two deciles, (D10 + D9 − D1 − D2)/2. All returns are expressed in percentage. Return data end in Dec. 2020; the H–H measure starts in Dec. 1984 and ends in Dec. 2015. *, **, and *** represent statistical significance for abnormal returns and return spreads at the 10%, 5%, and 1% confidence intervals, respectively. Standard errors are obtained using the Newey–West (1987) procedure with a lag equal to the total number of months in the return measurement horizon minus one.

	Value Weighted				Equally Weighted			
	NET_RET	NET_CAPM α	NET_4-F α	DGTW	NET_RET	NET_CAPM α	NET_4-F α	DGTW
1-month (avg. # funds per decile: 87)								
D1 (short)	0.84	−0.08	−0.10*	0.01	0.88	−0.05	−0.06	0.03
D2	0.88	−0.05	−0.06	0.06	0.92	−0.02	−0.03	0.03
D3	0.89	−0.06	−0.04	0.04	0.93	−0.02	−0.02	0.02
D4	0.90	−0.04	−0.02	−0.01	0.94	−0.01	−0.00	0.04
D5	0.88	−0.05	−0.02	0.02	0.92	−0.03	−0.02	0.02
D6	0.93	0.00	0.02	0.04	0.96	0.02	0.02	0.04
D7	0.87	−0.06	−0.04	0.03	0.91	−0.03	−0.02	0.03
D8	0.91	−0.01	0.01	0.04	0.90	−0.02	−0.00	0.02
D9	0.91	0.00	0.01	0.03	0.93	0.02	0.01	0.05
D10 (long)	0.96	0.08*	0.06	0.10***	0.96	0.08	0.05	0.07**
D10 − D1	0.12**	0.16***	0.16***	0.09**	0.08	0.12***	0.11***	0.04
(D10 + D9 − D1 − D2)/2	0.07*	0.10***	0.11***	0.03	0.04	0.08**	0.08***	0.03
1-quarter (avg. # funds per decile: 84)								
D1 (short)	2.52	−0.24*	−0.23	0.05	2.66	−0.12	−0.10	0.11
D2	2.69	−0.12	−0.09	0.15	2.74	−0.08	−0.04	0.08
D3	2.73	−0.12	−0.05	0.07	2.79	−0.06	0.02	0.07
D4	2.72	−0.10	−0.03	0.09	2.78	−0.05	0.03	0.13
D5	2.72	−0.10	−0.00	0.09	2.76	−0.07	0.05	0.09
D6	2.87	0.07	0.17	0.15	2.81	0.00	0.10	0.11
D7	2.54	−0.23*	−0.12	0.02	2.67	−0.12	−0.01	0.05
D8	2.74	0.02	0.09	0.10	2.68	−0.04	0.04	0.09
D9	2.70	−0.00	0.06	0.13	2.76	0.05	0.12	0.14
D10 (long)	2.83	0.22*	0.19*	0.25***	2.83	0.22	0.20*	0.21**
D10 − D1	0.30**	0.46***	0.42***	0.20**	0.18	0.34***	0.30***	0.10
(D10 + D9 − D1 − D2)/2	0.16	0.29***	0.28***	0.09	0.10	0.24**	0.23***	0.09
1-year (avg. # funds per decile: 81)								
D1 (short)	10.59	−0.78	−0.88	0.42	11.04	−0.17	−0.25	0.44
D2	11.10	−0.45	−0.22	0.38	11.38	0.06	0.08	0.40
D3	11.36	−0.36	−0.14	0.48	11.66	0.22	0.34	0.47
D4	11.05	−0.55	−0.35	0.31	11.51	0.04	0.22	0.52
D5	11.37	−0.23	0.05	0.60	11.53	0.08	0.23	0.45
D6	11.36	0.18	0.40	0.61	11.33	0.20	0.29	0.35
D7	10.83	−0.32	−0.04	0.23	11.01	−0.09	0.13	0.17
D8	11.32	0.31	0.23	0.42	11.00	0.16	0.10	0.30
D9	11.40	0.26	0.13	0.53	11.55	0.77	0.66	0.61
D10 (long)	11.80	1.09*	0.81**	1.16***	11.72	1.15	0.87*	0.94**
D10 − D1	1.21**	1.87***	1.69***	0.74**	0.69	1.32**	1.11**	0.51*
(D10 + D9 − D1 − D2)/2	0.76	1.29**	1.02**	0.44	0.43	1.02**	0.84**	0.36
2-year (avg. # funds per decile: 78)								
D1 (short)	21.92	−0.94	−1.05	0.75	22.55	0.23	−0.07	0.83
D2	23.09	−0.24	0.19	1.09	23.31	0.76	0.39	0.97
D3	23.33	−0.21	0.31	1.21	23.82	1.23	0.97	1.12
D4	23.44	0.01	0.36	0.90	24.01	1.30	0.86	1.23
D5	23.21	−0.11	0.05	1.07	23.68	1.02	0.79	1.01
D6	23.68	1.38	1.25	1.25	23.34	1.27	0.91	0.75
D7	22.96	0.58	0.10	0.69	22.92	0.80	0.22	0.44
D8	23.57	1.57	1.20	0.69	22.90	1.22	0.73	0.64
D9	23.58	1.12	−0.08	1.43	23.70	2.14	1.29	1.39
D10 (long)	24.70	2.84***	2.26***	2.68**	24.34	3.09**	2.32**	2.22**
D10 − D1	2.79***	3.77***	3.31***	1.93***	1.79*	2.86**	2.38**	1.39***
(D10 + D9 − D1 − D2)/2	1.64*	2.57**	1.52	1.13**	1.09	2.12**	1.64*	0.90**

(continued on next page)

TABLE 2 (continued)

Informativeness of Fund Holdings: Fund Portfolio Performance

	Value Weighted				Equally Weighted			
	NET_RET	NET_CAPM α	NET_4-F α	DGTW	NET_RET	NET_CAPM α	NET_4-F α	DGTW
3-year (avg. # funds per decile: 75)								
D1 (short)	34.14	−0.66	−1.23	1.69	34.94	1.02	−0.13	1.64
D2	35.25	0.18	−0.29	1.58	35.93	1.82	0.56	1.57
D3	36.25	1.51	1.41	2.26	36.64	3.26**	1.86	1.95
D4	36.81	1.58	1.61	2.15	37.06	3.08**	1.50	2.07
D5	36.17	1.02	0.55	1.83	36.40	2.73**	1.55	1.66
D6	36.78	2.70	2.29	2.05	36.05	2.73**	1.60	1.39
D7	36.32	2.18	1.66	1.12	36.02	2.58**	1.67	1.18
D8	36.36	3.04**	1.64	1.29	35.54	3.05***	1.96*	1.28
D9	36.73	3.07**	1.09	2.29	36.25	3.92***	2.10**	2.04
D10 (long)	38.50	5.33***	4.42***	4.66**	37.61	5.45***	4.10***	3.80**
D10 − D1	4.36***	5.99***	5.66***	2.97**	2.66*	4.43***	4.23***	2.16***
(D10 + D9 − D1 − D2)/2	2.92**	4.44***	3.52***	1.84***	1.50	3.26***	2.88***	1.31**
4-year (avg. # funds per decile: 72)								
D1 (short)	46.99	−0.39	−1.47	1.72	47.82	1.42	−0.61	1.69
D2	49.34	0.98	0.43	1.86	50.18	3.50*	1.51	1.85
D3	50.57	2.47	1.63	3.00	50.49	4.92***	2.19	2.31
D4	51.38	1.98	2.95	2.50	51.72	4.44***	2.74*	2.79
D5	50.36	2.51	1.63	2.41	50.60	4.69**	2.60	2.25
D6	51.77	4.26*	3.91*	2.70	50.40	4.22***	2.76	1.79
D7	50.26	3.23	2.34	1.27	49.90	3.84***	2.46**	1.41
D8	50.06	3.54**	1.83	1.32	49.34	4.51***	2.56***	1.55
D9	51.13	4.95***	2.20**	3.30*	50.55	5.96***	3.12***	3.13*
D10 (long)	53.93	8.00***	6.65***	6.45***	52.48	7.87***	5.88***	5.24***
D10 − D1	6.93***	8.39***	8.13***	4.73***	4.66***	6.45***	6.49***	3.55***
(D10 + D9 − D1 − D2)/2	4.36***	6.18***	4.95***	3.08***	2.52*	4.45**	4.05***	2.41***
5-year (avg. # funds per decile: 69)								
D1 (short)	61.57	−0.62	−2.97	2.48	62.25	1.44	−2.30	2.42
D2	64.90	0.73	0.52	2.56	65.59	3.84*	1.64	2.59
D3	65.78	2.34	2.19	3.73	66.01	5.27***	2.57	3.33
D4	67.00	1.74	2.82	3.88	67.50	4.84***	2.94	4.22
D5	64.94	2.95	1.26	3.36	66.18	5.20***	2.78	3.31
D6	66.56	5.69**	4.65*	3.53	65.26	5.19***	2.70	2.51
D7	64.66	2.99	1.32	1.84	65.25	4.12***	2.22	2.13
D8	65.52	4.11**	2.34	1.55	64.31	5.84***	3.53**	2.19
D9	67.38	7.20***	4.05**	5.63**	66.35	7.97***	4.15***	4.97**
D10 (long)	70.21	10.93***	8.99***	8.47***	68.59	10.27***	7.94***	7.43***
D10 − D1	8.63***	11.55***	11.96***	5.99***	6.34***	8.83***	10.24***	5.01***
(D10 + D9 − D1 − D2)/2	5.56***	9.01***	7.74***	4.53***	3.55*	6.48***	6.38***	3.70***

can reduce fund performance significantly (Edelen (1999)). Fund managers, thus, are expected to compete for investors having a low probability of liquidity needs (or long-term investors). Because long-term capital is relatively scarce, fund managers with high long-term forecasting skills can be expected to attract more of this capital, by sharing higher economic rents they achieve with their investors (Nanda et al. (2000)). Our empirical results in Table 3 support this interpretation; after separating high load funds from low load funds, long H–H funds' superior performance is strengthened.

Because the CRSP mutual fund database provides only the tiers of load fees (at different investment levels) and the effective load that a share class actually charges is unavailable, in constructing this table, we calculate the value-weighted proportion of the share classes of a given fund that charges load fees as a proxy for the effective load of that fund.[21] After sorting funds into deciles on their H–H

[21] We conduct this approximation for front-end and back-end loads separately, then add up the corresponding proportions of AUM. If we use the proportion of a fund's AUM charging front-end or back-end load alone, our conclusions remain the same. Our results are also robust if we use the AUM-weighted average of maximum load fees for each share class instead.

TABLE 3

Informativeness of Fund Holdings: Fund Portfolio Performance Conditional on Loads

In Table 3, we calculate the AUM-weighted proportion of the share classes of a given fund that charge load fees (either front-end or rear-end) as a proxy for the effective load of that fund. Each month, funds are sorted into deciles (quintiles) according to the style-adjusted H–H measure, with D1 (Q1) consisting of short-horizon funds and D10 (Q5) consisting of long-horizon funds. Then, each decile or quintile is divided into two portfolios according to the median level of the effective load. This table reports buy-and-hold fund portfolio net returns (NET_RET) and abnormal returns over the next month, next quarter, and next 1–5 years after portfolio formation. As explained in Section II.B, the abnormal returns are the CAPM net alphas (NET_CAPM α) and Carhart 4-factor net alphas (NET_4-F α), which are computed from buy-and-hold net returns, as well as DGTW-adjusted returns (DGTW), which are computed from holdings-based returns. Portfolios are equally weighted at the formation month and are then updated following a buy-and-hold strategy. If funds drop out of a decile (quintile) portfolio during a return measurement horizon, we distribute the value of the disappearing funds to the remaining funds in the decile (quintile) in proportion to the portfolio values of the remaining funds. The table also reports the average number of funds in each decile, the return spreads between the D10 and D1 portfolios and the spreads between the Q5 and Q1 portfolios. All returns are expressed in percentage. Return data end in Dec. 2020; the H–H measure starts in Dec. 1984 and ends in Dec. 2015. *, **, and *** represent statistical significance for abnormal returns and return spreads at the 10%, 5%, and 1% confidence intervals, respectively. Standard errors are obtained using the Newey–West (1987) procedure with a lag equal to the total number of months in the return measurement horizon minus one.

