Return Horizon and Mutual Fund Performance*

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Initial draft: March 2020
Current Draft: October 2020

*The first version of this paper was titled "Mutual Fund Performance at Long Horizons." The authors thank Stephen Brown, Mikhail Chernov, Wayne Ferson, Chris Hrdlicka, Haim Levy, Lars Lochstoer, Zhongjin (Gene) Lu, Seth Pruitt, Sunil Wahal, Morad Zekhnini, and seminar participants at Arizona State University, Southern Methodist University, Michigan State University, the University of Utah and the University of Georgia for valuable comments and discussions.

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Abstract

Investment performance depends on return measurement horizon. The percentage of U.S. equity mutual funds that outperform the SPY is 46.9% in monthly returns, 39.9% in annual returns, and 29.5% in full-sample (1991-2008) returns. Further, true alphas vary with return measurement horizon, and the effect of horizon on alpha is asymmetric in beta. We introduce and implement methods to estimate long-horizon alphas and betas. Compared to a benchmark of 40.9% in monthly returns, the percentage of funds with positive alpha estimates decreases to 16.7% (increases to 49.1%) at long return measurement horizons for funds with high (low) estimated monthly market betas.

(*JEL* G10, G23)

1. Introduction

The majority of the research that considers investor outcomes studies rates of return that are measured over relatively short time horizons, most often monthly. However, the parameters that describe the distribution of returns and that are relied on by investors to guide portfolio selection decisions and researchers to test asset pricing models, including means, variances, skewness, and covariances, not only depend on the horizon over which returns are measured, but are generally not proportionate to the return horizon or to each other.[1]

It may be tempting to reason that, since investors can periodically rebalance their portfolios, the sole focus should be on returns measured over agents' rebalancing horizons rather than their investment horizons. Indeed, Samuelson (1969) proposes that expected-utility-maximizing investors optimally rebalance to maintain constant investment weights that depend on single-period parameters, regardless of the number of periods in the investment horizon. However, Mossin (1968) shows (and Samuelson acknowledges), that this result is obtained *only* in the special case where investors maximize the expectation of a power utility function, while also requiring that returns are independently and identically distributed over time.[2] Objective functions can differ across investors, and both investment and rebalancing horizons may not only differ across investors but can stretch to decades.[3] Further, the parameters of multiperiod portfolio return distributions (means, variances, covariances, skewness, etc.) differ from the parameters of single-period return distributions, *with or without* periodic rebalancing. We know of no reason to think that parameters that describe the distribution of monthly returns are necessarily the most relevant to investors with disparate objectives and investment horizons.

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[1] See, for example, Arditti and Levy (1975), Levhari and Levy (1977), Handa, Kothari and Wasley (1989), Longstaff (1989), Lee, Wu and Wei (1990), Levy and Levy (2011), and Farago and Hjalmarsson (2019).

[2] An additional complexity relates to market clearing. Investors in aggregate must hold the market portfolio, and therefore cannot rebalance to constant (or any other non-market) weights.

[3] For example, Ameriks and Zeldes (2004) report that nearly half of participants in a sample of defined contribution retirement plans made no changes to their allocations over a ten-year period.

Theory, particularly with regard to asset pricing models, provides little guidance. The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) focuses on expected returns and beta coefficients measured over a single period of unspecified length. More recent factor models, such as the five-factor model of Fama and French (2015), the Q-factor model of Hou, Xue, and Zhang (2015) and the four-factor model of Carhart (1997), are motivated in part based on their ability to explain aspects of the empirical distribution of monthly returns, but without explicit consideration of whether the monthly horizon is the most relevant or informative.

In this paper, we focus attention on the information obtained when returns are measured over differing horizons, focusing in particular on mutual fund performance.[4] The literature that studies mutual fund return performance is vast, and numerous important empirical regularities have been documented (see Cremers, Fulkerson, and Riley, 2019, for a recent survey). However, these studies, like the broader literature, have mainly focused on return data measured over short (usually monthly) horizons. We show that measures of mutual fund performance, including simple comparisons of fund returns to market benchmarks as well as more sophisticated measures such as Jensen's alpha, that are based on longer return horizons contain substantively different information regarding mutual fund performance than measures constructed from monthly returns.

Importantly, our emphasis is not on forecasting (e.g. the degree to which returns measured from a short sample period are informative about returns measured over a subsequent period), learning (e.g. the Bayesian updating of parameter estimates as the sample becomes larger with the passage of time), or

[4] To our knowledge, we are the first to consider return horizon in the context of mutual fund performance. Further, the prior literature has mainly assessed the effect of return horizon over relatively short periods ranging from daily to annual, where informational and trading frictions are most relevant. Kothari, Shanken, and Sloan (1995) estimate a positive return premium associated with CAPM betas when returns are measured at the annual horizon, but not at the monthly horizon. Gilbert, Hrdlicka, Kalodimos, and Siegel (2014) estimate alphas and betas for equity portfolios over horizons ranging from daily to quarterly, and argue that differences across horizon are explained by differences in firms' opacity, i.e., in investors difficulty in assessing the value implications of events. Boguth, Carlson, Fisher and Simutin (2016) focus on slow information diffusion as an explanation for differing mean equity portfolio returns for horizons ranging from daily to annual. Kamara, Korajczyk, Lou, and Sadka (2016) also focus on heterogeneous stock price reactions and assess the extent to which systematic factors earn risk premia at some horizons from monthly to biannual, but not others. Our study differs from these because we focus on returns measured over longer horizons where these frictions are less important, to highlight the effect of horizon *per se*.

changes in parameters as the economy evolves (as in conditional asset pricing models). Rather, we focus purely on the effects of altering the time interval over which returns are measured, e.g. from monthly to annual to decadal. Our theoretic analysis focuses on a stable probability distribution, while our empirical analysis focuses on a fixed sample of return data. Despite the fact that each long-horizon return is obtained by simply compounding the relevant shorter-horizon returns, we show that performance measures constructed from long-horizon returns contain notably different information than measures constructed from monthly returns.

We study U.S. equity mutual funds for the 1991 to 2018 period. Initially, we focus on a simple comparison of compound fund returns to compound market proxy returns, showing that the percentage of funds that outperform market benchmarks decreases with return horizon. In the monthly data, equity mutual fund returns exceed the matched-month return to the SPY ETF (taken as a proxy for the overall market that investors could have captured) for 46.9% of observations. The percentage of sample funds that generate compound returns that exceed the compound return to the SPY decreases to 39.9% at the annual horizon, 39.2% at the decade horizon, and 29.5% at the (fund-specific) lifetime horizon.

Prior researchers, including Levhari and Levy (1977), Handa, Kothari and Wasley (1989), Longstaff (1989), and Kothari, Shanken, and Sloan (1995), have observed that beta coefficients depend on the horizon over which returns are measured. While several of these papers considered the role of return horizon in tests of the CAPM, they did not emphasize the related point that alphas also depend on the horizon over which returns are measured.[5] We show that alphas not only depend on return measurement horizon, but that the sign of the short-horizon (e.g. monthly) alpha does not necessarily reveal the sign of the longer-horizon alpha.[6] We also develop the testable implication that the effect of

[5] Levhari and Levy (1977) show how betas vary with horizon and note that tests of the CAPM that are conducted using returns measured over a horizon that differs from the model's true horizon are biased. Handa, Kothari and Wasley (1989) show that the estimated return premium associated with firm size is sensitive to the length of return interval used to estimate beta. However, these papers do not develop expressions for true alpha as a function of return measurement horizon.

[6] We focus on single factor market models and simple comparisons of fund returns to market benchmarks. This reflects our understanding that practitioners most often focus on such relatively simple measures, as well as the evidence indicating that relatively simple measures such as Morningstar rankings (Ben-David, Li, Rossi, and Song

return measurement horizon on alpha is asymmetric: an asset's short-horizon alpha overestimates (underestimates) its long-horizon alpha when its true beta is greater (smaller) than one. Importantly, these results pertains to parameters, and hold even in the absence of estimation issues.

The estimation of fund alphas and betas when returns are measured over longer horizons presents substantive challenges. We introduce an empirical procedure for estimating long-horizon betas that is a modification of the formulas introduced by Levhari and Levy (1977), guided by the outcomes of simulations. We show that the estimates of annual return betas obtained by our modified Levhari and Levy approach are quite similar to the noisy but unbiased (under standard assumptions) beta estimates obtained by implementing standard time series regressions in annual returns. Using the beta estimates obtained by the modified Levhari and Levy method we show that, consistent with theory, long-return-horizon alphas not only differ from short-return-horizon alphas, but that the differences are asymmetric depending on estimated short-horizon betas. For the full sample, 40.9% of alphas estimated from monthly returns (using the SPY as the market aggregate) are positive, while 35.8% of alphas estimated from long-horizon (full-sample) data are positive. More striking, among mutual funds with a monthly return beta estimate less than one, the percentage of funds with positive long-horizon return alphas increases to 49.1%, while among funds with a monthly return beta estimate greater than one the percentage of funds with positive long-return horizon alphas decreases dramatically to 16.7%. Focusing on the subset of funds with positive alphas estimated from monthly returns, almost all (93.3%) have positive long-horizon alpha estimates if the monthly beta estimate is less than one. In contrast, despite their positive monthly return alpha estimates, only a minority (45.4%) of these funds have positive long-horizon alpha estimates if their monthly beta estimate is greater than one.

These results imply that a given fund's risk-adjusted performance can be abnormally positive over short return measurement horizons and abnormally negative over long return measurement horizons (or vice versa), even when results are based on a single sample. The results therefore imply that the

(2019) or CAPM alphas (Barber, Huang, and Odean, 2016 and Berk and van Binsbergen, 2016) better predict funds flows as compared to measures that adjust for multiple factor beta exposures.

degree to which returns are abnormal cannot be evaluated independent of investors' horizons; some managers (particularly those with low short-horizon betas) may have a relative advantage in generating alpha for investors who are concerned with long-horizon returns, while others (particularly those with large short-horizon betas) are more likely to generate positive alphas for investors who are focused on short-horizon outcomes. Further, measures of mutual fund performance that are based on short-horizon returns may be uninformative or even misleading regarding fund performance over the longer horizons that may be relevant to many investors.

Our goal in this paper is to demonstrate the importance of return measurement horizon in simple settings, including the direct comparison of fund returns to benchmark returns and the estimation of single-factor alphas. It would be of interest to extend the analysis to multiple systematic risk factors. It would also be of interest to assess the potential interaction between time variation in relevant parameters (as, for example, in a conditional asset pricing framework) with the impact of measuring returns over alternative horizons. Finally, it would be of interest to apply our results to the mutual fund forecasting literature. In particular, is the evidence that estimated alphas persist out-of-sample sensitive to return measurement horizon?

Perhaps the most intriguing issues relate to the question of which return measurement horizon is most relevant, both to investors and to researchers who study the capital markets. Consider, for example, a pension fund with an investment horizon that stretches to decades, where managers are compensated based on comparisons of fund returns to benchmark returns measured at an annual horizon, and where the investment committee meets and potentially recommends changes in investment positions on a quarterly basis. Should the focus be on return parameters estimated at the quarterly, annual, multi-decade, or some other horizon? Some relevant evidence might be obtained by assessing the return measurement horizon that best explains mutual fund performance-flow relations. Additional evidence might be provided by assessing the return measurement horizon for which various asset pricing models perform best.

2. Data and Sample Construction

We obtain data for the 1991 to 2018 period from the CRSP survivorship bias free Mutual Fund Database. We begin our study with data from 1991, as monthly data regarding fund total net assets (TNA) is largely unavailable for earlier periods. We focus on domestic equity funds (CRSP fund style code starting with "ED"), while excluding exchange traded funds, funds that take short positions (CRSP fund style "EDYS"), commodity funds (CRSP fund style "EDSC") and real estate funds (CRSP fund style "EDSR"). We also exclude target date funds, since these hold substantial non-equity positions.[7] We further exclude hedged funds (CRSP fund style of "EDYH" and Lipper fund style code of "LSE"), market neutral funds (CRSP fund style "EMN") and absolute return funds (CRSP fund style "ABR"). We also exclude funds that have fewer than twelve months of non-missing return data.

Prior studies (e.g., Elton, Gruber, and Blake, 2001) have documented the presence of errors in the CRSP mutual fund data. We manually verify and when necessary correct monthly return observations that differ from the value-weighted market return in the same month by 30% or more, using data from *Datastream* or *Yahoo Finance*. Since missing TNA data may be indicative of additional data integrity issues, we also verify and when necessary correct return observations that differ from the same-month market return by 5% or more if TNA data is missing in the current or prior month.

Many mutual funds have multiple share classes. We aggregate return and expense ratio data across share classes based on a weighted average of TNAs when classes have a common Wharton Financial Institution Center Number (WFICN) in the WRDS mutual fund links file. For sample mutual funds without a WFICN number, we identify share classes of the same fund based on fund names following Berk and van Binsbergen (2015).[8]

[7] To identify target date funds, we first extract a list of funds whose name contains one of these numbers – "199", "200", "201", and so on until "210", but that do not contain "Russell 2000" or "Russell2000". Among these, we exclude funds with names that contain any of "retirement", "retire", "target", "lifetime", "lifecycle", "lifepath", "term", "destination", "freedom", "2005", "2010", "2015", and so on until "2070". In addition, we manually identify an additional 256 funds (of the remaining 302 initially listed) as target date funds based on visual examination of their names and fund profiles.

