J Prod Anal (2014) 41:141–151
DOI 10.1007/s11123-012-0331-x

Market conditions and the effect of diversification on mutual fund performance: should funds be more concentrative under crisis?

Jin-Li Hu · Tzu-Pu Chang · Ray Yeutien Chou

Published online: 10 January 2013

Abstract This paper investigates the non-monotonic and non-linear effect of diversification on mutual fund performance. We apply a frontier-based efficiency measure, the stochastic frontier approach, to estimate fund efficiency and the benefit of diversification. The empirical results indicate that concentration strategy may not be appropriate for fund managers, and the benefit of diversification disappears or negatively affects performance when a fund holds too large a number of different stocks. Moreover, this paper examines whether market conditions moderate the relation between diversification and fund performance. The result shows that the benefit of diversification increases within low market return, high market volatility, and financial crisis, implying that the number of stocks needed to achieve a well-diversified portfolio increases under such market conditions.

Keywords Diversification · Market conditions · Mutual funds · Non-monotonic effect · Stochastic frontier · Crisis

JEL Classification C30 · G11

J.-L. Hu (✉) · R. Y. Chou
Institute of Business and Management, National Chiao Tung University, 118, Chung-Hsiao W. Rd., Sec. 1, Taipei City 100, Taiwan
e-mail: jinlihu@mail.nctu.edu.tw; jinlihu@yahoo.com

T.-P. Chang · R. Y. Chou
Institute of Economics, Academia Sinica, 128, Academia Road, Section 2, Nankang, Taipei City 115, Taiwan

1 Introduction

The performance of mutual funds is not only the concern of investors, but is also regarded as an indicator to assess managers' achievements. Accordingly, the evaluation of fund performance has become a significant study issue over the past several decades. Interest in performance evaluation has more recently shifted to an emphasis on the determinants of fund performances, such as fund size, age, expenses, and the manager's tenure and education. Instead of the above various factors, this study focuses on the effect of diversification on fund performances. Asset allocation policy is a key factor to explain the variation of performance among funds or across time (Ibbotson and Kaplan 2000). Hence, it is valuable to analyze how diversification, one of the asset allocation policies, affects fund performance.

Diversification is widely accepted as a key principle of modern portfolio management (Shawky and Smith 2005). It is a fact that fund performance is composed of return and risk. In regards to risk, portfolio risk depends on the share of individual stock holdings and the variance–covariance matrix among its holdings (Statman 1987). Hence, theoretical models imply that an investment portfolio should be fully diversified to cut down risks (unsystematic risks), but how to construct a well-diversified portfolio still remains to be studied. Several research studies have suggested that a strong risk reduction of holdings can be realized by increasing the number of stocks (Domian et al. 2003, 2007; Statman 1987, 2004).

How portfolio diversification affects mutual fund performance has been proceed in recent research. In general, the literature finds that increasing the number of different stocks in a fund (or other diversification indices) will improve the fund's performance (Kaushik and Barnhart

2009; Pollet and Wilson 2008; Sapp and Yan 2008).[1] However, Shawky and Smith (2005) argue that there is a trade-off between diversification benefits and monitoring costs. Sapp and Yan (2008) also suggest that an over-diversified fund might underperform versus others when the manager is overloaded with a much larger number of stocks. Hence, it is reasonable that there exists an optimal number of stock holdings for mutual fund portfolios if the marginal diversification benefit is equal to the marginal monitoring costs.

For example, Evans and Archer (1968), one of the earliest studies on diversification effect, find that the economic benefits of diversification will be exhausted if a portfolio contains about ten stocks. Statman (1987) uses the securities market line method and concludes that a well-diversified portfolio should include at least 30 and 40 securities for a borrowing investor and a lending investor, respectively. Newbould and Poon (1993, 1996) summarize that a portfolio with 8 to 20 stocks can achieve the full benefit of diversification. However, they calculate the confidence intervals for both return and risk and recommend that an investor would need more than 100 stocks if he/she wants to be within 5 % of the average return as well as within 20 % of the average risk. Fabozzi (1999) suggests that firm-specific risk could be sufficiently diversified by constructing a portfolio of 20 randomly selected common stocks.