	High Loads				Low Loads			
	NET_RET	NET_CAPM α	NET_4-F α	DGTW	NET_RET	NET_CAPM α	NET_4-F α	DGTW
1-month (avg. # funds per decile: 35)								
D1 (short)	0.88	−0.04	−0.04	0.03	0.85	−0.05	−0.06	0.05
Q1	0.91	−0.02	−0.02	0.03	0.86	−0.05	−0.07	0.04
Q5	0.97	0.07	0.05	0.08**	0.87	0.01	0.00	0.05
D10 (long)	0.97	0.10*	0.06	0.09**	0.91	0.06	0.05	0.08**
D10 − D1	0.09*	0.14***	0.10**	0.06	0.06	0.10**	0.11***	0.03
Q5 − Q1	0.06	0.09**	0.07**	0.05	0.02	0.06	0.08**	0.01
1-quarter (avg. # funds per decile: 35)								
D1 (short)	2.62	−0.13	−0.09	0.08	2.61	−0.12	−0.12	0.14
Q1	2.68	−0.11	−0.04	0.06	2.61	−0.12	−0.12	0.13
Q5	2.88	0.21	0.22*	0.25***	2.61	0.01	0.05	0.12
D10 (long)	2.91	0.29*	0.26**	0.28***	2.69	0.13	0.14	0.20**
D10 − D1	0.29**	0.42***	0.35***	0.21*	0.09	0.25**	0.26**	0.07
Q5 − Q1	0.20	0.31**	0.27***	0.19**	−0.01	0.13	0.17**	−0.01
1-year (avg. # funds per decile: 33)								
D1 (short)	10.73	−0.38	−0.44	0.46	11.10	−0.02	−0.18	0.48
Q1	10.89	−0.38	−0.29	0.34	11.13	−0.01	−0.11	0.54
Q5	12.02	1.30	0.98*	1.04**	10.99	0.41	0.39	0.56
D10 (long)	12.17	1.62*	1.23**	1.40***	11.26	0.62	0.52	0.76*
D10 − D1	1.44**	2.00**	1.67***	0.94***	0.17	0.64	0.70	0.28
Q5 − Q1	1.13**	1.68**	1.27**	0.70*	−0.14	0.42	0.50	0.02
2-year (avg. # funds per decile: 32)								
D1 (short)	21.81	−0.51	−0.73	0.82	23.31	0.94	0.49	0.86
Q1	22.40	−0.21	−0.36	0.90	23.08	0.38	−0.02	0.86
Q5	24.69	3.42**	2.59**	2.20**	23.09	1.16	0.42	1.49
D10 (long)	25.11	4.11**	3.06***	2.92***	23.66	1.62	1.01	1.81*
D10 − D1	3.30***	4.62***	3.79***	2.10***	0.35	0.68	0.52	0.96
Q5 − Q1	2.30**	3.62**	2.94***	1.30**	0.01	0.78	0.44	0.62
3-year (avg. # funds per decile: 31)								
D1 (short)	33.94	0.10	−0.94	1.64	36.33	1.75	0.45	1.73
Q1	34.86	0.56	−0.57	1.67	35.81	1.11	−0.02	1.49
Q5	37.78	6.10***	4.23***	3.42**	35.92	2.26*	0.84	2.56*
D10 (long)	38.79	6.94***	4.88***	5.05***	36.91	3.25**	2.35	3.18**
D10 − D1	4.85***	6.84***	5.82***	3.42***	0.58	1.50	1.91*	1.45
Q5 − Q1	2.92**	5.54***	4.80***	1.75**	0.11	1.15	0.86	1.07**
4-year (avg. # funds per decile: 30)								
D1 (short)	46.66	0.14	−1.90	1.71	49.81	2.69	0.32	1.71
Q1	48.13	1.09	−0.96	1.69	49.81	2.57	0.69	1.71
Q5	52.79	8.68***	5.66***	4.97***	50.15	4.35**	2.14	3.69*
D10 (long)	54.16	9.49***	6.30***	7.08***	51.76	5.76***	4.60**	4.64**
D10 − D1	7.50***	9.35**	8.20***	5.37***	1.95	3.07	4.28**	2.93**
Q5 − Q1	4.67**	7.60***	6.63***	3.28***	0.34	1.78	1.45	1.98***
5-year (avg. # funds per decile: 29)								
D1 (short)	60.42	0.02	−3.80	2.27	64.66	3.02	−1.03	2.58
Q1	62.32	0.89	−1.91	2.22	65.05	2.89	0.07	2.52
Q5	69.25	11.04***	6.95***	7.63***	65.03	6.16**	3.50*	5.19**
D10 (long)	70.95	11.70***	7.85***	9.99***	66.91	8.11***	6.70**	6.51**
D10 − D1	10.53***	11.68**	11.65***	7.72***	2.25	5.09*	7.73***	3.93***
Q5 − Q1	6.92***	10.15***	8.86***	5.41***	−0.02	3.27	3.43	2.67***

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measure, we further divide each decile of funds into two groups, according to the median level of this estimated effective load.[22] For brevity, we only present fund net returns and risk-adjusted returns for the two extreme deciles, as well as the differences between these two deciles.

Take the 1-year horizon as an example. For funds in the longest H–H decile (D10), 4-factor net alphas and DGTW abnormal returns are 1.23% and 1.40%, respectively, for high-load funds, compared with 0.52% and 0.76% for low-load funds (which include no-load funds). Similarly, 5-year 4-factor net alpha and DGTW abnormal returns are 7.85% and 9.99%, respectively, compared with 6.70% and 6.51%.[23] Sorting funds into quintiles on their H–H measure, then dividing into high and low-load groups provides qualitatively similar results, as shown in Table 3.

B. Fund Performance Using Fama–MacBeth Regressions

In this section, we further explore the predictive ability of H–H for future fund performance using Fama and MacBeth (1973) regressions, while controlling for several other fund characteristics that, as prior research indicates, are related to fund performance. Specifically, each month we run weighted least square cross-sectional regressions, using fund size as weights, of abnormal buy-and-hold fund returns on H–H and a list of standard fund characteristics. Abnormal buy-and-hold fund returns are measured using either 4-factor net alphas or DGTW-adjusted returns. Fund characteristics include fund age (measured by log since-inception age), fund size (measured by log TNA), fund expense ratio, past-year fund flow (as a fraction of lagged fund TNA), flow volatility (the volatility of monthly fund flows over the past 12 months), and the most recently available CRSP_TR. We also control for "factor-related returns" (FRR) in the regressions, as Song (2020) demonstrates that investor flows to high-FRR funds tend to be excessive so that high-FRR funds become oversized and exhibit negative future alphas due to diseconomy-of-scale.[24] Next, we calculate the time-series means of these first-stage coefficient estimates

[22] Note that funds without loads information are excluded from Table 3, so this fund sample is smaller than that reported in Table 2.

[23] Table A5 in the Supplementary Material reports, for the full sample of funds as well as high- and low-load subsamples, 4-factor alphas associated with net returns after front-load adjustments at various return measurement horizons. Because there is no exact front-end load charged by each fund share class available in the CRSP Mutual Fund Database, we assume two scenarios for front-end load adjustments —using either the min or the max front-end load reported by CRSP. Since front load is a lump sum payment at the beginning of investments, as expected, short-term (1-month) front-load-adjusted net alphas are essentially negative for both long and short H–H funds. In contrast, long H–H funds exhibit significantly positive long-term (5-year) front-load-adjusted net alphas regardless of fund samples and the assumption of front loads being used, except that in one case (using the max reported front loads in the high-load subsample of funds) front-load-adjusted net alpha is positive but statistically insignificant. Our evidence suggests that in the "real world," patient long-term investors are more likely willing to pay front loads to gain access to superior long H–H funds with such loads, and enjoy a positive abnormal return even after front-load payments.

[24] Using a 7-factor model that includes the four factors of Carhart (1997) and three industry factors of Pástor and Stambaugh (2002), we follow Song (2020) and calculate FRR as the return component for a mutual fund, over the past 4 years, that can be attributed to exposures to nonmarket factors, after these factors are orthogonalized to the market factor.

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using the inverse of the standard error of the first-stage estimates as weights, following the suggestion of Fama (1998). Our results remain similar if we use the time-series means of equally weighted first-stage coefficient estimates instead. Because we use monthly observations of overlapping dependent variables over a return measurement horizon, n, standard errors are calculated using the Newey and West (1987) approach, with a lag of $n-1$.

The first four columns of Table 4 report estimation results, based on 4-factor net alphas in Panel A and DGTW-adjusted returns in Panel B. Notably, fund H–H is a significant predictor of abnormal fund returns; the coefficient estimates on H–H are significantly positive for all horizons. In the baseline regressions (column 4), for example, controlling for fund characteristics, a 2-standard-deviation increase in H–H raises the fund 4-factor net alpha by 4.8% (Panel A) and the fund DGTW-adjusted return by 2.1% (Panel B) over the 5-year future return measurement horizon, where the standard deviation of H–H is 1.45 years. Note that FRR has a negative impact on 4-factor net alphas at horizons of 1 year and longer, which is consistent with Song's (2020) evidence, while its statistical significance is overall weak.

Further, we separate high-load funds from low-load funds and find that the predictive power of H–H among high-load funds is much stronger than that of low-load funds (the fifth to eighth columns of Table 4). Reinforcing the pattern in Table 3, this evidence suggests that via managing a large proportion of their AUM that charge load fees, long H–H, high load funds have a large capacity to cater to long-term capital, which helps to reduce mutual fund liquidity costs; in turn, these funds share relatively high economic rents with their investors to reward their investors's long-time capital commitment (Nanda et al. (2000)).

Next, we test whether fund H–H retains its explanatory power for future fund alphas, after controlling for other metrics of active management proposed by prior studies, which include Active Share (Cremers and Petajisto (2009)), R^2 (Amihud and Goyenko (2013)), and return gap (Kacperczyk et al. (2008)). As shown in the last 12 columns of each panel of Table 4, while these other proxies for manager activeness predict alphas, as documented in their respective papers,[25] the power of our horizon measure changes only slightly with their inclusion in the models.

C. Value Added from Financial Markets

Berk and van Binsbergen (2015) propose the value-added measure that accounts for the scale of funds in measuring manager skills. This measure is built on Berk and Green's (2004) insight, in which if manager skills are in short supply, fund net alpha is determined in equilibrium by competition among investor capital rather than manager skills. In this section, we evaluate Berk and van Binsbergen's value-added measure for funds with different levels of H–H.

Following Berk and van Binsbergen (2015), we compare active fund performance with an alternative passive fund benchmark that was tradable and marketed at that time. We select a set of index funds offered by Vanguard as an alternative

[25]We note that Kacperczyk et al. (2008) provide evidence that return gap positively predicts future four-factor alphas while controlling for fund characteristics, but do not provide results for DGTW abnormal returns.

TABLE 4

Fama–MacBeth Regressions of Fund Performance

Table 4 reports the coefficient estimates and p-values (in parentheses) of Fama–MacBeth (1973) regressions of the 4-factor alpha associated with buy-and-hold fund net returns (Panel A) or buy-and-hold DGTW-adjusted abnormal returns (Panel B). The look-ahead return measurement horizons are 1 month, 1 year, 3 years, and 5 years. Explanatory variables include the style-adjusted H–H measure, the H–H measure interacted with a high or low load dummy, fund size measured as log of total net assets, the expense ratio, fund age in logs, past 12-month fund flow volatility, past 12-month fund flows, the CRSP turnover ratio (CRSP_TR), factor-related return (FRR), the high load dummy, the Active Share of Cremers and Petajisto (2009), the R^2 of Amihud and Goyenko (2013), and the return gap of Kacperczyk et al. (2008). We calculate the AUM-weighted proportion of the share classes of a given fund that charge load fees (either front-end or rear-end) as a proxy for the effective load of that fund. A high (low) load dummy, HIGH_LOAD (LOW_LOAD), is equal to 1 if the effective load is above (below) the median level, and 0 otherwise. We use weighted least square in the first-stage cross-sectional regressions using the fund size as weights. Return data end in Dec. 2020; the H–H measure and the other explanatory variables start in Dec. 1984 and end in Dec. 2015. Standard errors are calculated using the Newey–West (1987) procedure with a lag equal to the total number of months in the return measurement horizon minus one.