[8] When funds have multiple share classes CRSP fund names contain "/" or ";". The part of the fund name after the last "/" or ";" refers to the sub share class, while the prior part refers to the main fund name. For example, the fund

Table 1 presents summary statistics regarding the sample, which contains 7,689 domestic equity mutual funds.[9] Of these, 602 are index funds. The sample includes 1,019,541 fund/months, and TNA data is available for 1,005,705 of these. The pooled (across funds and years) mean monthly fund return (net of fees and expenses) is 0.63%, while the mean monthly expense ratio is 0.09%. Mean TNA is $1.085 billion. However, the TNA distribution is strongly positively skewed, reflecting the presence of a few very large funds, and the median TNA is $154 million. The pooled distribution of monthly fund returns is not strongly skewed; the sample skewness coefficient is -.355, and the median return of 0.661% is similar to the mean return of 0.631%. However, as documented below, long-horizon mutual fund returns are positively skewed, and this skewness is important in understanding the distribution of long-horizon mutual fund performance.

Figure 1 displays the number of funds contained in the sample and total TNA for sample funds on an annual basis. The number of domestic equity mutual funds increased rapidly from about 1,000 in 1991 to about 4,000 in 2001, remaining relatively constant thereafter. However, sample funds' aggregate TNA not only rose rapidly in the early years of the sample period, from about $200 billion in 1991 to over $2 trillion in 2001, but continued to increase thereafter, to over $5.5 trillion in 2018.

To assess the performance of mutual funds at various horizons we compute the compound (i.e., buy-and-hold) return to the fund. Since the return data includes any dividends or other cash distributions, the compound return implicitly assumes that dividends and distributions are reinvested in fund shares. For comparison, we compute compound returns to one-month US Treasury Bills, to the value-weighted market portfolio of CRSP common stocks, and to the SPY ETF.[10] The periods over which benchmark

named "*MainStay Funds: MainStay Small Cap Growth Fund; Class A Shares*" is Class A of the *MainStay Small Cap Growth Fund*; the fund named "*Alliance Strategic Balanced Fund/A*" is Class A of the *Alliance Strategic Balanced Fund*. We rely on this naming convention to combine multiple share classes.

[9] While we exclude international equity funds from our main analysis, we report some results for international funds in the Internet Appendix. Figure A1 there shows that international funds share of total industry net assets grew from about 15% in the early years of our study to near 30% in later years.

[10] The value-weighted market return is obtained from Professor Kenneth French's website.

returns are computed are always matched to fund returns. If, for example, a given fund has return data for 105 months during a given decade then benchmark returns are computed based on the same 105 months.

Value-weighted market returns comprise a natural and widely-used benchmark. However, investors cannot directly capture the value-weighted market return, since transaction costs would be incurred in the requisite trades at the times of dividends, stock repurchases, or new equity issues, and fees must be paid on index funds that seek to track the overall market. We therefore include the SPY ETF as an alternative market benchmark.[11] Since SPY returns are net of any fees and other expenses, investors could in principle have captured compound SPY returns.

We also construct indicator variables that equal one when a given fund outperforms a benchmark over a specified time period, and zero otherwise. The cross-sectional means of the indicator variables measure the percentage of fund observations that outperform the indicated benchmarks. Table 1 reports the means of these indicator in the monthly return data. Only a slight majority (54.9%) of the fund/month return observations exceed the one-month Treasury bill return in the matched month, reflecting the high volatility of equity returns. A slight minority, 46.3%, of fund-month returns exceed the value-weighed market return during the same month, while 46.9% of fund-month returns exceed the SPY ETF return during the same month.

3. Mutual Fund vs. Market Returns at the Annual, Decade, and Lifetime Horizons

We assess equity mutual fund performance when returns are measured at four horizons: monthly, annual, decade, and "lifetime." The last designation refers to all months that the fund is contained in the sample, and does not literally equal the lifetime of the fund in those cases where a fund was present prior to the 1991 sample start date or for the funds that continue after the 2018 sample end date. In those cases where a given mutual fund has data for only a portion of a given period the computation pertains only to the months with data, as the alternative of computing returns only for funds with data for the entire period

[11] The SPY ETF started trading in January of 1993. For 1991 and 1992, we rely on the return on the Vanguard S&P500 index fund (ticker symbol VFINX) instead.

would introduce survivorship biases. While Table 1 reports summary statistics for monthly returns, Panels A, B, and C of Table 2 present results at the annual, decade, and lifetime horizons, respectively.

3.1 Mutual Fund Performance at the Annual Horizon

Panel A of Table 2 shows the database contains return data for funds for an average of 11 months per year. The pooled mean annual return is 7.64%. By comparison, the mean matching SPY return (pooled across funds and years) is 8.42% and the mean value-weighted market return is 8.87%. Annual fund returns are moderately positively skewed; the estimated skewness coefficient is 0.742, and the median fund return is 6.97%, as compared to the mean return of 7.64%.

Only a minority of funds outperform market benchmarks at the annual horizon. In particular, 38.5% outperform the value-weighted market portfolio and 39.9% outperform the SPY ETF. By comparison, 60.3% of funds outperform one-month US Treasury Bills in a given year. Each rate of outperformance differs significantly from a benchmark of 50%, with p-values less than 1%.

Figure 2 displays the percentage of funds that outperform the market benchmarks and Treasury bill benchmarks on an annual basis. The majority of funds underperform the market benchmarks in most, but not all, calendar years. In particular, more than half of funds outperformed market benchmarks in 2001 and 2009. The percentage of funds that outperform Treasury bills vary dramatically across years, from essentially zero in 2008 to over 90% in 1991, 1995, and seven of the ten years from 2009 to 2018.

We also assess the performance of mutual funds when we compound pre-fee returns. The mean pre-fee annual return to sample mutual funds is 8.76%, which exceeds the mean matching SPY return of 8.42%. Nevertheless, only a minority, 46.9%, of funds outperform the SPY even on a pre-fee basis.

3.2 Mutual Fund Performance at the Decade Horizon

Panel B of Table 2 reports results based on decade horizon buy-and-hold returns.[12] On average, return data is available for 68 months per decade, and the mean fund return pooled across funds and

[12] Since our sample spans twenty-eight years, our "decades" do not contain exactly ten years. Specifically, we focus on the periods 1991 to 1999, 2000 to 2008, and 2009 to 2018.

decades is 77.42%. By comparison, the mean SPY return over matched months of the same decade is 89.86% and the mean value-weighted market return over the same months of the same decade is 93.86%. Decade returns to mutual funds are more highly skewed than annual returns; the estimated skewness coefficient for decade returns is 2.993 (compared to 0.742 for annual returns), and the median decade fund return is just 24.18%, well below the mean of 77.42%.[13]

Equity mutual funds outperform market benchmarks less often at the decade horizon as compared to the annual horizon. In particular, 34.9% of funds outperform the value-weighted market at the decade horizon, as compared to 38.5% at the annual horizon. Only a minority (39.2%) of equity funds outperformed the SPY at the decade horizon. While the mean pre-fee decade-horizon return to sample mutual funds of 91.22% exceeds the mean matching SPY return of 89.86%, only 48.8% outperform the SPY even on a pre-fee basis.

3.3 Mutual Fund Performance When Returns are Measured over Long horizons

Panel C of Table 2 reports corresponding results when returns are measured over each fund's full lifetime in the database.[14] Return data is available for all of the 336 sample months for only 375 of the 7,689 funds. On average across funds, return data is available for 133 months (median of 111 months). The mean lifetime compound return for domestic equity funds is 191.17%. By comparison, the mean matched-period compound return to the SPY is 204.89% and the mean matched-period compound return to the value-weighted stock market is 224.10%.

The estimated skewness coefficient in the distribution of lifetime equity mutual fund returns is 4.56. Reflecting this skewness, the median lifetime return to domestic equity mutual funds of 74.26% is substantially less than the mean compound return of 191.17%. Seventy six percent of domestic equity funds outperform one-month Treasury bills over their lifetimes. Stated alternatively, a surprisingly high

[13] Arditti and Levy (1975), Bessembinder (2018), and Farago and Hjalmarsson (2019) all observe that the compounding of random short horizon returns on a given asset introduces positive skewness into long horizon returns (even if short horizon returns are symmetric). The results here verify that compounding generates substantial skewness in longer horizon returns for the periodically rebalanced (based on managers' disparate objective functions) portfolios that underlie mutual fund returns as well.
[14] Table A1 in the Internet Appendix breaks out full sample results for deciles of funds with various characteristics.

share, twenty-four percent, of equity mutual funds fail to outperform one-month Treasury bills over their lifetimes. Only 23.8% of domestic equity funds outperform the value-weighted market return over their lifetimes. Over their lifetimes, only 29.5% of domestic equity funds outperform the SPY ETF, a benchmark that could have been captured by any investor who simply held the SPY and reinvested dividends.

The mean pre-fee lifetime return to sample funds is 257.25%, which exceeds not only the mean matched-horizon return to the SPY of 204.89% but also the mean matched-horizon return to the value-weighted market of 224.10%. Nevertheless, only a minority of funds, 45.1% when comparing to the SPY and 38.6% when comparing to the value-weighted market, outperform these benchmarks. These results imply that the low rate of outperformance vs. market benchmarks when returns are measured over long horizons is not simply attributable to the accumulated effect of fund fees. Rather, it is primarily attributable to the skewness that is observable in the distribution of long-horizon returns but that is not observable in monthly returns.

In Panel D of Table 2 we report lifetime compound returns for four groups of funds, delineated based on the length of time that the database contains return data for the fund. While information on fund life would not have been available to investors *ex ante*, the results are informative regarding conditional return distributions. The four groups are funds with lives of 1 to 5 years (2,287 funds), 5 to 10 years (1,787 funds), 10 to 15 years (1,201 funds), and 15 to 28 years (2,414 funds). Not surprisingly, since poorly performing funds are likely to be shut down sooner, funds with shorter lives have worse average performance. For example, only 22.6% of funds with lives less than five years have lifetime buy-and-hold returns that outperform SPY, and only a slight majority (53.6%) of these funds outperform one-month Treasury bills. In contrast, almost all (96.8%) of funds with lives that exceed fifteen years outperform Treasury bills. The most informative fact observable in Panel D of Table 2 is that, even in the longest lived and best performing group (those that are in the database for 15 to 28 years), less than half (40.8%) of funds outperform the SPY, and only 31.5% outperform the value-weighted market.[15]

Fama and French (2010) document that equity mutual funds as a class underperform market benchmarks. The results here show that the rate of underperformance increases at longer return horizons, a result that can be attributed at least in part to the fact that the compounding of returns over time leads to positive skewness in the distribution of long-horizon returns. However, the rate of underperformance is lower for funds with longer lives, which can be attributed to the fact that the poorest performing funds tend to be shut down before their lives become long.

In Panel E of Table 2 we report on lifetime returns for index vs. non-index mutual funds. The mean index fund lifetime return of 186.9% is slightly lower than the mean non-index fund return, which is 191.5%, but index funds have a slightly longer average life as well. While the 33.2% of index funds with cumulative returns that exceed the SPY is greater than the 29.2% of non-index funds that do so, each percentage is significantly less than 0.5.

The key conclusion that can be drawn from the results reported in Tables 1 and 2 is that the likelihood that a given mutual fund outperforms market aggregates in terms of compound return decreases

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[15] As noted, our analysis focuses on domestic equity funds. To assess robustness, we also report in the Internet Appendix some results for international equity funds (CRSP fund style code starting with "EF"), contained in the CRSP database. As benchmarks, we consider returns to the SPY ETF and to tradeable Vanguard Funds (from 1991 to 1995 we rely on Vanguard's European index fund, VEURX and thereafter we rely on their Total International Index Fund, VGTSX). On average, international equity funds underperform the SPY, but outperform VGTSX. At the annual horizon (Panel B of Table A2 in the Internet appendix), the mean fund return is 6.47%, as compared to a mean VGTSX return of 5.82% and a mean SPY return of 9.13%. At the decade horizon (Panel C of Table A2) the mean fund return is 43.16%, compared to a mean VGTSX return of 35.30% and a mean SPY return of 91.76%. At the lifetime horizon (Panel D of Table A2) the mean fund return is 91.56% compared to a mean VGTSX return of 68.73% and a mean SPY return of 186.71%. These results reflect that the SPY comprised a notably higher hurdle during the 1991 to 2018 sample period, with a mean monthly return (Panel A of Table A2 in the Internet appendix) of 0.76%, compared to 0.47% for VGTSX, and that international equity funds most often also hold some US stocks. Notably, however, only a minority of international equity funds outperformed either benchmark, even while the cross-fund mean outperforms VGTSX. Rates of outperformance relative to SPY are 39.2%, 26.8%, and 13.9% at the annual, decade, and lifetime horizons, respectively, while rates of outperformance relative to VGTSX are 48.4%, 47.9%, and 47.5% at the annual, decade, and lifetime horizons, respectively. These low rates of outperformance reflect that buy-and-hold returns to international equity funds are also positively skewed; standardized skewness coefficients are 0.936 at the annual horizon, 2.315 at the decade horizon, and 7.133 at the lifetime horizon.

monotonically as the time horizon over which returns are measured increases from monthly to annual to decade to lifetime. Importantly, this finding holds within a given sample.

While the comparison of compound fund returns to compound market proxy returns is simple and informative, it does not allow for fund exposure to systematic risk. In particular, a fund that earned returns identical to the overall market on the portion of its portfolio invested in risky assets but that also kept some funds in cash would have a market beta less than one and would underperform the market during any time period where the market return exceeded the cash return. We therefore next assess mutual fund performance when returns are measured over alternative horizons, while allowing for betas to differ from one.

4. Long vs. Short-horizon Alpha

Jensen (1968) introduced "alpha" as a measure of mutual fund performance that allows for systematic (i.e. beta) risk, motivating it as a "direct application" of the asset pricing model now broadly referred to as the CAPM. The CAPM is a single-period model, but the length of the period is unspecified. In practice, investment and decision horizons can differ across investors, a fact not explicitly considered by the CAPM. Nevertheless, investors are interested in assessing fund performance after allowing for risk, and researchers are interested in testing asset pricing models. Alpha estimates are central to each exercise. Of course, researchers have adapted the concept of alpha to multi-factor models. Our intent here is to focus attention on the fact that alphas depend on return horizon in the simplest possible setting, where alphas are measured with respect to the market factor. Despite the single factor model's simplicity, there is evidence it is of substantial relevance to investors. In particular, both Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016) present evidence that the single factor model better explains investor flows into and out of mutual funds as compared to more complex models.

