Slow and Steady Wins the Race: The Impact of Chasing Returns on Quartile Rankings

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Abstract

Purpose – *The investment management industry is competitive in which managers compete for the top-quartile (1st) rank. This study shows that a manager who aims to be in the 2nd quartile (above average) instead of the 1st will end up in the 1st in the long run.*

Method – *The study uses monthly historical returns from 01/01/1979 to 01/01/2018 and creates 4,000 bootstrap-simulated funds that invest in four different return strategies and levels of risk. After analyzing 240,000 annual returns over 60 years, it ranks these funds every year and assesses their return, assets under management (AUM), and quartile performance.*

Findings – *Investment fund managers are torn between staying in the 1st quartile and growing AUM over a long-time horizon. This study shows that if a fund's goal is to achieve higher AUM, it should aim at the 1st quartile every year. However, if a fund's long-term goal is to stay in the 1st quartile, it should aim at the 2nd quartile every year.*

Limitations – *In this study, the entire dataset is used for validating two hypotheses. Therefore, it would be helpful to split the full dataset into training and test datasets and conduct an out-of-sample analysis. Besides, the bootstrap method samples data for one year at a time and ignores any lagged-year effects.*

Implications – *Investors pay a significantly higher fee to hedge fund managers, hoping that the manager has the skill to produce higher risk-adjusted returns. Therefore, investors (of public pension funds) need to know if a manager is producing excess returns due to luck or skill.*

Originality – *Our findings are counter-intuitive since most investors do not believe that merely staying "above average" every year can lead to "excellent" long-term performance.*

Keywords: asset management, risk, return, quartile, fund performance, benchmark, investment performance.

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Introduction

A contest is a game where contestants exert costly and irretrievable efforts to obtain one or more prizes with some probability (Corchón & Serena, 2018). The application of contest theory in economics (Vojnović, 2015) is motivated by a real-world phenomenon that market participants care about their performance relative to peers and sometimes are rewarded for topping their rivals (Jin, 2020). Contest theory proposes a tournament-like behavior in which winners take all prize money. Frick (2003) applies contest theory in a tournament-like setting to analyze sports compensation. The contest theory is applied to the investment management industry by viewing the mutual fund industry as a tournament (Brown, Harlow, & Starks, 1996; Prendergast, 1999; Taylor, 2003). "Top quartile" performance is a widely-prized status in the investment industry (Harris, Jenkinson, & Stucke, 2012).

In the investment industry, researchers argue that the mutual fund industry is appropriately viewed as a tournament (i.e., funds compete with one another for new assets and hence higher compensation as a percentage of those assets) based on their relative performance (Brown *et al.*, 1996).

Some funds may close to new investors because their fund strategy may not work as AUM grows. Fund families typically claim that closing a fund protects its superior performance from growing too large to be managed efficiently (Zhao, 2004). Once capacity is attained, funds take a course correction by closing the fund to the new money (O'Neill & Warren, 2019).

However, most funds prefer AUM more than less because of their pay structure. Fund profits maximize the assets under management since their fees are based on assets instead of performance. Therefore, it is evident that the corporate officers and managers will be obsessively consumed with attracting more assets (Lowenstein, 2008). Besides, the bonus component of the fund manager compensation is explicitly tied to the fund investment performance for most funds (Ma, Tang, & Gómez, 2019). This study explores what strategy should be used if the fund manager wants a higher AUM or be placed in the top quartile.

The AUM growth may be achieved in two ways: earning higher returns on the current AUM or bringing in new investor capital. Funds attract this new capital by exhibiting superior performance compared to their peers. This organic growth is the most important driver of value in the capital markets. However, sustained organic growth is difficult to achieve (Meer, 2005). Investment funds vie to be ranked first among thousands of funds on the market and aim at least in the top or 1st quartile (the top 25th percentile). Clients exit when performance falls below the top quartile, and a floundering fund can find itself with a disappearing clientele. Funds may be replaced to address fund outflow since poorly performing funds that replace their managers incur less fund outflow than funds that retain existing management (Chevalier & Ellison, 1997).

This winner-takes-all approach can be seen in the mutual fund industry, where the market is concentrated among the top ten funds: the top-ten funds comprise 85 percent of the inflows (Beardsley *et al.*, 2017). In addition, despite the long-term trend in the industry toward passive rather than active strategies, investors continue to demand products that outperform the market (Beardsley *et al.*, 2017). Indeed, in the past few years in the United States, only active five-star funds and new products have captured significant net inflows, leaving one- to four-star ratings to suffer net outflows. However, this investor strategy of hiring 1st quartile "winners" in fund management and firing 4th quartile "losers" can ultimately lead to losses (Arnott, Kalesnik, & Wu, 2018) or simply fruitlessness because there is no guarantee that fund performance can be reproduced (Harvey & Liu, 2018).

Howard Marks of Oak Tree Capital (Marks, 2021), a leading global alternative investment management firm with expertise in credit strategies and $120 billion of AUM, has criticized investors who chase high returns. He proposes that attempting to achieve a superior long-term record by stringing together a run of top-decile years is unlikely to succeed (Marks, 1990). Our research supports the fund strategy (Marks, 1990) of targeting slightly above average performance (but not for the 1st quartile) to secure top performance in the long run. Our results indicate that if a fund aims to achieve higher AUM, it should aim at the 1st quartile every year. However, if a fund aims to win the quartile race and be in the 1st quartile over a long period, aiming for consistent performance in the 2nd quartile every year is a safer bet.

Our paper is structured as follows: Section 2 provides an overview of the literature on fund strategy, performance, and fund flows; Section 3 discusses the methodology and data; Section 4 shows our main findings, and Section 5 concludes.

Literature Review

The contest theory literature primarily explains games where contestants exert costly and irretrievable efforts to obtain one or more prizes with some probability. This theory is surveyed in various books (Konrad, 2009; Vojnović, 2015) and papers (Chowdhury & Gürtler, 2015; Corchón & Serena, 2018; Fu & Wu, 2019). The literature on fund strategies and fund performance is extensive. Since Jensen (1968), studies have shown little evidence that mutual funds outperform passive benchmarks (Bollen & Busse, 2005; Carhart, 1997; Gruber, 1996; Zheng, 1999). The relative performance of mutual funds appears to be the most unpredictable when past relative performance is used. While some persistence evidence exists, it concentrates on low liquidity sectors or at shorter horizons. Nevertheless, mutual fund investors appear to "herd" or chase performance – 77 percent of the mutual funds were "momentum investors," buying stocks that were past winners (Grinblatt, Titman, & Wermers, 1995). Flows into and out of mutual funds are related to lagged excess returns measures (Chevalier & Ellison, 1997; Sirri & Tufano, 1998). A leading explanation for this relationship is that investors rationally update their beliefs about fund skills based on past performance (Berk & Green, 2004).

Though alternative investments are not the focus of our study, other researchers have expanded the definition of funds to include alternative investments such as hedge funds and private equity while analyzing the fund performance. For example, Fung *et al.* (2008) examine fund-of-funds in the hedge fund industry and documents that the alpha-producing funds are not as likely to liquidate as those that do not deliver alpha and experience far higher and steadier capital inflows than their less fortunate counterparts. In addition, several researchers show that the hedge funds pursuing the unique strategies outperform the most general hedge funds as measured by the Strategy Distinctiveness Index (Sun, Wang, & Zheng, 2012) and R-square concerning systematic factors (Bollen, 2013; Titman & Tiu, 2011). Similarly, Korteweg and Sorensen (2017) find high long-term persistence in private equity funds and report a net-of-fee annual return difference of 7 to 8 percentage points between top and bottom quartile PE firms.

Several studies examine the motivation behind the fund portfolio decisions. For example, Brown *et al.* (1996) find that those more likely to be "losers" will increase fund volatility to boost performance, with this strategy being more pronounced when investors are more aware of fund performance. Their findings support the theory that the competitiveness of funds and drive to become "winners" by performing better than their peers can affect the fund portfolio decisions. Funds that engage in risk-shifting (i.e., increasing risk levels significantly over time) perform worse than funds that keep stable risk levels (Huang, Sialm, & Zhang, 2011).

Since pay depends on relative performance (Nalebuff & Stiglitz, 1983; Rosen, 1985), fund managers vie for 1st quartile ranking. In a contest, economic agents expend costly effort to vie for limited prizes, and they are rewarded for "getting ahead" of their opponents instead of their absolute performance metrics (Fu & Wu, 2019). Funds may chase rankings not just for bragging rights but also to receive more fund flows from investors. Investors respond to mutual fund rankings, and funds with the highest rankings receive a higher share of inflows. A general positive relationship between performance and flows has been demonstrated previously (Jones & Martinez, 2017; Sirri & Tufano, 1998).

Besides fund performance, researchers examined fund families and found that a fund reaching a top-ranking receives large inflows and that a change in position from the bottom two deciles to the top two deciles also leads to an increase in fund flows (Cici, Dahm, & Kempf, 2018; Kempf & Ruenzi, 2008). In terms of inflows, it makes a huge difference of whether a fund reaches a top position within its family or not. The top 10% of funds in a family grow assets by an additional 6.87% per year.

Investors may invest in funds that have performed well in the past because they believe they will perform well in the future and thus increase fund flows to "winners" who exhibit higher ranking and consistently good performance (Brown, Draper, & McKenzie, 1997). Besides consistency, fund performance is attributed to the fund manager's stock selection and market timing abilities (Andreu, Matallín-Sáez, & Sarto, 2018; Brown *et al.*, 1997). Also, net new investment money goes into recent winning funds (Ellis, 2017). This may also be the case for individual investors, who tend to hold onto funds that have increased in value and sell funds that have lost value (Ivković & Weisbenner, 2009).