Panel A. Using 4-Factor Alphas

	1M	1Y	3Y	5Y	1M	1Y	3Y	5Y	1M	1Y	3Y	5Y	1M	1Y	3Y	5Y	1M	1Y	3Y	5Y
H–H	0.01	0.22	0.85	1.65					0.01	0.20	0.80	1.52	0.01	0.20	0.72	1.39	0.01	0.23	0.85	1.65
	(0.00)	(0.00)	(0.00)	(0.00)					(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
H–H × HIGH_LOAD					0.02	0.30	1.04	2.07												
					(0.00)	(0.00)	(0.00)	(0.00)												
H–H × LOW_LOAD					0.01	0.20	0.79	1.46												
					(0.01)	(0.00)	(0.00)	(0.00)												
FUND_SIZE	0.00	0.05	0.38	0.42	−0.00	0.02	0.31	0.17	0.00	0.04	0.46	0.60	0.00	0.06	0.45	0.52	0.00	0.05	0.39	0.41
	(0.75)	(0.36)	(0.02)	(0.23)	(0.87)	(0.68)	(0.09)	(0.59)	(0.84)	(0.45)	(0.01)	(0.07)	(0.55)	(0.24)	(0.01)	(0.10)	(0.58)	(0.27)	(0.02)	(0.23)
EXPENSE	−0.08	−0.87	−1.39	−1.68	−0.08	−0.92	−1.50	−2.20	−0.09	−1.08	−2.54	−4.29	−0.08	−0.91	−1.70	−2.38	−0.07	−0.83	−1.34	−1.73
	(0.00)	(0.00)	(0.02)	(0.11)	(0.00)	(0.00)	(0.03)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.02)	(0.10)
FUND_AGE	0.02	−0.09	−1.67	−3.51	0.02	−0.10	−1.69	−3.55	0.02	−0.12	−1.68	−3.38	0.02	−0.17	−1.81	−3.66	0.02	−0.12	−1.70	−3.52
	(0.02)	(0.40)	(0.00)	(0.00)	(0.03)	(0.36)	(0.00)	(0.00)	(0.03)	(0.30)	(0.00)	(0.00)	(0.08)	(0.15)	(0.00)	(0.00)	(0.03)	(0.27)	(0.00)	(0.00)
FLOW_VOLATILITY	0.22	3.59	6.78	20.59	0.22	3.61	6.34	14.10	−0.04	0.97	−1.49	5.85	0.22	3.22	2.39	12.81	0.20	3.57	7.02	20.61
	(0.08)	(0.02)	(0.11)	(0.02)	(0.11)	(0.03)	(0.20)	(0.14)	(0.73)	(0.55)	(0.59)	(0.17)	(0.09)	(0.05)	(0.56)	(0.08)	(0.12)	(0.02)	(0.10)	(0.02)
FUND_FLOW	0.02	0.02	0.06	0.18	0.02	0.01	0.02	0.27	0.01	−0.00	0.07	0.09	0.01	0.00	0.04	0.14	0.02	0.02	0.05	0.16
	(0.01)	(0.82)	(0.75)	(0.68)	(0.00)	(0.95)	(0.96)	(0.65)	(0.02)	(0.99)	(0.73)	(0.85)	(0.02)	(0.97)	(0.83)	(0.74)	(0.01)	(0.82)	(0.78)	(0.71)
CRSP_TR	0.00	0.20	0.62	0.35	0.00	0.22	0.76	0.42	−0.01	0.12	0.39	0.06	−0.00	0.15	0.37	−0.13	0.00	0.19	0.60	0.31
	(0.94)	(0.39)	(0.36)	(0.67)	(0.77)	(0.31)	(0.25)	(0.62)	(0.46)	(0.61)	(0.58)	(0.95)	(0.92)	(0.52)	(0.58)	(0.87)	(0.89)	(0.43)	(0.38)	(0.71)
FRR	0.00	−0.09	−0.20	−0.18	0.00	−0.08	−0.21	−0.18	0.00	−0.13	−0.28	−0.22	0.00	−0.10	−0.26	−0.27	0.00	−0.09	−0.20	−0.18
	(0.53)	(0.19)	(0.24)	(0.50)	(0.55)	(0.20)	(0.21)	(0.53)	(0.74)	(0.05)	(0.07)	(0.37)	(0.63)	(0.13)	(0.10)	(0.26)	(0.52)	(0.18)	(0.23)	(0.50)
HIGH_LOAD					0.02	0.17	0.63	0.53												
					(0.08)	(0.12)	(0.06)	(0.48)												
ACTIVE_SHARE									0.19	2.44	12.69	27.22								
									(0.04)	(0.02)	(0.00)	(0.00)								
R^2													−0.08	−2.48	−14.31	−26.98				
													(0.62)	(0.22)	(0.01)	(0.00)				
RETURN_GAP																	0.60	5.41	11.97	18.32
																	(0.30)	(0.02)	(0.04)	(0.01)

(continued on next page)

TABLE 4 (continued)

Fama–MacBeth Regressions of Fund Performance

Panel B. Using DGTW-Adjusted Returns

	1M	1Y	3Y	5Y	1M	1Y	3Y	5Y	1M	1Y	3Y	5Y	1M	1Y	3Y	5Y	1M	1Y	3Y	5Y
H-H	0.01	0.14	0.38	0.74					0.01	0.13	0.39	0.74	0.01	0.11	0.25	0.52	0.01	0.14	0.38	0.73
	(0.08)	(0.01)	(0.01)	(0.01)					(0.07)	(0.01)	(0.00)	(0.00)	(0.11)	(0.02)	(0.07)	(0.05)	(0.07)	(0.01)	(0.01)	(0.01)
H-H × HIGH_LOAD					0.02	0.22	0.59	1.13												
					(0.01)	(0.00)	(0.01)	(0.01)												
H-H × LOW_LOAD					0.00	0.09	0.35	0.70												
					(0.49)	(0.10)	(0.03)	(0.01)												
FUND_SIZE	0.00	0.01	−0.03	−0.12	0.00	0.02	−0.00	−0.10	0.00	0.01	0.05	−0.00	0.00	0.02	0.03	−0.04	0.00	0.01	−0.04	−0.14
	(0.58)	(0.89)	(0.74)	(0.45)	(0.52)	(0.75)	(0.97)	(0.53)	(0.49)	(0.76)	(0.58)	(0.98)	(0.44)	(0.67)	(0.78)	(0.78)	(0.41)	(0.86)	(0.67)	(0.41)
EXPENSE	−0.00	−0.23	−0.77	−0.96	−0.01	−0.26	−1.09	−1.66	−0.01	−0.30	−1.12	−1.53	−0.01	−0.31	−1.15	−1.58	−0.00	−0.21	−0.76	−0.99
	(0.79)	(0.22)	(0.12)	(0.30)	(0.75)	(0.19)	(0.02)	(0.08)	(0.42)	(0.11)	(0.01)	(0.08)	(0.71)	(0.10)	(0.02)	(0.09)	(0.92)	(0.25)	(0.11)	(0.27)
FUND_AGE	0.01	0.01	−0.10	−0.25	0.01	0.01	−0.19	−0.42	0.01	−0.01	−0.16	−0.44	0.00	−0.02	−0.20	−0.46	0.01	0.01	−0.08	−0.24
	(0.28)	(0.87)	(0.71)	(0.62)	(0.32)	(0.92)	(0.47)	(0.40)	(0.36)	(0.94)	(0.56)	(0.40)	(0.69)	(0.77)	(0.38)	(0.28)	(0.30)	(0.85)	(0.76)	(0.63)
FLOW_VOLATILITY	0.15	3.11	6.32	12.18	0.21	3.91	6.79	12.51	−0.03	1.48	3.60	4.78	0.13	2.71	3.20	8.06	0.16	3.19	6.62	12.40
	(0.30)	(0.04)	(0.12)	(0.07)	(0.18)	(0.02)	(0.10)	(0.07)	(0.86)	(0.41)	(0.37)	(0.53)	(0.36)	(0.07)	(0.40)	(0.28)	(0.28)	(0.04)	(0.09)	(0.07)
FUND_FLOW	0.01	−0.10	−0.31	−0.55	0.01	−0.21	−0.58	−0.94	0.01	−0.10	−0.31	−0.52	0.01	−0.11	−0.34	−0.59	0.01	−0.10	−0.32	−0.56
	(0.18)	(0.14)	(0.03)	(0.00)	(0.36)	(0.03)	(0.00)	(0.00)	(0.25)	(0.15)	(0.02)	(0.01)	(0.19)	(0.11)	(0.01)	(0.00)	(0.17)	(0.13)	(0.03)	(0.00)
CRSP_TR	0.01	0.04	0.02	0.02	0.01	0.06	0.28	0.43	0.00	−0.01	0.07	0.15	0.01	−0.00	−0.22	−0.43	0.01	0.04	0.03	−0.00
	(0.57)	(0.84)	(0.97)	(0.98)	(0.66)	(0.73)	(0.55)	(0.56)	(0.83)	(0.96)	(0.88)	(0.84)	(0.57)	(0.99)	(0.66)	(0.59)	(0.58)	(0.82)	(0.95)	(1.00)
FRR	0.01	0.04	−0.00	−0.13	0.01	0.05	0.00	−0.11	0.01	0.02	−0.05	−0.19	0.01	0.03	−0.05	−0.21	0.01	0.04	−0.01	−0.14
	(0.18)	(0.49)	(0.98)	(0.63)	(0.16)	(0.45)	(0.98)	(0.73)	(0.25)	(0.72)	(0.78)	(0.52)	(0.19)	(0.59)	(0.75)	(0.45)	(0.19)	(0.50)	(0.95)	(0.61)
HIGH_LOAD					−0.00	0.00	0.20	0.51												
					(0.73)	(0.98)	(0.56)	(0.45)												
ACTIVE_SHARE									0.11	1.16	5.64	10.23								
									(0.21)	(0.18)	(0.01)	(0.00)								
R^2													−0.11	−3.01	−15.41	−24.36				
													(0.49)	(0.04)	(0.00)	(0.00)				
RETURN_GAP																	−0.56	0.46	−2.00	−4.25
																	(0.59)	(0.88)	(0.76)	(0.67)

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investment opportunity set. Let R_{it} be the month-t gross return (net return plus 1/12 annual expense ratio) of an actively managed fund i, in excess of 1-month T-bill rate. We define fund i's passive benchmark return in month t as $R_{it}^B = \sum_{j=1}^{n(t)} \beta_t^j R_t^j$, where R_t^j is the month-t excess return earned by investors of the jth Vanguard index fund, $n(t)$ is the total number of index funds offered by Vanguard in month t, and β_t^j is the sensitivity of R_{it} to R_t^j. The month-t benchmark-adjusted gross return of fund i is simply the difference between R_{it} and R_{it}^B. The Berk and van Binsbergen's (gross) value-added measure of fund i in month t is computed as the benchmark-adjusted gross return, $R_{it} - R_{it}^B$, multiplied by the fund's real size (inflation-adjusted total net assets in constant Jan. 2000 dollars) at the end of month $t-1$.

We select eight Vanguard U.S. index funds listed in Table 1 of Berk and van Binsbergen (2015) as an alternative passive investment opportunity set.[26] Because some of these index funds were not available to investors in early periods of our sample, we follow the algorithm described in the Appendix of Berk and van Binsbergen (2015) to estimate betas and calculate the passive benchmark returns for our actively managed funds.