To assess how mutual fund alphas depend on the horizon over which returns are measured, we must accommodate the fact, previously noted by Levhari and Levy (1977), Handa, Kothari and Wasley

(1989), Longstaff (1989) and Levy and Levy (2011) among others, that betas depend on the time horizon over which returns are measured. That is, betas defined based on monthly returns differ from betas defined based on annual returns which differ from betas defined based on decade returns, etc.

We highlight that alphas also depend on the horizon over which returns are measured, and in complex ways. It is an important point of perspective that alphas and betas *as parameters* vary as a function of return horizon, even in the absence of estimation issues. With the exception of Levy and Levy (2011), this fact does not appear to have been emphasized in the literature.[16]

We first demonstrate the theoretical relation between short-return-horizon and long-return-horizon alphas, assuming for simplicity that returns are independently and identically distributed over time. We then describe the empirical methods we use to estimate long-return-horizon alphas and betas for the funds in the sample. Finally, we describe the resulting empirical evidence regarding long-return-horizon alphas for US equity mutual funds.

4.1 Return Horizon, Beta, and Alpha

In this section we demonstrate relations between short-horizon and long-horizon alphas and betas, in the simplest possible setting, where returns are iid over time. This discussion focuses on parameters; estimation issues are considered in section 4.2.

Consider an individual fund or asset *i* and the overall market *m*, and let μ_i and μ_m denote their respective short-horizon (e.g. monthly) mean returns. Let σ_m^2 denote the variance of short-horizon market returns, σ_{im} the covariance between short-horizon asset *i* and market returns and $\beta_i = \frac{\sigma_{im}}{\sigma_m^2}$ denote asset *i*'s short-horizon market beta. Assume for expositional simplicity that the risk-free interest rate is zero. The short-horizon alpha is defined as:

$$\alpha_i = \mu_i - \beta_i \mu_m. \tag{1}$$

[16] Levy and Levy (2011) note that if the CAPM holds (i.e. implies zero alphas) for a horizon longer than that used to measure returns, then positive alphas are mechanically induced for small firms, due to their high betas. They do not, however, develop an expression for true alpha as a function of return horizon.

Let a superscript L denote long-horizon (e.g. decade) returns, which are short-horizon returns compounded over *N* periods. Let σ_m^{2L} denote the variance of long-return-horizon market returns, σ_{im}^L the covariance of between long-horizon asset *i* and long-horizon market returns, and let $\beta_i^L = \frac{\sigma_{im}^L}{\sigma_m^{2L}}$ denote asset *i*'s long-return-horizon market beta. The alpha for long-horizon returns is:

$$\alpha_i^L = \mu_i^L - \beta_i^L \mu_m^L. \tag{2}$$

Expressions (1) and (2) are conceptually identical definitions of alpha, differing only in the horizon over which returns are measured. Any long-horizon return can also be stated by compounding shorter horizon returns. If returns are iid, then $\mu_i^L = (1+\mu_i)^N - 1$ and $\mu_m^L = (1+\mu_m)^N - 1$. Substituting into (2), the long-return-horizon alpha can be stated as a function of short-return-horizon alpha and long and short-horizon betas as:

$$\alpha_i^L = (1+\ \alpha_i + \beta_i\mu_m)^N - \beta_i^L\{(1+\mu_m)^N - 1\} - 1. \tag{3}$$

Note that in the special case where $\mu_m = 0$ the expression for the long-return-horizon alpha simplifies to $\alpha_i^L = (1+\ \alpha_i)^N - 1$, implying that the long-return-horizon alpha is the compounded equivalent of the short-return-horizon alpha. This simplification reflects that both short and long-return-horizon betas are eliminated from the expression in this special case. More generally, the relation between short and long-horizon alphas depends on both short and long-horizon betas as well as the mean short-horizon market return, μ_m. Levhari and Levy (1977) show that when returns are independently and identically distributed:

$$\sigma_m^{2L} = (\sigma_m^2 + (1+\mu_m)^2)^N - (1+\mu_m)^{2N} \text{ and} \tag{4}$$

$$\sigma_{im}^L = (\sigma_{im} + (1+u_i)(1+u_m))^N - (1+\mu_i)^N(1+\mu_m)^N. \tag{5}$$

The long-horizon variance of a given asset's return (the market in this case) and the long-horizon covariance between a pair of asset returns not only depends on the length of the return horizon, *N*, but in a non-linear manner. Further, the long-return-horizon variance depends on the own asset mean return, while the covariance depends on the mean return on each of the two assets. The covariance of asset *i* returns with the market (or, more generally the covariance between any pair of asset returns) typically grows with *N* at a different rate than the market variance (or more generally, the variance of a given asset return). Combining (4) and (5), the long-horizon beta per Levhari and Levy (1977) is:

$$\beta_i^L = \frac{\left(\beta_i \sigma_m^2 + (1+u_i)(1+u_m)\right)^N - (1+\mu_i)^N (1+\mu_m)^N}{\left(\sigma_m^2 + (1+\mu_m)^2\right)^N - (1+\mu_m)^{2N}}, \quad (6)$$

which depends not only on the short-return-horizon beta, β_i, and on the number of periods over which returns are compounded, N, but also the mean short-horizon market return, u_m, the mean short-horizon security return, u_i, and the variance of short-horizon market returns, σ_m^2.[17] It can be verified that (6) implies that long and short-return-horizon betas are equal only if $\alpha_i = 0$ and $\beta_i = 1$.

To illustrate the implications of expression (6), Panel A of Figure 3 displays long-horizon (10-year) asset *i* betas that are implied by various combinations of short-horizon (monthly) betas and short-horizon alphas.[18] Three points are noteworthy. First, the long-horizon beta is equal to the short-horizon beta only if the short-horizon beta is one *and* the short-horizon alpha is zero. Second, long-horizon betas are increasing in short-horizon alphas. Third, while long-horizon betas increase monotonically with short-horizon betas, the relation is non-linear, and the effect of longer horizons is greater for short-horizon betas that are greater than one as compared to short-horizon betas that are less than one. This last observation is the basis for testable asymmetries in the relation between short and long-return-horizon alphas, as discussed below.

Combining expressions (3) and (6), long horizon alpha depends on short horizon alpha and other parameters according to:

$$\alpha_i^L = (1 + \alpha_i + \beta_i \mu_m)^N - 1 - \frac{\left(\beta_i \sigma_m^2 + (1+u_i)(1+u_m)\right)^N - (1+\mu_i)^N (1+\mu_m)^N}{\left(\sigma_m^2 + (1+\mu_m)^2\right)^N - (1+\mu_m)^{2N}} \{(1+\mu_m)^N - 1\}. \quad (7)$$

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[17] A limitation of the Levhari and Levy (1977) analysis is that they take the asset return and the market return to simply be correlated variables, without explicitly considering that the asset is itself a component of the market. We develop an extension of the Levhari and Levy that explicitly incorporates the fact that the asset is a component of the market, and obtain results that are qualitatively identical to those obtained by applying their analysis, as long as the weighting on the asset in question remains small.

[18] The illustration relies also on $\mu_m = .0075$ *and* $\sigma_m = .055$, which are reasonable in view of estimates obtained from actual data.

Panel B of Figure 3 displays long-return-horizon alphas implied by expression (7) for various combinations of short-return-horizon alphas and short-return-horizon betas. To make short and long-return-horizon alpha estimates comparable, the long-return-horizon alphas displayed on the Figure are annualized by taking the tenth root of one plus the decade-horizon alphas, and subtracting one, while monthly return alphas are annualized by taking one plus the monthly return alpha to the twelfth power and subtracting one.

The most notable result that can be observed on Panel B of Figure 3 is that zero short-return-horizon alpha does not imply zero long-return-horizon alpha, except in the special case where short-return-horizon beta is one. Cremers, Fulkerson, and Riley (2019) write that "almost all academic papers measure the skill of an active manager as the net alpha of the fund."[19] The fact that alpha can change sign across return measurement horizons, even in the absence of estimation issues, calls into question the economic interpretation of alpha as a measure of managerial skill.

More broadly, Panel B of Figure 3 shows that long and short-return-horizon alphas are approximately equal (when each is converted to a common time period such as annual) *only* if the short-return-horizon beta is one. For assets with short-return-horizon betas less than one the long-return-horizon alpha is greater than the short-return-horizon alpha, while for assets with short-return-horizon betas greater than one the long-horizon alpha is less than the short-horizon alpha. That is, alpha, the measure of risk- adjusted returns introduced by Jensen (1968), depends on the horizon over which returns are measured. Investors who are concerned with outcomes measured over short horizons will experience different alphas than investors who are concerned with outcomes over long horizons, even if returns are iid and in the absence of estimation issues.

This analysis has an important testable implication. Specifically, estimated long-return-horizon alphas are more likely to be negative if short-return-horizon betas are greater than one, while estimated

[19] Berk and van Binsbergen (2015) argue that skill should be measured based on the combination of gross alpha estimates and assets under management. However, the fact that alpha depends on return horizon is relevant to these authors' interpretations as well.

long-return-horizon alphas are less likely to be negative if short-return-horizon betas are less than one, other things equal. Further, the functions displayed on Figure 3 are not linear. That is, the effect of return horizon on alpha is asymmetric, and is of greater consequence for funds or assets with larger short-return-horizon betas.

The observation that single-factor alphas depend on return horizon in complex ways is a manifestation of the broader fact (e.g., Chernov, Lochstoer, and Lundeby, 2020) that a linear factor model that is valid (i.e. generates zero alphas) at a single-period horizon does not generally extend (as a linear model in compound factor outcomes) to multiperiod horizons. However, the theory underlying factor models does not generally specify the horizon at which the model should hold, and we know of no theory with the implication that the CAPM or other models should hold at the monthly horizon in particular. Our focus in this paper is not on testing the implications of factor models per se, but on assessing the information content of performance measures that are implemented in returns measured over alternative horizons. We argue that the results here imply that the performance of mutual funds cannot be evaluated independent of the question of which return horizon is most relevant to investors.

4.2 Estimating Long-horizon Alphas and Betas

Short-horizon (e.g. monthly) betas are typically estimated by time series regressions, where the sample size is the number of months for which the requisite data is available. Here, we seek to estimate betas for longer return horizons. On average, funds are included in our sample for only slightly more than one decade, so time series regression methods cannot be implemented based on non-overlapping decade or lifetime returns. We instead proceed as follows.

First, we estimate single factor alphas and betas using standard time series regressions of monthly excess returns for each fund on monthly excess SPY returns over the matched sample periods. We also record fund-specific estimates of the mean excess fund monthly return, the mean and variance of the excess market monthly return, and the fund's residual monthly return variance. In light of the fact that some of these estimates are obtained from short samples we winsorize these estimates at the 10^{th} and 90^{th} percentiles. We then employ the fund-specific estimates of the mean excess fund return, the mean excess market return, fund monthly return beta, and variance of market excess returns in expression (6) to obtain corresponding estimates of long-horizon betas at the annual, decade, and lifetime horizons. Denote these long-horizon estimates as $\hat{\beta}_i^L$. However, since expression (6) is non-linear in its parameters, the resulting $\hat{\beta}_i^L$ estimates are not only noisy, but are likely biased. We rely on Bayesian reasoning and simulations to assess relations between true long-horizon betas and long-horizon betas estimated by this procedure in order to adjust these noisy estimates, as described below.

For each of the 7,689 funds in our sample we create a matched simulated fund and assign to it a true monthly beta, β_i, as a random draw from a normal distribution with mean equal to the sample fund's empirically estimated monthly beta and variance equal to the cross-sectional sample variance of monthly fund beta estimates. We assign a true monthly alpha, α_i, to each simulated fund as a random draw from a normal distribution with mean equal to the matched sample fund's alpha estimate and variance equal to the cross-sectional variance of sample monthly alphas across all funds, and we assign μ_m and σ_m^2 parameters to the simulated fund that are equal to matched sample outcomes for the same months. Having done so, we use expressions (1) and (6) and the generated parameters to compute a true long-horizon beta for each simulated fund, denoted β_i^L.

We then create simulated sample returns. If the sample for the actual fund includes N monthly returns, we generate for the matched simulated fund N monthly excess market returns, R_{mt} as random draws from a normal distribution with mean and variance equal to the matching fund sample estimates of such and create N monthly excess simulated fund returns as $R_{it} = \alpha_i + \beta_i * R_{mt} + e_{it}$, where each e_{it} is a random draw from a zero-mean normal distribution with variance equal the sample residual volatility for the sample fund. Having generated a N-month return sample for each simulated fund, we obtain an estimated monthly beta for each simulated fund by standard regression methods, and convert that monthly estimate to a corresponding long-horizon estimate (denoted as $\hat{\beta}_i^{LS}$, where the S in the superscript denotes that the estimate is simulation based) using expression (6) and other estimated parameters estimates from the simulated sample.

We repeat the procedure described in the prior paragraph 1,000 times, to obtain for each simulated fund a distribution of 1,000 true long-horizon betas as well as 1,000 estimates of long-horizon betas that are obtained by employing short-horizon parameter estimates in expression (6). We then estimate relations between true long-horizon betas and long-horizon beta estimates obtained when using monthly return sample estimates in expression (6). In particular, we estimate fund-specific regressions of the form $\beta_i^L = a + b * \hat{\beta}_i^{LS} + u$ across the 1,000 simulated outcomes.