Domian et al. (2003) consider the concept of shortfall risk and show that investors need more than 60 stocks to avoid a significant shortfall risk. Sequentially, in later research they demonstrate that investors need at least 164 stocks to have a 1 % probability of underperforming Treasury bonds (Domian et al. 2007). Statman (2004) points out that the optimal level of diversification, where the marginal benefit is equal to the marginal cost of diversification, would exceed 300 stocks.

Instead of randomly selected or simulated portfolios discussed above, Shawky and Smith (2005)—the first study to examine the diversification issue for actual mutual fund portfolios—demonstrate a quadratic relation between risk-adjusted returns and the number of stocks held for US domestic equity funds after controlling several fund characteristics. They find that the optimum number of stocks is about 480 and a 90 % confidence interval ranges between 40 and 4,000 stocks in their work.

Whether a positive or a quadratic relation between fund performance and the degree of diversification is found in previous studies, those papers assume this relationship is consistent over a long time. In other words, the effect of diversification on fund performance is steady regardless of market conditions. These articles ignore the variability of market conditions and may lack some insights. Therefore, our paper proposes that market conditions may moderate the relationship between diversification and fund performance.

The main purpose of this study is to find out the time-varying effect of diversification on mutual fund performance in Taiwan's mutual fund industry. There are two reasons why we focus our analysis on Taiwan's case. First, the above-mentioned literature on the diversification effect places emphasis upon advanced countries' cases, especially the US market, but there is no focus on this issue for emerging markets. Taiwan's equity market, one of the major emerging markets in the world, is a shallow-plate market, meaning that it appears relatively volatile and risky. Thus, the diversification effect on portfolio may be more substantial in emerging markets. Second, with respect to Taiwan's mutual fund industry, it is a young and growing business that was established in 1983 and in the early stage highly controlled by the government. In contrast to the mutual fund industry in the US, a less developed one (e.g., that in Taiwan) provides a worse return-risk trade-off and less product sophistication (Ramos 2009). This implies that further analysis of the diversification effect to maximize the return-risk trade-off will benefit fund managers and investors in Taiwan.

This paper uses a stochastic frontier analysis (SFA), which can be proved to be a generalized Sharpe or Treynor index, to measure fund performance. Kothari and Warner (2001) and Cuthbertson et al. (2008) consider that one good performance measurement should handle the luck of a fund. The SFA approach could deal with such luck to capture statistical noises, including measurement errors or sampling biases. A special feature in Wang's (2002) SFA model is that it allows the determinants to have non-monotonic effects on fund performance. By adopting this model, the marginal diversification effect can be detected and the optimal level can be seen.

This paper tries to benefit previous works in the following issue. The relation among stocks and the variance–covariance matrix among holdings will change under different market conditions, implying that the marginal effect of diversification may be time-varying or market-dependent. With respect to this, it is true that the relation among stocks is time-varying (Ferson and Schadt 1996). Actually, stock market volatility can be approximated by the product of the average correlation between all pairs of stocks and the average volatility of all individual stocks (Pollet and Wilson 2010). Campbell et al. (2001) indicate that

[1] Kacperczyk et al. (2005) show a positive relationship between fund performance and portfolio concentration at industry levels. Sapp and Yan (2008) consider that the number of stock holdings is more intuitive than the divergence index used in Kacperczyk et al. (2005) to measure the degree of diversification. Pollet and Wilson (2008) and Sapp and Yan (2008) also present that the number of stock holdings is statistically and economically significant, but the divergence index is not.

aggregate stock market volatility remains stable while individual stocks become more volatile over the 1962–1997 periods, implying that there is a downward trend in the correlation among individual stocks. This finding can also be interpreted as an increase in the benefit of diversification, meaning that the number of stocks needed to achieve a well-diversified portfolio increases over time. In addition, the stock returns are more highly correlated when the market drops, such as during a financial crisis (Pollet and Wilson 2010). Hence, it is unclear how the effect of diversification on mutual fund portfolios varies within a devastating financial crisis, which may result in higher market volatility, individual stock volatility, and stronger correlation among all pairs of stocks.

The remainder of the paper is organized as follows. Section 2 introduces the used heteroscedastic stochastic frontier model as well as describes the data in details. Section 3 provides an empirical analysis and explains the nonlinear relationship between the benefit from diversification and fund performance. Section 4 concludes our study.

