Diversification and Mutual Fund Performance

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April 21, 2017

ABSTRACT

A common belief about fund managers with superior performance is that they are more likely to succeed in stock selection with an informational advantage, far from diversifying their portfolio. Although some empirical studies support this view, it contradicts modern portfolio theory, in which well-diversified portfolios have higher returns. To address this inconsistency, this paper re-examines the effects of diversification by applying a comprehensive diversification measure, the diversification ratio (DR), to the actual mutual fund portfolio. Our results show that high-DR funds have more efficiently diversified portfolios than low-DR funds do and significantly higher risk-adjusted returns over a long period, consistent with theoretical predictions. Most importantly, we find a surprising positive relation between the DR and managerial skill measures such as Active Share, R-squared, and Industry concentration index. Considering both the portfolio weights and its correlation structure, we find that fund managers with superior skill have more concentrated portfolios, while their concentrated bets are less correlated with existing portfolios. Therefore, we suggest that deviating from the benchmark market index with concentrated investments is ultimately in line with the efficient construction of a diversified portfolio in terms of achieving superior performance. Consequently, our paper contributes to reconciling the conflicting empirical literature on the benefits of portfolio concentration with the diversification effect of modern portfolio theory.

Keywords: Diversification, concentration, correlation, modern portfolio theory, mutual fund performance

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1. Introduction

In modern portfolio theory, the equity risk premium is defined as the return of an undiversified portfolio. Markowitz (1952) has emphasized the benefits of diversification and investors should invest in well-diversified portfolios to maximize their expected returns. However, regarding mutual fund performance, academics and practitioners recommend against diversification, focusing more on portfolio concentration and suggesting that the skill of an active fund manager is in making concentrated bets and deviating from the market portfolio. Our paper focuses on the benefits of diversification on mutual fund performance by introducing a comprehensive measure of diversification. We propose a novel way to explain how the skills of fund managers are related to diversification under the classical framework.

Markowitz's (1952) main argument is that diversification is the only free lunch in finance and implicitly states that one can reduce portfolio risk without necessarily reducing its expected return. Much effort has been devoted to developing modern portfolio theory within Markowitz's mean–variance framework. The most remarkable model is the capital asset pricing model developed by Sharpe (1964). Many studies have fiercely debated whether the assumption of capital asset pricing model reflect actual market conditions and whether its conclusions can be applied to actual portfolio management. In particular, the efficiency of the capitalization-weighted market index has been questioned. Haugen and Baker (1991) provide theoretical arguments and empirical evidence that matching the market to cap-weighted stock indexes is an inefficient strategy, even in an informationally efficient market. In the mutual fund industry, as reported by Sensoy (2009), almost all active mutual funds are benchmarked to such inefficient cap-weighted market indexes. Moreover, Cremers and Petajisto (2009) point out that a significant portion of actively managed mutual funds are closet indexers. Since the cap-weighted benchmark index is not sufficiently diversified, it is still possible for fund managers to have more diversified portfolios than their benchmark. Within a mean–variance framework, this implies that a skillful fund manager could certainly achieve a higher Sharpe ratio by efficiently enhancing diversification over a cap-weighted benchmark index.

Despite the obvious benefits of diversification, the literature on mutual fund manager skills has focused primarily on portfolio concentration, referring to the extent to which fund portfolios deviate from the market portfolio. First, Kacperczyk, Sialm, and Zheng (2005) have proposed their Industry Concentration Index (ICI) and suggest that funds that focus on a few industries have better future performance. Subsequently, Baks, Busse, and Green (2006), Brands, Brown, and Gallagher (2006), and Hiraki, Liu, and Wang (2015) have adopted similar types of divergence indexes at either the stock or country level to demonstrate the outperformance of concentrated funds. Sapp and Yan (2008) present the number of stocks in a portfolio as a simple measure of concentration. More recent studies have proposed other measures of the degree of deviation from the benchmark. Cremers and Petajisto (2009) and Petajisto (2013) have proposed the Active Share measure, the share of portfolio holdings that deviate from the benchmark index holding, and determine that funds with a high Active Share outperform other funds. Amihud and Goyenko (2013) have proposed R-squared, the proportion of the fund return that is explained by the multifactor benchmark model, and show that a lower R-squared value indicates greater selectivity and predicts better performance. These studies summarize that, contradicting the benefits of diversification, fund managers who deviate from the market by making concentrated bets perform better than managers who hold less concentrated portfolios. Although there are methodological differences, most studies measure portfolio concentration using the weights of the assets in the portfolio. We believe the discrepancy is due to the concentration measures used in those studies not being an exact inverse of the measure of the diversification effect.

In modern portfolio theory, a portfolio's risk–return profile depends on the following three components: first, the standard deviation or variance of each asset return; second, the allocation or weight of each asset in terms of its proportional value to the portfolio; and, last and most importantly, the correlation of each asset's return with the return of every other asset in the portfolio. Note that existing concentration measures are constructed based only on the second component, the weight of assets in the portfolio. Since these measures do not take into account correlation among the assets, which is the key source of the diversification effect, their results in terms of portfolio concentration should not be interpreted as being in the opposite direction of the diversification effect. Therefore, we should not conclude that well-diversified funds underperform poorly diversified funds based on the evidence in these studies. In fact, portfolios with the same weighting structure can exhibit significantly different levels of diversification for different portfolio correlation structures. That is, the degree of diversification can differ depending on how concentrated bets are correlated with the existing portfolio. The study of concentration and the diversification effect in mutual fund performance should therefore take into account the impact of correlation structures on portfolio risk.

In this paper, we introduce a comprehensive diversification measure, the diversification ratio (DR), to examine the effect of diversification in the mutual fund industry. The DR was originally proposed by Choueifaty and Coignard (2008) and is defined as the ratio of a weighted average of individual risks to the overall portfolio risk. Given volatility as a risk measure, the volatility of a diversified portfolio should be less than the sum of individual volatilities, with a larger DR indicating a higher degree of diversification. Since the DR directly measures diversification, it accounts for both the allocation of assets in a portfolio and the correlation of an asset with the other assets in the portfolio, which gives rise to the diversification effect. Therefore, we propose the DR appropriately measures the comprehensive effect of the diversification of mutual funds.

Our main objective is to investigate the benefits of diversification in the performance of actively managed equity mutual funds. Consistent with modern portfolio theory, we determine that high-DR funds have more efficiently diversified portfolios and exhibit significantly higher returns than low-DR funds do. Specifically, sorting funds into DR deciles, we find that the differences in annualized return and alpha between the highest- and lowest-DR funds have statistically and economically significant values of 8.16% and 3.48% per year, respectively. We check for persistence in the performance difference attributed to the DR value and find the alpha value of a high-DR fund remains higher than for a low-DR fund for over a year. In addition, our cross-sectional regression analysis show that the DR positively predicts the future performance of a fund after controlling for fund characteristics and various managerial skill measures. The DR measure has the highest predictability for future fund returns among existing fund skill measures. The results remain qualitatively unchanged, regardless of whether we use volatility, value at risk (VaR), or the expected shortfall (ES) as a risk measure to construct the DR. Thus, our empirical results demonstrate that funds with highly diversified portfolios perform better than funds with less diversified portfolios, which indicates the benefits of diversification in the active mutual fund industry.

We determine that high-DR funds have various characteristics related to diversification and asset allocation. First, high-DR funds have greater exposure to stocks with higher expected returns and greater volatility and skewness but exhibit higher portfolio returns with lower portfolio volatility, that is, a higher portfolio Sharpe ratio. This finding is consistent with the effect of diversification encapsulated in the DR measure. Second, high-DR funds also have large number of stocks, lower portions of common stocks, and higher portions of cash and bonds in their portfolios. This evidence is consistent with their diversification efforts from an overall portfolio perspective. Third, high-DR funds have positive capital inflow and good past performance, encouraging diversification rather than increases in idiosyncratic bets. Lastly, high-DR funds tend to be small and young and have high turnover, expenses, and fees, corresponding to the characteristics of funds with good performance. Therefore, because our DR measure properly captures the portfolio diversification effect, high-DR funds exhibit characteristics that are consistent with an effectively diversified portfolio.

The most distinctive feature of the DR is its relation with skill measures. First, we conduct a cross-sectional regression to identify the determinants of the DR and find that Active Share, R-squared, the ICI, and risk shifting are significant determinants of the DR. It is important to note that the DR is positively explained by managerial activity and selectivity. In addition, when we examine the characteristics of high-DR funds through a portfolio sorting procedure, high-DR fund portfolios show high Active Share and low R-squared values, as well as a high ICI. That is, higher-DR funds have higher concentration-related skill measures. This evidence, that fund managers who deviate from the market by making concentrated bets actually have a higher degree of diversification, is surprising. By decomposing the DR into the concentration ratio (CR) of the weights and the correlation (CORR) among the assets , we identify that the high DR of funds with concentration-related skill is the result of a lower CORR. Since active concentrated bets indeed are weakly correlated with the existing portfolio, the degree of diversification can increase with concentration-related skill. Finally, the results of a double-sorting portfolio analysis demonstrate that the DR has stronger explanatory power for future fund performance than other skill measures do. In particular, Active Share, R-squared, and the ICI have explanatory power only for high-DR fund portfolios and not for the other DR groups.

This study presents a new perspective on the debate on diversification versus concentration. In previous studies, the dominant evidence is that concentrated funds outperform diversified funds. However, this evidence contradicts the diversification benefits Markowitz (1952) emphasizes in modern portfolio theory. We introduce a comprehensive diversification measure, the DR, and demonstrate that funds with well-diversified portfolios outperform funds with less-diversified portfolios. We suggest that the reason for the conflicting evidence is that existing measures of diversification or concentration consider only the weight of the asset in the portfolio, neglecting asset correlation within the portfolio. Note that correlation among assets is the key to the diversification effect. By introducing a new DR measure to account for this correlation, we propose an important link between diversification and existing concentration-related skill measures, where efficiently concentrated investments deviating from the market are in line with an efficiently diversified portfolio.

The rest of this paper proceeds as follows. Section 2 describes the data. Section 3 presents the DR measure and its characteristics. Section 4 examines the performance of diversified funds. Section 5 discusses the characteristics of diversified funds. Section 6 concludes the paper.

2. Mutual fund data

To obtain the main data to construct our sample of actively managed US equity funds, we merge the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database and the CDA/Spectrum holding database using the MFLINK file based on the work of Wermers (2000) and available from Wharton Research Data Services. Specifically, we obtain data on daily fund returns and other fund characteristics from the CRSP Mutual Fund Database and detailed information about fund holdings from the CDA/Spectrum Database. We link these holding data to the CRSP stock data to obtain the returns and other information on individual stocks. For funds with multiple share classes in the CRSP database, we use the CRSP class group variable to combine them into a single fund and compute the value-weighted average return, expenses, turnover ratio, and other characteristics for each fund.