Table 3 provides summary statistics regarding the resulting distribution of regression coefficient estimates across the simulated funds, when the simulations are applied based on annual, decade, and lifetime return horizons. If the use of monthly parameter estimates in expression (6) yields unbiased estimates of long-horizon betas then intercepts in these regressions should not differ significantly from zero and slope coefficients should not differ significantly from one. In actuality, intercepts are positive for virtually all simulated funds (the fifth percentile is positive at all three horizons), and average 0.25 in annual returns, 0.18 in decade horizon returns, and 0.22 in lifetime returns. Slope coefficients are virtually all less than one (the ninety fifth percentile is less than one at all three horizons) and average 0.73 in annual returns and 0.79 in both decade and lifetime returns.

While these results imply that employing monthly parameter estimates in expression (6) leads to biased estimates of long-horizon betas, they also suggest a solution, which we implement. Long-horizon beta estimates can be obtained as fitted values from the simulated fund regressions. In particular, we estimate the long-horizon beta for each actual fund as the intercept obtained in the regression across the 1,000 simulation outcomes for the matched fund plus the slope coefficient from the same regression times $\hat{\beta}_i^L$, the estimate of the long horizon beta obtained by inserting parameter estimates from the actual fund *i* sample in expression (6). Note that this estimate can be viewed as a weighted average of the estimate obtained when employing monthly parameter estimates in expression (6) and 1.0, which is the mean (across all securities comprising the market) true beta at any return horizon. As such, the final estimate is similar in concept to that obtained by the Bayesian adjustment of short-horizon beta estimates proposed by Vasicek (1973). However, since the method relies on expression (6), which is attributable Levhari and Levy (1977), we refer to this procedure as the modified LL method.

The modified LL procedure adjusts for biases that are revealed by the simulated data. However, the simulation as well as expression (6) itself rely on simplifying assumptions, including that returns are independently distributed over time, that are unlikely to be precisely accurate in the actual data. We therefore provide additional evidence regarding the validity of the procedure. As noted, it is not feasible to estimate long-horizon betas for decade or full-sample return horizons using standard time series regression methods, due to insufficient return observations. However, it is viable to obtain estimates of annual return horizon betas using standard time series methods. While the time series estimates of beta obtained from annual returns may be quite noisy due to small sample sizes, they are unbiased under standard assumptions.

In Table 4 we report data regarding beta estimates obtained for annual returns using standard time series regressions and those obtained based on the procedure described above. Results pertain to all funds with at least ten annual returns, i.e. where the time series regression includes at least ten observations. The results on Table 4 show that the distribution of beta estimates is quite similar across the two methods. Across all 4,080 funds with at least ten annual return observations, the mean annual beta estimated by either time series regressions or the modified LL method is 0.912. Mean beta estimates remain similar when the sample is broken into funds with an estimated monthly beta greater versus less than one. In general, it can be observed that annual beta estimates obtained by the modified LL method are less volatile and less skewed as compared to annual beta estimates obtained by time series regressions. On balance we view the data reported in Table 4 as supporting the conclusion that the modified LL method provides reasonable beta estimates.

To obtain long-horizon alpha estimates, we employ sample estimates in expression (2). We rely on the modified LL method described above to obtain market beta estimates at the annual, decade, and lifetime horizons. We rely on time series means of returns measured over the indicated horizon for each fund (in excess of the compound return on one-month Treasury bills over the matched horizon) as the estimate of the long-horizon expected fund excess return μ_i^L, and the time series mean compound return to the SPY over the matched horizon (also in excess of the compound one-month Treasury bill return) as the estimate of the long-horizon expected market (excess) return μ_m^L. For the lifetime results the time series mean is simply the single sample observation for each fund.

4.3 Empirical Estimates of Long-horizon Beta

In Table 5 we report on estimates of short-return-horizon (monthly) betas obtained by standard time series regressions and long-return-horizon (annual, decade, and lifetime) betas obtained by the modified LL approach. Results reported are based on the SPY return as the market proxy; results obtained when using the CRSP value-weighed return instead are similar (see Tables A3 and A4 in the Internet Appendix).

The mean beta estimated against SPY in monthly returns across the 7,689 sample funds is 0.940, while the mean betas measured from annual, decade, and lifetime returns by the modified LL method are 0.912, 0.850, and 0.917, respectively. As might be expected, betas estimated from long-horizon returns are more volatile, as the standard deviation of the estimates increases from 0.328 for monthly returns to 0.504 for lifetime returns. The distribution of betas estimated from long-horizon returns is also more highly skewed as compared to estimates from monthly returns; the skewness coefficient for lifetime return beta estimates is 1.83, compared to 0.98 for monthly returns.

The mean beta estimated from monthly returns for the 3,153 funds with monthly beta estimates greater than one is 1.201. For these funds, estimated betas at the one-year, decade, and lifetime horizons are 1.142, 1.108, and 1.234, respectively. Thus, the average beta for these funds does not increase notably with return horizon. As discussed below, we estimate negative average alphas for these funds, which as shown on Figure 3, reduce longer horizon beta estimates. For the 4,536 funds where the beta estimated from monthly returns is less than one, the mean monthly return beta is 0.759. For these funds, mean beta estimates are 0.752, 0.671, and 0.696 at the annual, decade, and lifetime horizons. Thus, the estimates display a tendency for beta estimates that are less than one at the monthly return horizon to decrease as returns are measured over longer horizons.

4.4 Empirical Estimates of Long-Return Horizon Alpha

Perhaps the most striking implication of the analysis presented in Section 4 is that a fund that has a positive alpha when returns are measured at a monthly horizon can have a negative alpha when returns are measured at a longer horizon, and vice versa. This result is not simply a matter of sampling error; that is, the sign of the true alpha can differ depending on return horizon. Of course, empirical estimates of long-horizon alphas will be affected by random sampling noise as well as changes in true alphas as a function of horizon. To distinguish between the effects of noise and changes in true alpha as a function of return horizon we focus on the asymmetry implication noted in section 4.1 above. In particular, the theory developed there implies (i) alpha estimates will tend to be smaller at longer return measurement horizons for funds with short-horizon beta estimates that are greater than one, and vice versa, and (ii) the effect of return measurement horizon on alpha estimates will be stronger for funds with estimated short-horizon betas that are greater than one.

We next report on the extent to which the sign of alpha estimates in our sample depend on the horizon over which returns are measured. In interpreting these results, it is important to recall that each alpha estimate is obtained from the identical sample; annual, decade, and lifetime returns are all obtained by compounding the same monthly sample returns.

Table 6 reports on the in-sample probabilities that alphas estimated from long-horizon (annual, decade, and lifetime) returns have the same sign as alphas estimated for the same fund based on monthly returns. We report overall results, as well as results delineated by the sign of short-horizon alpha estimates. The results in Panel A, which pertain to all funds in the sample, show that the likelihood that long-horizon alpha estimates are of the same sign as alphas estimated from monthly returns decreases with the return measurement horizon, from 93.6% at the annual horizon to 87.6% at the decade horizon and 85.5% at the lifetime horizon. The rates of agreement are relatively high, 99.2%, 91.7%, and 92.0% at the annual, decade, and lifetime horizons when the alphas estimated from monthly returns are negative.

In contrast, rates of agreement are notable lower, 85.6%, 81.7%, and 76.1% at the annual, decade, and lifetime horizons, respectively, when alphas estimated from monthly returns are positive. The finding that nearly one fourth of funds with positive alphas estimated from monthly returns have negative alpha estimates when focusing on long-horizon returns is striking.

On Panel B of Table 6 we report results on the frequency that the sign of short and long-return-horizon alpha estimates agree, based on subsamples that are defined by the length of time that a fund is included in the database. Results for funds with longer lives are of particular interest for two reasons. First, lifetime betas for funds with relatively long lives are estimated over a longer horizon and, based on expression (7), should differ more from short-return-horizon betas, leading to larger potential divergences in alpha estimates as a function of return horizon. Second, funds with longer lives also have larger sample sizes, so both short and long-horizon betas and alphas should both be estimated more accurately.[20]

The results reported on Panel B of Table 6 show that the effect of return horizon is indeed strongest for funds that are in the database for longer time periods. The sample probability that the sign of the alpha estimate is consistent across monthly and lifetime return horizons is 95.1% for funds with a life of 1 to 5 years, 89.4% for funds with a life of 5 to 10 years, 86.8% for funds with a life of 10 to 15 years, and 72.8% for funds that are in the database for over 15 years. Focusing on the subsample of funds where the alpha estimated from monthly returns is positive, the probability that alpha estimate implied by lifetime returns is also positive is 86.7%, 80.9%, 82.2%, and 67.7% for funds with sample lives of 1-5 years, 5-10 years, 10-15 years, and over 15 years, respectively. To restate the final result, among those funds that are in the database for more than fifteen years and for which alpha estimates obtained in monthly returns are positive, more than 30% have negative alpha estimates when returns are measured over the life of the fund.

[20] Funds with long lives also have better overall performance, as documented on Panel D of Table 2. However, while survivorship bias may increase performance measured at any given horizon, this should not explain *differentials* in alpha estimates across short and long horizon return intervals.

In Table 7 we report on the distribution of alpha estimates, including means, medians, and standard deviations. Panel A contains results pertaining to all sample funds. Each alpha estimate, regardless of return horizon, is restated as a monthly equivalent to make estimates directly comparable.[21] While the hypothesis that mean alphas are equal across return measurement horizons can be rejected (p-value < .01), mean alphas for the full sample do not differ dramatically across return measurement horizons. The cross-fund mean alpha estimate is -0.11% in monthly returns, -0.16% in annual returns, -0.06% in decade returns, and -0.19% in full-sample horizon returns. Corresponding median alpha estimates are -0.05% in monthly returns, -0.08% in both annual and decade returns, and -0.12% in lifetime returns.

In Panels B and C of Table 7 we report corresponding results for subsamples where the beta estimated from monthly returns is greater (Panel B) or less (Panel C) than one. As noted in Section 4.1, our analysis implies asymmetries in the effect of return horizon on alpha estimates as a function of short-horizon beta estimates, while random sampling error does not imply such asymmetry. In particular, Panel A of Figure 3 shows that long-return-horizon betas not only increase with short-return-horizon betas, but that the relation is stronger for high beta funds. As a consequence, alphas for funds with small short-return-horizon betas tend to increase with return horizon, while alphas for funds with large short-return-horizon betas tend to decline, and more so the higher the beta.

The empirical results on Table 7 are consistent with this implication. For the 3,153 funds with short-horizon beta estimates that are greater than one (Panel B), mean alpha estimates decrease notably with return measurement horizon, from -0.16% for monthly returns, to -0.27% for annual returns, -0.22% for decade returns, and -0.46% for full-sample horizon returns. In contrast, for the 4,536 funds with monthly beta estimates that are less than one, alpha estimates increase modestly with return horizon, from

[21] We restate long horizon alphas as monthly equivalents by dividing by the number of months in the sample. The more natural alternative, to focus on the Nth root (where N is the number of months in the sample) of one plus the long horizon alpha, is precluded for more than 650 funds because the estimated long horizon alpha is less than -100%.

-0.07% in monthly returns to -0.09% in annual returns, 0.05% in decade horizon returns, and 0.00% in full-sample horizon returns (which does not differ significantly from zero).

We also report in Table 7 the fraction of funds with positive alpha estimates when returns are measured at various horizons. For the full sample of 7,689 funds, the proportion with positive alpha estimates decreases moderately from 40.9% when returns are measured at the monthly horizon to 35.8% when returns are measured at the lifetime horizon. Among those funds with a negative alpha estimate based on monthly returns, only 8.0% have a positive alpha estimate based on lifetime returns. In contrast, among those funds with a positive alpha estimate based on monthly returns, 23.9% have a negative alpha estimate based on lifetime returns.

The divergence is more notable when focusing on funds with monthly beta estimates greater than one (Panel B of Table 7). Among the funds with a monthly return beta estimate greater than one and a monthly return alpha estimate that is negative, less than 0.01% have a positive alpha estimate based on lifetime returns. In contrast, among the funds with a monthly return beta estimate greater than one and a monthly return alpha estimate that is positive, more than half (54.6%) have a negative alpha estimate based on lifetime returns. This striking outcome can also be contrasted to results for funds that have a monthly return beta estimate less than one and a monthly return alpha estimate that is positive, where only 6.7% have a negative alpha estimate based on lifetime returns. These results are consistent with the empirical prediction made in Section 4.1 that the effect of return horizon on alpha estimates is asymmetric, being stronger for funds with larger short-horizon beta estimates.

Finally, we report in Panel D of Table 7 information regarding the magnitudes of divergences between short-horizon and long-horizon alpha estimates for sample funds. These divergences increase with return horizon. Considering the full sample of 7,689 funds, the difference in alpha estimates as compared to those obtained in monthly returns exceeds five percent per year for 2.6% of funds when returns are measured at the annual horizon, 8.2% of funds when returns are measured at the decade horizon, and 12.0% of funds when returns are measured at the lifetime horizon.

The asymmetry predicted by our analysis in Section 4.1 is observable on Panel D as well. Focusing the subsample of funds with monthly return beta estimates that exceed (are less than) one, the difference in alpha estimates as compared to those obtained in monthly returns exceeds five percent per year for 5.0% (1.0%) of funds when returns are measured at the annual horizon, 12.3% (5.4%) of funds when returns are measured at the decade horizon, and 20.6% (5.9%) of funds when returns are measured at the lifetime horizon

To summarize, estimates of alpha depend on the horizon over which returns are measured, even when focusing on a single sample. This result arises because means, variances, and covariances of returns all depend on the horizon over which returns are measured, but do not generally increase with horizon in a linear manner or proportional to each other. A key testable implication of our analysis is that the effect of return horizon is asymmetric, being greater for funds with high betas measured in short-horizon returns. The results reported here verify this prediction, and show that differences in alphas estimated from monthly returns and those estimated from the same data but focusing on longer horizon returns are economically substantive.

