The Impact of Ownership Concentration on Green Fund Performance

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Abstract: Due to the "carbon peak" and "carbon neutrality" targets proposed in 2020, investors do not understand green investment concepts and find assessing funds' actual performance and operation challenging. This paper uses Chinese stock and equity-biased green funds from 2016 to 2022 as a sample, constructing a comprehensive return index as the performance evaluation indicator. A panel data model is established for multiple linear regression to study the relationship between ownership and industry concentration of green funds and their performance. The study finds that ownership concentration in green funds positively correlates with fund performance, while industry concentration negatively correlates with fund performance. This suggests that fund managers have good stock-picking abilities and informational advantages.

1. Introduction

Green, low-carbon development has become a common pursuit and trend in the international community. Portfolios that include the green economy in diversified investments continue to attract attention for their potential to reduce asset allocation risk. This poses challenges to portfolio theory and impacts the construction of efficient portfolios, making asset allocation in new green funds a critical issue, particularly under the regulatory constraints of the Chinese market.

Fund types such as open-end stock funds and equity-biased hybrid funds tend to invest heavily in stocks, resulting in higher performance volatility and risk. By analyzing the investment patterns of green fund managers, we can further explore their impact on fund performance, using ownership concentration as a proxy for stock-picking ability. Analyzing how ownership concentration affects fund returns helps understand fund managers' investment strategies. It allows investors to select funds managed by skilled managers, aligning with their risk-return preferences.

Tsolas and Charles (2015)[1] used two types of Data Envelopment Analysis (DEA) to evaluate the performance of green ETFs. Their findings are valuable for investors and fund managers in risk mitigation and portfolio selection. Fulkerson and Riley (2019)[2] found a strong positive correlation between concentration and fund performance in high-risk portfolios. Qin and Wang (2021)[3] noted that changes positively influence abnormal returns in corporate bond funds in portfolio concentration. Goldman et al. (2016)[4] observed that increasing the number of managers reduces industry concentration and deteriorates fund performance. Despite a general decline in concentration over the past two decades, Eide et al. (2021)[5] showed a significant positive relationship between concentration and profitability in the Norwegian market.

This paper uses Chinese open-end stock green funds as samples to analyze the impact factors on fund performance, focusing on stock and industry concentration. It delves into the investment strategies of green funds and explores the relationship between fund performance and holding concentration.

The study is divided into five chapters: Chapter 2 reviews the literature, Chapter 3 covers research methods and data, Chapter 4 presents empirical results, and Chapter 5 provides conclusions and suggestions.

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2. Literature review

Some papers have studied the relationship between fund performance and holding concentration. Fulkerson and Riley (2019)[2] found a strong positive correlation between concentration and fund performance in high-risk portfolios. They argue that fund managers only increase portfolio concentration when they believe their information is highly valuable and can offset increased concentration risks. Qin and Wang (2021)[3] concluded that abnormal returns in corporate bond funds are positively influenced by changes in portfolio concentration, suggesting that funds concentrated in corporate bonds bring more value than diversified funds. However, concentrated investments can incur liquidity costs that erode the potential informational benefits. Goldman et al. (2016)[4] noted that when the number of fund managers increases, industry concentration decreases, and fund performance deteriorates.

Fleta-Asín and Munoz (2023)[6] found that funds with portfolios concentrated in a single country positively impact financial performance, while a large formal institutional distance between investor and investee markets negatively impacts international mutual fund performance. However, country portfolio concentration can mitigate the negative impact of institutional distance on fund performance. Jiang et al. (2024)[7] pointed out that supplier concentration is negatively correlated with corporate innovation, while customer concentration is positively correlated; industry concentration enhances the positive impact of customer concentration on corporate innovation performance. Cremers et al. (2022)[8] discovered that funds with benchmark discrepancies tend to be riskier than indicated by their prospectus benchmarks. Paudel and Naka (2023)[9] found that as ETF size increases, size-adjusted returns decrease, with negative returns for the largest funds. This indicates that economies of scale negatively impact traditional actively managed mutual funds and ETFs. Liang et al. (2024)[10] showed that ESG fund performance positively correlates with institutional ownership, with external institutional investors preferring historically high-performing funds and fund management companies holding historically underperforming ones.