Our sample includes 2,467 unique funds and 245,462 fund–month observations between January 1, 2000, and December 31, 2013.[1] We restrict our sample to actively managed equity funds with the most complete and reliable holding data. Therefore, we exclude balanced, bond, index, international, and sector funds either by stated style or by name. We require that a fund have at least 80% and less than 105% of its assets invested in common stocks. Following Elton, Gruber, and Blake (1996), we require funds to have at least $15 million in total net assets, since the inclusion of smaller funds can create survivorship bias due to reporting conventions. To avoid the incubation bias of Evans (2010), we eliminate observations before the reported starting year of the fund and exclude funds less than one year old. We also restrict our sample to funds with at least $15 million in assets. Following Kacperczyk, Sialm, and Zheng (2008), we also exclude funds that did not disclose an equity position over the last 12 months and delete funds with names missing from the CRSP.

[1] The daily return file of a mutual fund is available from the CRSP database from September 2, 1998, onward. The first year of the sample is required to construct the variables in the analysis.

3. Diversification Ratio

We introduce the DR to measure the degree of diversification of each fund. This measure was first proposed by Choueifaty and Coignard (2008), who investigate the theoretical and empirical properties of diversification as a criterion in portfolio construction.[2] Technically, the DR of a certain portfolio is defined as

$$DR(\mathcal{R}) = \frac{\sum_i w_i \mathcal{R}_i}{\mathcal{R}_p},$$

where w_i is the portfolio weight of the ith asset, $\mathcal{R}_i$ is the risk of the ith asset, and $\mathcal{R}_p$ is the total risk of the portfolio. For the risk measure $\mathcal{R}$, we consider volatility a primary measure and VaR and ES metrics as alternative risk measures.

Adopting volatility as a risk measure, we can express our primary measure, DR(Vol), as

$$DR(\text{Vol}) = \frac{\sum_i w_i \sigma_i}{\sqrt{\sum_i w_i^2 \sigma_i^2 + \sum_i \sum_{i \neq j} w_i w_j \sigma_{ij}}},$$

where w_i is the portfolio weight in the ith asset, σ_i is the volatility of the ith asset, and $\sigma_{i,j}$ is the covariance between the ith and jth assets. Alternatively, when we use VaR and ES as risk measures, the DR measure is defined as

$$DR(\text{VaR}) = \frac{\sum_i w_i VaR_i}{VaR_p} \text{ and } DR(\text{ES}) = \frac{\sum_i w_i ES_i}{ES_p},$$

where w_i is the portfolio weight of the ith asset; VaR_i and VaR_p are the VaR of the ith asset and of the portfolio, respectively; and ES_i and ES_p are the ES of the ith asset and of the portfolio, respectively. In the overall analysis, we use a volatility-based DR measure, DR(Vol), as our primary measure, since various useful characteristics of the DR are derived from manipulating volatility, as discussed below.

In the equation above, DR(Vol) is the ratio of the weighted average volatility of assets in the portfolio to the overall portfolio volatility. The numerator of DR(Vol), the allocation-only weight portfolio volatility, is identical to the overall portfolio's volatility if every asset in the portfolio is perfectly correlated. However, since the assets will not all be perfectly correlated, the portfolio's volatility will be less than the sum of the individual volatilities. This key feature of diversification is the main concept encapsulated in the DR measure. The DR captures the benefits of diversification gained from holding assets that are not perfectly correlated. We determine that a portfolio is poorly diversified when its DR value is close to one and consider a portfolio to be

[2] To measure the diversification effect, De Wit (1997) and Cheng and Roulac (2007) also use a similar concept to analyze the effectiveness of diversification in real estate portfolios. See Hight (2009) for a discussion on measuring the diversification effect.

highly diversified is it has a high DR value. Note that the DR has a value of one only if there is only one asset in the portfolio. For a portfolio containing N independent assets, the DR value is $\sqrt{N}$.

One of the important features of the DR is that it can be decomposed into two other components that also measure the degree of diversification. Specifically, as shown by Choueifaty, Froidure, and Reynier (2013), the DR of a portfolio can be decomposed in terms of its weighted correlation and weighted concentration measures as

$$DR = [CORR(1 - CR) + CR)]^{-0.5},$$

where CORR is the volatility-weighted average correlation of the assets in the portfolio,

$$CORR = \frac{\sum_{i \neq j}\left(w_i \sigma_i w_j \sigma_j\right)\rho_{i,j}}{\sum_{i \neq j}\left(w_i \sigma_i w_j \sigma_j\right)},$$

and CR is the volatility-weighted concentration ratio of the portfolio,

$$\mathrm{CR} = \frac{\sum_i (w_i \sigma_i)^2}{(\sum_i w_i \sigma_i)^2}$$

A fully concentrated long-only portfolio, that is, a single-asset portfolio, exhibits a CR value of one, while an equal-volatility-weighted portfolio has the lowest CR value, equal to the inverse of the number of assets.[3] The intuition incorporated in this decomposition is that a poorly diversified portfolio is the result of either a more highly concentrated weighting in the portfolio or more highly correlated holdings; that is, a lower DR value is the result of either a higher CR value or a higher CORR value. In the extreme, the DR is equal to one if the CORR increases to one, regardless of the CR value, because a portfolio of assets is no more diversified than a single-asset portfolio.

The literature introduces a number of measures related to diversification (or concentration), but there is no direct diversification measure such as the DR measure. Note that portfolio risk is affected by the volatility of each asset's returns, the allocation or weights of the assets, and the correlation of each asset's return with the returns of the other assets in the portfolio. First, the seminal paper of Kacperczyk, Sialm, and Zheng (2005) proposes the ICI to measure the degree of industry concentration. A number of similar measures exist in the mutual fund literature, including divergence indexes at either the stock, industry, or country level, including those of Baks, Busse, and Green (2006), Brands, Brown, and Gallagher (2006), Sapp and Yan (2008), and Hiraki, Liu, and Wang (2015). The critical drawback of these weight-based measures is that they do not account

[3] As mentioned by Choueifaty, Froidure, and Reynier (2013), CR is an applied version of the Herfindahl–Hirschman Index, which is used by US authorities to measure sector concentration. So we can consider the CR measure the concentration of weights, as well as the concentration of risks with which assets are weighted in proportion to volatility.

for correlation among assets. That is, a portfolio with the same weight structure but a completely different covariance structure can exhibit markedly different levels of diversification. Second, Sapp and Yan (2008) use the number of stocks in the portfolio as a simple measure of diversification and its effectiveness was first demonstrated by Evans and Archer (1968). However, the degree of diversification depends not only on the number of assets but also on the fractions of assets invested in the constituent. In addition, the number of assets does not account for their correlations in a portfolio. Since existing measures do not account for the covariance structure among assets, we choose the DR as a comprehensive measure of diversification to gauge the degree of diversification for a specific portfolio.

To construct the DR measures of our sample, we calculate the volatility, VaR, and ES of each fund's return and the stock return held by the fund in each month of the fund's disclosure. We use daily returns over the past year for all the variables and adopt a 5% value for the VaR and ES parameters.

[Insert Table 1]

Table 1 present the summary statistics for our DR measures. The average and standard deviation of DR(Vol) are 1.94 and 0.46, respectively, with a positive skewness and kurtosis of 1.36 and 3.72, respectively. Since the lower bound of the DR is one, the positive skew with a fat-tailed distribution of DR is quite reasonable. The minimum and maximum values of 1.12 and 5.63 are also reasonable. Note that DR(Vol) and the alternative DR measures DR(VaR) and DR(ES) have almost identical distributions and the correlation structures, especially, show that these DR measures are highly correlated. Therefore, we proceed with our main analysis with DR(Vol) and the robustness check will use DR(VaR) and DR(ES) throughout the paper.

4. Performance of diversified funds

4.1. Performance of DR-sorted fund portfolios

We first explore the performance of highly and weakly diversified mutual funds by sorting funds into portfolios based on their past DR. At the beginning of each month, we sort funds into deciles based on the DR for the recent year. We then calculate the equal-weighted returns for each decile portfolio.

[Insert Table 2]

Table 2 shows the average monthly returns and the Fama–French four-factor alphas for the DR-sorted portfolios.[4] Focusing on net returns, we find the average monthly return for high-DR portfolios to be 0.86%, compared with only 0.18% for low-DR portfolios. The annualized difference between high- low-DR portfolios is 8.16% per year, which is economically and statistically significant at the 1% level. Note that it is impossible for investors to directly capture this difference in performance, since mutual funds cannot be sold short, unlike common stocks. Instead, the difference corresponds to the opportunity costs of investing in high-DR funds instead of low-DR funds.

The Fama–French four-factor alpha and factor exposure also exhibit significant differences between high- and low-DR funds.[5] The high-DR portfolio has an alpha of 0.08% per month, while the low-DR portfolio has an alpha of -0.20% per month. The annualized difference in alpha between the high- and low-DR portfolios amounts to about 3.48% per year, which is significant at the 5% level. High-DR funds more likely to tilt on low-beta, small, and value styles than low-DR funds are. That is, high-DR funds have greater exposure to stocks with a favorable style but such exposure does not fully explain the performance of these high-DR funds. As discussed by Choueifaty, Froidure, and Reynier (2013), it is important to note that maximizing the DR is equivalent to maximizing the Sharpe ratio under the assumption that risk is homogeneously distributed across the universe. Consistent with this intuition of the DR, high-DR funds have statistically and economically significantly higher returns and alpha values than low-DR funds do.

4.2. Performance persistence of DR-sorted fund portfolios

We test the persistence of the fund DR as a predictor of future fund performance. Whereas, in Section 4.1, we employ the DR of each fund measured in month t to form portfolios in month $t + 1$, in this section we construct the fund portfolios similarly, except we introduce a time lag between the DR's measurement and portfolio formation. The time lag varies from month t through month $t + 60$. In each formation month, we divide funds into deciles based on their DR measures. We then calculate the monthly Fama–French four-factor alpha for each fund portfolio corresponding to its formation month. The method to test for performance persistence is similar to that of Carhart (1997), who suggests that past fund returns predict only short-term future performance.

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[4] In the Appendix, we report additional portfolio sorting results for an alternative definition of the DR. The alternative measures calculate the DR by adopting risk measures such as the VaR and ES for robustness checks. The results are consistent even for alternative measures of the DR.

[5] The market, size, and value factors of Fama and French's (1993) model and the momentum factor of Carhart (1997) are obtained from Kenneth French's webpage (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data Library).

[Insert Table 3]

In Table 3, we find that a high-DR fund portfolio outperforms a low-DR fund portfolio, even with a long lag between DR measurement and portfolio formation. Panel A shows a statistically significant monthly difference in the raw returns of 0.22% between high- and low-DR fund portfolios at the 10% level, with lags of up to 36 months, and Panel B shows a statistically significant monthly performance difference for the Fama–French four-factor alpha of 0.21% at the 10% level, after 12 months of DR measurement. These differences in performance are the one-month return for each imposed lag at each point in time. Since the difference between high- and low-DR fund portfolios is not reversed when we consider cumulative returns, high-diversification funds will perform better than low-diversification funds over the next five years, controlling for risk factors. Untabulated results show that highly diversified funds have a 0.65% higher return and a 0.28% higher alpha compared to less diversified funds at the 1% significance level. In contrast to the momentum effect investigated by Carhart (1997), the effect of diversification on future fund performance is highly persistent.