5. Conclusions

The literature that studies funds' return performance (including mutual funds, hedge funds, pension funds, etc.) is vast, but most of the evidence is based on returns measured over short, most often monthly, horizons. Investment horizons differ across investors, and can stretch to decades. While it is true that many investors periodically rebalance their portfolios, the parameters of return distributions (means, medians, standard deviations, covariances, skewness, etc.) vary with return horizon in complex and non-linear ways, with or without periodic portfolio rebalancing. We know of no compelling reason to believe that parameters estimated from monthly returns are necessarily the most relevant to investors with disparate investment horizons.

In this paper, we focus attention on the effects of measuring returns over various horizons such as monthly vs. annual vs. decadal. Importantly, our emphasis is not on forecasting, learning, or time-varying parameters, but rather on the effects measuring returns from a given sample over varying horizons. We study U.S. equity mutual funds for the 1991 to 2018 period. We first show that return horizon is relevant in simple comparisons of fund returns to market benchmark returns. In the monthly data, equity mutual fund returns exceed the matched-month return to the SPY ETF (taken as a proxy for the overall market that investors could readily have captured) for 46.9% of observations. In contrast, the percentage of sample funds that generate compound returns that exceed those to the SPY is only 29.5% at the (fund-specific) lifetime horizon.

Of course, investors are generally concerned with the systematic risk they are exposed to, and want to know whether the expected return on their position compensates for that risk. In short, they are concerned with alphas and betas. While the literature has taken note of the fact that market betas are not invariant to return horizon, we focus additional attention on how alphas depend on the horizon over which returns are measured. We show theoretically and empirically that the sign of the short-horizon (e.g. monthly) alpha does not necessarily reveal the sign of the longer horizon alpha, and that the relation depends on the magnitude of short-horizon betas. Our analysis also predicts an important asymmetry in the effect of return horizon on alpha. In particular, alphas will tend to increase for funds with smaller short-return-horizon betas and will tend to decrease for funds with larger short-horizon betas as the return measurement interval increases, and more so when short-horizon beta estimates are larger.

We estimate long-horizon betas using a modification of the formulas introduced by Levhari and Levy (1977) that is guided by the outcomes of simulations. Using these methods, we show that, consistent with theory, long-horizon alphas not only differ from short-horizon alphas, but that the differences vary systematically based on short-horizon betas. For the full sample, 40.9% of alphas estimated from monthly data are positive, while among funds with a short-horizon beta estimate greater than one the percentage of funds with positive long-horizon alphas is decreased dramatically to only 16.7%. Even among those funds with a positive alpha estimated from monthly returns, only a minority (45.4%) of these funds have positive long-horizon alpha estimates if their short-horizon beta is greater than one.

The interpretation of these results is intrinsically related to the evaluation of asset pricing models. Jensen (1968) introduced alpha as a measure of mutual fund performance, explicitly referencing existing asset pricing models. He stated in particular (page 390) that "the measure of portfolio performance summarized below is derived from a direct application of the theoretical results of the capital asset pricing models derived independently by Sharpe, Lintner and Treynor." More broadly, a central implication of linear factor based asset pricing models is that alphas estimated with respect to the model's factors should not differ significantly from zero. However, linear factor models generally apply at a single horizon. The Capital Asset Pricing Model (CAPM) of Sharpe (1965) and Lintner (1965) is explicitly a single period model, though the length of the period is left unspecified. Levhari and Levy (1977) demonstrate that tests of the CAPM are biased if researchers implement tests using returns measured over the wrong horizon. More recently, Chernov, Lochstoer, and Lundeby (2020) observe that a linear factor model that is valid (i.e. generates zero alphas) at a single period horizon does not generally extend (as a linear model in compound factor outcomes) to multiperiod horizons.

Our results raise questions regarding the interpretation of alpha estimates over different return horizons. If zero short-horizon alpha need not imply zero long-horizon alpha, and positive (negative) short-horizon alpha can be consistent with negative (positive) alpha, even within a single dataset, can alpha still be interpreted as being informative regarding managerial skill? Our results suggest that the appropriate interpretation is that the degree to which returns are abnormal cannot be evaluated independent of issues related to investors' horizons; some managers have a relative advantage in generating alpha for investors who measure outcomes over long horizons, while others are more likely to generate better alphas for investors who measure outcomes over short horizons. Further, measures of mutual fund performance that are based on short-horizon returns may be uninformative or even misleading regarding fund performance over the longer horizons that may be relevant to many investors.

References

Ameriks, John, and Stephen Zeldes, 2004, "How Do Household Portfolio Shares Vary with Age?" Working Paper, Columbia University.

Arditti, Fred and Haim Levy, 1975, Portfolio efficiency in three moments: The Multiperiod case", *Journal of Finance*, 30, 797-809.

Barber, Brad, Xing Huang, and Terrance Odean, 2016, Which factors matter to investors? Evidence from mutual fund flows, *Review of Financial Studies,* 29, 2600-2642.

Ben-David, Itzhak, Jiacui Li, Andrea Rossi, and Yang Song, 2019, What do mutual fund investors really care about?, working paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3292317.

Bessembinder, Hendrik, 2018, Do stocks outperform treasury bills? *Journal of Financial Economics*, 129, 440-457.

Berk, Jonathan, and Jules H. van Binsbergen, 2016, Assessing asset pricing models using revealed preference, *Journal of Financial Economics*, 119, 1-23.

Berk, Jonathan, and Jules H. van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics*, 118, 1–20.

Boguth, Oliver, Murray Carlson, Adlai Fisher, and Mikhail Simutin, 2016, Horizon effects in average returns: The role of slow information diffusion, *Review of Financial Studies*, 29, 2241-81.

Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance*, 52, 57-87.

Chernov, Mikhail, Lars Lochstoer, and Stig Lundeby, 2020, Conditional dynamics and the multi-horizon risk-return tradeoff. Working paper, available at https://sites.google.com/site/mbchernov/CLL_MHR_latest.pdf.

K.J. Martijn Cremers, Jon A. Fulkerson & Timothy B. Riley, 2019, Challenging the Conventional Wisdom on Active Management: A Review of the Past 20 Years of Academic Literature on Actively Managed Mutual Funds, *Financial Analysts Journal*, 75, 8-35.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2001, A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and Morningstar mutual fund databases, *Journal of Finance*, 56, 2415–2430.

Fama, Eugene, and Kenneth French, 2015, A five-factor asset pricing model, *Journal of Financial Economics*, 116, 1–22.

Fama, Eugene, and Kenneth French. 2010. Luck versus skill in the cross-section of mutual fund performance. *Journal of Finance,* 65, 1915-1947.

Fama, Eugene, and Kenneth French. 2015. A five-factor asset pricing model. *Journal of Financial Economics,* 116:1–22.

Farago, A., Hjalmarsson, E., 2019, Compound returns, Working paper, Department of Economics, University of Gothenburg. Download at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3398501.

Gilbert, Thomas, Christopher Hrdlicka, Jonathan Kalodimos, and Stephan Siegel, 2014, Daily data is bad for beta: Opacity and Frequency-Dependent Betas, *Review of Asset Pricing Studies*, 4, 78-117.

Hou, K., C. Xue, and L. Zhang, 2015, Digesting anomalies: An investment approach. Review of Financial Studies, 28, 650–705.

Jensen, Michael, 1968, The performance of mutual funds in the period 1945-1967, *Journal of Finance*, 23, 389-416.

Kamara, Avraham, Robert Korajczyk, Xiaoxia Lou, and Ronnie Sadka, 2016, Horizon pricing, *Journal of Financial and Quantitative Analysis,* 51, 1769-1793.

Kothari, S.P., Jay Shanken, and Richard Sloan, 1995, Another Look at the Cross-section of Expected Stock Returns, *Journal of Finance*, 50, 185-224.

Lee, Cheng, Chunchi Wu, and K.C. John Wei, 1990, The heterogeneous investment horizon and the capital asset pricing model, *Journal of Financial and Quantitative Analysis*, 25, 361-376.

Levhari, David, and Haim Levy, 1977, The capital asset pricing model and the investment horizon, *Review of Economics and Statistics*, 54, 92–104.

Levy, Haim, and Moshe Levy, 2011, The small firm effect: A financial mirage?, Journal of Portfolio Management, 37, 129-139.

Lintner, John, 1965, Security prices, risk, and maximal gains from diversification, *Journal of Finance*, 20, 587-616.

Longstaff, Frances, 1989, Temporal aggregation and the continuous-time Capital Asset Pricing Model, *Journal of Finance*, 44, 871-887.

Mossin, J., 1968, Optimal Multiperiod portfolio policies, *Journal of Business*, 41, 212-229.

Samuelson, P., 1969, Lifetime Portfolio Selection by Dynamic Stochastic Programming, *The Review of Economics and Statistics,* 51, 239-246.

Sharpe, William, 1964, Capital Asset Prices: A theory of market equilibrium under conditions of risk, *Journal of Finance*, 19, 425-442.

Vasicek, Oldrich A., 1973, A note on using cross-sectional information in Bayesian estimation of security beta, *Journal of Finance*, 28, 1233–1239.

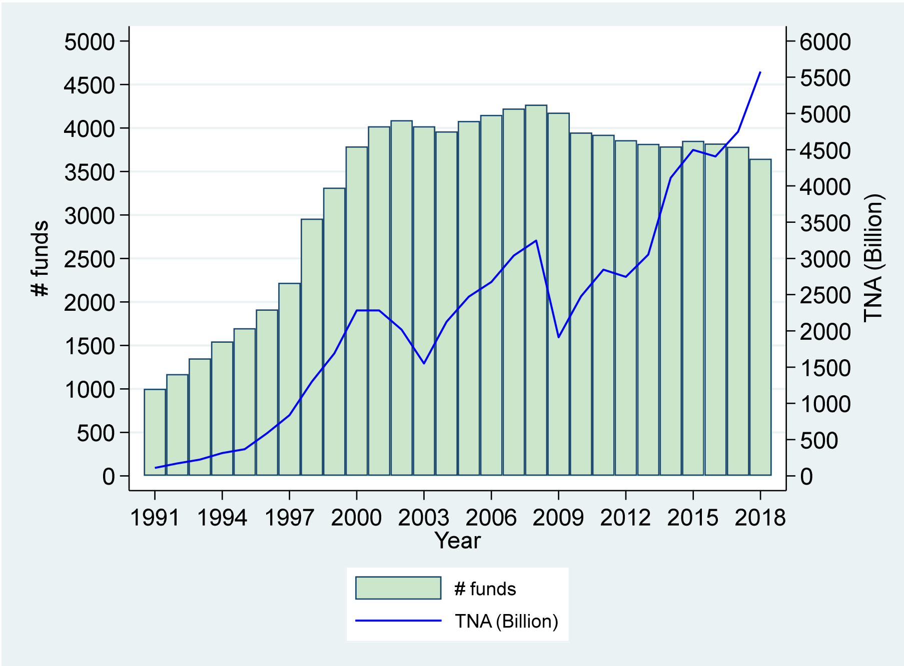

Figure 1
Number of funds and aggregate TNA, by year
This figure plots the annual number of active equity funds (left axis) and the aggregate TNA in $Billion (right axis) in each year.

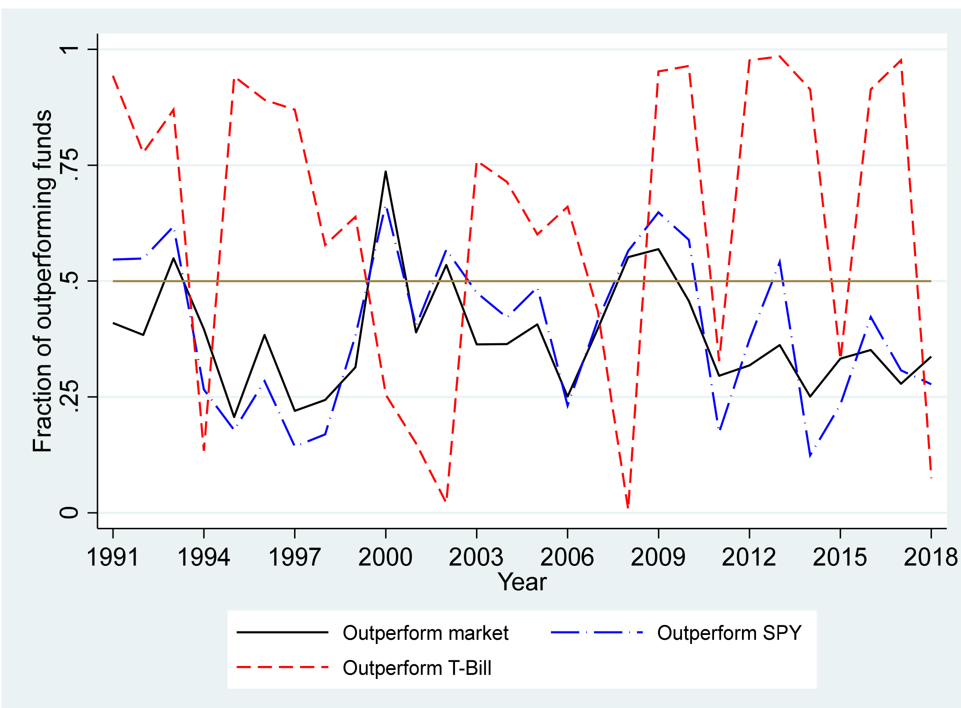

Figure 2
Fraction of funds that outperform three benchmarks, by year
This figure plots the fraction of funds that outperform each of three benchmarks in each year. The benchmarks are the CRSP value-weighted market return, the SPDR S&P 500 ETF return (SPY), and the one-month T-Bill rate.