2 Methodology and data

2.1 Research methods: fund performance with efficiency measurement

This paper uses the efficiency measurement to measure funds' performance. Actually, the efficiency measurement is a relative performance measure, assuming that a best performing fund should be placed on the efficient frontier and provides a certain expected return at minimum risk. The distance from the frontier can then be deemed as the degree of each fund's underperformance.

With respect to the SFA method, one major efficiency measurement, only a few portfolio-related studies use this approach. Annaert et al. (2003) apply the SFA method to construct a CAPM-based performance index. Santos et al. (2005) then use the same idea to study the performance of Brazilian mutual funds. This paper applies the SFA to measure a generalized Sharpe ratio following the concepts of Shawky and Smith (2005). Although none of the previous literature has shown that the SFA approach is a generalized Sharpe ratio, a proof can be given in a straightforward way according to the idea of Choi (2006) and Brandouy et al. (2010) which prove that the Sharpe and Treynor indices are shown as special cases of the nonparametric efficiency performance measurement.

We illustrate this consideration with Fig. 1, which compares the SFA efficiency measure to the Sharpe ratio. Considering funds A and A* in Fig. 1, the Sharpe ratios for A and A* are R_A/σ_A and R^*/σ_A, respectively, indicating that fund A* has better performance in terms of the Sharpe ratio. With respect to the SFA measure, fund A* is the best (efficient) performer (i.e., $R^*/\beta\sigma_A = 1$) since A* lies on the efficient frontier obtained by SFA.[2] Therefore, the efficiency score of fund A is equal to $R_A/\beta\sigma_A$. In addition:

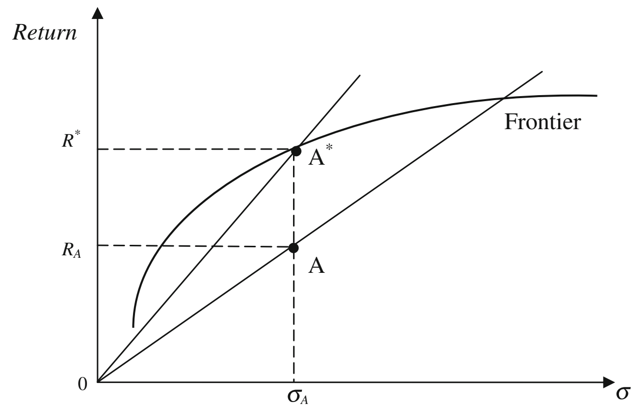

Fig. 1 The relation of efficiency measure and Sharpe ratio

$$\frac{R_A}{\beta\sigma_A} = \frac{R_A}{(R^*/\sigma_A)\sigma_A} = \frac{R_A/\sigma_A}{R^*/\sigma_A}.$$

This shows that the SFA efficiency score of fund A is its Sharpe ratio over that of the best-performing fund (A*). Hence, we can prove that the SFA measure is the Sharpe ratio relative to that of the best performer.

The stochastic frontier model for portfolio evaluation used in this paper is interpreted as follows. Suppose that the raw return for the ith fund and the risk-free return in year t are R_{it} and R_{ft}, respectively, where X_{it} and CV_{it} are vectors of the input variable and control variables, respectively. The SFA model specification for the production function, describing how the inputs efficiently generate the output, can be presented as below:

$$R_{it} - R_{ft} = f(X_{it}, CV_{it}) + \varepsilon_{it}, \quad \varepsilon_{it} = v_{it} - u_{it}, \quad v_{it} \sim N(0, \sigma_v^2),\ u_{it} \sim N^+(\mu_{it}, \sigma_{it}^2) \tag{1}$$

$$\mu_{it} = \delta_0 + Z_{it}\delta \tag{2}$$

$$\sigma_{it}^2 = \exp(\gamma_0 + Z_{it}\gamma) \tag{3}$$

Here, v_{it} is the stochastic error term with i.i.d. normal distribution, and u_{it} is the non-negative inefficiency effect that has a truncated normal distribution following observation-specific mean (μ_{it}) and variance (σ_{it}^2) of the pre-truncated distribution (for more detail, see Kumbhakar and

[2] Since this paper investigates the diversification effect within active portfolio management, the most efficient portfolio (i.e. capital market line) does not appear in our discussion. β is a parameter that satisfies $R^*/\beta\sigma_A$ is equal to one. In our following analysis, β is obtained through SFA according to Eq. (1).