After calculating the monthly value-added for all active funds in our sample, we accumulate it over various look-ahead measurement horizons, up to 5 years. In the calculation of n-period value-added, we require at least 75% of observations of monthly value-added nonmissing over the n-period. This requirement balances two considerations: i) If all observations are required nonmissing, it would rule out many funds in a sorting period and might lead to a survivor bias issue; ii) if the number of nonmissing observations is much less than 75%, then the accumulated measure may not precisely reflect the value-added over the n-period. Nevertheless, our conclusion does not rely on this requirement. Next, we sort our actively managed funds, each month, into deciles according to their H–H, as in Section IV.A. For a given look-ahead measurement horizon n, we take the average n-period value-added across all funds in each decile, and then overall sorting periods. Panel A of Table 5 reports the results.

Notice that the average long H–H fund (D10) extracts significant amount of money from financial markets and adds to its managed assets over all look-ahead measurement horizons: \$2.3 million over a month (\$27.6 million/year) and \$182.5 million over 5 years (\$36.5 million/year). On the other hand, the gross value-added measure is small and insignificant for short H–H funds (D1). The differences between the two extreme deciles are both economically and statistically significant over all horizons. For example, over the 5-year horizon, the average long H–H fund earns \$180.6 million more value from financial markets than the average short H–H fund, or \$36.1 million/year. These results suggest that long H–H funds are skillful and therefore manage funds of a large size.

We further investigate the value-added of funds with different levels of H–H from an investors' perspective. We call this measure net value-added, which is defined, analogously to Berk and van Binsbergen's (gross) value-added, by replacing an actively managed fund's excess gross return with its excess net return. That is, for an active fund, we multiply its monthly benchmark-adjusted

[26]We do not include the three Vanguard international index funds listed in Table 1 of Berk and van Binsbergen (2015) because our study focuses on actively managed U.S.-domiciled equity mutual funds.

TABLE 5

Value-Added Measure

In Table 5, we first compute the monthly value-added measure as a benchmark-adjusted gross return (net return plus 1/12 annual expense ratio) in Panel A or a benchmark-adjusted net return in Panel B, multiplied by the previous-month-end inflation-adjusted total net assets (in constant Jan. 2000 dollars). Benchmark returns are calculated based on the procedure described in the Appendix of Berk and van Binsbergen (2015) using the eight domestic Vanguard index funds listed in their Table 1. Next, we sort funds each month into deciles on their style-adjusted H–H measure, with D1 consisting of short-horizon funds and D10 consisting of long-horizon funds. For each fund, we then sum the monthly value-added measure over the next month, next quarter, and next 1–5 years after portfolio formation; for each look-ahead measurement horizon, we require at least 75% monthly value-added observations nonmissing. This table reports the average value-added measure (in $ millions) across all funds in each decile, and then across all sorting periods. Return data end in Dec. 2020; the H–H measure starts in Dec. 1984 and ends in Dec. 2015. *p*-values reported in parentheses are calculated based on standard errors using the Newey–West (1987) procedure with a lag equal to the total number of months in the look-ahead measurement horizon minus one.

Panel A. Gross Value-Added

	1M	1Q	1Y	2Y	3Y	4Y	5Y
D1 (short)	−0.20	−0.41	1.59	2.19	0.63	−2.95	1.94
	(0.55)	(0.68)	(0.74)	(0.78)	(0.95)	(0.82)	(0.88)
D2	0.26	0.49	−1.84	−3.42	−2.10	0.83	4.36
	(0.51)	(0.67)	(0.71)	(0.75)	(0.90)	(0.96)	(0.76)
D3	−0.12	−0.10	0.44	0.65	−0.27	0.19	0.80
	(0.76)	(0.93)	(0.93)	(0.96)	(0.99)	(0.99)	(0.96)
D4	0.04	0.01	−1.03	3.77	9.74	17.07	28.09
	(0.93)	(0.99)	(0.83)	(0.74)	(0.56)	(0.39)	(0.20)
D5	0.41	1.05	4.59	2.24	2.61	7.23	5.68
	(0.46)	(0.52)	(0.50)	(0.83)	(0.87)	(0.75)	(0.82)
D6	0.58	1.89	3.02	15.12	20.95	31.44	38.52
	(0.31)	(0.23)	(0.72)	(0.43)	(0.35)	(0.21)	(0.18)
D7	−0.19	−0.38	1.27	6.67	10.94	21.22	29.37
	(0.73)	(0.81)	(0.88)	(0.71)	(0.64)	(0.31)	(0.12)
D8	0.21	0.52	4.98	9.39	18.44	24.63	35.39
	(0.77)	(0.80)	(0.61)	(0.66)	(0.48)	(0.37)	(0.20)
D9	1.14	3.31	11.23	24.18	44.10	64.79	101.14
	(0.13)	(0.14)	(0.27)	(0.20)	(0.07)	(0.02)	(0.00)
D10 (long)	2.30	6.42	26.47	58.19	93.47	133.94	182.51
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
D10 − D1	2.50	6.83	24.87	56.00	92.84	136.89	180.57
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)

Panel B. Net Value-Added

	1M	1Q	1Y	2Y	3Y	4Y	5Y
D1 (short)	−0.59	−1.71	−4.27	−9.13	−18.13	−33.04	−44.04
	(0.06)	(0.06)	(0.39)	(0.27)	(0.10)	(0.03)	(0.02)
D2	−0.32	−0.94	−8.23	−15.50	−24.13	−33.86	−42.59
	(0.38)	(0.42)	(0.05)	(0.06)	(0.07)	(0.05)	(0.05)
D3	−0.61	−1.42	−5.13	−13.45	−19.93	−29.04	−43.05
	(0.15)	(0.22)	(0.16)	(0.10)	(0.19)	(0.16)	(0.12)
D4	−0.37	−1.58	−8.75	−12.51	−12.89	−20.19	−21.34
	(0.40)	(0.18)	(0.02)	(0.16)	(0.35)	(0.17)	(0.18)
D5	−0.76	−2.23	−4.89	−13.41	−22.30	−30.95	−44.92
	(0.12)	(0.10)	(0.34)	(0.20)	(0.17)	(0.12)	(0.07)
D6	0.02	0.23	−5.83	−4.86	−11.83	−17.64	−27.40
	(0.96)	(0.88)	(0.32)	(0.71)	(0.44)	(0.31)	(0.19)
D7	−0.46	−2.73	−9.05	−16.98	−24.65	−26.01	−31.57
	(0.36)	(0.04)	(0.12)	(0.13)	(0.12)	(0.13)	(0.12)
D8	−1.06	−2.48	−6.25	−14.92	−19.45	−29.45	−34.10
	(0.04)	(0.08)	(0.30)	(0.22)	(0.34)	(0.30)	(0.36)
D9	0.49	1.06	1.44	0.67	6.76	8.17	19.43
	(0.36)	(0.45)	(0.79)	(0.95)	(0.65)	(0.71)	(0.52)
D10 (long)	0.65	1.62	7.89	24.46	46.56	66.89	92.82
	(0.28)	(0.29)	(0.14)	(0.01)	(0.00)	(0.00)	(0.00)
D10 − D1	1.24	3.33	12.16	33.59	64.68	99.93	136.85
	(0.04)	(0.04)	(0.10)	(0.01)	(0.00)	(0.00)	(0.00)

net return by its last-month-end inflation-adjusted total net assets (in constant Jan. 2000 dollars) to get its net value-added. Following the same procedure as we adopt in the test of Panel A of Table 5, we summarize in Panel B the average *n*-period net value-added of funds with different levels of H–H.

Note that the average long H–H fund (D10) generates positive values for their investors over all look-ahead measurement horizons, which are statistically significant at a horizon longer than 1 year. On the other hand, the net value-added measure for short H–H funds (D1) is negative over all horizons. The differences between the two extreme deciles are both economically and statistically significant over all horizons. For example, over a 5-year period, the average long H–H fund yields $92.8 million ($18.6 million/year) to their investors, which is $136.9 million ($27.4 million/year) more than that delivered by the average short H–H fund. These results suggest that long H–H funds share some economic rents with their (patient) investors. These results also reinforce that, relative to investments on other passive index funds available in the market, investors earn positive abnormal returns by investing in long H–H funds but are worse off from their investments on short H–H funds.

V. The Horizon-Performance Relation at the Stock Level

Some stock positions are included in a fund portfolio for nonperformance purposes, so their existence tends to disguise the detection of the horizon-performance relation at the fund level. If these nonperformance related holdings are common across long- and short-horizon funds, then using differential information possessed by long- versus short-horizon funds can help to remove the effect of such nonperformance related holdings and improve the power in detecting the horizon-performance relation. In this section, we implement this stock-level approach by first aggregating holdings information about each stock from long-horizon funds and short-horizon funds separately. Then, we study the future performance of stocks that are largely held by one type of funds over the other.

A. Informativeness of Fund Holdings

We first construct a stock-level metric that reflects aggregate holdings information from long-horizon funds relative to short-horizon funds. Specifically, we rank all funds each month into terciles based on their H–H. Funds in the top and bottom terciles are classified as long-horizon funds and short-horizon funds, respectively. We then define long-horizon fund holdings (LFH) and short-horizon fund holdings (SFH) for each stock, similar to Yan and Zhang (2009), as the aggregate holdings of the stock by long-horizon funds and short-horizon funds, respectively, divided by that stock's total number of shares outstanding. Mutual funds often hold stocks for reasons unrelated to their perceived future performance, due to fiduciary guidelines or legal restrictions, the requirements of investment objectives and styles, fund flows, and so forth (Brown, Harlow, and Starks (1996), Del Guercio (1996)). LFH minus SFH can remove the common non-performance stock-picking by long- and short-horizon funds and, therefore, sharpen the differential information contained in the consensus opinions of one type of funds over the other. Then, we study future stock performance with respect to LFH minus SFH.

Each month, stocks are grouped into quintiles according to the relative holdings of long-horizon funds versus short-horizon funds (LFH minus SFH). The top quintile (Q5) contains stocks that are held, in aggregate, as a fraction of their market capitalization, most heavily by long-horizon funds relative to short-horizon funds; the bottom quintile (Q1) contains stocks held most heavily by short-horizon funds. Stocks in each quintile are equally weighted in the formation month. Following the sorted-portfolio method discussed in Section II.B, we calculate buy-and-hold returns and abnormal returns for each quintile portfolio over the next month, and up to the next 5 years after portfolio formation. We also calculate the return spreads between top and bottom quintile portfolios (Q5–Q1) to examine the outperformance of stocks with large long-horizon fund ownership versus stocks with predominant short-horizon fund ownership.

Consistent with our fund-level evidence, Table 6 shows that stocks with large long-horizon fund ownership offer significantly positive abnormal returns at all horizons, using either the Carhart or DGTW model to adjust risk exposure. Take the 5-year horizon as an example. The 4-factor alpha (DGTW-adjusted return) for the top quintile portfolio is 18.23% (17.62%), over the next 5 years, or about 3.6% (3.5%) per year. Both are statistically and economically significant. These abnormal returns are about 18% and 15%, respectively, larger than those for the bottom quintile over the 5-year horizon (more than 3% per year). In contrast, stocks largely

TABLE 6

Informativeness of Fund Holdings: Stock Portfolio Performance

Table 6 reports buy-and-hold returns (RETURN), 4-factor alphas (4-F α), and DGTW-adjusted returns (DGTW) of stock portfolios sorted on the relative fund holdings—long-horizon fund holding (LFH) minus short-horizon fund holding (SFH). A mutual fund is classified as short-term (long-term) if it ranks in the bottom (top) tercile based on the style-adjusted H–H measure. LFH (SFH) is defined as the aggregate holdings of a stock by long-horizon (short-horizon) funds divided by the stock's total number of shares outstanding. Each month we group stocks into quintiles according to LFH-SFH, with stocks in Q5 held more by long- and less by short-horizon funds and stocks in Q1 held more by short- and less by long-horizon funds. These stock portfolios are equally weighted at the formation date and are updated following a buy-and-hold strategy. Stock portfolio returns and abnormal returns in percentage are examined over the next month, the next quarter, and the next 1–5 years after portfolio formation. The table also reports the performance difference between the top and bottom quintile portfolios (Q5–Q1). *, **, and *** represent statistical significance for abnormal returns and return spreads at the 10%, 5%, and 1% confidence intervals, respectively. Return data end in Dec. 2020; the relative fund holdings measure, LFH-SFH, starts in Dec. 1984 and ends in Dec. 2015. Standard errors are obtained using the Newey–West (1987) procedure with a lag equal to the total number of months in the return measurement horizon minus one.