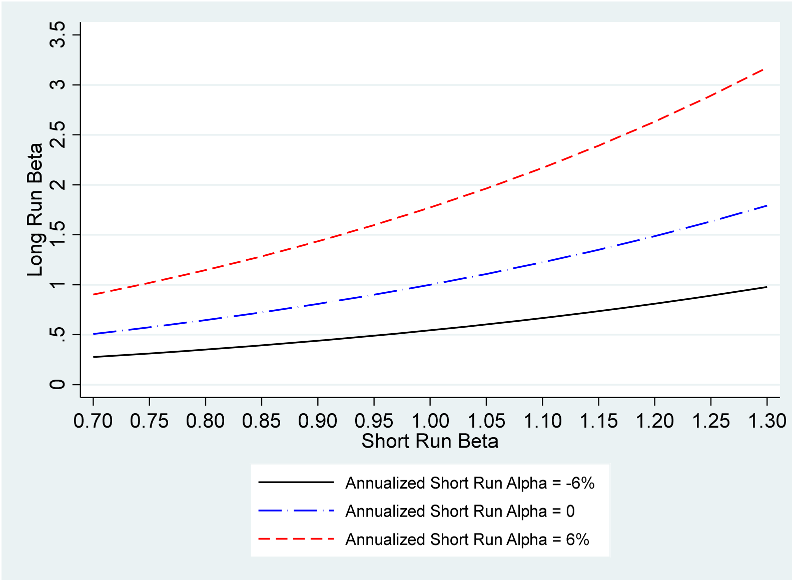

Figure 3, Panel A
Relation between short-horizon beta and long-horizon beta.
This figure displays long-horizon betas implied by text equations (1) and (6), for a variety of possible short-horizon betas and alphas. The computations incorporate $\mu_m = .0075, \sigma_m = .055$ and N = 120.

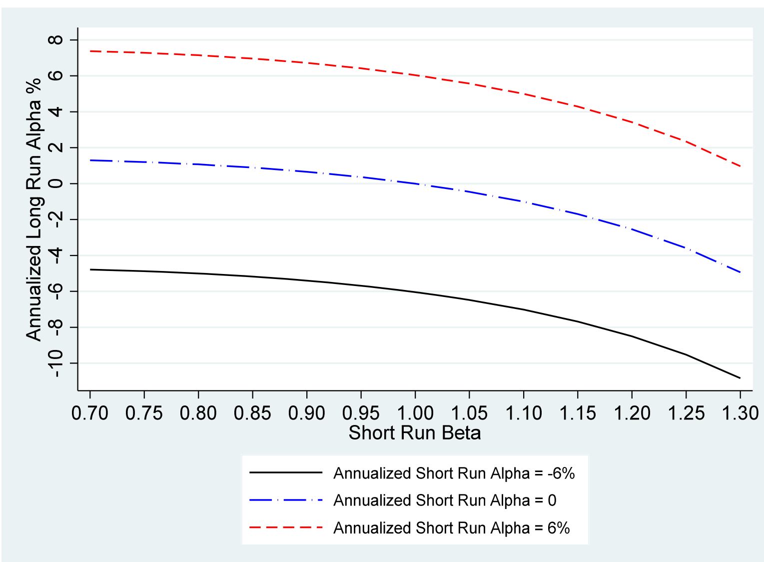

Figure 3, Panel B
Relation between short-horizon beta and long-horizon alpha
This figure displays long-horizon alphas implied by text equations (2) and (6) for a variety of possible short-horizon betas and alphas. The computations incorporate $\mu_m = .0075, \sigma_m = .055$ and N = 120. The long-horizon alpha is annualized computing the tenth root of one plus the long-horizon alpha and subtracting one.

Table 1: Summary statistics of fund return, expense ratio and TNA

This table reports summary statistics of fund expense ratios and TNA at the fund-month level, as well as monthly fund returns and monthly returns to three benchmarks: the CRSP value-weighted market return, the SPDR S&P 500 ETF return (SPY), and the one-month T-Bill rate. A fund outperforms a benchmark in a month if its monthly return is greater than that of the benchmark. Our sample includes active U.S. equity mutual funds from 1991 to 2018.

Variable	# unique funds	# fund-months	Mean	Median	Std. dev.	Skewness
Fund return (%), monthly	7,689	1019541	0.631	0.661	5.096	-0.355
Market return (%), monthly	7,689	1019541	0.737	1.280	4.338	-0.713
SPY return (%), monthly	7,689	1019541	0.699	1.111	4.200	-0.670
Rf return (%), monthly	7,689	1019541	0.176	0.130	0.173	0.521
Outperform market	7,689	1019541	0.463	0.000	0.499	0.148
Outperform SPY	7,689	1019541	0.469	0.000	0.499	0.124
Outperform T-Bill	7,689	1019541	0.549	1.000	0.498	-0.196
Expense ratio (%), monthly	7,689	1019541	0.094	0.096	0.050	1.441
TNA ($B), monthly	7,689	1005705	1.085	0.154	6.766	41.885

Table 2: Fund returns at annual, decade, and lifetime horizons

Panels A-C present summary statistics of buy-and-hold returns to the fund, the CRSP market portfolio, the SPDR S&P 500 ETF (SPY), and the one-month T-Bill in each calendar year (Panel A), over each of three ten- or nine-year periods (1991-1999, 2000-2008, 2009-2018; Panel B), and over the fund's whole lifetime (Panel C). The sample includes 7,689 funds, 14,991 fund/decades, and 92,393 fund/years. A fund outperforms a benchmark if its buy-and-hold return is greater than that of the benchmark over the same horizon. Panel D presents the mean of the variables for the sample funds divided into four groups based on their lifespan. Panel E presents the mean of the variables for four types of funds. We carry out t-test of whether the likelihood of a fund outperforming the market/SPY/T-Bill equals a half. ***, **, and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively.

A. Summary statistics of annual fund returns

Variable	# Fund-years	Mean	Median	Std. dev.	Skewness
Fund life (months)	92393	11.0	12.0	2.3	-2.7
Outperform market	92393	0.385***	0.000	0.487	0.474
Outperform SPY	92393	0.399***	0.000	0.490	0.411
Outperform T-Bill	92393	0.603***	1.000	0.489	-0.420
Fund buy-and-hold return (%)	92393	7.64	6.97	20.32	0.742
Market buy-and-hold return (%)	92393	8.87	11.71	17.37	-0.712
SPY buy-and-hold return (%)	92393	8.42	10.74	16.83	-0.797
Fund buy-and-hold return (%), Pre-fees	92393	8.76	8.07	20.58	0.783
Outperform market, Pre-fees	92393	0.440***	0.000	0.496	0.241
Outperform SPY, Pre-fees	92393	0.469***	0.000	0.499	0.125
Outperform T-Bill, Pre-fees	92393	0.636***	1.000	0.481	-0.567

B. Decade horizon returns

Variable	# Fund-periods	Mean	Median	Std. dev.	Skewness
Fund life (months)	14991	68.0	71.0	40.6	-0.1
Outperform market	14991	0.349***	0.000	0.477	0.633
Outperform SPY	14991	0.392***	0.000	0.488	0.442
Outperform T-Bill	14991	0.580***	1.000	0.494	-0.325
Fund buy-and-hold return (%)	14991	77.42	24.18	138.17	2.993
Market buy-and-hold return (%)	14991	93.86	36.30	135.41	1.055
SPY buy-and-hold return (%)	14991	89.86	32.77	132.42	1.031
Fund buy-and-hold return (%), Pre-fees	14991	91.22	30.13	154.60	3.197
Outperform market, Pre-fees	14991	0.440***	0.000	0.496	0.241
Outperform SPY, Pre-fees	14991	0.488***	0.000	0.500	0.047
Outperform T-Bill, Pre-fees	14991	0.607***	1.000	0.488	-0.439

C: Lifetime fund returns

Variable	N	Mean	Median	Std. dev.	Skewness
Fund life (months)	7689	132.6	111.0	93.2	0.6
Outperform market	7689	0.238***	0.000	0.426	1.230
Outperform SPY	7689	0.295***	0.000	0.456	0.898
Outperform T-Bill	7689	0.760***	1.000	0.427	-1.217
Fund buy-and-hold return (%)	7689	191.17	74.26	373.71	4.560
Market buy-and-hold return (%)	7689	224.10	124.01	327.51	2.393
SPY buy-and-hold return (%)	7689	204.89	120.35	296.45	2.323
Fund buy-and-hold return (%), Pre-fees	7689	257.25	90.25	515.09	4.776
Outperform market, Pre-fees	7689	0.386***	0.000	0.487	0.468
Outperform SPY, Pre-fees	7689	0.451***	0.000	0.498	0.197
Outperform T-Bill, Pre-fees	7689	0.800***	1.000	0.400	-1.503

D: Lifetime fund returns by fund life

Fund life	[1y, 5y]	(5y, 10y]	(10y, 15y]	(15y, 28y]
Number of funds	2287	1787	1201	2414
Fund life (months)	34.8	88.3	148.6	250.1
Outperform market indicator	0.204***	0.187***	0.223***	0.315***
Outperform SPY indicator	0.226***	0.232***	0.294***	0.408***
Outperform T-Bill indicator	0.536***	0.699***	0.858***	0.968***
Fund buy-and-hold return (%)	6.99	59.98	119.44	498.46
Market buy-and-hold return (%)	22.95	98.34	162.31	538.50
SPY buy-and-hold return (%)	22.10	95.24	150.95	486.07

E: Lifetime Returns, Index vs Non-Index Funds

Fund type	Non-index funds	Index funds	S&P index funds	Non-S&P index funds
Number of funds	7087	602	93	509
Fund life (months)	131.1	150.2	168.0	146.9
Outperform market indicator	0.237***	0.251***	0.215***	0.257***
Outperform SPY indicator	0.292***	0.332***	0.333***	0.332***
Outperform T-Bill indicator	0.752***	0.854***	0.817***	0.861***
Fund buy-and-hold return (%)	191.54	186.85	218.69	181.03
Market buy-and-hold return (%)	225.06	212.84	253.84	205.35
SPY buy-and-hold return (%)	205.88	193.24	230.55	186.42

Table 3: Estimating relations between the true long-horizon beta and the sample long-horizon beta

This table presents summary statistics the regression results of the true long-horizon beta on the long-horizon beta computed from an observed sample in bootstrap simulations. In each simulation, we generate a true monthly beta for each fund and compute the corresponding true N-month beta (β_i^L) using Equation (6). We then generate a random sample of N-month fund excess returns and SPY/MKT excess returns using the true monthly beta and other parameters detailed in Section 4.2. Lastly, we estimate the fund's monthly beta in this randomly generated sample and compute the corresponding N-month beta ($\hat{\beta}_i^{LS}$) estimate using Equation (6) and other parameters estimated from this random sample. We repeat the simulation 1,000 times for each fund and then estimate the following regression: $\beta_i^L = a + b * \hat{\beta}_i^{LS} + u$. We consider three long-horizon investment horizons for each fund: 12 months, and 120 months, and lifetime.

Variable	N	mean	sd	p5	p25	p50	p75	p95
				1-year beta				
$\hat{a}$	7689	0.256	0.194	0.043	0.102	0.195	0.364	0.673
$\hat{b}$	7689	0.732	0.167	0.423	0.618	0.757	0.880	0.945
R-squared	7689	0.722	0.166	0.419	0.607	0.746	0.871	0.935
				10-year beta				
$\hat{a}$	7689	0.176	0.180	0.011	0.054	0.109	0.240	0.572
$\hat{b}$	7689	0.794	0.143	0.493	0.720	0.830	0.905	0.964
R-squared	7689	0.833	0.115	0.598	0.772	0.860	0.926	0.965
				Lifetime beta				
$\hat{a}$	7689	0.218	0.264	0.015	0.059	0.123	0.284	0.695
$\hat{b}$	7689	0.785	0.149	0.467	0.705	0.820	0.900	0.966
R-squared	7689	0.830	0.121	0.572	0.770	0.862	0.926	0.963

Table 4: Comparing annual betas estimated using the modified LL approach to annual beta estimated based on time-series return regressions.

For those mutual funds with available returns in at least 10 calendar years, we estimate the 1-year beta against the S&P 500 ETF (SPY) by estimating standard time series regressions and by the modified Levhari and Levy (LL) approach described in Section 4.2.

Variable	N	Mean	Median	Std. dev.	Skewness
All funds with at least 10 annual return observations					
Monthly beta estimated by time series regression	4080	0.921	0.960	0.279	0.371
Annual beta estimated by modified LL method	4080	0.912	0.956	0.251	-0.314
Annual beta estimated by time series regression	4080	0.912	0.904	0.310	0.761
Funds with monthly beta estimate > 1					
Monthly beta estimated by time series regression	1641	1.155	1.097	0.204	3.687
Annual beta estimated by modified LL method	1641	1.135	1.100	0.131	2.261
Annual beta estimated by time series regression	1641	1.150	1.093	0.274	2.499
Funds with monthly beta estimate < 1					
Monthly beta estimated by time series regression	2439	0.764	0.814	0.203	-1.449
Annual beta estimated by modified LL method	2439	0.762	0.807	0.194	-0.887
Annual beta estimated by time series regression	2439	0.753	0.772	0.217	-1.445

Table 5: Long-horizon beta versus short-horizon beta

We compute each fund's monthly beta by regressing excess monthly fund return on excess return to the SPDR S&P 500 ETF (SPY) and compute its long-horizon beta against SPY over three return horizons (1 year, 10 years, and the fund's lifetime) using the modified Levhari and Levy (LL) approach described in Section 4.2. This table compares the monthly versus long-horizon fund betas for all funds, for funds with monthly SPY beta above 1, and for funds with monthly SPY beta below 1, respectively. ***, ***, and * indicate that the mean long-horizon (1-year, 10-year, or lifetime) beta is statistically different than the mean monthly beta at the 1%, 5% and 10% levels, respectively.