4.3. Persistence of the DR measure

Given the performance persistence of DR-sorted funds, this section analyzes the persistence of the DR measure itself. Similar to the methodology used in Section 4.2, we calculate the DR of each fund in month t to form decile portfolios. We then calculate the average DR for each decile fund portfolio from month t to month $t + 60$. To understand the magnitude of the difference in the DR in economic terms, we also calculate the number of independent risk factors using the square of the DR value, following Choueifaty, Froidure, and Reynier (2013). The DR-squared value of any portfolio can be interpreted as the number of independent risk factors required for a portfolio to allocate the same risk to independent risk factors to achieve the same DR.

[Insert Table 4]

Table 4 shows a statistically significant difference in the value of the DR itself over a long horizon. During the formation period, the differences in DR and DR-squared between high- and low-DR fund portfolio are 1.09 and 4.55, respectively. The difference in DR-squared indicates that high-DR funds have greater exposure to 4.55 independent risk factors compared to low-DR funds. Note that the DR value of the high-DR fund portfolio is 2.64 and that of the most diversified portfolio of Choueifaty, Froidure, and Reynier (2013) is 2.6 in 2010.[6] We

[6] See the index listed by Choueifaty, Froidure, and Reynier (2013) to better understand the magnitude of DR values. At the end of 2010, the DR of the MSCI World Index was 1.7, which implies that a passive MSCI World Index investor was effectively exposed to 2.89 (= 1.7^2) independent risk factors.

suggest that funds in the highest DR decile have a portfolio that is diversified as much as the most diversified portfolio, which is actually constructed by maximizing DR at the time of formation. As the lag increases, the value of the DR gradually decreases in the high-DR fund and increases in the low-DR fund, so that the gap between high- and low-DR funds is gradually reduced. After 36 months of lag, the difference in DR values falls below 0.5 and the difference in the number of independent risk factors falls below two. Considering that performance persists for lags of up to 36 months, the difference in the number of risk factors between high- and low-DR funds should be more than two to make a significant difference in performance.

4.4. Cross-sectional regression

We perform a cross-sectional regression analysis to test the role of the DR in predicting future mutual fund performance, controlling for various fund characteristics and well-known fund managers skills. Specifically, we use a Fama–MacBeth (1973) style regression model to forecast future fund performance based on the DR and control variables. The dependent variable of the regression is the performance of the individual fund in month $t + 1$. The independent variables include the DR variables and the control variables associated with fund characteristics and managerial skill. Note that the variables are all standardized to have a mean of zero and a standard deviation of one to identify which of the independent variables has a greater effect on the dependent variable in the multivariate regression. Therefore, the coefficient is standardized and indicates by how many standard deviations the dependent variable increases as the independent variable increases by one standard deviation.

Our main variables of interest in the regression are three versions of the DR. The DR types vary depending on how we define risk, such as DR(Vol), DR(VaR), and DR(ES), which adopt the risk measures of volatility (Vol), VaR, and ES, respectively. We calculate these variables by using the daily return series and apply the VaR and ES parameters at the 1% level. Our purpose for using various DR measures is to test the robustness of the variables, that is, determine how the DR variables can explain the cross-sectional returns of mutual funds, regardless of how we define the DR in terms of risk.

The primary control variables related to the fund characteristics include the log of total net assets, the log of age, the turnover ratio, expenses, flow, the number of stocks, and past performance. We also use five variables related to fund manager skill as control variables: The first is the Active Share measure of Cremers and Petajisto (2009) and Petajisto (2013), which is defined as the sum of the absolute deviation of the fund's portfolio holdings from its benchmark index holdings. A higher Active Share predicts superior performance. The second variable is the R-squared measure of Amihud and Goyenko (2013), which is obtained from a regression of fund returns on a multifactor benchmark model. A lower R-squared value is related to greater selectivity and better future performance. The third variable is the ICI of Kacperczyk, Sialm, and Zheng (2005), which is constructed as the sum of the squared deviations of a fund's stock holdings in each industry from the industry weights of the total stock market. A higher-ICI fund has superior future performance, since mutual funds that are concentrated in a few industries outperform their more diverse counterparts. The fourth variable is the return gap of Kacperczyk, Sialm, and Zheng (2008), which is the difference between the gross fund return and the holding-based return. The return gap is a proxy for the unobserved actions of the fund manager and leads to higher future performance. The last variable is the risk shifting of Huang, Sialm, and Zhang (2011), which is defined as the difference between current holdings volatility, based on the most recently disclosed position, and past realized volatility, based on realized returns. Since funds that increase risk perform worse, lower risk shifting is related to better future performance.

[Insert Table 5]

Table 5 shows the results for the regression analysis. The first and fifth columns show the baseline results of adding only the primary control variables or adding the skill variables as explanatory variables to predict future fund returns. Not surprisingly, past performance has strong predictability for future fund performance and the remaining predictive variables are fund size, flow, and the number of stocks in the portfolio. Among the predictive skill measures, the Active Share measure of Cremers and Petajisto (2009) has the highest coefficient, 0.22, statistically significant at the 1% level. The number of stocks held by a fund, which is an unsophisticated measure of diversification discussed by Sapp and Yan (2008), also has a significant coefficient at the 1% level. These baseline results show that the characteristics of various funds predict future returns in a direction consistent with previous literature.

The three columns following each of first and fifth columns of baseline results in Table 5 report the main results of testing the predictive power of the DR measures DR(Vol), DR(VaR), and DR(ES). Regardless of the definition of DR, the DR measure has a significant positive coefficient for future fund performance. The coefficient of our main volatility-based DR variable, DR(Vol), is 0.17 and statistically significant at the 1% level when we control only for fund characteristics in the second column. When we further control for various skill measures in the sixth column, the coefficient is 0.24 and statistically significant at the 5% level. The explanatory power of the number of stocks, a naive measure of diversification, and skill measures, such as Active Share, R-squared, and the ICI, notably decreases when the DR variable is added. Note that the coefficient of the DR variable is 0.24, which is 33% larger than the 0.18 of Active Share, indicating that a one standard deviation change in the DR has a 33% greater effect on future fund performance relative to Active Share. Furthermore, the DR has greater predictive power for future performance than any other variable when past performance variables are excluded. Thus, we conclude that funds with a higher degree of diversification have significantly better future fund performance, even after controlling for various fund characteristics and managerial skills.

5. Features of diversified funds

5.1. Determinants of the DR

The DR value of each fund is a salient predictor of the fund's future performance. To identify the determinants of the DR measure, we perform a regression analysis with the DR as a dependent variable. The regression specification is similar to the Fama–MacBeth (1973) type of regression in the previous section and the independent variables include the fund characteristic variables—for size, age, turnover, expenses, flow, number of stocks, and past performance—as well as managerial skill measures, such as Active Share, R-squared, the ICI, and the return gap. In the case of the dependent variable, three types of DR—DR(Vol), DR(VaR), and DR(ES)—are analyzed, depending on the choice of risk measure in the calculation of the DR measure.

[Insert Table 6]

Table 6 shows the results of the regression to examine the determinants of the three different versions of the DR. Among the variables related to fund characteristics, those that explain the DR in a statistically significant and consistent direction under any conditions are the number of stocks, flow, and past performance. First, it is natural that the number of shares exhibit a significant coefficient to explain the DR. The number of shares can be regarded as a simple measure of the degree of diversification, as suggested by Sapp and Yan (2008). However, the DR has information that is different from that provided by the number of stocks, as shown in the results of the previous analysis and past literature.[7] Second, fund flow and past performance also have a significantly positive coefficient for explaining the DR. Berk and Green (2004) suggest that fund flow rationally responds to past performance in their model and these two variables are closely interconnected. That is, a well-

[7] As shown by Choueifaty, Froidure, and Reynier (2013), a large number of stocks is not a necessary condition for a higher degree of diversification. The authors show that the most diversified portfolio is more diversified with a smaller number of shares than the market index. Shawky and Smith (2005) also point out that the cost is greater than the benefit over a certain number of stocks, so it has a negative effect on performance. In this respect, the authors analyze the optimal number of stocks to maximize fund performance.

performing fund draws capital inflow and funds with inflow also perform better in the future. We believe that prosperous fund managers with positive inflow or good performance could avoid speculative investment, so they are more likely to focus on diversification rather than to increase idiosyncratic betting or gambling.[8] In summary, among fund characteristics, the number of stocks, fund flow, and past performance are positively related to the DR measure.

Among the managerial skill measures, variables with a statistically significant coefficient in explaining the DR measure are the Active Share, R-squared, ICI, and risk shifting measures. The Active Share and R-squared variables, which seemed to be largely unrelated to diversification, account most of all for the DR measure and significantly. The result indicates that fund manager activity and selectivity are positively associated with portfolio diversification behavior. Intuitively, three measures commonly represent more efficient investments, leading to a higher Sharpe ratio. The relation between skill measures and the DR is discussed in more detail in the following section. Second, it is easy to understand that the ICI negatively explains the DR measure, since the two variables have opposite concepts of concentration and diversification. Third, the risk shifting measure is technically related to the DR measure by definition, since the two variables are negatively related to the past realized volatility of daily fund returns, which is the denominator of the DR measure and also the subtracted part of the risk shifting measure. Accordingly, the lower the portfolio's volatility, the greater the value of the DR and risk shifting. In sum, we find that the DR has a positive relation with various skill measures and, most surprisingly, these skill measures include Active Share and R-squared.

5.2. Characteristics of DR-sorted fund portfolios

In this section, we focus on the characteristics of high-DR funds that generate superior future performance. We conduct a portfolio sorting analysis to examine the direct relation between the DR and fund characteristics. First, we sort funds by the DR measure for each month and divide the fund sample into deciles to construct the portfolios. We then calculate the variables for the characteristics of the decile portfolios by averaging the values of the funds in each decile. We include various characteristics, from general information to performance evaluation, portfolio composition, investment style, and managerial skills.

[Insert Table 7]

[8] Fund managers have strong incentives to make idiosyncratic bets to win tournaments. Brown, Harlow, and Starks (1996) suggest that unskilled fund managers are likely to be tempted to make large idiosyncratic bets to raise their tournament ranking, like a lottery winner. Funds with such betting behavior tend to increase their volatility or skewness. See also Brown, Goetzmann, and Park (2001), Huang, Sialm, and Zhang (2011), Lin (2011), and Chang and Luo (2013).