Some scholars found that industry concentration affects fund managers' effort levels, impacting fund performance. For example, Feldman et al. (2020)[11] used the Active Fund Management Industry (AFMI) theoretical model, showing that AFMI performance and scale depend on industry concentration. They argued that as AFMI concentration decreases, fund managers' effort motivation diminishes, leading to lower AFMI performance and a smaller scale.

3. Data and Method

In this study, we selected hybrid funds and stock funds. If graded funds were available, we chose the A-grade or leading fund. Additionally, we used keywords to filter green funds, including terms such as "beautiful China," "green environment protection," "low carbon," "new energy," and "sustainable development," resulting in 153 green funds. After excluding samples that had been missing data for less than three months since their inception on January 1, 2016, we obtained 35 funds. The sample period is from January 1, 2016, to December 31, 2022, providing seven years of data for analysis. The sample data were sourced from the "Wind" and "East Money Choice" databases. Table 1 provides the definitions of the main variables used in this paper.

Table 1 Definitions

Variables	Abbreviation	Definitions
Ownership Concentration	OC	The concentration of ownership in individual stocks.
Industry Concentration	IC	The concentration of investments in specific industries.
Turnover rate	Turnover	The ratio of the total value of stocks bought and sold by the fund to the fund's net asset value.
Shareholding ratio	Ratio	The ratio of the total market value of all stock investments in the fund's portfolio to the fund's net asset value.
Fund size	Size	The fund's net asset value at the end of the year, with the logarithm of this value used as a control variable.
Risk	Risk	Measured by subtracting the standard deviation of the benchmark return from the standard deviation of the fund's net asset growth rate.
Volatility	Volatility	The annualized standard deviation of the historical returns of the green fund during the sample period.

3.1. Construction of Composite Return Indicators for Fund Performance

Table 2 presents the composite performance evaluation indicator for fund performance, established using the principal component analysis (PCA) method, and shows the results of the Eigenvalue distribution. Since a single fund performance indicator cannot comprehensively reflect fund income, this paper uses PCA to construct a composite indicator that better reflects overall performance. Table 3 displays the component score coefficient matrix, incorporating seven fund performance indicators used in PCA: excess return rate (P), Sharpe ratio (S), Jensen's Alpha (A), Treynor ratio (T), Sortino ratio (S), Jensen index (J), and Calmar ratio (C). Before conducting PCA, these indicators are standardized to avoid significant differences between variables that could affect the analysis.

Table 2 PCA results

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp. 1	6.255	5.729	0.894	0.894
Comp. 2	.527	.436	0.075	0.969
Comp. 3	.091	.014	0.013	0.982
Comp. 4	.076	.043	0.011	0.993
Comp. 5	.034	.019	0.005	0.998
Comp. 6	.015	.013	0.002	1.000
Comp. 7	.002	-	0.000	1.000

Notes: The KMO (Kaiser-Meyer-Olkin) value is 0.845, which exceeds the threshold of 0.6, indicating the data is suitable for principal component analysis (PCA). The P-value is less than 0.05, confirming that PCA can be performed.

Table 3 Component Score Coefficient Matrix

Variable	Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5	Comp. 6	Comp. 7
Z_P	0.390	0.045	-0.169	-0.699	0.396	0.415	0.018
Z_S	0.387	-0.291	-0.279	0.323	-0.210	0.270	0.683
Z_A	0.377	0.398	0.161	-0.289	-0.762	-0.089	-0.041
Z_T	0.393	-0.146	-0.402	-0.076	0.157	-0.794	-0.050
Z_S	0.386	-0.320	-0.131	0.321	-0.123	0.307	-0.720
Z_J	0.334	0.731	0.029	0.463	0.371	0.045	0.012
Z_C	0.376	-0.313	0.830	0.021	0.202	-0.145	0.102

The results show that only one principal component has an eigenvalue greater than 1, with the first component being 6.255. This component explains 89.4% of the variance, resulting in a cumulative variance explanation rate of 89.4%. Therefore, the principal component analysis extracts only one principal component. We use the eigenvalue greater than 1 of this single principal component to weight and obtain the composite performance indicator for the fund, as follows:

$$\begin{aligned} Y = {} & 0.390\times Z\_P + 0.387\times Z\_S + 0.377\times Z\_A + 0.393\times Z\_T + 0.386\times Z\_S \\ & + 0.334\times Z\_J + 0.376\times Z\_C \end{aligned} \tag{1}$$