Studies also find that "persistence of performance" holds in the short-term for mutual funds (Bollen & Busse, 2005) and is more pronounced for small-cap/growth funds (Huij & Verbeek, 2007). This short-term persistence may stem from investors using "hot hands" strategies, where investors only select the top performers every quarter based on the previous four quarters (Hendricks, Patel, & Zeckhauser, 1993). Funds with "hot hands" and "icy hands" tend to have portfolio similarities consistent with riskier positions: compared to no-streak funds, they hold fewer stocks, invest more in the top ten holdings, and have a higher portfolio beta (Berkowitz, Schorno, & Shapiro, 2017). Funds that use a "hot hands" strategy tend to perform better than the average mutual fund, and that in the context of "icy hands," the opposite of hot hands, the inadequate performing funds tend to have inferior performance and continue to underperform (Hendricks *et al.*, 1993). For mutual funds, past performance may also predict future risk-adjusted performance (Elton, Gruber, & Blake, 1996), which may also hold in the long-term (Wermers, 2003) and extend to periods ranging from five to ten years (Elton *et al.*, 1996; Elton, Gruber, Das, & Hlavka, 1993; Grinblatt & Titman, 1992).

Multiple studies find that mutual fund flows strongly correlate with lagged excess returns (Chevalier & Ellison, 1997; Sirri & Tufano, 1998). Fund flows may also be affected by new information about product quality (Ippolito, 1992). Lynch and Musto (2003) find a convex relationship between past returns and fund flows in mutual funds that shift strategy after a poor performance. Based on Ellis (2017), we assume a linear model of fund flows that adjusts according to fund return to determine which funds will have higher AUM. Crane and Crotty (2018) compared passive (index) mutual funds and active mutual funds to examine the relationship between net fund flows and one-month lagged performance for both active and passive funds. Their findings support the literature widely documented for active funds; new money growth is positively correlated with lagged fund performance.

An increase in Fama–French–Carhart's abnormal performance of 10 bps per month is associated with increased flows of 3.8 bps of AUM for index funds. This is significantly greater than the 1.8 bps increase in AUM for active funds, so new money growth in index funds is more sensitive to past performance than in active funds. This result is inconsistent with investors rationally updating about fund skill if index funds have no skill. It is puzzling that index funds would be more responsive to past gross returns than active funds.

Finally, a desire to outperform peers for non-monetary "rank" incentives is found to be a driver of excessive risk-taking among finance professionals (Kirchler, Lindner, & Weitzel, 2018). This can either be the intrinsic desire to be better than others and thereby create a positive self-image (Bénabou & Tirole, 2003; Köszegi, 2006; Maslow, 1989) or the extrinsic desire for status signaling superior performance to peers (Frank, 1993; Moldovanu, Sela, & Shi, 2007). Thus, rank incentives promise a non-monetary utility to those at the top of the ranking and a disutility to those at the bottom (Barankay, 2012).

Our contribution to the literature is examining the linkages between fund performance, fund flows, and quartile ranking. Previous literature addresses these three topics in isolation while we combine them and study the interdependence over the analysis window. Though we simulate the strategy for up to 60 years in this paper, a 10-year or 30-year time horizon is more realistic in real life. The median age of the conventional mutual fund was 15 years in 1980 and six years in 2002 (Bollen, 2007). Therefore, the 60-year simulation results are provided only for theoretical purposes.

Hypothesis Development

In this paper, we examine strategies that passive funds–those who invest in an underlying index of securities, should adapt to stay in the 1st quartile in the long run. Staying in the 1st quartile matters to fund managers since their pay depends on relative performance (Nalebuff & Stiglitz, 1983; Rosen, 1985), and as economic agents, they are rewarded for their absolute performance metrics (Fu & Wu, 2019). In addition, a passive fund manager has discretion over the investment time horizon (how long to keep the fund going) and the underlying benchmark (or index). Focusing on passive funds is justified for three reasons — (a) the investments industry is rushing towards passive funds: passive funds had grown from 18% of the fund market share in 2008 to 36% in 2018 ; (b) contrary to popular belief, passive fund skill exists, is persistent, and is in similar proportion as inactive funds (Crane & Crotty, 2018); (c) investors are likely to achieve higher returns by employing a passive indexing strategy than they are likely to obtain from active portfolio management (Statman, 2020) and perform better in the long-run (Blanchett, 2010).

In addition, the evidence strongly supports passive investment management in all markets — small-cap and large-cap equities, U.S. markets, international markets, and bonds and stocks (Malkiel, 2003). After analyzing 69 indexes, Elton *et al.* (2019) reported that the return on about 78% of the passive funds was higher than the return on the active funds, with the average differential return with no short sales being 1.37% annually. If active fund loads were taken into account, the passive fund beat the active fund about 90% of the time.

In our paper, we explore an investment strategy to achieve higher AUM. Passive funds are a large part of the market, and active funds respond to performance. Therefore, we are curious to see whether aiming for the top quartile as a benchmark will lead to higher AUM. Because of this, we come to the following hypothesis:

Hypothesis 1: A fund that wants a higher AUM should strive to be in the 1st quartile every year.

Next, we explore whether the fund strategy of being in the first quartile will lead to a winning strategy. Howard Marks (1990) argues that a strategy aiming for a run of the top-decile year to achieve superior long-term performance is not likely to succeed. Instead, a fund only needs to be slightly above average to be considered a top performer in the long run. Thus, our next hypothesis is as follows:

Hypothesis 2: A fund that wants to win the quartile race should stay in the 2nd quartile (instead of the 1st quartile) every year.

Our study contributes to the literature on fund strategy by exploring how a fund strategy is related to fund performance, fund flows, and quartile ranking in combination using analysis windows ranging from 10-, 30-, and 60- years.

Data and Methodology

Since fund profits maximize the AUM and base their fees on AUM (Lowenstein, 2008), we model that every fund in our analysis tries to stay in the 1st quartile and increase AUM at any given point in time. We categorize available passive fund strategies into four types: high risk–high return ("most-risky," similar to small-cap stocks), medium risk–medium return ("risky," similar to large-cap stocks), low risk–low return ("less-risky," similar to U.S. treasury bonds), and least risk–least return ("least-risky," similar to U.S. treasury notes). We choose four strategies (instead of five or six), each corresponding to an investable stock index because they neatly fit into four quartile bins in the end. As an example, when a fund follows the most-risky strategy each year, the fund implicitly aims for the highest return and 1st quartile position in that year. The fund manager has to pick the appropriate index initially and cannot change the strategy (i.e., index) mid-course.

Data

Since we assume that a passive fund follows one of the four strategies (most-risky, risky, less-risky, and least-risky) to stay in the 1st quartile, we identify a representative passive index that mirrors the fund strategy. We use data over 39 years for all asset classes from January 1, 1979, the earliest available date for Russell Price Indices (London Stock Exchange Group (2021), to January 1, 2018.

Most-risky: Russell 2000 Price Index, annually, not seasonally adjusted, average aggregation method. The data for this index is obtained from the Federal Reserve Economic Database (Federal Reserve System, 2021a). The Russell 2000 Index measures the performance of the small-cap segment of the U.S. equity universe. It is a subset of the Russell 3000 Index and includes approximately 2,000 of the smallest securities based on a combination of their market cap and current index membership. The Russell 2000 represents about 10% of the U.S. market.

Risky: Russell 1000 Price Index, annually, not seasonally adjusted, average aggregation method. The data for this index is obtained from the FRED. The Russell 1000 Index measures the performance of the large-cap segment of the U.S. equity universe. It is a subset of the Russell 3000 Index and includes approximately 1,000 of the largest securities based on a combination of their market cap and current index membership. The Russell 1000 represents about 90% of the U.S. market.

Less-Risky: Ten-year constant maturity Treasury bond (Federal Reserve System, 2021b). The 10-year T-bond (GS10) return includes the promised coupon at the start of the year and the price change due to interest rate changes. Since GS10 is reported every month, the annual bond yield is reported at the end of each year. Thus, GS10 is a 10-year treasury constant maturity rate, in percent, reported monthly and not seasonally adjusted. Detailed calculations of these returns are available on Professor Aswath Damodaran's website (Damodaran, 2021).

Least-Risky: Three-month Treasury bill, available in the dataset H.15-selected interest rates as TB3MS (Federal Reserve System, 2021c). It is a 3-month treasury bill, a secondary market rate, reported monthly, and not seasonally adjusted.

Methodology

We use a seven-step process to decide if a fund following a specific strategy stays in the 1st quartile. First, the annual return, R_{t+1}, is defined using Equation 1.

$$R_{t+1} = \frac{P_{t+1} - P_t}{P_t} \sim \mathbb{N}(\mu, \sigma^2) \quad (1)$$

where R_{t+1} is fund return, before fees, at time t+1,
P_{t+1} is the index value at t+1, adjusted for any dividends and stock splits,
P_t is the index value at t, adjusted for any dividends and stock splits, μ is the fund normally-approximated mean annual return,
σ is the fund's standard deviation of annual return.

Second, mean (μ) and standard deviation (σ) for each asset class are derived using a curve fitting to a normal distribution. Annual return distributions (actual and fitted to a normal distribution) based on Rt+1 are shown in Figure 1.