	1M	1Q	1Y	2Y	3Y	4Y	5Y
RETURN							
Q1 (short)	0.98	2.96	12.48	26.31	40.50	56.93	75.11
Q2	0.99	3.03	13.23	27.86	43.22	59.70	78.54
Q3	1.04	3.06	12.88	26.62	41.68	59.74	77.97
Q4	1.06	3.15	13.31	28.57	44.53	62.87	82.59
Q5 (long)	1.10	3.32	14.19	30.21	48.22	69.32	92.54
Q5 − Q1	0.12	0.36*	1.70	3.90**	7.72***	12.39***	17.43***
4-Fα							
Q1 (short)	−0.08	−0.34**	−1.71**	−1.15	0.08	0.93	0.36
Q2	0.03	0.02	0.12	1.61	4.09	5.23	6.45
Q3	0.06	0.11	0.41	0.70	2.51	6.39**	9.45***
Q4	0.08	0.22*	1.02	3.75**	6.90***	12.07***	16.79***
Q5 (long)	0.14**	0.45***	2.47**	5.18***	9.45***	14.89***	18.23***
Q5 − Q1	0.21**	0.78***	4.18***	6.33***	9.37***	13.95***	17.87***
DGTW							
Q1 (short)	−0.02	−0.09	0.02	0.43	0.68	1.68	2.49
Q2	−0.00	−0.02	0.52*	1.17**	2.02**	2.73**	4.47***
Q3	0.07***	0.14**	0.74***	1.37**	2.33***	4.25***	5.32***
Q4	0.10***	0.22***	1.16***	3.22***	4.94***	7.22***	9.79***
Q5 (long)	0.16***	0.45***	2.04***	4.66***	7.96***	12.13***	17.62***
Q5 − Q1	0.17***	0.54***	2.02**	4.22***	7.28***	10.45***	15.13***

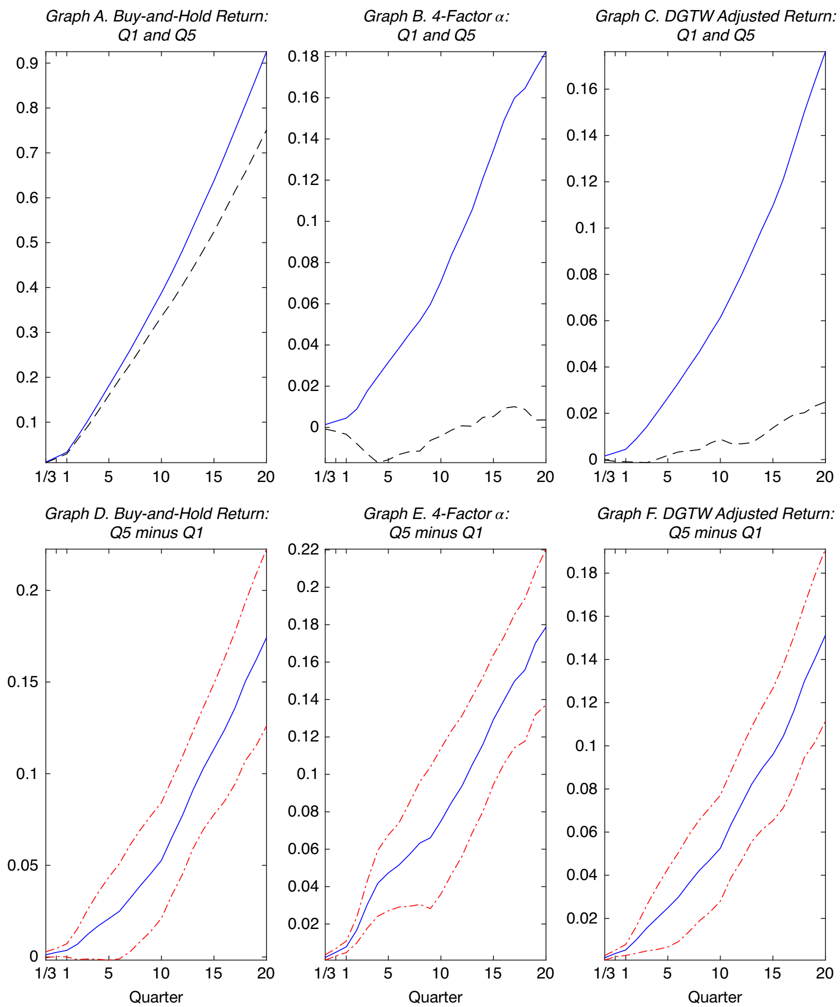
held by short-horizon funds exhibit no good performance; both the 4-factor alphas and DGTW-adjusted returns are either negative or insignificantly positive.

Visually, the 4-factor alpha and DGTW abnormal return for the top quintile increase with the return measurement horizon, as illustrated in Graphs A, B, and C of Figure 2, whereas in the bottom quintile, both are close to zero at all horizons. As a result, the abnormal returns of the Q5–Q1 portfolio, shown in Graphs D, E, and F, are positive at all horizons, and exhibit an increasing pattern with the return measurement horizon.

FIGURE 2

Informativeness of Fund Holdings: Stock Portfolio Performance

In Figure 2, stocks are sorted into quintiles according to LFH minus SFH, where LFH (SFH) is the percentage of the shares of a stock held by long- (short-) horizon funds. Q5 (Q1) is the portfolio consisting of stocks with large long-horizon (short-horizon) fund ownership. A mutual fund is classified as short-horizon (long-horizon) if it ranks in the bottom (top) tercile based on the style-adjusted H–H measure. Graphs A, B, and C plot buy-and-hold returns, 4-factor alphas, and DGTW-adjusted returns for the Q1 (dashed line) and Q5 (solid line) portfolios, and Graphs D, E, and F for the Q5–Q1 position that is long the Q5 and short the Q1 portfolios. For the Q5–Q1 portfolio, the plots also include the 90% confidence intervals computed based on the Newey–West approach.



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If long-horizon fund managers have a superior ability in exploiting long-term information and discriminate in their holdings of stocks for which they have better information, we would expect that long-term stock positions would be likely to outperform short-term stock positions in their portfolios. Table A6 in the Supplementary Material conducts such a test. To refine the informativeness of fund stock-picking we distinguish stocks that are, on average, held for a long or short time in a long-horizon fund portfolio. Section A5 of the Supplementary Material provides further detail. We find that stocks held for a long period by long-horizon funds exhibit superior future long-term performance, much better than those of stocks held for a short period. For example, at the 5-year return measurement horizon, long-period holdings exhibit a 4-factor alpha of 23.9% and a DGTW-adjusted return of 18.5%, both statistically and economically significant. These abnormal returns are much better than the counterparts for short-period holdings, and also better than the abnormal returns for stocks largely held by long-horizon funds before distinguishing long- versus short-period holdings (results for Q5 in Table 6).

The preceding findings about the differing informativeness of fund holdings along with the low across-stock correlation between LFH and SFH (roughly 0.1) imply that long- and short-horizon funds generally overweight different groups of stocks. One possibility is that long- and short-horizon funds apply different investment strategies that are implementable to different groups of stocks, which we will further explore in the next section.

B. Economic Source

In this section, we delve into a central issue regarding the economic source of manager skills—firm fundamentals reflected in funds' stock selection. If fund managers make use of corporate fundamental information in picking stocks, we would expect that long-horizon fund managers are skillful at exploiting information related to long-term firm fundamentals. Accordingly, it is likely that the patterns of future cash flows and profitability for stock portfolios sorted on relative fund holdings are analogous to the previously discussed return patterns of these portfolios.

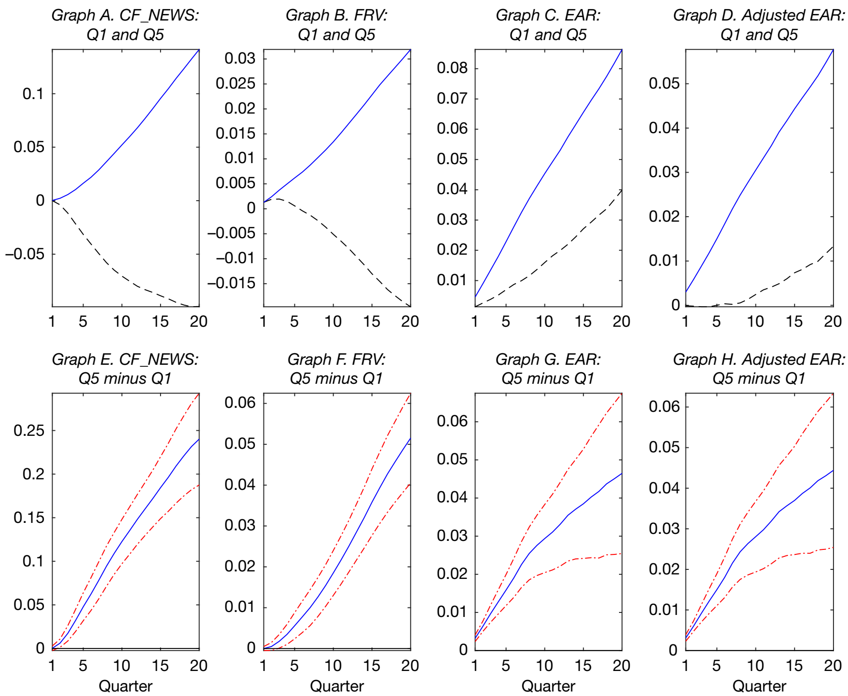
To measure information shocks to firm fundamentals, we use four variables: cash-flow news (CF_NEWS), analyst forecast revisions (FRV), earnings-announcement-window returns (EAR), and risk-adjusted EAR.[27] CF_NEWS is the cash-flow component of unexpected quarterly returns and is obtained via a Campbell and Shiller (1988) decomposition. FRV is the consensus EPS forecast for the current fiscal year, minus the 3-month lagged consensus EPS forecast for the same fiscal year, divided by the stock price 3 months ago. EAR is the buy-and-hold return during the $[-1, +1]$ trading-day-window around an earnings announcement date. If earnings are announced during a nontrading day, we treat the next immediate trading day as the announcement date. Adjusted EAR is the EAR minus the buy-and-hold return on the NYSE, AMEX, and Nasdaq market index during the same trading-day-window. To reduce the effect of outliers, all these information variables are cross-sectionally winsorized at the top and bottom 1%. These four

[27]Since EAR is available only at a quarterly frequency, we construct all variables of fundamental shocks at this frequency, for simplicity. Details about the construction of CF_NEWS are provided in the Appendix.

FIGURE 3

Fundamentals for Stocks with Different Long- Versus Short-Horizon Fund Ownership

Figure 3 plots cumulative fundamental variables, including cashflow news (CF_NEWS), analyst forecast revision (FRV), earnings-announcement-window returns (EAR), and market-adjusted EAR, over the next 1–20 quarters after stock portfolio formation. Specifically, the average of each quarterly fundamental variable is calculated first for each stock portfolio in the *n*th quarter after the formation period, where $1 \le n \le 20$, and is then accumulated over 1–20 quarters into the future. Graphs A, B, C, and D plot future firm fundamentals for stock quintile portfolio Q1 (dashed line) that consists of stocks held heavily by short-horizon funds, and for stock quintile portfolio Q5 (solid line) that consists of stocks held heavily by long-horizon funds. Graphs E, F, G, and H exhibit the spreads of future fundamental variables between the Q5 and the Q1 portfolios, with the 90% confidence interval calculated using the Newey–West approach. Style-adjusted H–H measure is used as a metric of fund holding horizon.



variables capture fundamental shocks from different perspectives. CF_NEWS captures revisions of expected future cash flows over an infinite horizon that are reflected in stock returns. FRV reflects changes in earnings expectations over the current fiscal year, presumably due to new information arrival during the quarter. EAR and adjusted EAR measure the magnitude of earnings surprises in terms of stock returns and stock abnormal returns, respectively.