Lovell 2000). The efficient frontier is equal to $f(X_{it}, CV_{it})$, meaning that the efficient funds would be placed on the frontier and any deviation from the frontier is attributed to the inefficiency effect and noises. The individual fund performance (efficiency) is computed by $\exp(-u_{it})$. Therefore, if the standard deviation of fund return is the single input, then Eq. (1) becomes a standardized Sharpe ratio in the range 0–1.

Equations (2) and (3) presented above estimate how the inefficiency effect is affected by some determinants (Z_{it}). These are the most flexible and best specifications to model the distributions of v_{it} and u_{it} (Lai and Huang 2010). Wang (2002) introduces the marginal effect, which allows determinants to have non-monotonic effects on the inefficiency effect (u_{it}), meaning that Z_{it} can positively (negatively) affect the inefficiency effect when the values of Z_{it} are within a certain range, and turn negative (positive) for values of Z_{it} outside the range. The marginal effects on $\mathrm{E}(u_{it})$ of the jth element of Z_{it} can be estimated as follows[3]:

$$\frac{\partial E(u_{it})}{\partial z[j]} = \delta[j]\left[1 - \Lambda\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right] - \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right] + \gamma[j]\,\frac{\sigma_{it}}{2}\left[(1+\Lambda^2)\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right] + \Lambda\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right] \tag{4}$$

Here, ϕ and Φ are the probability and cumulative density functions of a standard normal distribution, respectively; $\Lambda = \mu_{it}/\sigma_{it}$; $z[j]$ is the jth element of Z_{it}; and $\delta[j]$ and $\gamma[j]$ are the corresponding coefficients in Eqs. (2) and (3).

The marginal effects discussed above may reveal more detailed facts about how the determinants affect the level of the inefficiency effect. The main purpose of this paper is to investigate the non-monotonic effect on fund performance. However, the closed-form calculation for $\partial E(e^{-u_{it}})/\partial z[j]$ is difficult to compute, if not intractable. Therefore, we turn to analyze the non-monotonic effect on fund underperformance. If there exists a non-monotonic effect of diversification (i.e., change the sign of the marginal effect on inefficiency effect), then there is a turning point of fund underperformance sorted by the degree of diversification. The optimal level of diversification provides valuable information for fund managers and investors at decision-making. Additionally, this paper further applies a simulation approach to show the pattern of $\partial E(e^{-u_{it}})/\partial z[j]$ (the simulation steps and results are listed in the appendix).[4]

[3] We can also estimate the marginal effect on $\mathrm{V}(u_{it})$, which may imply the diversification effect on the stability of fund performance, but we do not account for these effects in this paper.

[4] We heartily thank the editor's constructive suggestion.

2.2 Data and variables' descriptions

The data come from Taiwan Economic Journal (TEJ) database, which provides rich information on fund characteristics after 1987, including all variables used in this article. This paper focuses on domestic equity funds in Taiwan, excluding index funds and fund of funds since they are managed inactively. We also exclude international funds and balance funds to avoid the possible effect of asset allocation decisions. Unfortunately, information on total assets and the expense ratio of each fund are only available after 2001. Because these variables are considered as important determinants of fund performance in literature, the research period covers 2001–2008 and the final sample contains 211 funds comprising 1,334 fund-years. It is noteworthy that the economic and financial market conditions vary markedly over the research period that will be applicable to investigate our main work. For example, the recession in 2001 is the first one since the 1950s, followed by a booming business cycle from 2002 to 2007. Finally, the global financial crisis struck the local market and resulted in another recession in 2008.

This paper adopts the SFA model to construct a generalized Sharpe ratio. It is consistent with the work of Shawky and Smith (2005) who use the Sharpe ratio as the fund performance measure. This study takes the one-output and one-input SFA model, and the output variable is the adjusted fund return calculated as raw return minus risk-free return. The input variable is annualized standard deviation of returns.[5] Year dummies are the control variables of Eq. (1) to capture the yearly effect of a frontier shift and unobserved heterogeneity effect. With respect to the determinants of Eqs. (2) and (3), we refer to several related studies in the literature and select six variables as follows.