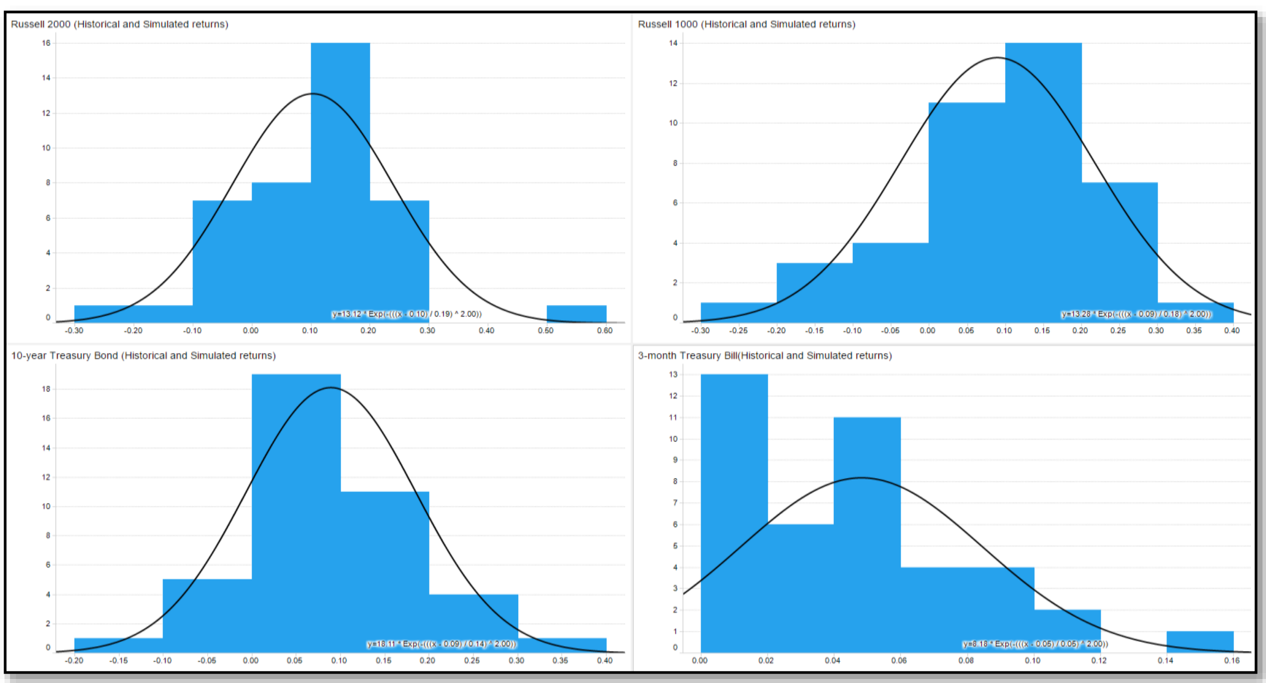


Figure 1: Histogram of Annual Returns from 1979 to 2018 for Four Asset Classes

Figure 1: Annual returns for the four asset classes included in the model with the sample period from 1979 to 2018. The asset classes are set as "most-risky" Russell 2000

small-cap stocks are approximated to have normally distributed annual returns with μ = 10.35% and σ = 14.73% (annualized risk). Likewise, "Risky" Russell 1000 large-cap stocks have μ = 9.68% and σ = 13.44%, less-risky" 10-year Treasury bonds have μ = 7.82% and σ = 10.17%, and "least-risky" 3-month Treasury bills have μ = 4.53% and σ = 3.65%.

"Most-risky" Russell 2000 small-cap stocks are approximated to have normally distributed annual returns with μ = 10.35% and σ = 14.73% (annualized risk). Likewise, "Risky" Russell 1000 large-cap stocks have a = 9.68% and σ = 13.44%, less-risky" 10-year Treasury bonds have a = 7.82% and σ = 10.17%, and "least-risky" 3-month Treasury bills have a = 4.53% and σ = 3.65%. We plot the probability density function for the four strategies in Figure 2 and confirm that the four asset classes conform to four distinct risk-return profiles. A scatter plot of the risk and return profile is shown in Figure 3. As one would expect, as the riskiness of the asset class increases, the return also increases. One can choose a different set of asset classes in our model if they represent four distinct risk-return profiles similar to those in Figures 2 and 3.

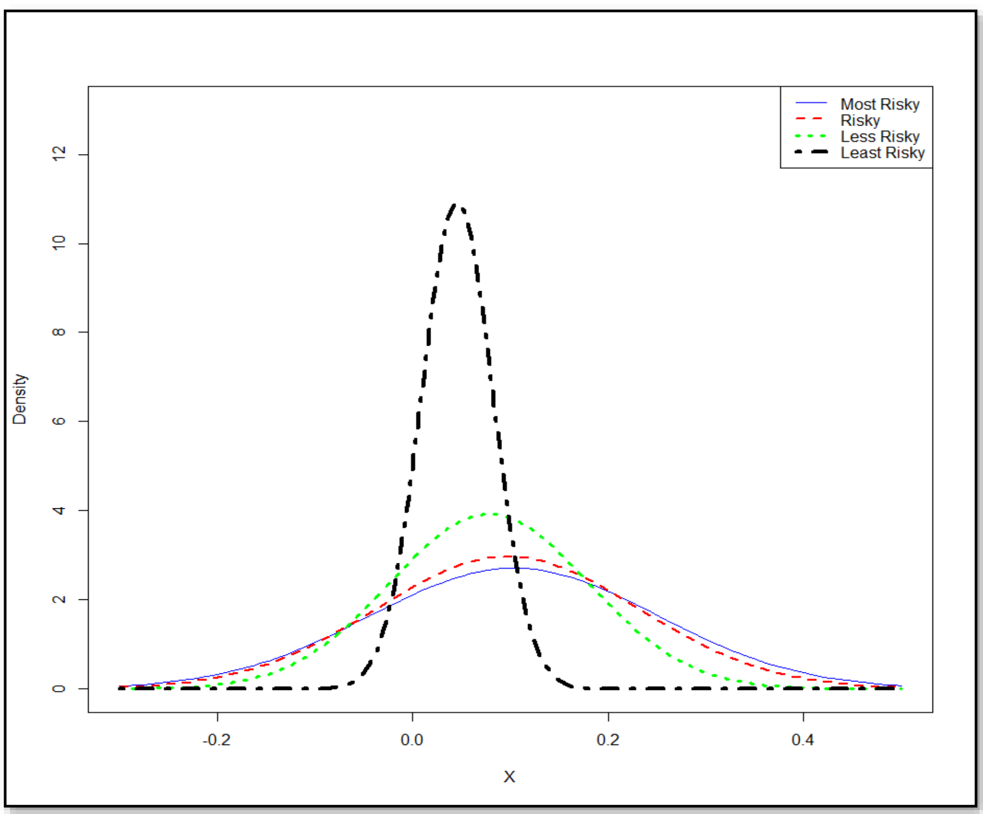


Figure 2: Probability Density Functions for Four Type of Strategies

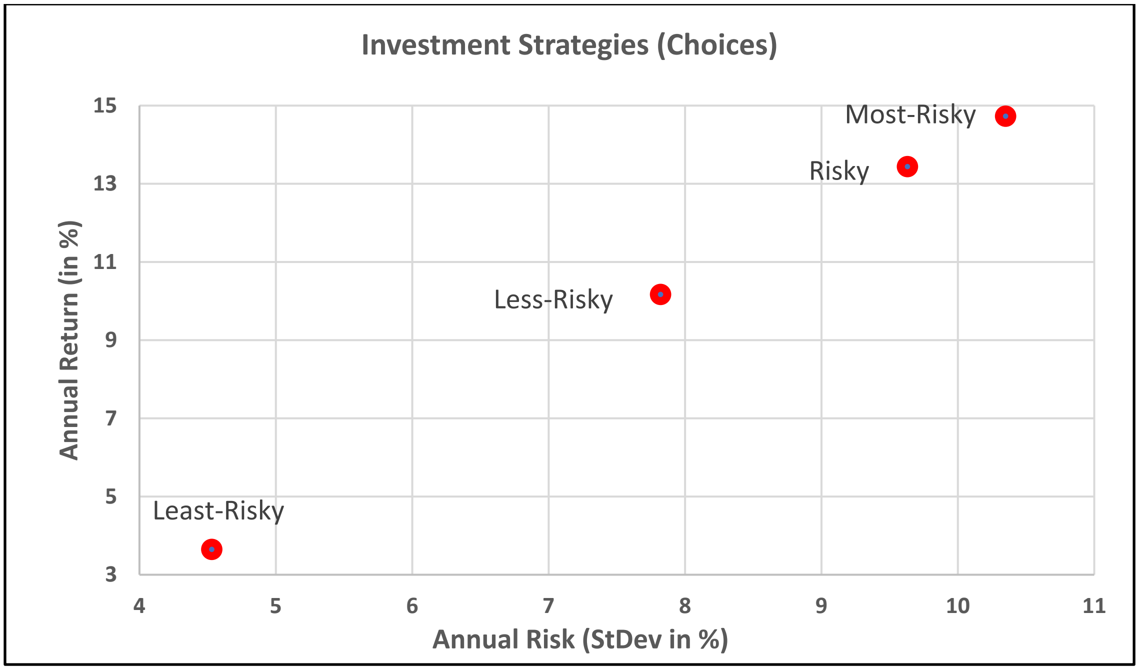


Figure 3: Risk and Return for Four Type of Strategies

Figure 2 shows the probability density functions for each of the four types of strategies used in the model: Most-Risky, Risky, Less-Risky, and Least-Risky. In Figure 3, the risk is measured by annual standard deviation, and the return is measured by mean yearly return for each of the four types of strategies. The risk-return profile is almost linear.