Figure 3 displays cumulative fundamental variables over the next 1 to 20 quarters following the stock portfolio formation. Specifically, each quarter we first sort stocks into quintiles according to their relative fund holdings, as we did in Section V.A. We then calculate the cross-sectional mean of each fundamental variable in each quintile and in the *n*th quarter after the formation quarter, where $1 \le n \le 20$, and we cumulate these quarterly means over one to 20 quarters. Finally, we compute an average across all portfolio formation dates for each of these cumulated measures.

Regardless of which fundamental measure we use, stocks with predominant long-horizon fund ownership have superior long-term firm fundamentals; the cash-flow and profitability patterns of these stocks are analogous to their return pattern. Notice that, Graphs A, B, C, and D of Figure 3, all cumulative fundamental variables are positive and increase with measurement horizons for stocks largely held by long-horizon funds (Q5). In contrast, cumulative fundamental variables can be negative (CF_NEWS and FRV), positive (EAR), or close to zero (adjusted EAR) for stocks with large short-horizon fund ownership (Q1). All of these four variables for the Q5–Q1 portfolio, as shown in Graphs E, F, G, and H, are significantly positive at long horizons. Take the 5-year horizon as an example. Stocks largely held by long-horizon funds (Q5) possess strong firm fundamentals, with cumulative CF_NEWS of 14.1%, FRV of 3.2%, EAR of 8.6%, and risk-adjusted EAR of 5.8% over the 5-year period (Table 7). These cumulative fundamental variables are both statistically and economically significant.

In summary, the patterns of portfolio performance in terms of cashflows and profitability are analogous to the patterns of portfolio returns. Our results indicate that long-horizon fund managers are able to buy and hold stocks with strong long-term firm fundamentals, which are associated with long-horizon funds' good performance.

TABLE 7

Fundamentals for Stocks with Different Long- Versus Short-Horizon Fund Ownership

Table 7 reports cumulative fundamental variables (including cashflow news (CF_NEWS), analyst forecast revision (FRV), earnings-announcement-window returns (EAR), and market adjusted EAR in percentage) over the next quarter and the next 1–5 years after stock portfolio formation. Fundamental data end in Dec. 2020; the H–H measure starts in Dec. 1984 and ends in Dec. 2015. Specifically, the average of each quarterly fundamental variable is calculated first for each stock portfolio in the nth quarter after the formation period, where $1 \leq n \leq 20$, and is then accumulated over 1–20 quarters into the future. Stock quintile portfolio Q1 consists of stocks held heavily by short-horizon funds, and stock quintile portfolio Q5 consists of stocks held heavily by long-horizon funds. The table also reports the spreads of future fundamental variables between the Q5 and the Q1 portfolios and associated p-values, which are calculated based on the Newey–West approach. Style-adjusted H–H measure is used as a metric of fund investment horizon.

	1Q	1Y	2Y	3Y	4Y	5Y
CF_NEWS						
Q1 (short)	0.00	−2.16	−5.79	−8.00	−9.17	−9.89
Q2	−0.01	−0.18	−0.26	0.31	1.05	2.39
Q3	0.11	0.55	1.67	3.78	6.89	9.88
Q4	0.36	1.53	3.92	7.22	10.74	15.03
Q5 (long)	0.02	1.04	3.64	6.81	10.46	14.14
Q5 − Q1	0.02	3.20	9.43	14.81	19.63	24.02
	(0.90)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FRV						
Q1 (short)	0.13	0.15	−0.24	−0.80	−1.45	−1.96
Q2	−0.04	−0.19	−0.30	−0.22	−0.06	0.25
Q3	0.09	0.30	0.50	0.84	1.43	2.02
Q4	0.19	0.69	1.33	2.06	2.84	3.75
Q5 (long)	0.13	0.50	1.03	1.71	2.48	3.19
Q5 − Q1	0.00	0.34	1.26	2.50	3.93	5.15
	(0.92)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
EAR						
Q1 (short)	0.13	0.52	1.16	1.99	2.93	3.99
Q2	0.10	0.38	0.84	1.40	2.01	2.88
Q3	0.20	0.78	1.59	2.50	3.50	4.53
Q4	0.34	1.25	2.49	3.80	5.13	6.48
Q5 (long)	0.46	1.80	3.71	5.31	6.96	8.64
Q5 − Q1	0.32	1.28	2.55	3.31	4.03	4.65
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted EAR						
Q1 (short)	−0.01	−0.03	0.06	0.41	0.81	1.33
Q2	−0.03	−0.17	−0.26	−0.20	−0.16	0.14
Q3	0.05	0.21	0.51	0.92	1.41	1.88
Q4	0.19	0.70	1.39	2.18	2.93	3.71
Q5 (long)	0.30	1.18	2.49	3.60	4.68	5.77
Q5 − Q1	0.31	1.21	2.43	3.19	3.87	4.44
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

VI. Comparison of H–H with Portfolio Turnover

Academics and practitioners use turnover to measure the level of fund trading activity (e.g., Bushee (2001), Gaspar et al. (2005), and Cremers and Pareek (2015)),[28] while our H–H is designed to measure fund holding horizon (portfolio-weighted holding periods of securities) of an actively managed fund. Although a fund that trades frequently has high turnover and, in many cases, has a low holding horizon, using (the inverse of) turnover as a proxy for fund holding horizon, as the literature occasionally does, is flawed and biased. Indeed, in our sample the (time-series average of cross-sectional) correlation of H–H with the inverse of CRSP_TR is small, at 0.47.

Further, we explore whether long-horizon funds are reliably low-turnover funds, as well as whether high-turnover funds are short-horizon funds. We find that, among the top 20% of funds, ranked on the H–H measure (the longest H–H funds), over 16% are in the highest three turnover quintiles and 24% in the fourth-highest turnover quintile. Therefore, only about 60% of the longest-H–H funds are in the lowest-turnover quintile of funds. Even more revealing is that only half (50%) of funds in the highest-turnover quintile are in the lowest-H–H quintile. These results indicate that H–H and turnover capture very different aspects of active management. We next explore the reason for this low correlation between turnover and H–H.

We appeal to Jensen's inequality to explain that the inverse of turnover is a downward-biased measure of the true portfolio-weighted holding horizon of securities in a fund portfolio. The greater the amount of heterogeneity in the holding horizons of securities within a fund portfolio, the more severe is this bias. Let us assume that stock holding-period, X, in a fund portfolio follows a log-normal distribution. Let $Y = lnX \sim N(\mu, \sigma)$, and let $p(X)$ be the probability density function of X. Then,

$$\text{(3)} \qquad \text{H–H} = \int X dp(X) = E(X) = E(e^Y) = \exp\left(\mu + \frac{1}{2}\sigma^2\right),$$

$$\text{(4)} \quad \text{TR} = \int \frac{1}{X} dp(X) = E\left(\frac{1}{X}\right) = E\left(e^{-Y}\right) = \exp\left(-\mu + \frac{1}{2}\sigma^2\right), \text{so} \, 1/\text{TR} = \exp\left(\mu - \frac{1}{2}\sigma^2\right).$$

Hence, $1/\text{TR} = \exp(-\sigma^2)\text{H–H}$. When grouping funds into long or short horizon using $1/\text{TR}$, the greater the level of heterogeneity in stock holding horizon in a given fund portfolio, the more likely a fund is incorrectly classified as short horizon.

In our fund sample the average fund in the top quintile, ranked according to H–H, has a standard deviation of stock-level holding period of 3.29 years, while in the bottom quintile it is 1.06 years (Panel C of Table 1). Since the standard deviation

[28]We note that reported turnover has the advantage of being able to capture round-trip trades that occur between two portfolio disclosure dates. However, this advantage has become minimal, with the new SEC requirement of monthly portfolio holdings disclosure that became effective in Apr. 2019, for larger fund groups, and in Apr. 2020, for smaller fund groups (see https://www.sec.gov/files/formn-port.pdf).

TABLE 8

Comparison of Fund Holding Horizon with CRSP Turnover

Table 8 reports the estimation results of panel regressions of next-year fund holding horizon (H–H; in the left columns) or next-year CRSP turnover (CRSP_TR; in the right columns) on current fund holding horizon, current CRSP turnover, and other fund characteristics. These regressions are panel regressions with no fixed effect, a fund-fixed effect, and a time-fixed effect. The style-adjusted H–H measure is used as the metric of fund holding horizon. The other fund characteristics include fund size, the expense ratio, fund age, past-year flow volatility, and past-year fund flow. *p*-values reported in parentheses are calculated based on heteroskedasticity-robust standard errors clustered by fund and by year.

	Next-Year H–H			Next-Year CRSP_TR		
Dependent Variable	No Fixed Effect	Fund Fixed Effect	Time Fixed Effect	No Fixed Effect	Fund Fixed Effect	Time Fixed Effect
H–H	0.937	0.732	0.937	−0.029	−0.022	−0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CRSP_TR	−0.068	−0.086	−0.070	0.771	0.511	0.773
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FUND_SIZE	0.018	0.064	0.017	−0.007	−0.014	−0.008
	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)
EXPENSE_RATIO	−0.003	−0.001	−0.015	0.038	0.041	0.047
	(0.84)	(0.96)	(0.36)	(0.00)	(0.03)	(0.00)
FUND_AGE	−0.000	0.002	−0.000	0.000	−0.002	0.000
	(0.68)	(0.35)	(0.55)	(0.07)	(0.33)	(0.02)
FLOW_VOLATILITY	0.535	−0.208	0.524	0.492	0.360	0.469
	(0.00)	(0.18)	(0.00)	(0.00)	(0.01)	(0.00)
FUND_FLOW	0.010	0.011	0.010	−0.015	−0.010	−0.015
	(0.14)	(0.00)	(0.13)	(0.00)	(0.00)	(0.00)

of stock holding-period is substantially larger for long-horizon funds than for short-horizon funds, the gap between the inverse of turnover and H–H is much larger for long-horizon funds. Therefore, the mismeasurement of horizon using inverse turnover is more severe for long-horizon funds.

To further compare H–H with turnover, Table 8 tests whether the next-year H–H (in the left panel), or next-year CRSP_TR (in the right panel) is predictable using current-year H–H and turnover, as well as other fund characteristics. Because CRSP reports annual turnover, we use yearly data as of Dec. of each year to run panel regressions. The regression results suggest that H–H and turnover, though related, are quite different variables. Each is quite persistent; its own lag explains the majority of its variation. Further, H–H has only tiny forecasting power for turnover, and vice versa.

Next, we run a horse race of H–H and turnover in predicting future fund alphas in panel regressions, while controlling for other fund characteristics. These panel regressions differ in their inclusion of no fixed effect, a fund fixed effect, and a time fixed effect. A regression with a fund fixed effect captures the forecasting power of within-fund time variation in fund H–H and turnover for future fund performance. A regression with a time-fixed effect captures the forecasting power of cross-sectional variation in these predictors for future fund performance. A regression with no fixed effect captures both types of variations in these regressors. Heteroskedasticity-robust standard errors are calculated based on 2-way clusters by fund and by month. Table 9 presents the results of forecasting future 4-factor net alphas.