3.2. Model

This study uses a panel regression model to analyze the impact of stock and industry concentration on fund performance. It explores the relationship between changes in fund ownership concentration and performance. It also controls for factors such as fund turnover rate, shareholding ratio, risk, fund size, and annualized volatility. The regression model is as follows:

$$Y_{it} = \alpha_0 + \beta_1 OC_{it} + \beta_2 IC_{it} + \sum_i^t \gamma_i controls_{it} + \varepsilon_{it} \tag{2}$$

where Y is the composite performance indicator of the fund, *OC* is the ownership concentration, *IC* is the industry concentration, and *Controls* represents the aforementioned control variables.

4. Results

Table 4 presents the descriptive statistics, showing that fund performance (Y) is variable, with a minimum of -3.853, a maximum of 5.683, and a standard deviation of 2.487. Ownership concentration (OC) averages 56.610, indicating that many funds focus on a few stocks. Industry concentration (IC) has a mean of 24.316, suggesting varied industry focus. The turnover rate averages 501.227, reflecting frequent trading. The shareholding ratio (Ratio) averages 83.874, indicating a high level of stock investment. Risk has a mean of 0.471, showing moderate variability. The logarithm of fund size (ln(Size)) averages 1.932, reflecting a wide range of fund sizes. Volatility averages 0.233, indicating consistent historical return volatility across the sample.

Table 4 Descriptive Statistics

Variable	N	Mean	Min	p50	Max	SD
Y	245	-0.004	-3.853	-0.353	5.683	2.487
OC	245	56.610	22.740	54.210	92.460	15.255
IC	245	24.316	0.009	22.118	66.878	15.538
Turnover	245	501.227	57.176	366.265	2390.040	451.473
Ratio	245	83.874	30.260	87.490	94.870	11.876
Risk	245	0.471	-0.330	0.460	1.410	0.342
ln(Size)	245	1.932	-2.120	2.249	5.080	1.668
Volatility	245	0.233	0.099	0.230	0.397	0.066

Empirical Results from Table 5, at the 5% confidence level, ownership concentration is significantly positively correlated with the new composite return indicator for fund performance. The industry concentration remains negatively correlated with the composite performance indicator at the 1% confidence level. The turnover rate is negatively correlated with the composite performance indicator but not significantly. Shareholding ratio and fund size positively correlate with the composite performance indicator at the 1% confidence level. Risk is negatively correlated with the 10% confidence level composite performance indicator. These results imply that stock and industry concentration significantly impact fund performance, demonstrating robustness even after constructing the new performance composite return indicator.

Table 5 Results

Variable	β	*t*-stat.
OC	0.037**	(3.01)
IC	-0.052***	(-4.83)
Turnover	-0.000	(-0.44)
Ratio	0.086***	(4.62)
Risk	-1.532*	(-2.10)
Ln (Size)	0.527***	(4.25)
Volatility	-4.067	(-1.34)
_cons	-7.354***	(-3.76)
N	245.000	
$R^{\wedge 2}$	0.211	

Notes: *<0.1; **<0.05; ***<0.01.

5. Conclusion and suggestion

This paper uses panel data to study Chinese open-end and equity-biased green funds from 2016 to 2022, analyzing how fund managers' stock and industry concentration affect fund performance. The dependent variable is the fund's comprehensive performance indicator, with stock and industry concentration as independent variables. Control variables include turnover rate, shareholding ratio, risk, size, and annualized volatility. Results show that (1) Ownership concentration positively correlates with fund performance at the 5% confidence level, indicating higher risk and potential returns. (2) Industry concentration is significantly negatively correlated with fund performance at the 1% significance level, suggesting that focusing on popular industries can lead to poor performance due to overconfidence and market shifts. Future research suggests that studies could explore the impact of different market conditions on these relationships and investigate the role of other factors, such as macroeconomic variables and regulatory changes.

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