Third, we use historical annual returns to create 240,000 data points by using bootstrap with replacement methodology. The advantages of using the bootstrap to rank fund performance are many. It eliminates the need to specify the exact distribution shape from which returns are drawn, and estimating correlations between portfolio returns is not required (Chen, Chu, & Leung, 2012; Devaney, Morillon, & Weber, 2016). The bootstrap methodology is commonly used for mutual fund performance evaluation in the literature (Cuthbertson, Nitzsche, & O'Sullivan, 2008; Fama & French, 2010; Kosowski, Timmermann, Wermers, & White, 2006). We create a yearly return matrix with 240,000 data points (1,000 funds in each strategy x 4 strategies x up to 60 years) for further analysis.

We investigate the long-term (i.e., 10, 30, 60 years) rankings of 4,000 passive funds that pursue four different return and risk strategies and identify those that rank in the 1st quartile. Thus, the fund manager has discretion over the investment time horizon and the underlying benchmark (or index). Each fund invests all assets in one index (i.e., all are index funds). It is observed that the average star ratings of seasoned funds are consistently higher than the average star ratings of younger funds (Morey, 2002). Thus, the time horizon plays a critical role in the survival of a fund and its ability to attract higher capital.

In the bootstrap method, we first select a year (between 1979 and 2018) and then use corresponding historical returns for the selected year for all four strategies. By doing so, we ensure that the correlations of asset returns are maintained. The descriptive statistics of the simulated dataset are shown in Table 1. The simulated annual return profile in Table 1 is very similar to the actual historical data in Figure 1. Thus, we show that the bootstrap method is robust.

Table 1: Descriptive Statistics for Four Type of Funds

	Most-Risky	Risky	Less-Risky	Least-Risky
N	60,000	60,000	60,000	60,000
Mean	10.27%	9.64%	7.74%	4.50%
Median	12.99%	11.84%	8.20%	4.64%
StdDev	14.46%	13.26%	10.02%	3.59%
Mean/StdDev	0.71	0.73	0.77	1.25
Skewness	0.25	-0.68	0.25	0.62
Kurtosis	1.06	-0.08	-0.29	-0.17
Mean/StDev	0.71	0.73	0.77	1.25

Table 1 exhibits the descriptive statistics for each of the four strategies. Notice a small difference between the actual historical data in Figure 1 and the simulated data in Table 1. (Example: Mean return = 10.35% vs. 10.27%).

Fourth, we rank all 4,000 funds each year based on the simulated annual returns and place them in four quartiles. The 1st quartile contains the best-performing 1,000 funds in that year, and the 4th quartile has the worst-performing 1,000 funds.

Fifth, we model the observation of Ellis (2017) that net new investment money goes into recent winning funds. We assume that fund inflows linearly respond to fund performance in the most recent two-year period, as shown in Table 2. For example, if a fund is in the 1st quartile two years before (t - 2) (i.e., $Qi(t\text{-}2) = 1$), where i, fund number, is between 1 and 4,000, and in the 2nd quartile last year (t - 1) (i.e., $Qi(t\text{-}1) = 2$), then that fund is in 12 bin and gains 20% net inflow. We denote this 20% as $Di,t(Qi(t\text{-}2), Qi(t\text{-}1))$ and refer to it as fund i's drawdown, or net inflow, after being in the quartiles, $Qi(t\text{-}2)$ and $Qi(t\text{-}1)$, during the past two years. A positive $Di,t(Qi(t\text{-}2), Qi(t\text{-}1))$ indicates fund inflows, and a negative value indicates fund outflows. Similarly, a fund in the 4th quartile for two years in a row (44 bin) loses 30% of assets due to outflows. This linearity restriction can be easily relaxed by changing values in Table 2. We have not found a fund-flow model in the literature that provides a specific framework that we can use in Table 2. Therefore, we develop a framework to accommodate a convex relationship between fund flows and past fund performance (Chevalier & Ellison, 1997; Huang, Wei, & Yan, 2007; Ippolito, 1992; Lynch & Musto, 2003; Sirri & Tufano, 1998). Our methodology can be easily adapted and modified by future researchers to use a different fund-flow model.

Table 2: Fund-flow Model

Last two rankings	Drawdown	Last two rankings	Drawdown
$Qi(t\text{-}2)$, $Qi(t\text{-}1)$	$Di,t(Qi(t\text{-}2), Qi(t\text{-}1))$	$Qi(t\text{-}2)$, $Qi(t\text{-}1)$	$Di,t(Qi(t\text{-}2), Qi(t\text{-}1))$
11	30%	31	10% (same as 13)
12	20%	32	0% (same as 23)
13	10%	33	-10% (same as 24)
14	0%	34	-20%
21	20% (same as 12)	41	0% (same as 14)
22	10% (same as 13)	42	-10% (same as 24)
23	0%	43	-20% (same as 34)
24	-10%	44	-30%

Table 2 lists the drawdowns used in the model for each of the rankings. We assume that fund inflows linearly respond to fund performance in the most recent two-year period. For example, if a fund is in the 1st quartile two years before (t - 2) (i.e., $Qi(t\text{-}2) = 1$), where i, fund number, is between 1 and 4,000, and in the 2nd quartile last year (t - 1) (i.e., $Qi(t\text{-}1) = 2$), then that fund is in 12 bin and gains 20% net inflow. We denote this 20% as $Di,t(Qi(t\text{-}2), Qi(t\text{-}1))$ and refer to it as fund i's drawdown, or net inflow, after being in the quartiles, $Qi(t\text{-}2)$ and $Qi(t\text{-}1)$, during the past two years. A positive $Di,t(Qi(t\text{-}2), Qi(t\text{-}1))$ indicates fund inflows, and a negative value indicates fund outflows. Similarly, a fund in the 4th quartile for two years in a row (44 bin) loses 30% of assets due to outflows.

The AUM of a fund at t + 1 is denoted as AUM_{t+1} and explained in Equation 2. AUM_{t+1} depends on the AUM at t, return R_{t+1}, and the drawdown at t + 1. Also, we impose a condition that the sum of all drawdowns is 0, as shown in Equation 3. During the first two years (i.e., t = 1 and t = 2), since investors do not have the past two years' returns, we assume that $D_{i,t}(Qi(t\text{-}2), Qi(t\text{-}1)) = 0$ for all i.

$$AUM_{t+1} = AUM_t \times (1 + R_{t+1}) \times \left(1 + D_{i,t}(Q_i(t-2), Q_i(t-1))\right) \quad (2)$$

$$\sum_{i=1}^{4}\sum_{j=1}^{4} D_t(Q_i(t-2), Q_j(t-1)) = 0 \quad (3)$$

Sixth, we compute every fund's AUM growth as shown in Equation 4, rank all 4,000 funds by Gt+1 each year, and place them in the appropriate quartile (i.e., 1, 2, 3, or 4) for every year.

$$G_{t+1} = \left(\frac{AUM_{t+1}}{AUM_t} - 1\right) = R_{t+1} + D_{i,t}(Q_i(t-2), Q_i(t-1)) + \left(R_{t+1} \times D_{i,t}(Q_i(t-2), Q_i(t-1))\right) \quad (4)$$

Finally, we compute the geometric annual growth of AUM, denoted as GR_m, using Equation 5 for each of the 4,000 funds, where m = 1 to 4000, and N is the number of years in the window of analysis. We studied the fund returns for N = 10, 30, and 60 years.

$$GR_m = \left(\frac{AUM_{t=N}}{AUM_{t=0}} - 1\right)^{\frac{1}{N}} - 1 \quad (5)$$

The cumulative ranking is computed based on GR_m at the end of N years. The top 1,000 funds based on this cumulative ranking are classified as 1st quartile funds (or winners). Likewise, the bottom 1,000 funds based on this cumulative ranking are 4th quartile funds. Finally, we observe the strategy of all 4,000 funds based on the cumulative rankings.

Results

This section summarizes the results for a 10-, 30-, and 60-year analysis window. Because of the constraint of space, we do not include all of the 10- and 30-year analysis results. Results are based on 240,000 annual returns between 1979 and 2018, as described in Section 3. Average cumulative quartiles for all 4,000 funds in the presence of drawdown (i.e., $Di,t(Qi(t\text{-}2), Qi(t\text{-}1)) \neq 0\%$ for all i) are shown in Figure 4. Ranking in the 1st quartile indicates that the fund's cumulative ranking is in the top 1,000 (winners). Likewise, ranking in the 4th quartile indicates that the fund's cumulative ranking is in the bottom 1,000. In the absence of drawdown, the investor is not sensitive to past two-year fund performance (i.e., $Di,t(Qi(t\text{-}2), Qi(t\text{-}1)) = 0\%$ for all i). The average cumulative quartiles for all 4,000 funds in the absence of drawdown are shown in Figure 5.