In the regressions with no fixed effect or with a time-fixed effect, H–H positively predicts future fund alphas over all horizons, ranging from 1 month to

TABLE 9

Fund Holding Horizon Versus CRSP Turnover: Fund Performance Prediction

Table 9 reports the coefficient estimates and *p*-values (in parentheses) of three-panel regressions of future 4-factor fund net alphas on fund holding horizon (H–H) and CRSP turnover (CRSP_TR) while controlling for other fund characteristics. These three-panel regressions differ by including no fixed effect, a fund fixed effect, and a time fixed effect. The dependent variables are the 4-factor net alphas in percentage associated with buy-and-hold net returns at return measurement horizons of 1 month, 1 quarter, and 1, 3, and 5 years. The style-adjusted H–H measure is used as the metric of fund holding horizon. The other fund characteristics (not reported in the table to save space) include fund size, the expense ratio, fund age, past-year flow volatility, and past-year fund flow. Return data end in Dec. 2020; the predictive variables start in Dec. 1984 and end in Dec. 2015. Heteroskedasticity-robust standard errors are calculated for panel regressions based on 2-way clusters by fund and by month.

	No Fixed Effect	Fund Fixed Effect	Time Fixed Effect
1 Month			
H–H	0.018	−0.004	0.018
	(0.01)	(0.61)	(0.00)
CRSP_TR	−0.011	0.030	−0.009
	(0.64)	(0.20)	(0.68)
1 Quarter			
H–H	0.059	−0.014	0.066
	(0.00)	(0.49)	(0.00)
CRSP_TR	−0.006	0.086	0.009
	(0.90)	(0.10)	(0.84)
1 Year			
H–H	0.242	−0.073	0.279
	(0.00)	(0.28)	(0.00)
CRSP_TR	0.200	0.264	0.290
	(0.22)	(0.14)	(0.08)
3 Years			
H–H	0.777	−0.134	0.814
	(0.00)	(0.45)	(0.00)
CRSP_TR	0.242	0.621	0.369
	(0.53)	(0.15)	(0.32)
5 Years			
H–H	1.400	−0.478	1.460
	(0.00)	(0.12)	(0.00)
CRSP_TR	−0.346	0.708	−0.277
	(0.53)	(0.25)	(0.62)

5 years, while fund turnover essentially plays an insignificant role. This result is consistent with the Fama–MacBeth regression result reported in Table 4. Together, these findings suggest that H–H best captures cross-sectional fund skills. Once we add a fund fixed effect to panel regressions, turnover becomes a significant indicator of future short-term (one-quarter) fund alpha. This evidence indicates that turnover reflects individual fund manager's detection of time-varying short-run investment opportunities, which is better captured by a fund-fixed effect. High-turnover funds do not perform well cross-sectionally primarily because short-term opportunities cannot be frequently found, consistent with Pástor et al. (2017).

VII. The Demand Side

In this section, we explore a potential reason why long H–H funds exhibit positive alphas, as shown in Section IV, from a demand-side perspective. Our exploration of the demand side is motivated by the varying level of share classes charging load fees among active funds, which we have discussed in Sections III.A and IV.A. Chordia's (1996) theoretical model suggests that investors with a low probability of redemption prefer to invest in load funds, while investors with a high

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probability of redemption are better off investing in no- or low-load funds, as high load charges are associated with smaller yearly 12b-1 fees (see https://www.sec.gov/news/studies/feestudy.htm#P328_72009). Since a low probability of redemption means a longer expected investment horizon, ex ante, Chordia's model also implies that long-term investors are more willing to invest in load funds. Indeed, we have shown evidence, in Section III.A, of an interesting clientele effect: long-horizon funds are sold to investors, to a greater extent, through share classes that carry load fees, as compared to short-horizon funds.

This clientele effect indicates that long H–H funds prefer to cater to long-term investors and that this preference leads to an important consequence: Long H–H funds share economic rents with their investors to compensate their investors' long-term capital commitment (Nanda et al. (2000)). To explain, the mutual fund structure is set up to provide daily liquidity to fund investors. Liquidity costs can be significant for mutual funds (Edelen (1999)), especially for long H–H funds relying on long-term strategies (Chordia (1996)). Nanda et al.'s (2000) theoretical model shows that fund managers compete for investors with a low probability of liquidity shocks. Because such long-term investors are relatively scarce, fund managers are willing to share some economic rents with their long-term investors. In the end, fund managers with high skills, which corresponds to long H–H fund managers in our article, are more able to provide load funds with positive expected net alpha to long-term investors, while low-skill managers operate no-load (or low-load) funds with zero expected net alpha, consistent with Berk and Green's (2004) argument, to short-term investors with high liquidity demand.

Rewarded with positive expected net alphas, long-term investors prefer purchasing load shares of a fund and provide an ex ante commitment to not redeem their shares in the short run. Because such a precommitment does not preclude investors from ex post redeeming, whether it results in a lower liquidity demand is an empirical issue. We cover this issue next by exploring the flow-performance relation.

Sirri and Tufano (1998) show that fund flows respond to past performance in a convex way. Following Sirri and Tufano, we run 12-month flows on past 12-month fund performance in a piece-wise linear regression while controlling for other characteristics that possibly affect fund flows. For each investment objective and year, fund net returns are ordered, and each fund is assigned a percentile rank (RANK) ranging from 0 (the poorest performance) to 1 (the best performance). The bottom performance quintile (LOWPERF) is defined as min(RANK,0.2), the middle three performance quintiles (MIDPERF) are combined into one group defined as min(RANK-LOWPERF,0.6), and the top performance quintile (HIGHPERF) is defined as RANK-LOWPERF-MIDPERF. Like Sirri and Tufano's Table II, Table 10 shows a pronounced convex response of fund flows to past performance: little to low past performance, modest to medium past performance, and strong to high past performance (column 1).

We next examine whether such a convex flow-performance response varies between long and short H–H funds. To ensure enough funds in bottom and top performance quintiles while classifying long or short H–H funds, each period, we sort funds into terciles according to their H–H measure; short, medium, and long H–H funds are denoted as HHT1, HHT2, and HHT3, respectively. Again, a clear

TABLE 10

Flow-Performance Sensitivities

In Table 10, we follow Sirri and Tufano (1998) and run piece-wise linear regressions of future 12-month fund flows on past 12-month fund performance while controlling for other characteristics. To measure fund performance, for each investment objective and year, fund net returns are ordered, and each fund is assigned a percentile rank (RANK) ranging from 0 (the poorest performance) to 1 (the best performance). The bottom performance quintile (LOWPERF) is defined as $\min(\text{RANK}, 0.2)$, the middle three performance quintiles (MIDPERF) are combined into one group defined as $\min(\text{RANK}-\text{LOWPERF}, 0.6)$, and the top performance quintile (HIGHPERF) is defined as RANK-LOWPERF-MIDPERF. Control variables include fund size measured as log of total net assets, the expense ratio, return volatility calculated as the standard deviation of monthly net returns over past 12 months, average flows to the same investment style, and factor-related return (FRR). Each year we sort funds into terciles according to their H–H measure; HHT1, HHT2, and HHT3 are dummy variables and equal to 1 if a fund in the short, medium, or long H–H tercile, respectively, and 0 otherwise. We calculate the AUM-weighted proportion of the share classes of a given fund that charge load fees (either front-end or rear-end) as a proxy for the effective load of that fund. A high (low) load dummy, HIGH_LOAD (LOW_LOAD), is equal to 1 if the effective load is above (below) the median level, and 0 otherwise. Three piece-wise linear regressions differ in whether fund performance variables, LOWPERF, MIDPERF, and HIGHPERF, are interacted with H–H tercile dummies and/or high and low load dummies. Fund flows end in Dec. 2016; the H–H measure and the other predictive variables start in Dec. 1984 and end in Dec. 2015. *p*-values in parentheses are calculated based on standard errors using the Newey–West (1987) procedure with one lag.

	1	2	3
LOWPERF	0.08 (0.27)		
MIDPERF	0.30 (0.00)		
HIGHPERF	0.86 (0.00)		
LOWPERF × HHT1		0.04 (0.63)	0.06 (0.48)
LOWPERF × HHT2		0.05 (0.47)	0.07 (0.31)
LOWPERF × HHT3		0.20 (0.01)	0.21 (0.01)
MIDPERF × HHT1		0.34 (0.00)	0.34 (0.00)
MIDPERF × HHT2		0.30 (0.00)	0.29 (0.00)
MIDPERF × HHT3		0.24 (0.00)	0.24 (0.00)
HIGHPERF × HHT1		1.25 (0.00)	
HIGHPERF × HHT2		0.71 (0.00)	
HIGHPERF × HHT3		0.58 (0.02)	
HIGHPERF × HHT1 × LOW_LOAD			1.50 (0.00)
HIGHPERF × HHT1 × HIGH_LOAD			1.01 (0.03)
HIGHPERF × HHT2 × LOW_LOAD			1.25 (0.01)
HIGHPERF × HHT2 × HIGH_LOAD			0.63 (0.03)
HIGHPERF × HHT3 × LOW_LOAD			0.46 (0.40)
HIGHPERF × HHT3 × HIGH_LOAD			0.42 (0.07)
FUND_SIZE	−0.02 (0.00)	−0.02 (0.00)	−0.02 (0.00)
EXPENSE_RATIO	0.05 (0.04)	0.05 (0.04)	0.05 (0.04)
RETURN_VOLATILITY	−0.10 (0.90)	−0.01 (0.99)	0.07 (0.94)
STYLE_FUND_FLOW	0.04 (0.09)	0.04 (0.07)	0.04 (0.08)
FRR	7.06 (0.04)	6.57 (0.05)	7.12 (0.04)
INTERCEPT	−0.04 (0.44)	−0.04 (0.43)	
LOW_LOAD			−0.04 (0.41)
HIGH_LOAD			−0.04 (0.48)

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convex flow-performance relation appears for each H–H group of funds (column 2). Interestingly, short H–H funds exhibit a strong convex relation, while long H–H funds' is much weaker. The considerably large difference in convexity mainly comes from the response to high past performance, while the response to low or medium past performance differ only modestly across three H–H groups of funds. Moving five percentile points down in the high past performance category (say from the 85th to the 80th percentile) is associated with 6.3% and 2.9% outflows for short and long H–H funds, respectively. The difference is both statistically and economically significant. This finding is also consistent with the evidence that flows to long H–H funds is less volatile than those to short H–H funds (Panel C of Table 1).

We further find that the flow response to high past performance differs for funds with different levels of load charges. Specifically, we define a LOW_LOAD (HIGH_LOAD) dummy equal to 1 if a fund's percentage AUM charging front- and/or back-end loads is below (above) the median level, and 0 otherwise. Note that funds with no load charge have LOW_LOAD equal to 1. Column 3 of Table 10 shows that, for each of three H–H groups, the flow-performance sensitivity is stronger among funds with low load charges than with high load charges. We also notice that long H–H, high-load funds exhibit the lowest flow-performance sensitivity among funds with high past performance.

Overall, with a larger proportion of their AUM charging load fees, long H–H funds are prone to catering to patient investors. That is, more "long-term" investors invest in long-horizon funds and more "short-term" investors invest in short-horizon funds. This segregation of demand leads long H–H funds to receive stable flows and helps to reduce the adverse effect of flows on long H–H funds' performance; long H–H funds, in turn, share some economic rents with their investors to reward their investors' long-time capital commitment.

VIII. Additional Analyses and Robustness Tests

In this section, we summarize the results of additional tests and tabulate the results in the Supplementary Material. Our main conclusion that long-horizon funds identified using H–H truly exhibit superior long-term performance is unaltered.

A. Being a New Dimension of Active Fund Management

To further test whether our fund horizon measure is truly a new proxy for active investing, we run a panel regression of H–H on a list of explanatory variables that we have used as the control variables in Section IV.B. The explanatory power of these variables combined is 36% (Table A7 in the Supplementary Material). This evidence suggests that H–H is not simply a proxy for fund characteristics, nor metrics of active fund management uncovered in prior research. It is consistent with our evidence, in Table 4, that H–H's strong predictive power for future fund performance remains, even when these variables are included as additional predictors.