Table 7 shows the general information of DR-sorted fund portfolios. First, the performance-related characteristics of high-DR funds coincide with the diversification concept, consistent with the background of the DR measure. High-DR fund portfolios exhibit a higher Sharpe ratio (i.e., higher average return and lower standard deviation), since Choueifaty and Coignard (2008) demonstrate that increasing the DR is equivalent to increasing the Sharpe ratio. In addition, high-DR fund portfolios exhibit reduced skewness and kurtosis compared to low-DR fund portfolios, corresponding to the result of diversification. Second, the basic properties of high-DR funds match the characteristics of funds with superior performance identified in the literature. The highest-DR funds are the smallest and youngest and rank the highest in terms of flow, turnover ratio, expense ratio, and management fees. The number of stocks increases with the DR but steeply decreases in the highest DR decile portfolio. This result is consistent with the notion of Shawky and Smith (2005) that an optimal number of stocks exists that reflects the trade-off between diversification benefits versus transaction and monitoring costs. Third, high-DR funds have a low proportion of equity holdings in their portfolios. In other words, high-DR funds hold more cash and invest more in bonds. We suggest that diversified funds actively utilize assets other than common stocks in their portfolios, consistent with the asset allocation perspective. Simutin (2014) also suggests that the benefits of cash holdings stem from their flexibility. To summarize, the characteristics of high-DR funds are closely related to diversification benefits and many fund characteristics favorable to performance.

[Insert Table 8]

Table 8 shows the investment style- and skill-related characteristics of DR-sorted funds. For the style score, we first rank stocks based on each style in the stock universe from one to ten and assign this rank value to the corresponding stock in the portfolio; we then calculate the average of the rank values for the stocks in the portfolio. First, high-DR funds have greater exposure to stocks with higher expected returns, such as small, value, and momentum stocks and stocks with low information, such as those with low analyst coverage and a low share of institutional holdings. We suggest that high-DR funds successfully achieve diversification benefits by exposure to various factors and a broad stock universe, regardless of information, compared to low-DR funds. Second, high-DR funds also hold more stocks with high volatility and skewness. Note that these characteristics would be direct evidence of the well-diversified properties of high-DR funds, considering that these funds have low portfolio return volatility and skewness. Finally, high-DR funds exhibit the characteristics of managers with superior skills. The results show that funds in the top DR decile have the highest Active Share, the lowest R-squared, and the second highest ICI. In line with the regression results of the DR determinants, funds with a high degree of diversification exhibit greater manager activity and selectivity. However, the ICI measure has a U-shaped relation with the DR in univariate analysis, in contrast to the negative coefficient of the ICI on the DR in the multivariate regression.

We discuss the relations between skill measures and the DR further in the following section. In summary, the results show that high-DR funds not only are well diversified but also invest in stocks with high expected returns in the broad sense, with superior managerial skill.

6. Diversification and managerial skill

6.1. Relation of diversification effects and skill measures

In this section, we decompose the DR measure to obtain more insight on how the DR and skill measures are related to each other. As shown earlier, the DR of a portfolio can be decomposed into two factors, the weighted concentration ratio (CR) and the weighted correlation (CORR). The fund can have a high DR value in both cases when it has a small concentration ratio or less correlated assets. Therefore, we consider both the CR and CORR values of each fund to analyze which factor drives the magnitude of the DR. We first sort funds into deciles based on each skill measure and then calculate the average DR and its factors CORR and CR for each decile skill fund portfolio. We also calculate the average number of stocks and the proportion of common stocks for each decile portfolio to analyze portfolio construction-related characteristics. We include various skill measures that are considered to be associated with the DR.

[Insert Table 9]

Table 9 shows the average values of the diversification-related measures of the portfolios sorted by various skill measures. In Panel A, the average DR value of a portfolio sorted by each skill measure indicates that portfolios with better skill measures have higher DR values. This finding is consistent with our previous result from analyzing the skill-related characteristics of DR-sorted fund portfolios. Panel B shows a difference between the DR and other skill measures in relation to the CR values. High-DR funds have relatively low CR values, so we can consider the CR value one of the factors that increases the DR value. However, funds with other superior skill measures have high CR values, in contrast to their higher DR values. This result implies that the high DR values of funds with superior skills are not the result of the weakly concentrated weights in their portfolios. As noted by Sebastian and Attaluri (2014), existing skill measures, especially Active Share, R-squared, the ICI, and the number of stocks, are closely related to the high-conviction strategy, so these managerial skills are more strongly related to concentration than to diversification with respect to the weighting scheme in their portfolios. In Panel C, we present the average CORR value of the portfolios sorted by each of the skill measures. Since high-DR funds have relatively low CORR values, we consider this CORR value another factor that increases the DR. For the portfolios sorted by the other skill measures, it is important to note that skillful funds have a low CORR value. Note that there is no change in the CR value as the number of stocks increases, since this measure contains only information about concentration. Therefore, the high DR value of funds with superior concentration skill, except in terms of the number of stocks, is the result of a weak correlation between concentrated bets and the assets within their portfolios.

We suggest that skillful funds could achieve investment success by lowering the correlations among their investments assets, efficiently deviating from the benchmark and a multifactor model (Active Share, R-squared), and efficiently concentrating on a few industries (ICI). That is, the comparative advantage of superior funds relative to inferior funds is that their investments are made in the direction of lowering portfolio correlations. Thus, their superior performance is consistent with the diversification benefit of classical financial theory, where efficient investments eventually lead to a higher Sharpe ratio. We conclude that the spirit of diversification is inherent in existing skill measures.

[Insert Table 10]

In Table 10, we repeat the previous analysis but replace the DR-related variables with the number of stocks and the portion of common stocks. The results indicate that funds with superior skills have a small number of common stocks in their portfolio, while these common stocks account for a small portion of total net assets. As shown above, we determine that the number of stocks simply proxies for the extent to which the investment bets are concentrated or diversified and does not account for the correlation among these bets at all. Regardless of the degree of diversification, if the number of stocks increases, the portfolio becomes similar to the market index, making it difficult to outperform the market index. Therefore, we suggest that skilled funds actively make concentrated bets in fewer stocks with high conviction, contributing to outperformance over benchmarks or the market index. Next, the measure of the proportion of common stock is used as a proxy for the extent to which fund managers consider asset allocation in portfolio management. In contrast to the number of stocks, the fact that skilled fund managers have smaller portions of common stocks in their total net assets is far from high-conviction investment. Rather, they seem to invest in consideration of asset allocation. In summary, although skilled fund managers make concentrated investments with confidence, they have diversified portfolios in terms of overall asset allocation.

6.2. Comparison of the DR and skill measures

In this section, we analyze how the explanatory power of existing skill measures on future fund performance varies with the DR value of the fund. We analyze the direct relation between the DR and the various skill measures through a double-sorting analysis. In each month, we first sort entire funds based on the DR and divide them into five quintiles. Next, we sort funds within each DR quintile into five quintiles based on each skill measure. After this 5×5 sort, we finally construct 25 portfolios and then calculate their average returns in the next month. If the explanatory power of the skill measure is maintained regardless of the value of the DR, the return of the high-minus-low portfolio in each DR quartile will be significant. For skill measures, we include Active Share and R-squared, which are highly relevant to the DR, and we also include the ICI and the number of stocks to match with the DR measure.

[Insert Table 11]

Table 11 shows the results of the predictive power of Active Share and R-squared after controlling for the DR measure. For the Active Share variable, Panel A shows statistically significant differences in raw returns of 0.34 and 0.44 at the 1% level between high- and low-Active Share funds in only the fourth and fifth DR quintiles, respectively. The Fama–French four-factor alpha of the high-minus-low Active Share shows a statistically significant difference only in the highest DR quintile, with a value of 0.19, significant at the 10% level. That is, after the DR is controlled for, the predictive power of Active Share for future fund returns exists only in high-DR fund groups. Panel B shows the results for the R-squared measure. In the case of raw returns, we find that the return differences between low- and high–R-squared funds are -0.20 in both the second and third DR quintiles, marginally significant at the 10% level. However, in the case of the Fama–French four-factor alpha, there is no statistically significant difference between low-minus-high R-squared funds. Therefore, we conclude that the DR variable subsumes the explanatory power of the skill variables of Active Share and R-squared to some extent.

[Insert Table 12]

Table 12 presents the results of the predictive power of the concentration- and diversification-related measures ICI and the number of stocks. In Panel A, we find significant differences in raw returns between high- and low-ICI funds in three of the five DR quintiles, although the direction predicted by the ICI is reversed in the lowest DR quintile. However, in the case of the Fama–French four-factor alpha, the statistical significance of the difference in future performance between high- and low-ICI funds disappears in all the DR deciles. Panel B shows the results of the variable for the number of stocks, a very simple substitute for the diversification measure. Funds with a high number of stocks appear to have higher raw returns than funds with a low number of stocks in the higher-DR group, but there is no statistically significant difference. In addition, for the Fama–French four-factor alpha, there is no statistically significant difference in any of the DR quintiles and the direction predicted by this measure is also reversed. Thus, we conclude that, although measures of the ICI and the number of stocks contain some information about concentration or diversification, their predictive power is not as strong as that of the DR.

7. Conclusion

Markowitz (1952) has emphasized the benefits of diversification, where investors can reduce risks without necessarily sacrificing returns and, in modern portfolio theory, investors should invest in well-diversified portfolios to maximize their expected returns. However, the literature on the skills of mutual fund managers has focused primarily on portfolio concentration rather than diversification. In this paper, we introduce a comprehensive diversification measure, the DR, defined as the ratio of the weighted average risk of individual assets in the portfolio to the overall portfolio risk. We construct the DR measure to examine the effect of diversification on mutual fund performance. Consistent with modern portfolio theory, we determine that high-DR funds have more efficiently diversified portfolios and exhibit significantly higher returns than low-DR funds do. Specifically, we find that the annualized return difference between the highest- and lowest-DR funds is 8.16% per year, which is statistically and economically significant. This fund performance persists over three years and significantly explains future performance, even after controlling for various fund characteristics and managerial skill measures. We also determine that high-DR funds have various favorable characteristics related to diversification and asset allocation. The most distinctive feature of the DR is its relation with skill measures, such as Active Share, R-squared, and the ICI. When concentrated bets that actively deviate from the market have a weak correlation with the existing portfolio, funds with concentration-related skill exhibit greater diversification. When comparing the explanatory power of the DR and existing skill measures, we demonstrate that the DR has stronger explanatory power for future fund performance and the explanatory power of Active Share, R-squared, and the ICI vanishes in low-DR fund portfolios. Thus, we conclude that a significant portion of mutual fund performance is ultimately driven by the benefits of diversification.

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Table 1. Summary statistics of the DR measures

This table summarizes the characteristics of the DR measures. Our primary DR measure, DR(Vol), is defined as the ratio of the weighted average volatility of assets in the portfolio to the overall portfolio volatility. The first alternative DR measure, DR(VaR), is defined as the ratio of the weighted average VaR of assets in the portfolio to the overall portfolio VaR. The second alternative DR measure, DR(ES), is defined as the ratio of the weighted average ES of assets in the portfolio to the overall portfolio ES. The Spearman rank correlations among DR measures are shown below.