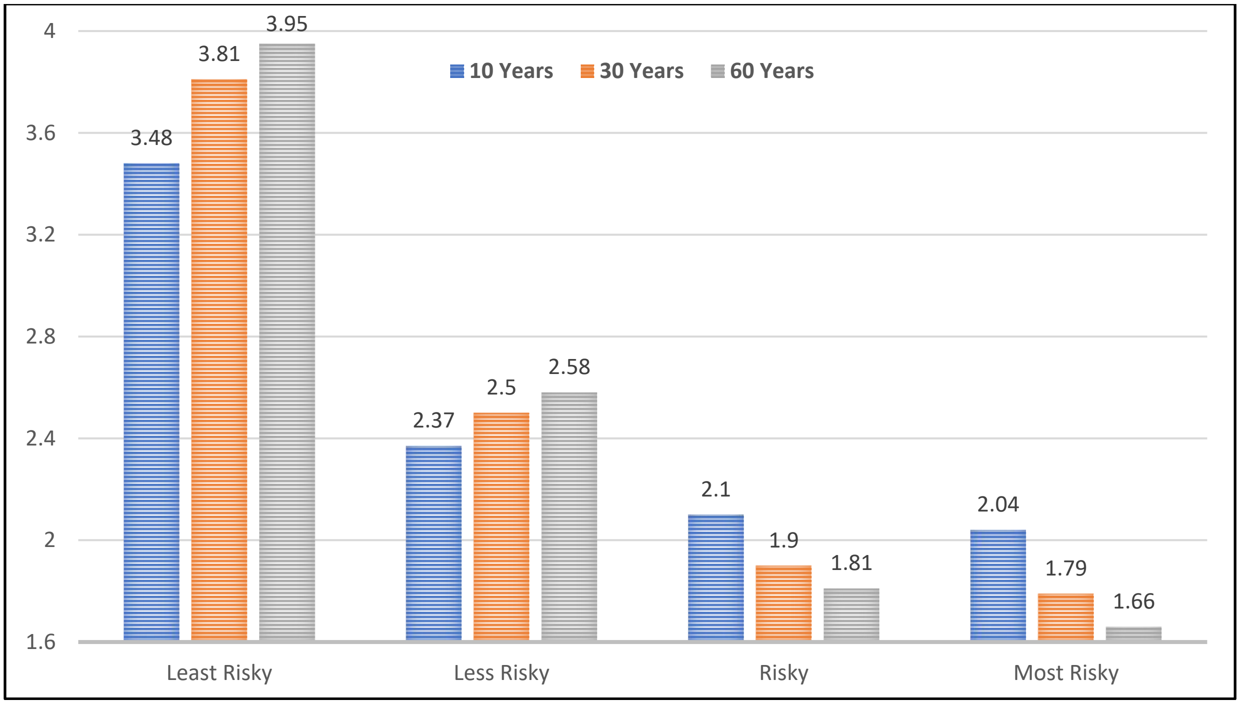


Figure 4: Cumulative Mean Quartile (with Drawdowns) after 10, 30, and 60 Years

Figure 4 displays the summary of average cumulative quartiles for all 4,000 funds in the presence of drawdown for 10-, 30-, and 60-year analysis windows. As time goes by, results are more pronounced.

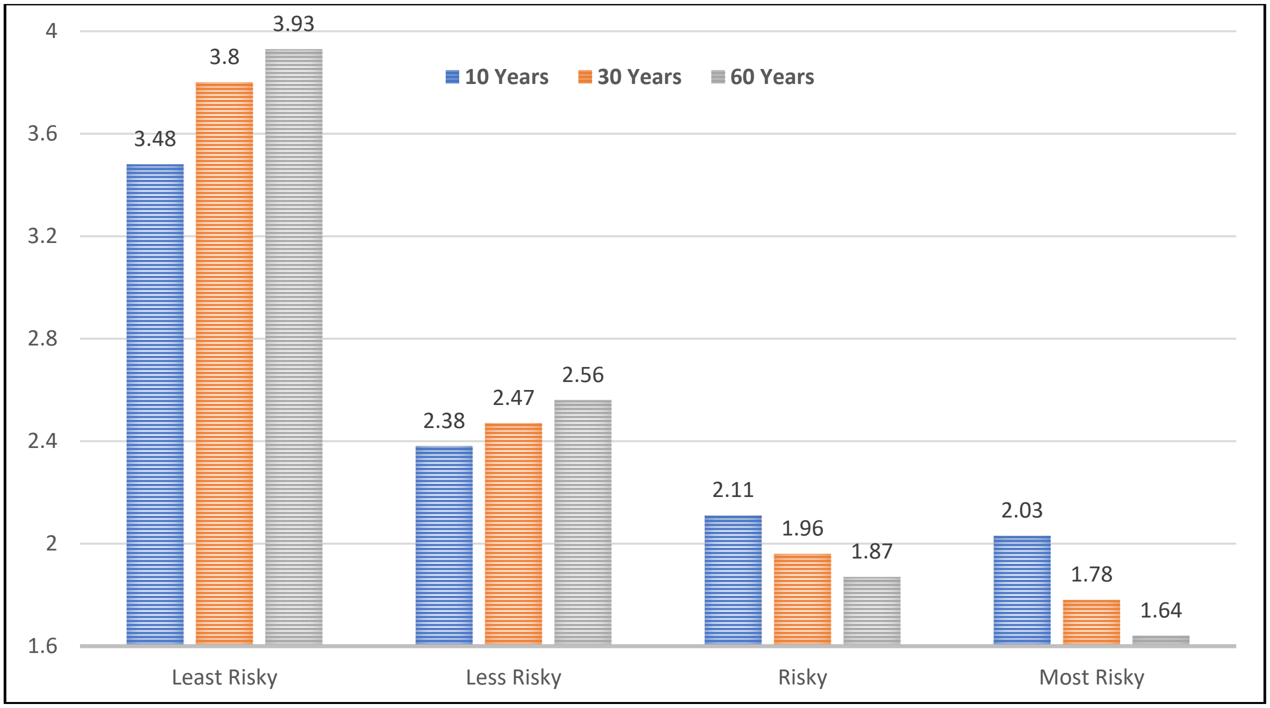


Figure 5: Cumulative Mean Quartile (without Drawdowns) after 10, 30, and 60 Years

Figure 5 shows the summary of average cumulative quartiles for all 4,000 funds in the absence of drawdown for 10-, 30-, and 60-year analysis windows. As time elapses, results are more pronounced.

We observe that as time progresses from 10-years to 60-years, the results are more pronounced. For example, the least-risky fund's average quartile increases from 3.48 to 3.95 as time proceeds, indicating that this strategy is more likely to result in the bottom quartile (4th) position in the long run. Similarly, the most-risky fund's average quartile decreases from 2.04 to 1.66 as time proceeds, indicating that this strategy is more likely to result in the 2nd or 1st quartile position in the long run. Nevertheless, previous studies find that a fund's informational advantage may be short-lived (Berk & Green, 2004). Bollen & Busse (2005) find that superior performance is a short-lived phenomenon observable only when funds are evaluated several times a year based on their mutual fund returns analysis between 1985 and 1995. Our results support this finding and show that these short-lived advantages disappear in the long run. What matters, in the long run, is the fund strategy. For example, one can compare the short-term versus long-term performance by taking a ratio of quartiles, which we call the quartile ratio. The higher this ratio, the more the contrast between fund strategies.

The 10-year quartile ratio of least-risky and most-risky fund types is 1.7 (i.e., 3.48/2.04) for 10 years and 2.4 for 60 years, as shown in Figure 4. Thus, it takes time for the fund strategy to result in performance. However, practitioners are increasingly concerned that investors, especially retail investors, are churning funds too frequently searching for returns. Using U.S. equity fund redemption data from the Investment Company Institute for the 15 years from 1999 through 2013, the average mutual fund holding period is estimated to be over three years (Vanguard, 2014). The fund quartile rankings do not change significantly in the absence of drawdowns, as shown in Figure 5. Therefore, going forward, we show only results in the presence of drawdown. Results without drawdown (which are less realistic) are not included.

Another interesting observation is that the percentage change in quartile rankings is asymmetric for different funds, as shown in Figure 6. As time progresses from 10-years to 60-years, the least-risky fund's quartile ranking changes by 13.5% (i.e. (3.95-3.48)/3.48). Whereas the most-risky fund's quartile ranking changes by 18.6%. The same metric for risky funds is 13.8% and 8.9% for less-risky funds. It means that the most-risky funds are susceptible to dramatic swings in their quartile positions from year to year. An individual fund in the most-risky type can have large fluctuations in quartile rankings because of the high standard deviation of returns.