B. Illiquidity

Table A8 in the Supplementary Material provides evidence that the outperformance of long H–H funds is not simply a consequence of capturing liquidity risk premium. We use Carhart's four factors plus the liquidity factor of Pástor and Stambaugh (2003) to control for additional liquidity risk exposure. Fund 5-factor net alphas are similar to the 4-factor alphas reported in Table 2.

Next, we conduct an additional test, which suggests that the outperformance of long H–H funds is neither a result of stock illiquidity premium. In this test, we divide stocks with large long-horizon fund ownership into two groups: liquid stocks and illiquid stocks, where the former (latter) have Amihud's illiquidity measure below (above) the median. Similarly, stocks with large short-horizon fund ownership are divided into liquid and illiquid groups. Table A9 in the Supplementary Material shows that liquid stocks largely held by long H–H funds have significantly positive future abnormal returns, better than or roughly equal to those of the illiquid counterparts. For example, the 5-year 4-factor alpha is 18% for liquid stocks versus 15% for illiquid stocks. Further, the difference in abnormal returns between stocks with large long-horizon versus short-horizon fund ownership is also larger for liquid stocks.

C. Out-of-Sample Test of H–H's Ex Ante Predictability

Following the spirit of the empirical methods of Pesaran and Timmermann (1995) and Cooper, Gutierrez Jr, and Marcum (2005), we employ a recursive out-of-sample approach to evaluate the ex ante predictability of our H–H measure, along with eight other leading predictors proposed by prior research for mutual fund return forecasting. This out-of-sample approach assumes that a hypothetical real-time investor has no prior belief in the efficacy of any of these predictive variables, and assesses whether she would discover H–H and/or any other variables useful for fund selection using real-time backtests. See Section A6 of the Supplementary Material for detail. As Table A10 in the Supplementary Material shows, the real-time investor frequently picks H–H amid the set of eight other leading predictors available for fund selection, using backtests. We also find that adding H–H to this list of eight other predictors improves out-of-sample fund performance, compared with the same set when H–H is excluded (Table A11 in the Supplementary Material). These results suggest that the H–H measure is an important ex ante predictor, and that employing it, even among other strong fund return predictors, provides better out-of-sample performance.

D. Fund Performance Conditional on Benchmarks

Frazzini et al. (2016) claim that the predictive power of Active Share (AS) is driven by the strong correlation between AS and fund benchmark types. As they argue, AS is higher for funds having certain benchmarks; for funds following the same benchmark, AS does not exhibit significant forecasting power. Of course, this could be due to more skilled managers locating in similar styles within the

U.S. equity universe. Regardless, we confirm their finding regarding AS using our sample. The forecasting power of H–H, however, is not subject to this benchmark-related "bias." In unreported tests, we rank funds into terciles according to H–H within each fund benchmark group, as in Frazzini et al. (2016). Outperformance of long-horizon funds remains. Further, we find that, conditional on fund benchmarks, the forecasting power of H–H is still strong after controlling for AS, but AS has virtually no predictive power.

Next, we compare the predictive power of H–H with the main measures used by CP. CP find that, among high AS funds, only those with patient investment strategies outperform. Patient strategies are identified as funds with either a long investment duration or a low turnover ratio. Specifically, we test whether H–H remains a significant predictor when controlling for AS interacted with the measures of patient strategies. We run two-panel regressions of 5-year 4-factor net alpha on H–H and control variables, which include dummies for high and low AS (top and bottom quintiles), and an interaction between the AS dummies and patient strategies. Each panel regression uses one of the two CP's measures of patient strategies. Following CP, we also include time and benchmark fixed effects. In unreported results, we show that, consistent with CP, the coefficients on their interaction variables are statistically significant. Importantly, even controlling for CP's measures, the coefficient on H–H remains statistically significant.

In a granular analysis that controls for benchmarks, we follow Frazzini et al. (2016) and run a separate panel regression for each benchmark type with a time-fixed effect. Given a smaller sample size for each regression, we use terciles to define high and low AS dummies. The dependent variable is 1-, 3-, or 5-year 4-factor net alpha. Table A12 in the Supplementary Material shows that the coefficient on H–H is positive and statistically significant for 7, 8, and 8 out of 10 benchmark categories, when the dependent variable is 1-, 3-, and 5-year alphas, respectively. By contrast, the coefficient on the interaction between the high AS dummy and duration is significantly positive (the correct sign) for only 2, 3, and 5 out of 10 benchmarks and significantly negative (the incorrect sign) for 4, 3, and 2 benchmarks, respectively. That is, CP's main measure loses its forecasting power within fund categories, as indicated by Frazzini et al. (2016). Surprisingly, we also notice that, for 1-year alpha, for example, the coefficient on the interaction between the *low* AS dummy and duration is significantly positive for 2 out of 10 benchmarks and significantly negative for 3 benchmarks, although, according to CP, this interaction variable should not be significant because their measure of skill is high AS rather than low AS. For robustness, we also use the interaction of turnover with high and low AS dummies, and the results are similar (Table A13 in the Supplementary Material).

This analysis provides further confirmation that H–H is robust to the Frazzini et al.'s (2016) critique as well as to the CP's measure. Further, our measure of fund investment horizon H–H is simple to compute and easy for fund investors to understand, much simpler than the computation of AS or the interaction of AS with patient strategies.

E. Other Tests

Based on 13-F institutional holdings data aggregated at the fund advisor level, Yan and Zhang (2009) show that both the level and the change in short-term institutional ownership are significant predictors of future stock returns, while there is no evidence of a similar result for long-term institutional ownership. Following Yan and Zhang, we use the holdings-based turnover ratio to classify a fund in our mutual fund sample as long- or short-term. Table A14 in the Supplementary Material shows that their result holds at the 1-month horizon but is reversed at a horizon of more than a year.

The conclusion of Yan and Zhang (2009) is different from ours for three reasons. First, as discussed in Section VI, our more direct measure of fund holding horizon, compared with turnover, facilitates the detection of long-horizon funds' outperformance. Second, a good deal of heterogeneity in holding horizon of different funds managed by the same advisor is lost in the 13-F data. In fact, many advisors manage pensions, other types of accounts, and even index funds, all of which are aggregated in 13-F data. Lastly, Yan and Zhang treat, homogeneously, different types of institutional advisors, such as those that advise pension funds and mutual funds. A fund with a relatively long H–H within a mutual fund group is likely to be classified as short-term relative to a typical pension fund.

Finally, we confirm that the evidence of superior long-term alphas of long H–H funds does not rely on style-adjustment of H–H (Table A15 in the Supplementary Material), and is also robust to subsample periods (Table A16 in the Supplementary Material) as well as to different benchmark models (Table A17 in the Supplementary Material), including a 6-factor model (Fama and French (2015) five factors plus momentum factor) and a passive benchmark model, proposed by Berk and van Binsbergen (2015) and constructed from Vanguard index fund returns. Furthermore, the strong fund horizon-performance relation that we have shown before disappears in a sample of "closet indexers," identified using Active Share as in Cremers and Petajisto (2009) (see Table A18 in the Supplementary Material). This evidence, along with the observation that H–H cannot be explained by other variables (Section VIII.A), suggests that long-horizon funds are not merely "closet indexers" that stay close to their benchmarks without trading for long periods of time.

IX. Conclusions

Using newly proposed direct measure of fund holding horizon, this article finds a positive fund horizon-performance relation. This new measure outperforms fund turnover and the main measure of Cremers and Pareek (2016) in predicting future U.S.-domiciled equity fund 4-factor alphas. Further, we show that stocks with large long-horizon fund ownership exhibit superior long-term fundamentals. Thus, the outperformance we document stems from long-horizon fund managers possessing valuable information about superior future firm long-term cashflow-generating prospects.

Our H–H measure can help investors to better identify long- or short-horizon funds. The finding of the superior long-term performance of long-horizon mutual funds critically depends on the use of our more direct measure than what was previously used in the institutional investors literature. There is evidence that individual investors have long rebalancing horizons (Ameriks and Zeldes (2004), Mitchell, Mottola, Utkus, and Yamaguchi (2006)). In Ameriks and Zeldes's sample of defined contribution plan participants, 47% (21%) made no (one) change to their allocation of contributions over a 10-year period. Our analysis suggests that those investors with long rebalancing horizons are better off selecting long- rather than short-horizon funds.

Finally, our evidence (that some mutual funds implement and succeed in long-term investing by exploiting fundamental information) contributes to the debate on the excessive short-term focus of institutional investors (Porter (1992)) as well as the undesirable consequences induced by short-termism (Bushee (1998), Gaspar et al. (2005), and Cella, Ellul, and Giannetti (2013)).

Appendix. Construction of Cashflow News (CF_NEWS)

This measure considers changing expectations of the sum of discounted cashflows of a firm over all future periods. It is constructed using the IBES summary unadjusted file. Specifically, we keep consensus earnings forecasts for the current and subsequent fiscal year (FE1_t, FE2_t), along with a long-term growth forecast (LTG_t). The earnings forecasts are denominated in dollars per share, and t denotes when a forecast is employed. The long-term growth forecast represents an annualized percentage growth rate and pertains to the next 3–5 years.

Similar to Frankel and Lee (1998), Pástor, Sinha, and Swaminathan (2008), Da and Warachka (2009), Balduzzi and Lan (2014), and Da, Liu, and Schaumburg (2014), we use a three-stage model to construct cashflow news by taking advantage of multiple earnings forecasts for different maturities. Let $X_{t,t+j}$ denote the time-t expectations of future earnings at $t+j$. In the first stage, expected earnings are computed directly using analyst forecasts as follows:

$$X_{t,t+1} = \text{FE1}_t, \quad X_{t,t+2} = \text{FE2}_t, \tag{A-1}$$

$$X_{t,t+j} = X_{t,t+j-1}(1+\text{LTG}_t), \quad j = 3,4,5. \tag{A-2}$$

In the second stage, expected earnings are assumed to converge to an economy-wide steady-state growth rate g_t from year six to year 10. Specifically,

$$X_{t,t+j+1} = X_{t,t+j}\left[1+\text{LTG}_t + \frac{j-4}{5}(g_t - \text{LTG}_t)\right], \text{for } j = 5,\ldots,9. \tag{A-3}$$

The steady-state growth rate g_t is the cross-sectional average of LTG_t.

Following Da and Warachka (2009), Balduzzi and Lan (2014), and Da et al. (2014), we assume the cash-flow payout is equal to a fixed portion (Ψ) of the ending-period book value. Under this assumption, the clean surplus accounting identity implies that the evolution of expected book value is $B_{t,t+j+1} = \left(B_{t,t+j} + X_{t,t+j+1}\right)(1-\Psi)$. The parameter Ψ is set to 5% since this percentage is close to the average payout rate for the firms in our sample.

In the third stage, expected earnings growth converges to g_t, which implies expected accounting returns converge to $\frac{g_t}{1-\Psi}$ beyond year 10. The expected log accounting returns $e_{t,t+j}$ is estimated at time t as:

(A-4)
$$e_{t,t+1+j} = \begin{cases} \log\left(1+\frac{X_{t,t+1+j}}{B_{t,t+j}}\right) & \text{for } 0 \le j \le 9 \\ \log\left(1+\frac{g_t}{1-\Psi}\right) & \text{for } j \ge 10 \end{cases}.$$

The three-stage growth model implies expected future cashflows:

(A-5)
$$E_t \sum_{j=0}^{\infty} \rho^j e_{t+1+j} = \sum_{j=0}^{9} \rho^j e_{t,t+1+j} + \frac{\rho^{10}}{1-\rho} \log\left(1+\frac{g_t}{1-\Psi}\right),$$

where ρ results from the log-linear approximation (Campbell and Shiller (1988)) and equals 0.96 in our sample. Vuolteenaho (2002) shows that the cashflow news are the difference between cashflow expectations over consecutive periods:

(A-6)
$$\text{CF\_NEWS}_{t+1} = E_{t+1} \sum_{j=0}^{\infty} \rho^j e_{t+1+j} - E_t \sum_{j=0}^{\infty} \rho^j e_{t+1+j}.$$

Supplementary Material

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