	DR(Vol)	DR(VaR)	DR(ES)
	Panel A: Distribution of the Measure		
Mean	1.94	1.77	1.92
Median	1.89	1.69	1.86
Std. Dev	0.46	0.45	0.50
Skewness	1.36	1.65	1.20
Kurtosis	3.72	4.55	2.92
Min	1.12	1.02	1.03
Max	5.63	4.75	5.43
	Panel B: Correlation Structure		
	DR(Vol)	DR(VaR)	DR(ES)
DR(Vol)	1.00	0.93	0.95
DR(VaR)	0.93	1.00	0.94
DR(ES)	0.95	0.94	1.00

Table 2. Future performance of the portfolios of funds sorted on the DR

This table shows the returns on the equal-weighted decile portfolios of active US equity mutual funds from January 2000 through December 2014. Our primary DR measure, DR(Vol), is defined as the ratio of the weighted average volatility of assets in the portfolio to the overall portfolio volatility. We form the portfolios sorted by the past DR(Vol) over the last 12 months. This table also report the Fama–French four-factor regression results for the monthly returns on the DR-sorted portfolios. Here, MKT, SMB, HML, and UMD represent, respectively, the coefficients of the market, size, value, and momentum factors of the Fama–French four-factor regression using the net return.

DR(Vol) Decile	Gross Return		Net Return		MKT	SMB	HML	UMD	Adj R2
	Return	Alpha	Return	Alpha					
Low DR	0.28 (0.65)	-0.11 (-1.17)	0.18 (0.42)	-0.20 (-2.22)	1.11 (50.17)	0.04 (1.55)	-0.25 (-8.67)	0.02 (1.32)	96%
2	0.35 (0.89)	-0.05 (-0.68)	0.26 (0.66)	-0.14 (-2.06)	1.06 (65.50)	0.00 (-0.17)	-0.14 (-6.70)	-0.01 (-0.87)	97%
3	0.42 (1.09)	0.00 (-0.08)	0.32 (0.85)	-0.10 (-1.61)	1.04 (72.10)	-0.02 (-1.08)	-0.07 (-3.70)	-0.01 (-0.96)	98%
4	0.51 (1.38)	0.04 (0.75)	0.42 (1.12)	-0.06 (-1.23)	1.02 (88.54)	0.01 (0.93)	0.02 (1.51)	0.00 (0.02)	98%
5	0.54 (1.46)	0.01 (0.26)	0.45 (1.20)	-0.08 (-1.54)	1.02 (78.50)	0.10 (6.02)	0.06 (3.34)	0.02 (1.88)	98%
6	0.66 (1.75)	0.09 (1.26)	0.56 (1.49)	-0.01 (-0.15)	1.00 (60.04)	0.16 (7.52)	0.10 (4.83)	0.01 (0.59)	97%
7	0.76 (1.98)	0.11 (1.52)	0.66 (1.71)	0.01 (0.15)	0.99 (55.71)	0.26 (11.34)	0.16 (7.05)	0.02 (1.74)	97%
8	0.82 (2.09)	0.13 (1.67)	0.72 (1.83)	0.03 (0.35)	1.00 (53.81)	0.33 (13.55)	0.19 (7.79)	0.04 (2.97)	96%
9	0.88 (2.24)	0.15 (1.85)	0.78 (1.98)	0.05 (0.57)	0.99 (49.51)	0.38 (14.86)	0.23 (8.89)	0.04 (2.92)	96%
High DR	0.97 (2.52)	0.20 (2.24)	0.86 (2.22)	0.08 (0.95)	0.92 (42.80)	0.46 (16.51)	0.30 (10.95)	0.01 (0.60)	95%
High-Low	0.69 (3.32)	0.31 (2.09)	0.68 (3.23)	0.29 (1.97)	-0.20 (-5.56)	0.41 (8.98)	0.55 (12.02)	-0.01 (-0.47)	53%

Table 3. Performance persistence of the portfolios of funds sorted on the DR

This table shows the monthly returns and Fama–French four-factor alphas of DR-sorted fund portfolios. Here, the DR is defined as the ratio of the weighted average volatility of assets in the portfolio to the overall portfolio volatility. We calculate the DR values for month *t* and use these to form DR-sorted decile portfolios from month *t* + 1 through month *t* + 60. In each formation month, we calculate the monthly average net return and the Fama–French four-factor alpha for each fund portfolio.

	Test Period in Months after Portfolio Formation								
DR(Vol)	*t* + 1	*t* + 3	*t* + 6	*t* + 9	*t* + 12	*t* + 24	*t* + 36	*t* + 48	*t* + 60
Panel A: Net Return									
Low DR	0.18	0.17	0.27	0.17	0.32	0.49	0.74	0.64	0.69
	(0.42)	(0.41)	(0.64)	(0.42)	(0.81)	(1.31)	(1.94)	(1.60)	(1.57)
2	0.26	0.29	0.33	0.27	0.39	0.53	0.74	0.67	0.66
	(0.66)	(0.74)	(0.86)	(0.71)	(1.05)	(1.44)	(1.95)	(1.68)	(1.52)
3	0.32	0.33	0.40	0.32	0.43	0.58	0.77	0.69	0.66
	(0.85)	(0.87)	(1.06)	(0.86)	(1.16)	(1.55)	(2.03)	(1.72)	(1.52)
4	0.42	0.43	0.43	0.40	0.49	0.61	0.78	0.72	0.66
	(1.12)	(1.18)	(1.15)	(1.08)	(1.33)	(1.61)	(2.02)	(1.77)	(1.51)
5	0.45	0.49	0.46	0.43	0.52	0.65	0.80	0.76	0.73
	(1.20)	(1.31)	(1.22)	(1.14)	(1.38)	(1.69)	(2.04)	(1.85)	(1.63)
6	0.56	0.51	0.56	0.49	0.60	0.67	0.86	0.77	0.73
	(1.49)	(1.34)	(1.46)	(1.28)	(1.55)	(1.71)	(2.18)	(1.81)	(1.59)
7	0.66	0.63	0.62	0.52	0.65	0.70	0.89	0.79	0.77
	(1.71)	(1.64)	(1.61)	(1.32)	(1.65)	(1.74)	(2.17)	(1.86)	(1.65)
8	0.72	0.67	0.68	0.59	0.69	0.76	0.92	0.77	0.78
	(1.83)	(1.72)	(1.73)	(1.49)	(1.72)	(1.87)	(2.20)	(1.76)	(1.65)
9	0.78	0.74	0.74	0.68	0.77	0.81	0.91	0.84	0.78
	(1.98)	(1.87)	(1.85)	(1.68)	(1.90)	(1.95)	(2.15)	(1.88)	(1.62)
High DR	0.86	0.80	0.82	0.74	0.84	0.85	0.96	0.83	0.76
	(2.22)	(2.10)	(2.12)	(1.88)	(2.11)	(2.06)	(2.30)	(1.88)	(1.59)
High-Low	0.68	0.63	0.56	0.57	0.52	0.36	0.22	0.19	0.07
	(3.23)	(3.13)	(2.88)	(3.05)	(2.95)	(2.59)	(1.79)	(1.64)	(0.56)
Panel B: Fama–French 4-Factor Alpha									
Low DR	-0.20	-0.21	-0.18	-0.20	-0.22	-0.18	-0.13	-0.14	-0.08
	(-2.22)	(-2.46)	(-2.20)	(-2.71)	(-2.89)	(-3.27)	(-2.04)	(-2.38)	(-1.23)
2	-0.14	-0.13	-0.15	-0.16	-0.18	-0.16	-0.13	-0.12	-0.10
	(-2.06)	(-1.92)	(-2.55)	(-2.67)	(-3.60)	(-3.80)	(-2.72)	(-3.03)	(-2.11)
3	-0.10	-0.11	-0.09	-0.14	-0.17	-0.13	-0.10	-0.10	-0.10
	(-1.61)	(-1.98)	(-1.77)	(-2.79)	(-3.75)	(-3.47)	(-2.63)	(-2.60)	(-2.39)
4	-0.06	-0.06	-0.11	-0.09	-0.12	-0.11	-0.11	-0.08	-0.11
	(-1.23)	(-1.11)	(-2.12)	(-2.03)	(-2.77)	(-3.19)	(-2.71)	(-2.08)	(-3.01)
5	-0.08	-0.04	-0.12	-0.09	-0.12	-0.10	-0.10	-0.05	-0.06
	(-1.54)	(-0.77)	(-2.35)	(-1.77)	(-2.61)	(-2.45)	(-2.47)	(-1.17)	(-1.23)
6	-0.01	-0.06	-0.08	-0.07	-0.09	-0.10	-0.06	-0.06	-0.07
	(-0.15)	(-0.91)	(-1.23)	(-1.34)	(-1.64)	(-2.37)	(-1.25)	(-1.24)	(-1.27)
7	0.01	0.00	-0.07	-0.09	-0.07	-0.11	-0.06	-0.04	-0.04
	(0.15)	(0.06)	(-1.02)	(-1.33)	(-1.11)	(-2.11)	(-1.12)	(-0.74)	(-0.70)
8	0.03	0.02	-0.05	-0.06	-0.08	-0.08	-0.06	-0.08	-0.04
	(0.35)	(0.21)	(-0.64)	(-0.80)	(-1.26)	(-1.41)	(-0.94)	(-1.36)	(-0.68)
9	0.05	0.04	-0.04	-0.02	-0.04	-0.06	-0.09	-0.02	-0.06
	(0.57)	(0.52)	(-0.46)	(-0.22)	(-0.57)	(-0.98)	(-1.40)	(-0.43)	(-0.97)
High DR	0.08	0.08	0.00	0.00	-0.01	-0.04	-0.03	-0.02	-0.07
	(0.95)	(0.88)	(0.05)	(0.02)	(-0.13)	(-0.64)	(-0.57)	(-0.36)	(-1.03)
High-Low	0.29	0.28	0.19	0.20	0.21	0.14	0.10	0.12	0.02
	(1.97)	(2.00)	(1.34)	(1.59)	(1.65)	(1.59)	(1.02)	(1.53)	(0.18)

Table 4. Measure persistence of the portfolios of funds sorted on the DR

This table shows the average DR values of DR-sorted fund portfolios. The DR is defined as the ratio of the weighted average volatility of assets in the portfolio to the overall portfolio volatility. We calculate the DR of each fund in month t and form DR-sorted decile portfolios. We then calculate the average DR for each decile fund portfolio from month t to month t + 60. Here, DR^2 represents the square of the DR, which can be interpreted as the number of independent risk factors required for a portfolio that allocate the same risk to independent risk factors to achieve the same DR. Here, Diff DR^2 represents the difference of the average DR-squared values between the high- and low-DR portfolios.