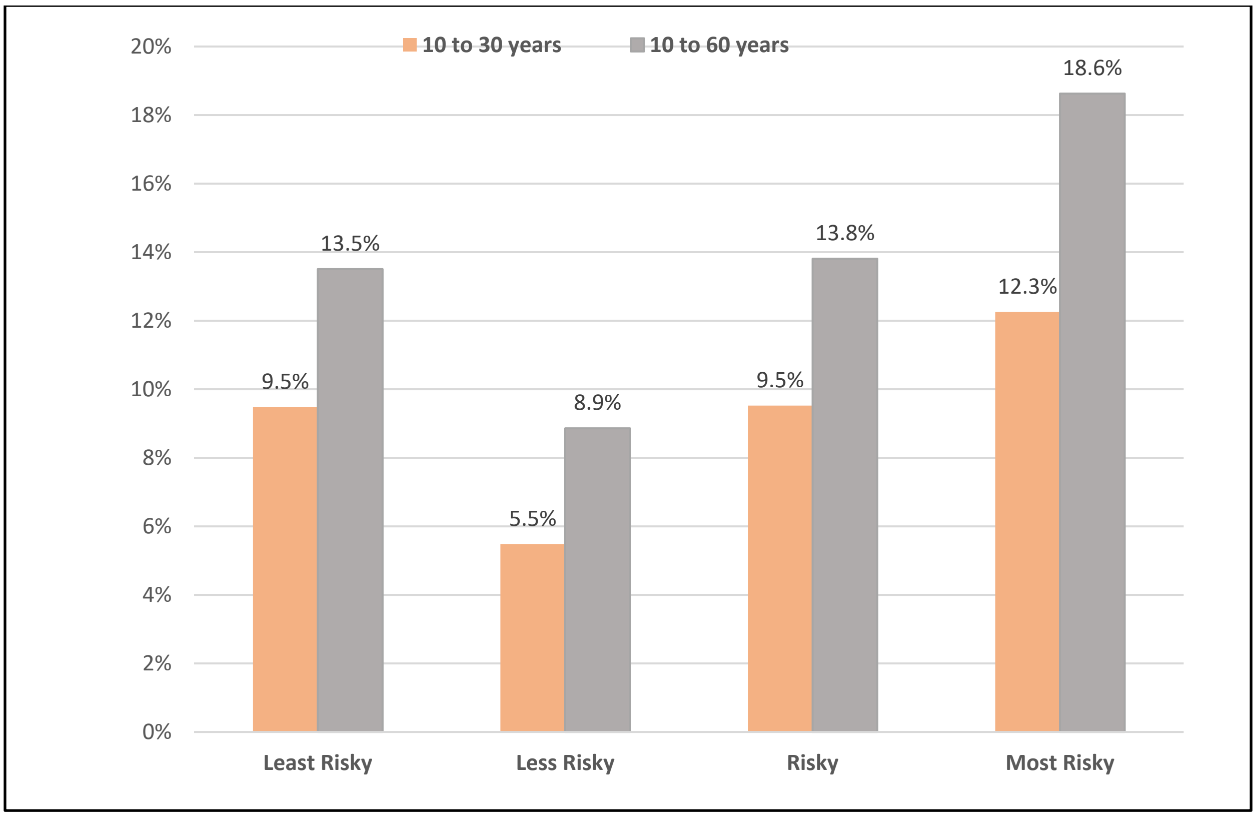
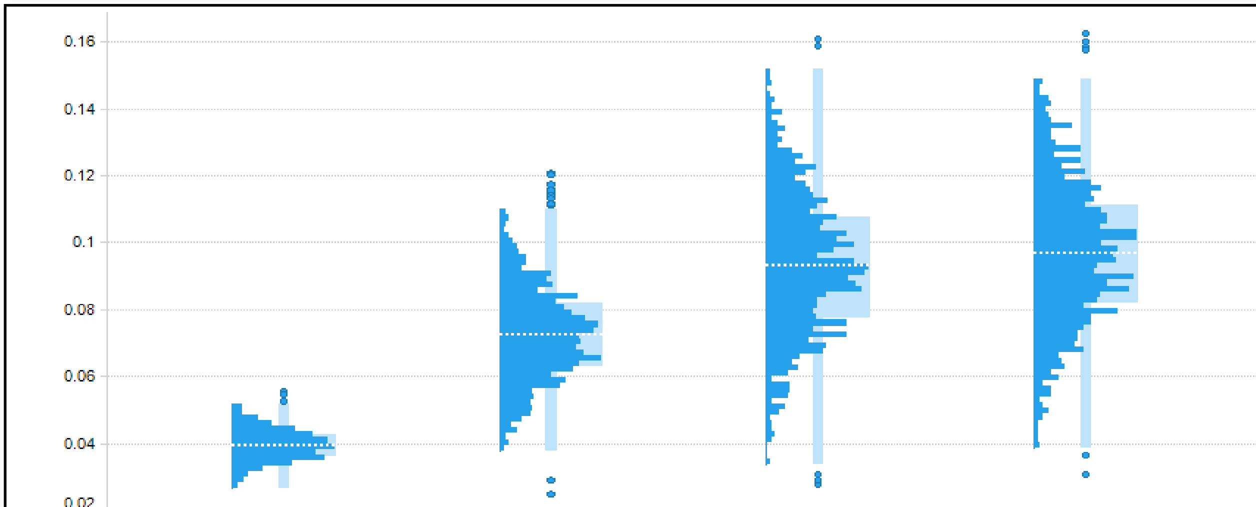


Figure 6: percentage change in quartile rankings (with Drawdown, from 10 to 30 and 10 to 60 years)

Figure 6 shows the summary of the percentage change in quartile rankings. Most-risky funds have the highest sensitivity to quartile changes.

Results of the annualized geometric return computed using Equation 5 are summarized in Figure 7. As expected, the most-risky fund has the highest annual geometric return at 9.68%, followed by the risky fund at 9.32%, the less-risky fund at 7.27%, and the least-risky fund, which has the lowest annual geometric return at 3.96%. However, the return to risk ratio (i.e., mean/standard deviation) shows an exactly opposite picture (i.e., 8.43 for least-risky, 5.01 for less-risky, 4.40 for risky, and 4.48 for most-risky). One can visually and numerically observe that the return distribution of the most-risky fund and the risky fund are identical after 60 years. So, it is evident that there is no significant benefit in pursuing a most-risky strategy — one that can cause severe losses and huge quartile swings. At the same time, one can achieve similar results by adopting a risky strategy.



	Least Risky	Less Risky	Risky	Most Risky
Count	1000	1000	1000	1000
Avg	3.96%	7.27%	9.32%	9.68%
Median	3.95%	7.24%	9.24%	9.70%
StdDev	0.47%	1.45%	2.12%	2.16%
Min	2.66%	2.51%	2.81%	3.07%
Max	5.56%	12.10%	16.10%	16.25%

Figure 7: Annualized Geometric Return by Fund Type with Drawdown (after 60 Years)

Figure 7 exhibits the annualized geometric return by fund type, with drawdown, after 60 years. The average annual return for least-risky, less-risky, risky, and most-risky funds is 3.96%, 7.27%, 9.32%, and 9.68%, respectively. However, the return to risk ratio (i.e., mean/standard deviation) shows an exactly opposite picture (i.e., 8.43 for least-risky, 5.01 for less-risky, 4.40 for risky, and 4.48 for most-risky).

So far, we have discussed aggregate results according to fund types. Now, we switch focus to cross-sectional results. As shown in Figure 8, a fund that follows a risky strategy has a higher probability (40.7% without drawdown and 39.7% with drawdown) of staying in the 1st quartile after 60 years than a fund that that follows a most-risky strategy (35.9% without drawdown and 38.6% with drawdown). This counter-intuitive result supports Howard Marks' (1990) assertion that a strategy aiming for a run of top-decile years to achieve superior long-term performance is unlikely to succeed. Instead, a fund needs only to be slightly above average to be considered a top performer in the long run.

Interestingly, as shown in Figure 9, a fund that follows a risky strategy has almost the same probability of staying in the 4th quartile as a fund that follows a most-risky strategy (23.2% with or without drawdown). Put simply, a fund that aims to be in the 1st quartile every year, by following a most-risky strategy, has a lesser probability of staying in the 1st quartile and the same probability of staying in the 4th quartile after 60 years, as a fund that follows a risky strategy. In the investment world, we rarely see such strategies that have an upside without a downside. Therefore, the risky strategy has a higher benefit (i.e., staying in the 1st quartile) and the same cost (staying in the 4th quartile) than the riskiest strategy. As Figures 8 and 9 show, the quartile rankings are very identical with or without drawdown. We have experimented with different linear combinations of drawdowns in Table 2, and the results shown in Figures 8 and 9 are consistent.

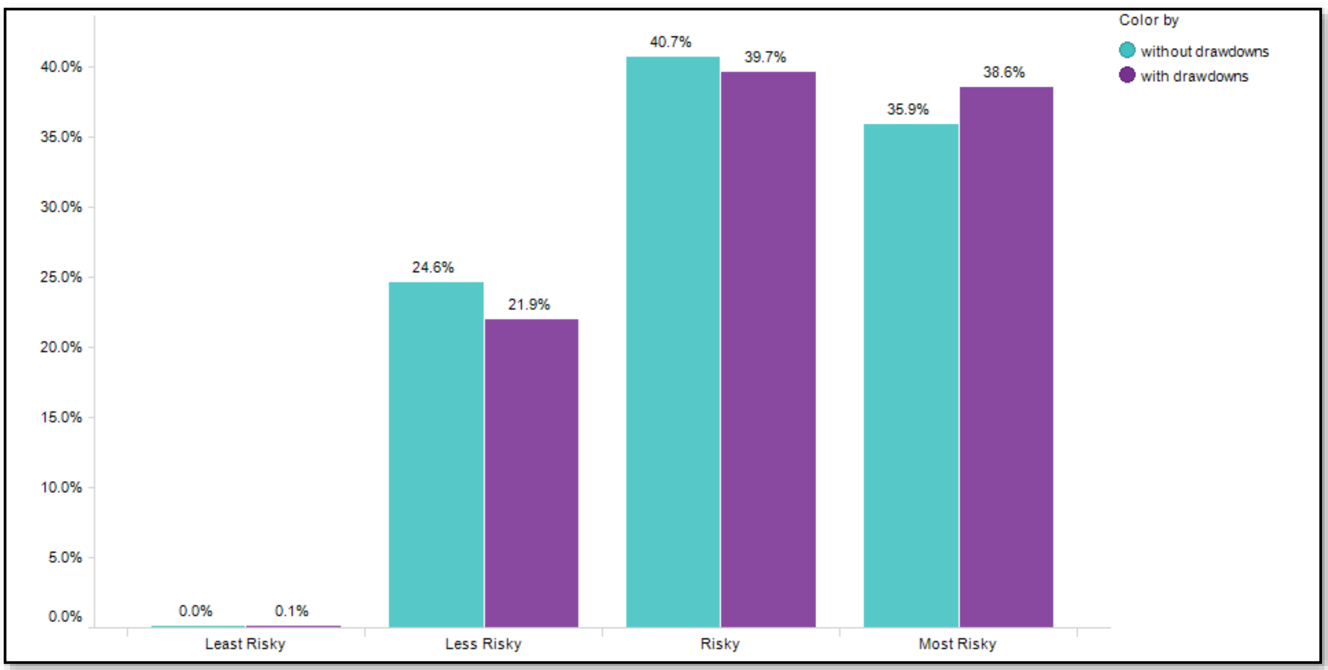


Figure 8: Percentage of Funds Staying in 1st Quartile (after 60 Years)