The main determinant discussed in this research is the diversification of each fund. The number of stocks held by a fund is a simple measure of the degree of diversification (Sapp and Yan 2008; Shawky and Smith 2005). Shawky and Smith (2005) and Kaushik and Barnhart (2009) also consider the percentage of assets invested in the top 10 holdings as a diversification measure since the number of stocks held may not fully reflect the dispersion of holdings. Accordingly, this paper uses both of those measures

[5] The present SFA measure is a kind of Sharpe ratio, but adjusts for statistical noises. It is noted that the Sharpe ratio may be biased due to its statistical properties, especially when returns of funds do not follow a normal distribution (see Lo 2002). Thus, we employ the Shapiro–Wilk normality test to test whether returns follow a normal distribution. Accordingly, only 4 of 211 funds' returns reject the null hypothesis (at the 5 % significance level), i.e. returns follow a normal distribution. Therefore, we suggest that the bias of our measure is slight.

separately to investigate the effect of diversification on fund performance. Shawky and Smith (2005) take the squared number of stocks to derive the non-linear effect of diversification and the optimal number of stocks. However, we do not account for this squared variable, because the non-linear effect can be detected by Eq. (4) directly.

The fund characteristics including expense ratio, total net assets, invested share, and OTC share are considered as control variables of Eqs. (2) and (3). It is noted that invested share is defined as the proportion of funds invested in Taiwan's equity market, while OTC share is calculated as the percentage of funds invested in equities listed on the over-the-counter (OTC) market, in order to control the effect of stock market capitalization. It means that a fund almost invests in all large-cap firms if its OTC share is close to zero. In addition, this paper tries to explore the relationship between market conditions and the effect of diversification. The following research considers the market conditions, such as high versus low volatility, high versus low market performance, and crisis events.

Panel A of Table 1 shows the descriptive statistics for fund characteristics, and Panel B presents the correlation matrix among selected variables. Across the entire sample, the average number of holdings is approximately 32, and the average percentage of assets invested in the top 10 holdings is about 48 %. Additionally, the maximum and minimum number of holdings is 12 and 143, respectively. Panel B indicates that the number of holdings is positively correlated with fund size, which is not surprising as large funds tend to hold a relatively lager number of stocks due to liquidity concerns. The number of holdings is also positively related to invested share while negatively related to OTC share. The percentage of assets invested in the top 10 holdings is an indicator for the degree of concentration. Hence, the correlation among the number of holdings and percentage of top 10 holdings is highly negative.

Table 1 Descriptive statistics for fund characteristics

	Mean	Median	SD
Panel A: sample statistics			
Number of holdings (N_HOLD)	31.80	30.0	11.08
Top10 invested shares (Top10), %	48.46	47.87	9.55
Total net assets (TNA), million NTD	1,518.38	894.84	1,780.38
Expense ratio (EXP), %	0.15	0.15	0.04
Invested share (INVEST), %	85.89	87.47	6.53
OTC share (OTC), %	16.37	13.21	13.82

	N_HOLD	Top10	TNA	EXP	INVEST	OTC
Panel B: correlation matrix						
N_HOLD	1					
Top10	−0.62*	1				
TNA	0.21*	−0.05*	1			
EXP	−0.04	−0.05	−0.11*	1		
INVEST	0.15*	0.31*	0.09*	−0.06*	1	
OTC	−0.07*	0.16*	−0.08*	−0.02	0.14*	1

* Statistical significance at 0.05 level

3 Results and discussion

This paper assumes that the efficient frontier is under a variable return to scale technology. Therefore, the input and output variable are both a logarithm. Notice that the adjusted returns are added an positive to guarantee that all adjusted returns are larger than zero.

3.1 Estimation results of SFA

Table 2 provides the estimation results of the stochastic production frontier and the determinants of the inefficiency effect. The frontier equation of Model 1 shows that the annualized standard deviation is significantly and positively associated with adjusted return. It is consistent with economic intuition that the expected return will be higher when a fund holds a riskier portfolio.

With respect to the mean equation of Model 1, it presents that the number of holdings has a negative effect on μ_{it}, indicating that a fund with a more diverse portfolio has better performance. Although this result is in line with previous literature, the coefficient is not statistically significant. One reasonable explanation is that the effect of diversification is non-linear, and we will verify this consideration in the next subsection. The result also illustrates that the fund with a larger size and a higher percentage invested in the OTC market would be more efficient than others. Nevertheless, the coefficient of invested share is positive and marginally significant, meaning that higher equity holdings are generally detrimental to fund performance. This may be due to a downward plunge of Taiwan's stock market over the research periods, i.e. the stock market dropped more than 30 % during 2001–2008.