	Test Period in Months after Portfolio Formation								
	t	$t+3$	$t+6$	$t+9$	$t+12$	$t+24$	$t+36$	$t+48$	$t+60$
Low DR	1.55 (95.45)	1.59 (99.11)	1.63 (100.42)	1.66 (100.02)	1.68 (99.42)	1.69 (95.89)	1.71 (82.19)	1.71 (71.78)	1.71 (62.16)
2	1.67 (90.02)	1.69 (92.65)	1.70 (94.73)	1.72 (93.70)	1.72 (94.02)	1.72 (94.07)	1.72 (81.74)	1.74 (69.69)	1.72 (61.20)
3	1.74 (85.77)	1.75 (88.98)	1.75 (90.36)	1.76 (90.07)	1.76 (89.91)	1.75 (93.74)	1.74 (81.65)	1.74 (72.32)	1.73 (62.83)
4	1.80 (82.34)	1.80 (85.34)	1.80 (87.00)	1.80 (87.22)	1.79 (88.65)	1.77 (91.69)	1.75 (85.57)	1.75 (75.18)	1.74 (67.80)
5	1.86 (79.61)	1.85 (82.96)	1.84 (84.72)	1.83 (86.14)	1.82 (87.51)	1.79 (88.66)	1.77 (84.09)	1.77 (77.18)	1.76 (69.58)
6	1.92 (77.10)	1.90 (81.13)	1.89 (83.36)	1.87 (84.11)	1.86 (85.21)	1.83 (84.78)	1.80 (80.63)	1.80 (77.69)	1.78 (72.81)
7	1.99 (73.75)	1.97 (77.54)	1.94 (81.15)	1.92 (83.46)	1.90 (85.46)	1.86 (82.49)	1.84 (81.95)	1.83 (76.94)	1.81 (74.13)
8	2.08 (69.06)	2.05 (73.66)	2.01 (78.34)	1.99 (80.42)	1.96 (82.92)	1.92 (80.41)	1.88 (81.66)	1.87 (76.51)	1.84 (72.41)
9	2.20 (62.67)	2.15 (68.23)	2.10 (73.66)	2.07 (76.22)	2.04 (79.65)	1.98 (79.17)	1.93 (81.07)	1.92 (74.32)	1.89 (69.86)
High DR	2.64 (57.39)	2.54 (61.55)	2.46 (66.48)	2.41 (68.77)	2.36 (71.71)	2.26 (74.20)	2.20 (77.87)	2.16 (76.98)	2.10 (77.99)
High-Low	1.09 (31.23)	0.95 (31.34)	0.84 (32.23)	0.75 (32.02)	0.68 (32.74)	0.57 (35.29)	0.49 (48.68)	0.45 (50.90)	0.39 (35.66)
Diff DR^2	4.55	3.92	3.42	3.05	2.74	2.25	1.92	1.75	1.50

Table 5. Fama–MacBeth cross-sectional regression on future fund performance

This table presents the estimated results of the Fama–Macbeth regression. The dependent variable is the net return of the fund in month t + 1. The DR is defined as the ratio of the weighted average risk of assets in the portfolio to the overall portfolio risk. Here, DR(Vol), DR(VaR), and DR(ES) use the risk measures of volatility, VaR, and ES, respectively. The fund controls include the natural log of total net assets, the natural log of age, the turnover ratio, the expense ratio, and fund flow. We also include the managerial skill measures Active Share, R-squared, the ICI, the return gap, and risk shifting. All the variables are standardized as demeaned and divided by their standard deviation. The t-statistics from robust standard errors are reported in parentheses.

Explanatory Variable	Dependent Variable: Future Performance							
Intercept	0.47 (1.22)	0.36 (0.91)	0.33 (0.83)	0.35 (0.90)	0.32 (0.65)	0.23 (0.44)	0.19 (0.36)	0.21 (0.41)
DR(Vol)		0.17 (2.66)				0.24 (2.54)		
DR(VaR)			0.16 (2.56)				0.22 (2.55)	
DR(ES)				0.17 (2.50)				0.24 (2.42)
Assets	-0.05 (-2.20)	-0.03 (-2.02)	-0.03 (-1.99)	-0.03 (-2.05)	-0.03 (-1.82)	-0.02 (-1.40)	-0.02 (-1.44)	-0.02 (-1.43)
Age	0.02 (1.93)	0.02 (1.56)	0.01 (1.52)	0.02 (1.63)	0.00 (0.24)	0.00 (-0.19)	0.00 (-0.23)	0.00 (-0.06)
Turnover Ratio	0.01 (0.17)	0.01 (0.35)	0.02 (0.47)	0.02 (0.50)	0.00 (-0.02)	0.01 (0.30)	0.02 (0.42)	0.02 (0.48)
Expense Ratio	0.00 (-0.10)	-0.02 (-0.98)	-0.01 (-0.84)	-0.02 (-0.97)	-0.03 (-2.70)	-0.04 (-3.41)	-0.03 (-2.88)	-0.03 (-3.25)
Flow	0.05 (3.17)	0.03 (2.47)	0.03 (2.33)	0.03 (2.27)	0.04 (2.29)	0.03 (1.77)	0.03 (1.64)	0.02 (1.53)
Number of Stocks	0.05 (2.72)	0.02 (1.76)	0.03 (1.88)	0.02 (1.79)	0.16 (3.26)	0.10 (2.62)	0.11 (2.65)	0.10 (2.57)
Past Performance	0.39 (2.49)	0.38 (2.56)	0.38 (2.54)	0.39 (2.57)	0.40 (2.21)	0.39 (2.19)	0.38 (2.13)	0.39 (2.21)
Active Share					0.22 (3.15)	0.18 (2.79)	0.19 (2.78)	0.18 (2.72)
R-Squared					-0.09 (-1.95)	-0.02 (-0.47)	-0.02 (-0.50)	-0.02 (-0.62)
Industry Concentration					-0.08 (-1.90)	-0.04 (-1.05)	-0.04 (-1.15)	-0.04 (-1.11)
Return Gap					0.04 (2.19)	0.05 (2.34)	0.04 (2.02)	0.04 (2.11)
Risk Shifting					-0.10 (-2.23)	-0.19 (-2.46)	-0.19 (-2.77)	-0.18 (-2.50)
Adjusted R-Squared	0.18	0.22	0.21	0.22	0.34	0.37	0.36	0.37

Table 6. Determinants of the regression of the DR

This table presents the estimated results of the Fama–Macbeth regression. The dependent variables are the DRs, defined as the ratio of the weighted average risk of assets in the portfolio to the overall portfolio risk. The DRs include DR(Vol), DR(VaR), and DR(ES), using volatility, VaR, and ES as the risk measures, respectively. The fund controls include the natural log of total net assets, the natural log of age, the turnover ratio, the expense ratio, and fund flow. We also include the managerial skill measures Active Share, R-squared, the ICI, the return gap, and risk shifting. All the variables are standardized as demeaned and divided by their standard deviation. The t-statistics from robust standard errors are reported in parentheses.

Explanatory Variable	Dependent Variable DR(Vol)		Dependent Variable DR(VaR)		Dependent Variable DR(CVaR)	
Intercept	2.00	2.08	1.84	1.90	1.97	2.08
	(32.91)	(32.14)	(30.21)	(28.44)	(29.26)	(29.75)
Assets	0.01	0.00	0.01	0.00	0.01	0.00
	(1.46)	(-0.16)	(1.31)	(0.29)	(1.19)	(0.32)
Age	-0.01	0.00	-0.01	0.00	-0.01	0.00
	(-2.43)	(2.33)	(-2.35)	(1.82)	(-3.37)	(-0.33)
Turnover Ratio	0.03	0.00	0.01	-0.01	0.00	-0.01
	(3.73)	(0.28)	(1.41)	(-2.18)	(0.42)	(-1.91)
Expense Ratio	0.06	0.01	0.05	0.00	0.06	0.00
	(20.20)	(3.74)	(18.35)	(2.10)	(18.34)	(2.32)
Flow	0.02	0.01	0.02	0.01	0.02	0.01
	(4.01)	(2.45)	(4.74)	(3.30)	(4.39)	(2.87)
Number of Stocks	0.04	0.11	0.03	0.09	0.04	0.11
	(4.03)	(6.11)	(3.67)	(5.47)	(4.32)	(6.72)
Past Performance	0.04	0.05	0.03	0.04	0.05	0.05
	(2.09)	(2.73)	(1.87)	(2.82)	(2.34)	(2.64)
Active Share		0.08		0.06		0.10
		(7.09)		(4.98)		(8.56)
R-Squared		-0.11		-0.10		-0.09
		(-10.90)		(-10.92)		(-9.66)
Industry Concentration		-0.06		-0.05		-0.06
		(-6.91)		(-7.63)		(-7.27)
Return Gap		0.00		0.00		0.01
		(-0.96)		(1.19)		(2.65)
Risk Shifting		0.38		0.35		0.41
		(8.50)		(8.47)		(8.11)
Adjusted R-Squared	0.11	0.56	0.09	0.52	0.11	0.56

Table 7. General characteristics of the portfolios of the funds sorted on the DR
This table shows the average characteristics for the funds in each DR decile portfolio. The DR is defined as the ratio of the weighted average volatility of assets in the portfolio to the overall portfolio volatility. In each month, we divide all the funds into decile portfolios based on the DR value. We then calculate the average fund information level for each decile portfolio. The proportion of the asset type represents the average percentage invested in each asset.

	Low DR	2	3	4	5	6	7	8	9	High DR
Average DR	1.55	1.67	1.74	1.80	1.86	1.92	1.99	2.08	2.20	2.64
Average Return	0.36%	0.40%	0.44%	0.50%	0.56%	0.65%	0.71%	0.82%	0.88%	0.86%
Standard Deviation	1.51%	1.38%	1.34%	1.31%	1.31%	1.32%	1.32%	1.32%	1.30%	1.20%
Skewness	-0.019	-0.034	-0.040	-0.050	-0.060	-0.068	-0.078	-0.093	-0.103	-0.125
Kurtosis	1.81	1.40	1.37	1.33	1.30	1.25	1.23	1.14	1.09	1.19
TNA (millions)	1270.2	1452.0	1442.1	1468.1	1426.7	1310.9	1314.3	1268.4	1241.0	1200.3
Age	14.1	14.9	14.8	14.5	14.3	13.9	13.6	13.1	12.4	11.9
Flow	-0.16%	-0.07%	0.00%	0.07%	0.19%	0.28%	0.31%	0.45%	0.56%	0.83%
Turnover Ratio	0.84	0.77	0.79	0.80	0.82	0.85	0.90	0.91	0.93	0.95
Expense Ratio	1.21%	1.15%	1.14%	1.17%	1.19%	1.21%	1.24%	1.26%	1.30%	1.40%
Management Fees	0.69%	0.66%	0.66%	0.67%	0.68%	0.70%	0.72%	0.74%	0.77%	0.86%
Number of Stocks	88.1	103.9	118.1	126.3	130.7	133.1	135.7	147.5	153.7	129.8
Proportion of Common Stock (%)	95.66	95.89	95.74	95.20	95.00	94.84	94.68	94.27	93.71	91.64
Proportion of Preferred Stock (%)	0.028	0.022	0.020	0.022	0.021	0.024	0.026	0.028	0.040	0.047
Proportion of Cash (%)	1.94	1.91	2.06	2.44	2.52	2.77	2.93	2.99	3.53	5.26
Proportion of Bonds (%)	0.27	0.25	0.25	0.36	0.40	0.38	0.38	0.51	0.72	0.89
Proportion of Others (%)	1.80	1.54	1.54	1.63	1.61	1.63	1.72	1.72	1.68	1.65

Table 8. Investment style- and managerial skill-related characteristics of the portfolios of funds sorted on the DR

This table shows the average characteristics for funds in each DR decile portfolio. The DR is defined as the ratio of the weighted average volatility of assets in the portfolio to the overall portfolio volatility. In each month, we divide all the funds into decile portfolios based on the DR value. We then calculate the average fund information level of each decile portfolio. We group stocks listed in the CRSP into respective deciles according to information style. Using the information decile of the stocks held by a mutual fund, we calculate the average style score for each DR-sorted fund portfolio. The style scores have values between one and ten, with a larger value indicating the fund has more stocks of the corresponding style.