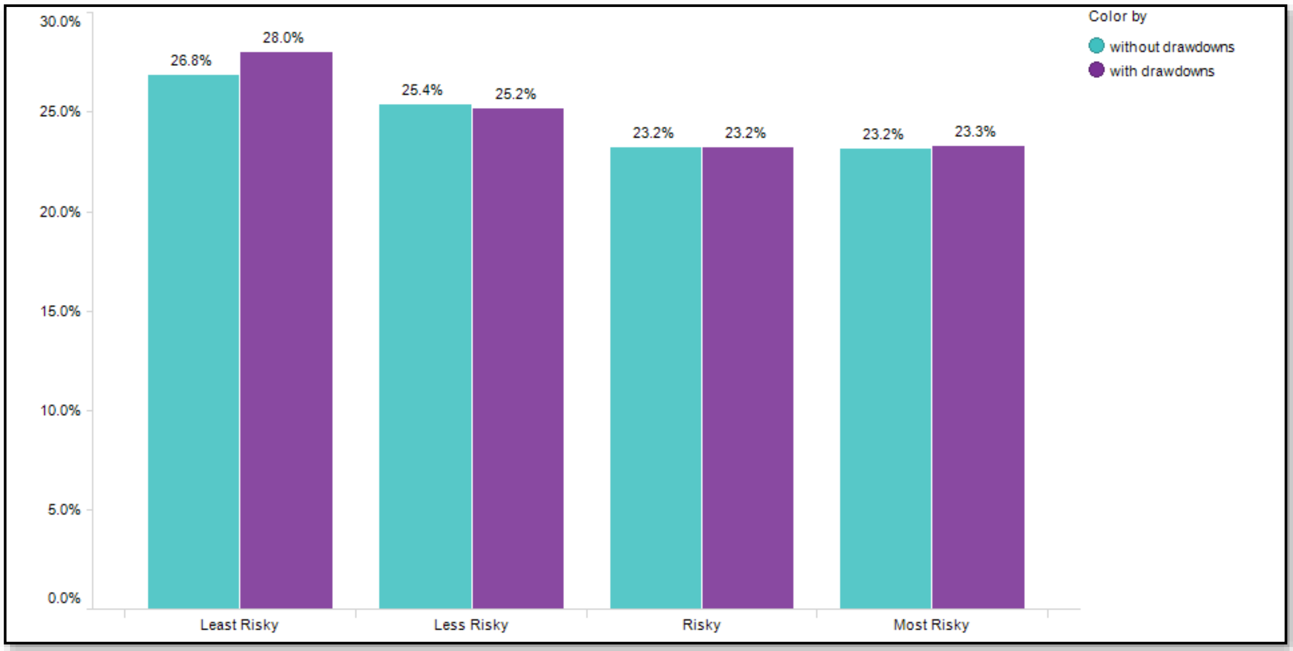


Figure 9: Percentage of Funds Staying in 4th Quartile (after 60 Years)

Figure 8 exhibits the percentage of funds that stay in the 1st quartile after 60 years by fund type, and Figure 9 displays the percentage of funds that stay in the 4th quartile after 60 years by fund type.

Several studies suggest that nonsurvivors in the U.S. mutual fund industry disappeared primarily because of multi-year underperformance (Carhart, Carpenter, Lynch, & Musto, 2002; Cogneau & Hübner, 2015). They also point out that aggressive growth funds perish at an annual rate, statistically more significant than the growth and income funds. Therefore, when funds aim for the 1st quartile, they risk falls into the 4th quartile instead. As shown in Figure 10, for all fund types, as funds increase risk profile and aim for the 1st quartile, the slope which measures the probability of falling in the 4th quartile is negative. Out of the four strategies, funds that pursue the risky strategy dominate the lower right corner of the figure, indicating that they have the highest probability of staying in the 1st quartile and the lowest probability of falling into the 4th quartile. On the other hand, the least-risky type funds have almost no chance (zero probability) of staying in the 1st quartile. This result is intuitive since it reinforces the age-old saying 'no pain, no gain". However, what is not intuitive is that the risky fund type has a steeper slope (of -0.43) than the riskiest fund type (-0.36). Thus, it reinforces our finding that a risky strategy has a higher chance of staying in the 1st quartile and a lower chance of falling into the 4th quartile.

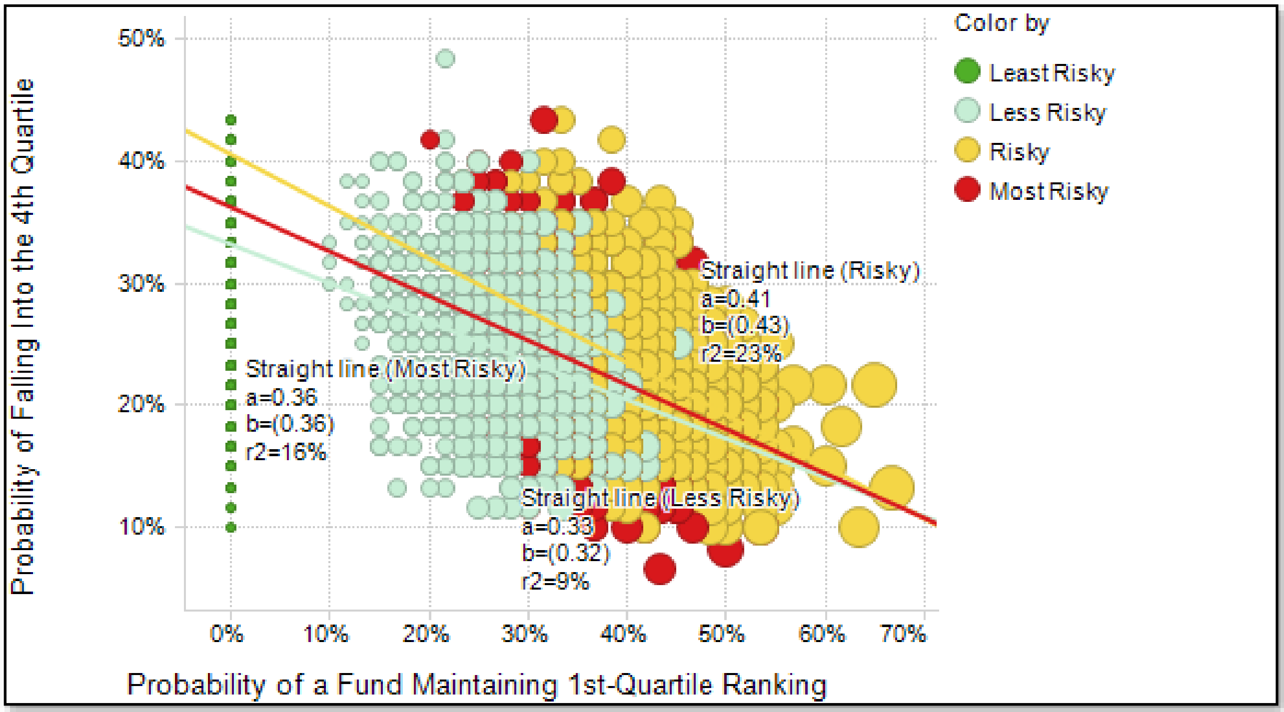


Figure 10: Probability of a Fund Maintaining 1st Quartile Ranking, by Fund Type (after 60 Years, with Drawdown)

Figure 10 contrasts the probability of a fund remaining in the 1st quartile ranking against falling into the 4th quartile after 60 years, segmented by fund type. Risky funds have a higher probability of being in the 1st quartile compared to the Most-Risky funds.

At the end of 60 years, the risky funds are more likely to be in the 1st quartile than the riskiest funds. As illustrated in Figure 11, more than 300 risky-strategy funds (or 30% of the total 1,000 funds) have a higher probability of staying in the 1st quartile than the riskiest strategy funds. To summarize, a fund that aims for the 2nd quartile every year has a 30% higher probability of eventually ranking in the 1st quartile than a fund that seeks to be in the 1st quartile every year by pursuing the riskiest strategy. Accordingly, we reject the hypothesis that if a fund aims to win the quartile race, it should strive for the 1st quartile every year.