The variance equation of Model 1 represents how these factors affect the variability of the inefficiency effect. The implication of the variance equation is to investigate the effect of determinants on the stability of fund performance (fund efficiency). The results of Model 1 show that the number of holdings has a positive effect on σ^2_{it}, implying that the performance of diversified funds would be more unstable than relatively focused funds. One possible explanation is that the variance–covariance matrix among holdings is more complicated as funds hold a large number of stocks. Additionally, funds with a large size and a higher

Table 2 Estimation results of the stochastic frontier approach

Dependent variable: log (adjusted return)	Model 1		Model 2	
	Coeff.	SE	Coeff.	SE
Frontier function				
Intercept	4.238***	0.121	4.241***	0.124
Log (SD)	0.132***	0.035	0.131***	0.036
Year 2002	−0.585***	0.02	−0.581***	0.019
Year 2003	0.044**	0.020	0.046**	0.021
Year 2004	−0.234***	0.019	−0.232***	0.019
Year 2005	0.212***	0.025	0.211***	0.025
Year 2006	−0.027	0.019	−0.026	0.020
Year 2007	−0.117***	0.019	−0.114***	0.019
Year 2008	−1.163***	0.026	−1.153***	0.025
Mean function				
Intercept	2.860	17.461	−13.077	48.702
N_HOLD	−0.387	0.352		
Top10			0.207	0.191
Log (TNA)	−1.328*	0.738	−1.899*	1.026
EXP	−0.351	6.024	−3.608	6.707
INVEST	0.198*	0.117	0.214	0.210
OTC	−0.572***	0.185	−0.600***	0.213
Variance function				
Intercept	6.146***	1.485	8.247**	3.367
N_HOLD	0.026**	0.012		
Top10			−0.025***	0.012
Log (TNA)	−0.266***	0.078	−0.226***	0.069
EXP	1.214	1.166	1.315	1.095
INVEST	−0.041***	0.012	−0.047***	0.014
OTC	0.018	0.012	0.020	0.015
σ_v	4.236***	0.073	4.250***	0.070
Log likelihood	728.399		728.281	

Adjusted return is calculated as raw return minus risk-free return; SD is annualized standard deviation of fund returns; N_HOLD is the number of different stocks held by a fund; Top10 is the percentage of highest-weighted 10 stocks; TNA is a fund's total net assets; EXP is the expense ratio; INVEST and OTC are the share of assets invested in equity and over-the-counter markets, respectively

***, **, and * Statistical significance at 0.01, 0.05, and 0.10 levels, respectively

ratio invested in equity have a relatively stable performance versus others.

Model 2 of Table 2 adopts "Top10" as the alternative proxy for diversification in order to compare with Model 1. The result seems to be completely compatible with the result obtained from Model 1. Except the coefficient of Top10, all parameters have the same sign in both Models 1 and 2, indicating our empirical results are consistent. Only one variable, i.e., invested share, becomes insignificant in mean and variance functions of Model 2. This change in fact does not influence the conclusions of this research.[6]

Table 3 Estimated fund efficiency scores (%)

	Mean	SD	Minimum	Maximum
All funds	93.23	5.49	22.88	98.49
By year				
2001	93.03	7.06	43.30	98.49
2002	92.17	5.04	71.81	98.25
2003	94.02	3.29	74.52	97.76
2004	93.86	3.11	78.58	97.81
2005	93.47	5.38	64.90	97.91
2006	94.83	2.01	86.60	97.72
2007	94.36	4.01	59.52	98.13
2008	89.67	9.45	22.88	98.12
By no. of holdings				
Focused funds	92.40	7.10	22.88	98.49
Diversified funds	93.58	5.01	59.52	98.01

The focused funds are funds in the lowest trisection based on the number of holdings. The diversified funds are funds in the highest trisection based on the number of holdings

According to the estimated parameters of Model 1, we can calculate the efficiency score of each fund and provide the characteristics of the efficiency score in Table 3. The overall average efficiency for the sample funds is 93.23 %. For the year partition, the yearly average efficiency scores are over 90 % except in the last year. Actually, the mutual funds, on average, perform poorly in 2008, because the market confronted a dramatic financial crisis. For the diversification partition, funds are sorted into trisections based on the number of holdings in their portfolios. This shows that focused funds (lowest trisection) have a mean efficiency of 92.40 %, which is significantly (p value < 0.01) lower than diversified funds (93.58 %).