	Low DR	2	3	4	5	6	7	8	9	High DR
Average DR	1.55	1.67	1.74	1.80	1.86	1.92	1.99	2.08	2.20	2.64
Beta Score	5.83	5.80	5.81	5.82	5.88	5.93	5.98	6.02	6.03	5.95
Size Score	9.67	9.65	9.58	9.49	9.34	9.14	8.89	8.58	8.22	7.62
Book-to-Market Score	3.90	3.94	3.91	3.93	3.96	4.04	4.10	4.16	4.25	4.57
Momentum Score	6.03	6.02	6.04	6.08	6.15	6.17	6.23	6.27	6.28	6.29
Standard Deviation Score	2.78	2.75	2.83	2.92	3.10	3.30	3.51	3.75	3.99	4.31
Skewness Score	4.32	4.32	4.36	4.39	4.46	4.53	4.61	4.68	4.76	4.89
Analyst Coverage Score	8.19	8.14	8.05	7.91	7.68	7.38	7.06	6.67	6.27	5.62
Numbers of Institutional Ownership Score	9.79	9.76	9.69	9.61	9.48	9.30	9.09	8.82	8.51	7.96
Active Share	69.01%	66.50%	67.08%	68.84%	71.73%	75.64%	78.92%	82.25%	85.22%	89.17%
Tracking Error	7.58%	5.96%	5.61%	5.64%	5.90%	6.35%	6.47%	6.79%	7.22%	8.77%
ICI	5.74%	3.78%	3.49%	3.63%	3.71%	3.97%	4.24%	4.27%	4.65%	5.71%
R-Squared	92.64%	94.04%	94.06%	93.67%	93.21%	92.61%	92.03%	91.58%	90.93%	88.21%
Risk Shifting	-0.10%	0.10%	0.16%	0.21%	0.26%	0.35%	0.45%	0.55%	0.71%	1.05%
Return Gap	-0.004%	-0.010%	-0.004%	-0.013%	-0.015%	-0.004%	-0.006%	-0.004%	0.002%	-0.025%

Table 9. DR, concentration ratio, and correlation of the assets of each skill measure-sorted portfolio

This table shows the average value of DR-related information for the decile portfolio formed by various skill measures, including the DR, Active Share, R-squared, the ICI, and the number of stocks. In each month, we divide all the funds into deciles based on each skill measure and calculate the average fund level of DR-related information for each decile portfolio. The DR is our primary measure, which is defined as the ratio of the weighted average volatility of assets in the portfolio to the overall portfolio volatility. We decompose the DR into a weighted concentration measure and a weighted correlation measure, according to the equation $DR = [CORR(1 - CR) + CR)]^{-0.5}$, where CORR is the volatility-weighted average correlation of the assets in the portfolio, $CORR = \frac{\sum_{i \neq j}(w_i \sigma_i w_j \sigma_j)\rho_{i,j}}{\sum_{i \neq j}(w_i \sigma_i w_j \sigma_j)}$, and CR is the volatility-weighted concentration ratio (CR) of the portfolio, $\mathrm{CR} = \frac{\sum_i (w_i \sigma_i)^2}{(\sum_i w_i \sigma_i)^2}$.

Sorting Variable	Low	2	3	4	5	6	7	8	9	High
Panel A: Average Value of the DR										
DR	1.55	1.67	1.74	1.80	1.86	1.92	1.99	2.08	2.20	2.64
Active Share	1.90	1.88	1.90	1.93	1.97	2.03	2.10	2.15	2.22	2.42
R-Squared	2.19	2.03	1.99	1.97	1.95	1.92	1.89	1.87	1.83	1.81
ICI	1.83	1.90	1.92	1.94	1.94	1.95	1.95	1.98	2.01	2.01
Number of Stocks	1.90	1.91	1.91	1.92	1.94	1.94	1.95	1.97	1.99	2.01
Panel B: Average Value of the Concentration Ratio (CR)										
DR	0.031	0.025	0.023	0.023	0.022	0.022	0.022	0.021	0.020	0.024
Active Share	0.014	0.018	0.021	0.024	0.025	0.024	0.023	0.023	0.025	0.035
R-Squared	0.039	0.029	0.026	0.025	0.023	0.022	0.020	0.019	0.017	0.014
ICI	0.015	0.018	0.020	0.021	0.022	0.022	0.023	0.025	0.027	0.038
Number of Stocks	0.053	0.035	0.029	0.025	0.022	0.019	0.017	0.015	0.012	0.008
Panel C: Average Value of the Correlation of the Assets (CORR)										
DR	0.40	0.34	0.31	0.29	0.27	0.25	0.24	0.22	0.19	0.12
Active Share	0.27	0.27	0.26	0.25	0.24	0.22	0.21	0.20	0.18	0.14
R-Squared	0.18	0.22	0.23	0.24	0.25	0.26	0.26	0.27	0.29	0.29
ICI	0.29	0.26	0.25	0.25	0.25	0.25	0.25	0.24	0.23	0.22
Number of Stocks	0.24	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.24	0.24

Table 10. Portfolio construction-related characteristics of each skill measure-sorted portfolio

This table shows the average value of the portfolio construction-related information for the decile portfolios formed by the various skill measures, including the DR, Active Share, R-squared, the ICI, and the number of stocks. In each month, we divide all the funds into decile portfolios based on each skill measure and calculate the average fund level of information, such as the number of stocks and the proportion invested in common stocks, of each decile portfolio.

Sorting Variable	Low	2	3	4	5	6	7	8	9	High
Panel A: Average Value of the Number of Stocks										
DR	88.1	103.9	118.1	126.3	130.7	133.1	135.7	147.5	153.7	129.8
Active Share	302.5	144.0	120.3	107.8	108.4	110.1	106.3	96.6	78.7	56.2
R-Squared	60.2	73.1	83.1	89.9	99.1	108.9	124.1	144.9	168.5	311.8
ICI	229.5	175.2	141.7	125.9	115.8	111.3	107.8	97.8	87.5	74.5
Number of Stocks	29.49	43.41	53.36	63.70	74.30	86.77	102.42	126.86	183.58	502.92
Panel B: Average Value of the Proportion of Common Stocks										
DR	95.66	95.89	95.74	95.20	95.00	94.84	94.68	94.27	93.71	91.64
Active Share	96.55	95.83	95.66	95.65	96.03	95.49	95.46	94.48	94.71	93.51
R-Squared	92.50	94.35	94.67	94.92	94.77	94.77	94.90	94.87	95.18	95.52
ICI	96.17	94.90	94.63	94.59	94.47	94.37	94.72	94.29	94.17	94.01
Number of Stocks	93.59	94.08	94.38	94.34	94.85	95.25	95.08	95.08	94.97	94.78

Table 11. Relation between the DR and fund activity and selectivity

This table shows future fund performance when the funds are double scored for 25 (5 x 5) fund portfolios. We first sort funds into quintiles by the DR and then subdivide the funds into quintile by Active Share or R-squared within each DR quintile. The raw return represents the average monthly net return of the fund portfolios. We also compute the monthly four-factor alpha of the Fama–French four-factor model, including the market, size, book-to-market, and momentum factors.

	Net Return					Four-Factor Alpha				
	Low DR	2	3	4	High DR	Low DR	2	3	4	High DR
Panel A: Funds sorted by the DR and then Active Share (AS)										
Low AS	-0.22	-0.04	0.04	0.28	0.37	-0.19	-0.08	-0.05	-0.02	-0.07
	(-0.47)	(-0.09)	(0.10)	(0.66)	(0.84)	(-2.27)	(-1.82)	(-0.94)	(-0.24)	(-0.64)
2	-0.15	-0.02	0.16	0.40	0.50	-0.16	-0.07	-0.04	0.05	0.04
	(-0.33)	(-0.04)	(0.37)	(0.92)	(1.08)	(-1.70)	(-1.32)	(-0.54)	(0.45)	(0.35)
3	-0.10	0.04	0.22	0.51	0.72	-0.09	-0.04	-0.04	0.09	0.11
	(-0.20)	(0.10)	(0.51)	(1.11)	(1.51)	(-0.76)	(-0.67)	(-0.50)	(0.81)	(0.81)
4	-0.09	0.14	0.39	0.50	0.74	-0.05	-0.04	0.04	0.04	0.14
	(-0.17)	(0.31)	(0.86)	(1.03)	(1.57)	(-0.34)	(-0.41)	(0.31)	(0.35)	(1.07)
High AS	0.14	0.18	0.36	0.62	0.85	-0.05	-0.02	0.01	0.12	0.12
	(0.23)	(0.35)	(0.69)	(1.25)	(1.69)	(-0.30)	(-0.12)	(0.05)	(0.99)	(1.02)
High-Low	0.36	0.22	0.29	0.34	0.44	0.15	0.07	0.06	0.14	0.19
	(1.36)	(1.05)	(1.28)	(2.38)	(3.08)	(0.98)	(0.48)	(0.46)	(1.30)	(1.80)
Panel B: Funds sorted by the DR and then R-squared (RSQ)										
Low RSQ	0.31	0.50	0.60	0.74	0.79	-0.16	-0.03	0.00	0.07	0.08
	(0.74)	(1.29)	(1.54)	(1.95)	(2.17)	(-1.73)	(-0.35)	(0.01)	(0.69)	(0.91)
2	0.23	0.42	0.50	0.69	0.90	-0.16	-0.04	-0.07	0.02	0.14
	(0.55)	(1.11)	(1.32)	(1.76)	(2.30)	(-1.68)	(-0.72)	(-1.03)	(0.20)	(1.37)
3	0.21	0.34	0.54	0.68	0.87	-0.18	-0.09	-0.01	0.02	0.10
	(0.52)	(0.89)	(1.42)	(1.76)	(2.18)	(-2.25)	(-1.34)	(-0.19)	(0.26)	(1.10)
4	0.20	0.30	0.48	0.68	0.77	-0.16	-0.12	-0.06	0.01	0.00
	(0.48)	(0.80)	(1.28)	(1.73)	(1.96)	(-1.79)	(-1.87)	(-1.06)	(0.15)	(0.00)
High RSQ	0.17	0.29	0.40	0.64	0.78	-0.20	-0.10	-0.10	-0.03	0.01
	(0.41)	(0.81)	(1.09)	(1.62)	(1.89)	(-2.50)	(-2.41)	(-2.21)	(-0.52)	(0.11)
High-Low	-0.14	-0.20	-0.20	-0.11	-0.01	-0.04	-0.08	-0.10	-0.10	-0.08
	(-1.13)	(-1.69)	(-1.82)	(-1.16)	(-0.11)	(-0.47)	(-0.94)	(-1.08)	(-1.18)	(-1.02)

Table 12. Relation between the DR and concentration-related skill measures

This table shows future fund performance when the funds are double scored for 25 (5 x 5) fund portfolios. We first sort funds into quintiles by the DR and then subdivide the funds into quintiles by the ICI or the number of stocks within each DR quintile. The raw return represents the average monthly net return of the fund portfolios. We also compute the monthly four-factor alpha of the Fama–French four-factor model, including the market, size, book-to-market, and momentum factors.