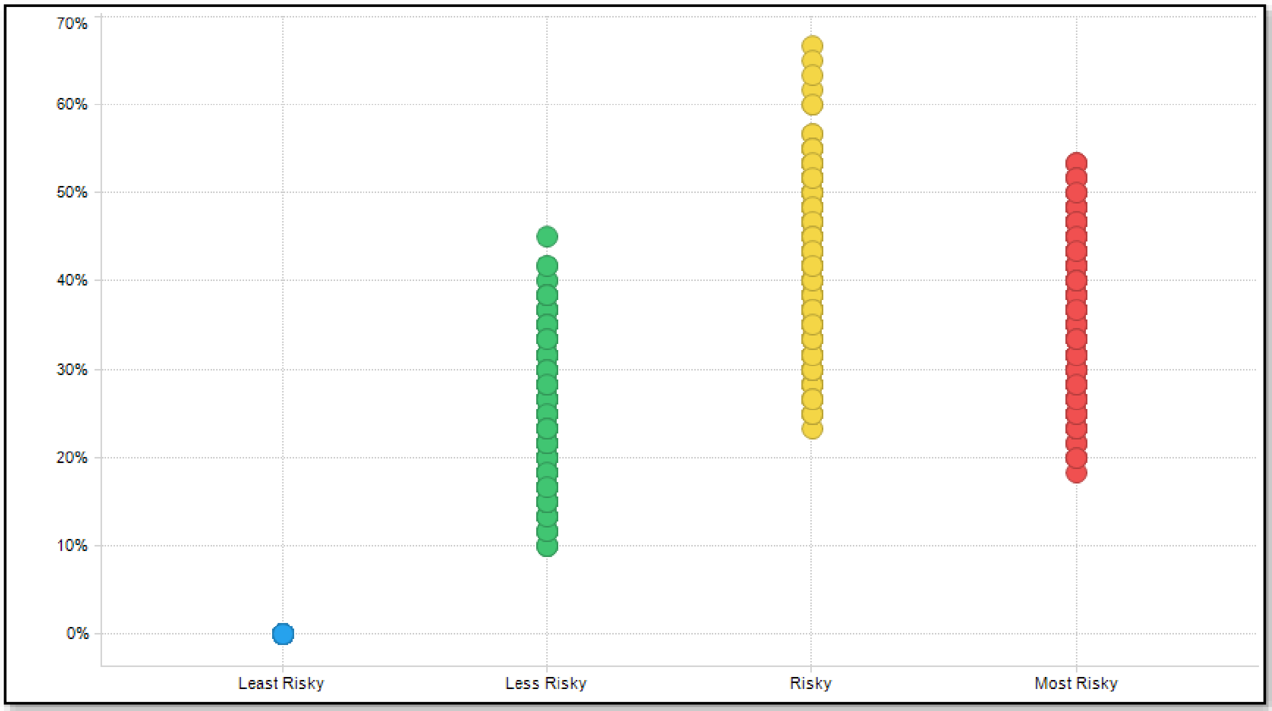


Figure 11: Individual Fund Probability of Maintaining 1st Quartile Ranking, by Fund Type (after 60 Years, with Drawdown)

Figure 11 exhibits the individual fund probabilities of remaining in the 1st quartile after 60 years, segmented by fund type. Risky funds have a 30% higher probability of being in the 1st quartile than the most-risky funds.

Finally, Figure 12 shows that aiming for the 1st quartile has one principal advantage—a higher AUM in aggregate. At the end of 60 years, a fund that aims for the 1st quartile will be able to turn a $1 investment into a median value of $258. However, a fund that strives for the 2nd quartile will reach a median value of $201. If we use mean values, the difference is even more substantial due to the outsized returns of a few 1st quartile outliers. Thus, the 1st hypothesis (i.e., if a fund aims to achieve higher AUM, it should strive to be in the 1st quartile every year) is not rejected. However, we reject the 2nd hypothesis and conclude that if a fund aims to win the quartile race, aiming for the 2nd quartile every year is a safer bet.

Figure 12 shows the annual geometric return & end-of-horizon assets under management (AUM) after 60 years, including drawdowns segmented by fund type.

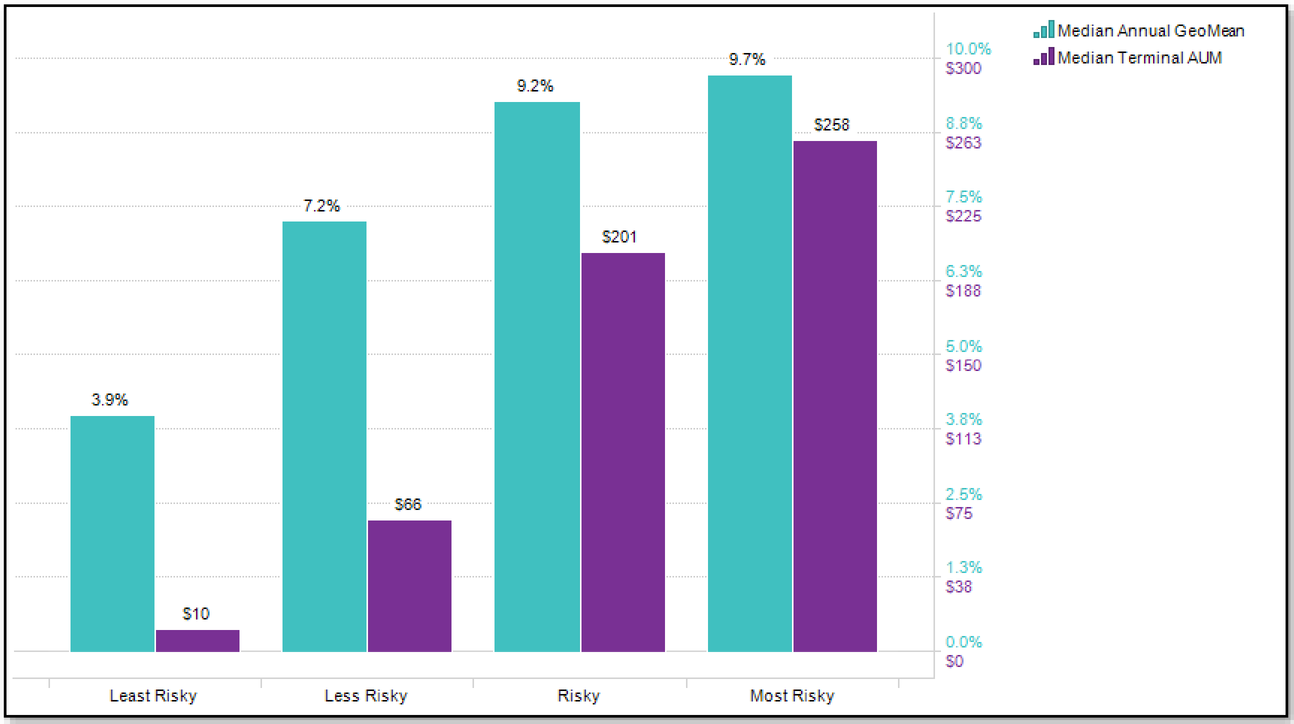


Figure 12: Annual Geometric Return & End-of-Horizon AUM by Fund Type (with Drawdown, after 60 Years)

Conclusion

A general perception is that to beat a benchmark, such as the S&P 500, a fund must be in the 1st quartile for several years in the long run. In this paper, we explore if passive funds aiming to be in the 1st quartile by chasing higher returns (i.e., higher risk) are more likely to achieve their goal than those that pursue somewhat lesser returns (i.e., lower risk). We also clarify the confusion that is often observed between a fund's two routes to stellar performance—grow AUM or stay in the 1st quartile over a long-time horizon. We show that each goal requires a different strategy.

Assuming that a fund follows one of the four strategies (most-risky, risky, less-risky, and least-risky) to remain in the 1st quartile, we identify an appropriate asset class that mimics the fund's strategy and use monthly historical returns from January 1, 1979, to January 1, 2018, for four strategies: Russell 2000 Price Index (most-risky), Russell 1000 Price Index (risky), 10-year constant maturity Treasury bond (less-risky), and 3-month Treasury bill (least-risky). The model we develop is flexible and can accommodate different asset classes if they represent four distinct risk-return profiles. Using bootstrap simulation with replacement methodology, we create a matrix of 240,000 annual returns (1,000 funds × 4 strategies × up to 60 years).

We show that if a fund aims to achieve higher AUM, it should aim at the 1st quartile every year. However, if a fund aims to win the quartile race, aiming for the 2nd quartile is a safer bet every year. This finding supports Howard Marks' (1990) claims that a fund needs only to be slightly above average to be considered a top performer in the long run. Previous studies have provided evidence that mutual fund team characteristics have a role in the extremity and riskiness of fund returns (Karagiannidis, 2012). This paper shows the importance of fund strategies.

In this study, the entire dataset is used for validating two hypotheses. Therefore, it would be helpful to split the full dataset into training and test datasets and conduct an out-of-sample analysis. Future research can extend the findings by creating equal-weighted portfolios that invest in all four strategies equally to determine if such an equal-weighted portfolio with an annual rebalancing method (DeMiguel, Garlappi, & Uppal, 2009; Malladi & Fabozzi, 2017; Plyakha, Uppal, & Vilkov, 2012) may result in better quartile rankings. Future studies might also examine a volatility-managed equity portfolio that may lead to higher returns and superior performance (Harvey & Liu, 2018). Finally, the bootstrap method samples data for one year at a time and ignores any lagged-year effects. Further research into the lagged-year effects is needed to compare them with the findings of this study.

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