[6] We also follow the work of Habib and Ljungqvist (2005) using a Durbin–Wu–Hausman test to examine the possible endogeneity problem of diversification measures. We treat the number of holdings and the percentage of top 10 holdings as endogenous. Additionally, only transactions cost is used as an instrumental variable since we do not adopt the number of holdings and the percentage of top 10 holdings in the same model. This instrument is not weak and does not correlate with adjusted returns (the t test statistic is 1.12). According to the result of the Durbin–Wu–Hausman test, the number of holdings (p value $= 0.32$) and the percentage of top 10 holdings (p value $= 0.38$) do not indicate that the endogeneity problem is a concern in this study.

Table 4 Average marginal effect of diversification on inefficiency effect ($\times$ 10^{-2})

Deciles	Number of holdings		Percentage of Top10	
	Level of sorting criteria	Avg. marginal effect	Level of sorting criteria	Avg. marginal effect
1—focused	17.707	−0.134***	66.446	0.019*
2	21.767	−0.052***	58.695	0.015*
3	24.519	−0.025***	54.441	0.011*
4	26.789	−0.018*	51.640	−0.027***
5	28.782	0.011**	49.117	−0.065***
6	31.164	0.015***	46.723	−0.080***
7	33.873	0.026***	44.336	−0.096***
8	37.090	0.039***	41.824	−0.114***
9	41.425	0.045***	38.617	−0.136***
10—diversified	54.714	0.078***	33.000	−0.173***
Total	31.795	−0.001	48.457	0.059**

***, **, and * Statistical significance at 0.01, 0.05, and 0.10 levels, respectively

3.2 Non-monotonic effect of diversification on fund underperformance

Although the results of Table 2 do not show any significant effect of diversification on the level of fund underperformance, we suggest that is attributed to the non-monotonic or non-linear effect of diversification. To examine this consideration, our study computes the marginal effect on inefficiency effect (u_{it}) for each observation based on Eq. (4) and simulate the marginal effect on fund efficiency score. We then sort all funds into deciles according to the number of holdings or the percentage of top 10 holdings. Table 4 reports the average marginal effect of diversification for each decile.

Based on the number of holdings, the effect on fund underperformance reveals a non-linear pattern. For example, for the most focused group, the average marginal effect on $E(u_{it})$ are −0.0013, implying that the adjusted return improves 0.13 % if the fund increases by one more stock holding. However, the average marginal effect on $E(u_{it})$ in the most diversified group become 0.0008, indicating that the adjusted return declines around 0.08 %, if the fund increases by one more stock holding. This finding is consistent with Shawky and Smith (2005) in which the benefit of diversification disappears when a fund holds too many stocks at the same time. We also find an optimal level of the number of holdings at the point of changing the sign of the marginal effect on inefficiency effect and hence the efficiency score. Accordingly, the optimal number of holdings is around 26–28 stocks since the sign of the marginal effect changes in between the fourth and fifth deciles.

It is interesting that the optimal number of holdings detected by this study is much smaller than that found in the work of Shawky and Smith (2005). We suggest that this dissimilarity may result from the striking difference between the scale of Taiwan and the US mutual fund industries. In fact, the average total assets of our paper's sample mutual funds are about NT$1.518 billion NTD (roughly US $50 million), which are only one-sixteenth of the sample in Shawky and Smith (2005, pp. 487). Moreover, both Taiwan and the US governments have regulated the limit of funds' holdings; i.e., the fund cannot hold more than 10 % of any one security, and no more than 5 % of the fund's assets can invest in any one security. The results in Shawky and Smith (2005) and this paper show that the optimal number of holdings in a giant market (e.g., the US) may be larger than a small market (e.g., Taiwan).