N	Mean	Median	Std. dev.	Skewness	Mean	Median	Std. dev.	Skewness
All funds								
	Monthly beta				1-year beta			
7689	0.940	0.963	0.328	0.978	0.912***	0.950	0.264	-0.249
	10-year beta				Lifetime beta			
7689	0.850***	0.810	0.473	1.634	0.917***	0.861	0.504	1.829
Funds with monthly beta against SPY > 1								
	Monthly beta				1-year beta			
3153	1.201	1.112	0.283	3.267	1.142***	1.106	0.148	1.846
	10-year beta				Lifetime beta			
3153	1.108***	1.033	0.478	1.694	1.234***	1.078	0.529	2.082
Funds with monthly beta against SPY < 1								
	Monthly beta				1-year beta			
4536	0.759	0.817	0.216	-1.737	0.752***	0.800	0.200	-0.940
	10-year beta				Lifetime beta			
4536	0.671***	0.642	0.376	2.087	0.696***	0.684	0.342	1.578

Table 6: Do short and long-horizon alphas have the same sign?

We compute each fund's monthly beta by regressing excess monthly fund return on excess return to the SPDR S&P 500 ETF (SPY) and compute its long-horizon beta against SPY over three investment horizons (1 year, 10 years, and the fund's lifetime) using the modified Levhari and Levy (LL) approach described in Section 4.2. Lastly, we compute each fund's long-horizon alpha using its long-horizon returns and the long-horizon beta. This table presents probabilities regarding the sign of the monthly alpha and long-horizon alpha.

Long-horizon alpha	1-year	10-year	Lifetime
Panel A: All funds			
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.856	0.817	0.761
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.992	0.917	0.920
Prob(monthly/long-horizon alphas same sign)	0.936	0.876	0.855
Panel B: Funds with different life spans			
	Fund life over [1y, 5y]		
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.867	0.858	0.867
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.994	0.935	0.984
Prob(monthly alpha < 0 | long-horizon alpha < 0)	0.951	0.945	0.951
Prob(monthly/long-horizon alphas same sign)	0.959	0.914	0.951
	Fund life over (5y, 10y]		
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.830	0.807	0.809
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.993	0.900	0.930
Prob(monthly/long-horizon alphas same sign)	0.945	0.872	0.894
	Fund life over (10y, 15y]		
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.854	0.826	0.822
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.984	0.919	0.901
Prob(monthly/long-horizon alphas same sign)	0.928	0.879	0.868
	Fund life over (15y, 28y]		
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.862	0.801	0.677
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.993	0.906	0.809
Prob(monthly/long-horizon alphas same sign)	0.913	0.842	0.728

Table 7: Long-horizon alpha versus short-horizon alpha and beta

We compute each fund's monthly beta by regressing excess monthly fund return on excess return to the SPDR S&P 500 ETF (SPY) and compute its long-horizon beta against SPY over three investment horizons (1 year, 10 years, and the fund's lifetime) using the modified Levhari and Levy (LL) approach detailed in Section 4.2. Lastly, we compute each fund's long-horizon alpha using its long-horizon returns and the long-horizon beta. Panels A-C compare the monthly versus long-horizon fund alphas for all funds, for funds with monthly SPY beta above 1, and for funds with monthly SPY beta below 1, respectively. ***, ***, and * indicate that the mean long-horizon (1-year, 10-year, or lifetime) alpha is statistically different than the mean monthly alpha at the 1%, 5% and 10% levels, respectively. Panel D presents the fraction of funds whose long-horizon and short-horizons differ by 1%, 2%, and 5% per year, respectively.

A-C: Summary statistics of long-horizon alpha and short-horizon alpha against SPY

N	Mean	Median	Std. dev.	All funds	Funds with monthly SPY alpha > 0	Funds with monthly SPY alpha < 0
Panel A: All funds						
Monthly alpha (%)				Fraction, monthly alpha > 0		
7689	-0.107	-0.051	0.464	0.409	1.000	0.000
1-year alpha (%, monthly rate)				Fraction, 1-year alpha > 0		
7689	-0.160***	-0.079	0.486	0.355	0.856	0.008
10-year alpha (%, monthly rate)				Fraction, 10-year alpha > 0		
7689	-0.057**	-0.082	2.099	0.383	0.817	0.083
Lifetime alpha (%, monthly rate)				Fraction, lifetime alpha > 0		
7689	-0.188***	-0.115	0.725	0.358	0.761	0.080
Panel B: Funds with monthly beta against SPY > 1						
Monthly alpha (%)				Fraction, monthly alpha > 0		
3153	-0.159	-0.085	0.538	0.358	1.000	0.000
1-year alpha (%, monthly rate)				Fraction, 1-year alpha > 0		
3153	-0.268***	-0.149	0.562	0.251	0.701	0.000
10-year alpha (%, monthly rate)				Fraction, 10-year alpha > 0		
3153	-0.217	-0.226	2.107	0.207	0.571	0.004
Lifetime alpha (%, monthly rate)				Fraction, lifetime alpha > 0		
3153	-0.455***	-0.315	0.782	0.167	0.454	0.007
Panel C: Funds with monthly beta against SPY < 1						
Monthly alpha (%)				Fraction, monthly alpha > 0		
4536	-0.071	-0.028	0.402	0.444	1.000	0.000
1-year alpha (%, monthly rate)				Fraction, 1-year alpha > 0		
4536	-0.085***	-0.038	0.410	0.427	0.943	0.015
10-year alpha (%, monthly rate)				Fraction, 10-year alpha > 0		
4536	0.054***	0.002	2.087	0.506	0.956	0.146
Lifetime alpha (%, monthly rate)				Fraction, lifetime alpha > 0		
4536	-0.002***	-0.007	0.617	0.491	0.933	0.138

Panel D: Fraction of funds whose long-horizon and short-horizon alphas differ significantly

N	Investment horizon	Fraction of funds whose long-horizon and short-horizon alphas differ by at least 1% / year	2% / year	5% / year
All funds				
7689	1 year	0.157	0.073	0.026
7689	10 years	0.474	0.257	0.082
7689	Lifetime	0.480	0.279	0.120
Funds with monthly beta against SPY > 1				
3153	1 year	0.301	0.139	0.050
3153	10 years	0.588	0.369	0.123
3153	Lifetime	0.588	0.411	0.206
Funds with monthly beta against SPY < 1				
4536	1 year	0.057	0.027	0.010
4536	10 years	0.395	0.179	0.054
4536	Lifetime	0.405	0.187	0.059

Internet Appendix

Return Horizon and Mutual Fund Performance

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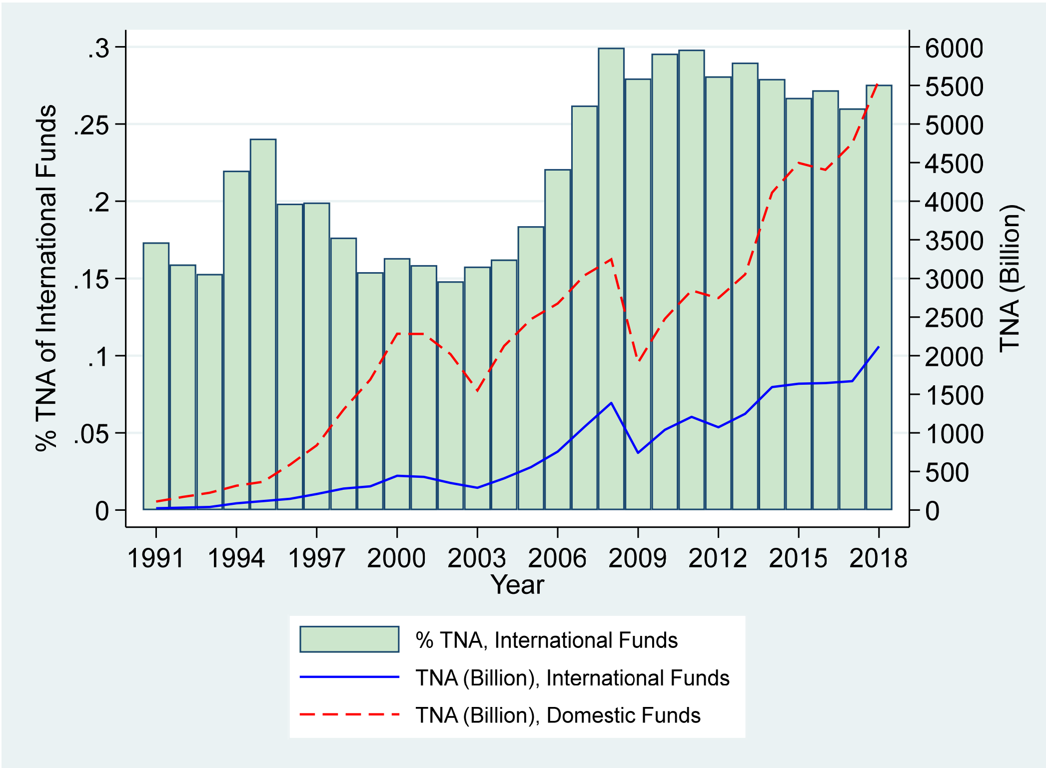

Figure A1
TNA of International Equity Mutual Funds VS. Domestic Equity Mutual Funds
This figure plots the aggregate TNA of U.S. equity funds that invest in domestic equities, the aggregate TNA of U.S. mutual funds that invest in international equities, and the TNA of international equity funds as a fraction of the total TNA of both international and domestic equity mutual funds.

Table A1: Lifetime fund returns by fund characteristics

This table presents summary statistics of lifetime fund returns, sorted by each of five fund characteristics. Fund R-squared is the R-squared of the regression of monthly excess fund return on monthly excess SPY return; Fund beta is the coefficient on excess SPY return. Expense ratio is the average monthly fund expense ratio. Fund return volatility and skewness are the standard deviation and the skewness of monthly fund returns. We compute lifetime buy-and-hold returns to the fund, and to the CRSP market portfolio, the SPDR S&P 500 ETF (SPY), and the one-month T-Bill over the fund's life. A fund outperforms a benchmark if its lifetime return is greater than benchmark returns over the fund's life. We carry out t-test of whether the likelihood of a fund outperforming the market/SPY/T-Bill equals a half. ***, **, and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively.

A. Lifetime fund returns by R-squared of the regression of excess fund return on excess SPY return

Decile	R2	Outperform market	Outperform SPY	Outperform T-Bill	Fund buy-and-hold return (%)	Market buy-and-hold return (%)	SPY buy-and-hold return (%)
1	0.292	0.205***	0.235***	0.471	77.41	154.50	141.68
2	0.482	0.239***	0.300***	0.785***	169.31	208.11	187.62
3	0.569	0.298***	0.360***	0.780***	299.64	286.49	259.73
4	0.648	0.338***	0.399***	0.810***	299.50	287.28	263.12
5	0.720	0.343***	0.378***	0.774***	235.99	237.86	217.50
6	0.775	0.258***	0.311***	0.803***	182.40	214.13	196.92
7	0.822	0.229***	0.298***	0.796***	201.14	250.12	228.96
8	0.866	0.215***	0.270***	0.788***	155.22	208.85	191.20
9	0.909	0.150***	0.215***	0.814***	147.27	202.69	186.58
10	0.961	0.107***	0.185***	0.778***	143.83	190.97	175.60

B. Lifetime fund returns by fund beta against SPY

Decile	Beta	Outperform market	Outperform SPY	Outperform T-Bill	Fund buy-and-hold return (%)	Market buy-and-hold return (%)	SPY buy-and-hold return (%)
1	0.397	0.130***	0.166***	0.616***	49.73	135.44	122.16
2	0.632	0.166***	0.230***	0.857***	126.32	192.28	172.43
3	0.766	0.252***	0.309***	0.817***	173.17	212.48	195.54
4	0.866	0.256***	0.315***	0.814***	204.11	232.34	214.46
5	0.935	0.252***	0.320***	0.817***	251.67	290.59	266.39
6	0.984	0.241***	0.309***	0.810***	239.89	266.88	244.22
7	1.026	0.283***	0.342***	0.834***	256.41	263.73	241.29
8	1.081	0.287***	0.358***	0.826***	256.06	263.63	241.65
9	1.163	0.308***	0.371***	0.759***	231.39	251.11	229.93
10	1.553	0.204***	0.233***	0.450***	123.03	132.58	120.90

C. Lifetime fund returns by fund expense ratio

Decile	Expense ratio (%)	Outperform market	Outperform SPY	Outperform T-Bill	Fund buy-and-hold return (%)	Market buy-and-hold return (%)	SPY buy-and-hold return (%)
1	0.015	0.176***	0.272***	0.932***	155.27	200.31	180.93
2	0.054	0.239***	0.287***	0.837***	219.98	251.70	230.08
3	0.077	0.218***	0.289***	0.819***	280.31	303.64	278.32
4	0.087	0.187***	0.225***	0.841***	199.37	241.93	223.17
5	0.095	0.267***	0.306***	0.879***	253.69	270.26	248.88
6	0.102	0.288***	0.354***	0.836***	191.45	227.98	205.47
7	0.109	0.324***	0.382***	0.668***	198.30	199.85	181.77
8	0.119	0.261***	0.321***	0.655***	175.32	201.70	184.51
9	0.137	0.256***	0.311***	0.676***	178.83	227.53	208.94
10	0.186	0.165***	0.205***	0.454***	59.19	116.12	106.85