	Net Return					Four-Factor Alpha				
	Low DR	2	3	4	High DR	Low DR	2	3	4	High DR
Panel A: Funds sorted by the DR and then the ICI										
Low ICI	0.24	0.30	0.40	0.59	0.71	-0.15	-0.10	-0.08	-0.03	-0.01
	(0.65)	(0.86)	(1.12)	(1.56)	(1.86)	(-3.10)	(-3.39)	(-1.71)	(-0.53)	(-0.16)
2	0.23	0.36	0.49	0.68	0.78	-0.17	-0.09	-0.05	0.01	0.04
	(0.60)	(0.98)	(1.32)	(1.75)	(1.96)	(-2.40)	(-2.16)	(-0.81)	(0.13)	(0.46)
3	0.23	0.40	0.51	0.67	0.82	-0.16	-0.07	-0.06	0.01	0.07
	(0.59)	(1.08)	(1.33)	(1.71)	(2.09)	(-1.96)	(-1.38)	(-0.98)	(0.13)	(0.74)
4	0.21	0.34	0.49	0.73	0.91	-0.19	-0.11	-0.07	0.04	0.13
	(0.51)	(0.86)	(1.26)	(1.86)	(2.33)	(-2.38)	(-1.41)	(-1.00)	(0.39)	(1.27)
High ICI	0.18	0.44	0.64	0.76	0.86	-0.18	-0.02	0.03	0.07	0.11
	(0.36)	(1.10)	(1.64)	(1.92)	(2.22)	(-1.29)	(-0.18)	(0.29)	(0.64)	(0.94)
High-Low	-0.06	0.14	0.24	0.17	0.15	-0.03	0.08	0.11	0.10	0.12
	(-0.28)	(1.26)	(2.35)	(1.86)	(1.89)	(-0.27)	(0.97)	(1.28)	(1.16)	(1.52)
Panel B: Funds sorted by the DR and then the number of stocks (NumStocks)										
Low NumStocks	0.23	0.40	0.47	0.68	0.72	-0.15	-0.03	-0.06	0.06	0.06
	(0.55)	(1.09)	(1.30)	(1.85)	(2.01)	(-1.97)	(-0.48)	(-0.82)	(0.74)	(0.73)
2	0.21	0.34	0.49	0.66	0.81	-0.15	-0.08	-0.02	0.04	0.07
	(0.54)	(0.92)	(1.32)	(1.77)	(2.04)	(-2.15)	(-1.44)	(-0.30)	(0.43)	(0.70)
3	0.20	0.35	0.53	0.70	0.88	-0.17	-0.09	0.00	0.03	0.11
	(0.50)	(0.93)	(1.43)	(1.78)	(2.21)	(-2.14)	(-1.47)	(0.06)	(0.31)	(1.08)
4	0.21	0.36	0.51	0.67	0.83	-0.19	-0.12	-0.06	-0.02	0.06
	(0.51)	(0.94)	(1.30)	(1.67)	(2.10)	(-1.81)	(-1.93)	(-0.91)	(-0.28)	(0.68)
High NumStocks	0.25	0.39	0.53	0.72	0.85	-0.20	-0.07	-0.09	-0.01	0.03
	(0.57)	(1.04)	(1.35)	(1.76)	(2.09)	(-2.11)	(-1.24)	(-1.81)	(-0.09)	(0.45)
High-Low	0.02	-0.01	0.06	0.04	0.12	-0.05	-0.04	-0.03	-0.07	-0.02
	(0.21)	(-0.15)	(0.58)	(0.43)	(1.48)	(-0.68)	(-0.91)	(-0.50)	(-1.21)	(-0.48)

Appendix: Future performance based on portfolios of funds

Table A.1. Future performance based on portfolios of funds sorted by DR(VaR)

This table shows the returns on the equal-weighted decile portfolios of active US equity mutual funds from January 2000 through December 2014. Our first alternative DR measure, DR(VaR), is defined as the ratio of the weighted average VaR of assets in the portfolio to the overall portfolio VaR. We form portfolios sorted by the past DR(VaR) over the last 12 months. This table also reports the Fama–French four-factor regression results for monthly returns on DR-sorted portfolios. Here, MKT, SMB, HML, and UMD represent, respectively, the coefficients of the market, size, value, and momentum factors of Fama–French four-factor regression using the net return.

DR(VaR) Decile	Gross Return		Net Return		MKT	SMB	HML	UMD	Adj R2
	Return	Alpha	Return	Alpha					
Low	0.29	-0.12	0.19	-0.22	1.11	0.07	-0.21	0.04	96%
	(0.69)	(-1.35)	(0.46)	(-2.43)	(50.60)	(2.32)	(-7.56)	(2.45)	
2	0.39	-0.02	0.29	-0.12	1.08	-0.01	-0.13	0.01	97%
	(0.97)	(-0.34)	(0.74)	(-1.76)	(68.20)	(-0.64)	(-6.44)	(1.24)	
3	0.41	-0.02	0.32	-0.11	1.05	-0.03	-0.05	0.00	98%
	(1.09)	(-0.29)	(0.84)	(-2.09)	(83.99)	(-1.74)	(-3.19)	(0.33)	
4	0.51	0.02	0.41	-0.07	1.03	0.05	-0.01	0.01	99%
	(1.35)	(0.56)	(1.09)	(-1.64)	(99.98)	(3.97)	(-0.53)	(1.43)	
5	0.56	0.04	0.46	-0.05	1.01	0.10	0.04	0.01	98%
	(1.50)	(0.85)	(1.25)	(-1.13)	(86.29)	(6.34)	(2.91)	(0.89)	
6	0.63	0.06	0.53	-0.04	1.00	0.15	0.10	0.02	97%
	(1.69)	(1.01)	(1.42)	(-0.56)	(66.37)	(7.90)	(4.96)	(1.52)	
7	0.71	0.08	0.61	-0.02	1.00	0.24	0.14	0.03	97%
	(1.87)	(1.27)	(1.60)	(-0.26)	(63.15)	(11.77)	(6.83)	(2.54)	
8	0.83	0.15	0.73	0.04	0.99	0.32	0.19	0.02	96%
	(2.12)	(1.85)	(1.86)	(0.56)	(51.72)	(12.92)	(7.68)	(1.41)	
9	0.90	0.17	0.79	0.06	0.98	0.39	0.24	0.01	96%
	(2.28)	(1.99)	(2.01)	(0.74)	(48.51)	(15.04)	(9.42)	(0.96)	
High	0.97	0.21	0.85	0.09	0.91	0.45	0.29	-0.01	95%
	(2.50)	(2.35)	(2.21)	(1.07)	(43.18)	(16.34)	(10.84)	(-0.86)	
High-Low	0.68	0.33	0.66	0.32	-0.20	0.38	0.51	-0.05	55%
	(3.52)	(2.47)	(3.45)	(2.36)	(-6.08)	(9.17)	(12.28)	(-2.24)	

Table A.2. Future performance based on the portfolios of funds sorted on DR(ES)

This table shows the returns on the equal-weighted decile portfolios of active US equity mutual funds from January 2000 through December 2014. Our second alternative DR measure, DR(ES), is defined as the ratio of the weighted average ES of assets in the portfolio to the overall portfolio ES. We form portfolios sorted by the past DR(ES) over the last 12 months. This table also reports the Fama–French four-factor regression results for the monthly returns on DR-sorted portfolios. Here, MKT, SMB, HML, and UMD represent, respectively, the coefficients of the market, size, value, and momentum factors of Fama–French four-factor regression using the net return.

	Gross Return		Net Return						
DR Decile	Return	Alpha	Return	Alpha	MKT	SMB	HML	UMD	Adj R2
Low	0.32	-0.11	0.22	-0.21	1.09	0.10	-0.20	0.06	96%
	(0.78)	(-1.28)	(0.54)	(-2.43)	(52.75)	(3.56)	(-7.57)	(3.64)	
2	0.39	-0.04	0.30	-0.13	1.05	0.10	-0.16	0.03	97%
	(1.00)	(-0.57)	(0.76)	(-1.96)	(64.68)	(4.87)	(-7.90)	(2.53)	
3	0.43	-0.02	0.33	-0.11	1.05	0.01	-0.06	0.01	99%
	(1.12)	(-0.40)	(0.87)	(-2.39)	(93.65)	(0.96)	(-4.25)	(1.60)	
4	0.50	0.02	0.41	-0.07	1.04	0.03	0.00	0.02	99%
	(1.34)	(0.54)	(1.09)	(-1.59)	(97.44)	(2.22)	(0.05)	(2.60)	
5	0.56	0.05	0.47	-0.05	1.03	0.08	0.03	0.02	99%
	(1.49)	(1.01)	(1.23)	(-1.02)	(90.70)	(5.61)	(1.97)	(2.01)	
6	0.62	0.06	0.52	-0.04	1.03	0.11	0.11	0.01	97%
	(1.64)	(1.01)	(1.38)	(-0.58)	(68.57)	(5.42)	(5.71)	(0.91)	
7	0.69	0.08	0.59	-0.02	1.00	0.18	0.15	0.00	97%
	(1.81)	(1.22)	(1.55)	(-0.24)	(60.40)	(8.45)	(7.26)	(-0.05)	
8	0.80	0.13	0.70	0.03	0.99	0.30	0.19	0.01	96%
	(2.07)	(1.64)	(1.81)	(0.34)	(51.91)	(12.13)	(7.96)	(1.02)	
9	0.90	0.19	0.80	0.09	0.96	0.37	0.23	0.00	95%
	(2.32)	(2.22)	(2.05)	(1.00)	(46.26)	(14.01)	(8.75)	(-0.25)	
High	0.96	0.20	0.85	0.09	0.92	0.44	0.31	-0.01	95%
	(2.49)	(2.23)	(2.20)	(0.98)	(42.61)	(15.83)	(11.13)	(-0.85)	
High-Low	0.65	0.31	0.63	0.29	-0.17	0.35	0.51	-0.07	54%
	(3.44)	(2.35)	(3.36)	(2.24)	(-5.43)	(8.43)	(12.49)	(-2.95)	