D. Lifetime fund returns by volatility of monthly fund return

Decile	Return standard deviation	Outperform market	Outperform SPY	Outperform T-Bill	Fund buy-and-hold return (%)	Market buy-and-hold return (%)	SPY buy-and-hold return (%)
1	0.022	0.056***	0.070***	0.827***	38.27	93.96	89.30
2	0.032	0.120***	0.160***	0.862***	94.78	149.41	137.02
3	0.036	0.165***	0.230***	0.878***	159.88	222.54	202.85
4	0.040	0.216***	0.313***	0.874***	267.30	332.29	302.48
5	0.043	0.235***	0.324***	0.905***	244.23	295.69	269.84
6	0.046	0.306***	0.376***	0.797***	258.59	268.96	245.01
7	0.050	0.324***	0.389***	0.789***	264.66	268.90	245.69
8	0.055	0.397***	0.455***	0.718***	274.29	252.79	230.71
9	0.063	0.349***	0.394***	0.611***	215.71	219.70	201.23
10	0.096	0.215***	0.241***	0.338***	94.10	136.84	124.83

E. Lifetime fund returns by skewness of monthly fund return

Decile	Return skewness	Outperform market	Outperform SPY	Outperform T-Bill	Fund buy-and-hold return (%)	Market buy-and-hold return (%)	SPY buy-and-hold return (%)
1	-1.611	0.187***	0.233***	0.524	38.67	74.72	67.96
2	-0.885	0.187***	0.259***	0.805***	139.58	189.86	173.29
3	-0.747	0.265***	0.334***	0.882***	247.33	280.29	255.20
4	-0.655	0.230***	0.321***	0.880***	302.91	353.02	321.22
5	-0.571	0.239***	0.295***	0.893***	266.15	316.79	289.33
6	-0.487	0.225***	0.294***	0.846***	244.36	290.92	265.38
7	-0.381	0.273***	0.322***	0.796***	244.59	258.29	235.84
8	-0.244	0.257***	0.308***	0.766***	182.58	193.82	179.64
9	-0.046	0.247***	0.283***	0.636***	137.76	148.96	138.08
10	0.476	0.269***	0.302***	0.571***	107.86	134.42	123.04

Table A2: Long-horizon performance of international equity funds

This table presents summary statistics of long-horizon and short-horizon returns to U.S. mutual funds that invest in international equities. Panel A reports summary statistics of fund expense ratios and TNA at the fund-month level, as well as monthly fund returns and monthly returns to three benchmarks: the Vanguard Total International Index Fund (VGTSX), the SPDR S&P 500 ETF return (SPY), and the one-month T-Bill rate. Panels B-D presents summary statistics of the international equity funds' annual, decade, and lifetime performance, respectively. We compute buy-and-hold returns to the fund, the VGTSX fund, the SPDR S&P 500 ETF (SPY), and the one-month T-Bill over three investment horizons: annum (1991 to 2018), decade (1991-1999, 2000-2008, 2009-2018), and the whole fund life. A fund outperforms a benchmark if its buy-and-hold return is greater than that of the benchmark over the period. We carry out t-test of whether the likelihood of a fund outperforming the market/SPY/T-Bill equals a half. ***, **, and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively.

A: Summary statistics of monthly fund return, expense ratio and TNA

Variable	# fund-months	Mean	Median	Std. dev.	Skewness
Fund return (%), monthly	339987	0.487	0.537	5.259	-0.375
VGTSX return (%), monthly	339987	0.467	0.726	4.801	-0.590
SPY return (%), monthly	339987	0.763	1.212	4.151	-0.675
Rf return (%), monthly	339987	0.166	0.100	0.174	0.609
Outperform VGTSX	339987	0.496	0.000	0.500	0.015
Outperform SPY	339987	0.459	0.000	0.498	0.164
Outperform T-Bill	339987	0.536	1.000	0.499	-0.143
Fees (%), monthly	339987	0.117	0.116	0.047	0.818
TNA ($B), monthly	335925	1.063	0.139	5.824	23.454

B. Summary statistics of annual fund returns

Variable	# Fund-years	Mean	Median	Std. dev.	Skewness
Fund life (months)	30746	11.1	12.0	2.4	-2.8
Outperform VGTSX	30746	0.484***	0.000	0.500	0.065
Outperform SPY	30746	0.392***	0.000	0.488	0.444
Outperform T-Bill	30746	0.553***	1.000	0.497	-0.212
Fund buy-and-hold return (%)	30746	6.47	4.51	23.45	0.936
VGTSX buy-and-hold return (%)	30746	5.82	5.03	19.07	-0.403
SPY buy-and-hold return (%)	30746	9.13	11.80	16.45	-0.784

C. Summary statistics of decade fund returns

Variable	# Fund-periods	Mean	Median	Std. dev.	Skewness
Fund life (months)	5179	65.6	62.0	39.8	0.0
Outperform VGTSX	5179	0.479***	0.000	0.500	0.084
Outperform SPY	5179	0.268***	0.000	0.443	1.048
Outperform T-Bill	5179	0.584***	1.000	0.493	-0.342
Fund buy-and-hold return (%)	5179	43.16	21.74	80.05	2.315
VGTSX buy-and-hold return (%)	5179	35.30	27.56	51.75	0.662
SPY buy-and-hold return (%)	5179	91.76	39.14	124.65	0.882

D. Summary statistics of lifetime fund returns

Variable	# Fund-periods	Mean	Median	Std. dev.	Skewness
Fund life (months)	2892	117.6	90.0	89.3	0.9
Outperform VGTSX	2892	0.475***	0.000	0.499	0.098
Outperform SPY	2892	0.139***	0.000	0.346	2.083
Outperform T-Bill	2892	0.679***	1.000	0.467	-0.769
Fund buy-and-hold return (%)	2892	91.56	31.70	200.09	7.133
VGTSX buy-and-hold return (%)	2892	68.73	34.24	92.10	1.783
SPY buy-and-hold return (%)	2892	186.71	112.61	263.86	2.543

Table A3: Comparing annual betas against the market estimated using the modified LL approach to annual beta estimated based on time-series return regressions.

For those mutual funds with available returns in at least 10 calendar years, we estimate the 1-year beta against the market (MKT) by estimating standard time series regressions and by the modified Levhari and Levy (LL) approach described in Section 4.2.

Variable	N	Mean	Median	Std. dev.	Skewness
All funds					
Monthly beta estimated by time series regression	4080	0.916	0.940	0.293	0.444
Annual beta estimated by modified LL method	4080	0.901	0.934	0.257	-0.205
Annual beta estimated by time series regression	4080	0.893	0.881	0.308	0.868
Funds with monthly beta against MKT > 1					
Monthly beta estimated by time series regression	1493	1.187	1.124	0.219	2.997
Annual beta estimated by modified LL method	1493	1.150	1.118	0.137	1.839
Annual beta estimated by time series regression	1493	1.151	1.097	0.282	2.316
Funds with monthly beta against MKT < 1					
Monthly beta estimated by time series regression	2587	0.759	0.810	0.201	-1.418
Annual beta estimated by modified LL method	2587	0.757	0.803	0.192	-0.906
Annual beta estimated by time series regression	2587	0.743	0.759	0.207	-1.424

Table A4: Long-horizon beta versus short-horizon beta against the market

We compute each fund's monthly beta by regressing excess monthly fund return on excess return to the market (MKT) and compute its long-horizon beta against the market over three return horizons (1 year, 10 years, and the fund's lifetime) using the modified Levhari and Levy (LL) approach described in Section 4.2. This table compares the monthly versus long-horizon fund betas for all funds, for funds with monthly market beta above 1, and for funds with monthly market beta below 1, respectively. ***, ***, and * indicate that the mean long-horizon (1-year, 10-year, or lifetime) beta is statistically different than the mean monthly beta at the 1%, 5% and 10% levels, respectively.

N	Mean	Median	Std. dev.	Skewness	Mean	Median	Std. dev.	Skewness
All funds								
	Monthly beta				1-year beta			
7689	0.936	0.941	0.342	1.034	0.901***	0.929	0.271	-0.114
	10-year beta				Lifetime beta			
7689	0.813***	0.761	0.458	1.577	0.877***	0.816	0.495	1.833
Funds with monthly beta against MKT > 1								
	Monthly beta				1-year beta			
2929	1.233	1.138	0.301	2.940	1.155***	1.119	0.158	1.724
	10-year beta				Lifetime beta			
2929	1.101***	1.038	0.484	1.469	1.236	1.085	0.532	1.941
Funds with monthly beta against MKT < 1								
	Monthly beta				1-year beta			
4760	0.753	0.811	0.214	-1.701	0.746***	0.793	0.198	-0.944
	10-year beta				Lifetime beta			
4760	0.636***	0.619	0.336	1.832	0.656***	0.657	0.305	1.222

Table A5: Do short and long-horizon alphas against the market have the same sign?

We compute each fund's monthly beta by regressing excess monthly fund return on excess return to the market (MKT) and compute its long-horizon beta against the market over three investment horizons (1 year, 10 years, and the fund's lifetime) using the modified Levhari and Levy (LL) approach described in Section 4.2. Lastly, we compute each fund's long-horizon alpha using its long-horizon returns and the long-horizon beta. This table presents probabilities regarding the sign of the monthly alpha and long-horizon alpha.

Long-horizon alpha	1-year	10-year	Lifetime
	All funds		
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.838	0.780	0.772
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.991	0.937	0.900
Prob(monthly/long-horizon alphas same sign)	0.937	0.882	0.855
	Fund life over [1y, 5y]		
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.841	0.837	0.873
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.983	0.932	0.978
Prob(monthly/long-horizon alphas same sign)	0.948	0.909	0.953
	Fund life over (5y, 10y]		
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.803	0.793	0.829
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.992	0.916	0.911
Prob(monthly/long-horizon alphas same sign)	0.942	0.884	0.889
	Fund life over (10y, 15y]		
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.878	0.821	0.852
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.995	0.956	0.879
Prob(monthly/long-horizon alphas same sign)	0.953	0.908	0.869
	Fund life over (15y, 28y]		
Prob(long-horizon alpha > 0 | monthly alpha > 0)	0.837	0.736	0.680
Prob(long-horizon alpha < 0 | monthly alpha < 0)	0.997	0.957	0.783
Prob(monthly/long-horizon alphas same sign)	0.913	0.841	0.729

Table A6: Long-horizon alpha versus short-horizon alpha against the market and beta

We compute each fund's monthly beta by regressing excess monthly fund return on excess return to the market (MKT) and compute its long-horizon beta against the market over three investment horizons (1 year, 10 years, and the fund's lifetime) using the modified Levhari and Levy (LL) approach described in Section 4.2. Lastly, we compute each fund's long-horizon alpha using its long-horizon returns and the long-horizon beta. Panels A-C compare the monthly versus long-horizon fund alphas for all funds, for funds with monthly market beta above 1, and for funds with monthly market beta below 1, respectively. ***, ***, and * indicate that the mean long-horizon (1-year, 10-year, or lifetime) alpha is statistically different than the mean monthly alpha at the 1%, 5% and 10% levels, respectively. Panel D presents the fraction of funds whose long-horizon and short-horizons differ by 1%, 2%, and 5% per year, respectively.

A-C: Summary statistics of long-horizon alpha and short-horizon alpha against the market

N	Mean	Median	Std. dev.	All funds	Funds with monthly MKT alpha > 0	Funds with monthly MKT alpha < 0
Panel A: All funds						
Monthly alpha (%)				Fraction, monthly alpha > 0		
7689	-0.141	-0.077	0.454	0.353	1.000	0.000
1-year alpha (%, monthly rate)				Fraction, 1-year alpha > 0		
7689	-0.189***	-0.110	0.472	0.302	0.838	0.009
10-year alpha (%, monthly rate)				Fraction, 10-year alpha > 0		
7689	-0.119	-0.134	1.993	0.316	0.780	0.063
Lifetime alpha (%, monthly rate)				Fraction, lifetime alpha > 0		
7689	-0.232***	-0.140	0.764	0.337	0.772	0.100
Panel B: Funds with monthly beta against MKT > 1						
Monthly alpha (%)				Fraction, monthly alpha > 0		
2929	-0.215	-0.138	0.543	0.295	1.000	0.000
1-year alpha (%, monthly rate)				Fraction, 1-year alpha > 0		
3153	-0.302***	-0.188	0.539	0.213	0.716	0.002
10-year alpha (%, monthly rate)				Fraction, 10-year alpha > 0		
3153	-0.304***	-0.291	1.845	0.155	0.512	0.005
Lifetime alpha (%, monthly rate)				Fraction, lifetime alpha > 0		
2929	-0.575***	-0.394	0.878	0.126	0.426	0.000
Panel C: Funds with monthly beta against MKT < 1						
Monthly alpha (%)				Fraction, monthly alpha > 0		
4760	-0.095	-0.049	0.382	0.389	1.000	0.000
1-year alpha (%, monthly rate)				Fraction, 1-year alpha > 0		
4536	-0.110***	-0.064	0.400	0.357	0.895	0.014
10-year alpha (%, monthly rate)				Fraction, 10-year alpha > 0		
4536	0.009***	-0.037	2.080	0.415	0.905	0.103
Lifetime alpha (%, monthly rate)				Fraction, lifetime alpha > 0		
4760	-0.021***	-0.020	0.593	0.468	0.934	0.171

Panel D: Fraction of funds whose long-horizon and short-horizon alphas differ significantly

N	Investment horizon	Fraction of funds whose long-horizon and short-horizon alphas differ by at least 1% / year	2% / year	5% / year
		All funds		
7689	1 year	0.141	0.065	0.025
7689	10 years	0.489	0.263	0.087
7689	Lifetime	0.490	0.288	0.123
		Funds with monthly beta against MKT > 1		
2929	1 year	0.259	0.126	0.053
2929	10 years	0.731	0.441	0.142
2929	Lifetime	0.624	0.454	0.233
		Funds with monthly beta against MKT < 1		
4760	1 year	0.068	0.027	0.009
4760	10 years	0.341	0.154	0.053
4760	Lifetime	0.407	0.187	0.056