Table 4 also shows the marginal effect of another diversification measure, the percentage of top 10 holdings. This result is similar to the finding discussed above that shows a non-linear effect on fund underperformance. However, only the first three focused groups present a positive effect on inefficiency effect, implying that the optimal percentage of top 10 holdings is about 51–54 %.[7] This paper further investigates the relation between the marginal effect of diversification and fund size. We double sort all funds into deciles based on the number of holdings and half based on the funds' total net assets. The result (not reported here) reveals no substantial difference in the marginal effect between large and small funds. It indirectly echoes the finding of Pollet and Wilson (2008), indicating that well-diversified funds should remain focused on their existing portfolios even though more cash flows are invested into them.

We therefore summarize that the concentrative strategy is not appropriate for fund managers, because managers can improve their portfolios' efficiency by diversifying their holdings. This finding is in accord with the conclusions of Pollet and Wilson (2008) and Sapp and Yan (2008), but the benefit of diversification disappears if funds are over-diversified. This paper provides evidence for the non-monotonic effect of diversification as well as the optimal level of two diversification measures: number of holdings and percentage of top 10 holdings.

3.3 Effect of diversification and market conditions

This subsection examines whether stock market conditions moderate the effect of diversification on fund underperformance. Three market condition variables are considered in this paper: stock market return, market volatility, and

[7] Since Top10 negatively and significantly correlates with N_HOLD (see Table 1), it is for sure that the signs of marginal effect of Top10 are almost opposite to those of N_HOLD.

Table 5 Marginal effect of diversification on inefficiency effect and market performance ($\times 10^{-2}$)

Deciles of number of holdings	Market return		
	Low	Medium	High
1—focused	−0.158**	−0.176*	−0.065
2	−0.130**	−0.034**	−0.019
3	−0.036**	−0.019	−0.021
4	−0.067**	−0.004	0.018*
5	−0.002	0.007	0.024***
6	0.009	0.016**	0.019**
7	0.022***	0.025***	0.033***
8	0.040***	0.029***	0.049***
9	0.042***	0.043***	0.051***
10—diversified	0.081***	0.072***	0.077***
Total	−0.011	−0.010	0.017***

***, **, and * Statistical significance at 0.01, 0.05, and 0.10 levels, respectively

Table 6 Marginal effect of diversification on inefficiency effect and market volatility ($\times 10^{-2}$)

Deciles of number of holdings	Lower volatility	Higher volatility
1—focused	−0.143*	−0.126***
2	−0.042***	−0.061**
3	−0.026*	−0.024**
4	0.002	−0.037**
5	0.013*	0.008
6	0.022***	0.005
7	0.029***	0.023***
8	0.041***	0.037***
9	0.046***	0.044***
10—diversified	0.076***	0.079***
Total	0.004	−0.007

***, **, and * Statistical significance at 0.01, 0.05, and 0.10 levels, respectively

crisis events (such as the global financial crisis in 2008). In the following investigation, we only use the number of stock holdings as the proxy for portfolio diversification since the results will not substantially change according to the criterion of percentage of top 10 holdings.

3.3.1 Does market return matter?

We perform an independent double sorting of the fund sample by number of holdings deciles and stock market return trisection. Table 5 reports the average marginal effects of diversification on inefficiency effect for these cells.

The second column of Table 5 present the marginal effect of diversification if the stock market performs poorly, indicating that the benefit of diversification will vanish when the number of holdings is located on the fifth and sixth deciles. This finding means that the maximum number of holdings could be 31–33 stocks to achieve the optimal level for fund efficiency. However, the turning point in the sign of the marginal effect changes if the market return becomes higher. For example, the last column of Table 5 shows the marginal effect of diversification in the highest return group. The turning point is among the third and fourth deciles, indicating that the optimal number of holdings is <26 stocks. Hence, the stock market performance could indeed affect the benefit of diversification, which is consistent with our expectation. In summary, the better the stock market performs, the lower the benefit of diversification would be. It also implies that fund managers should concentrate their portfolios on the best investment ideas in a good year and hold relatively diversified portfolios in a bad year.

3.3.2 Does market volatility matter?

This subsection uses a double sort meaning that all funds are ranked on the number of holdings and are independently sorted on market volatility in a particular year so as to investigate whether market volatility affects the benefit of diversification. Table 6 lists the average marginal effect of diversification for each group.

In the low market volatility years (the second column of Table 6), funds within the most focused group have a negative diversification effect on fund underperformance of −0.0014 on average, while the average marginal effect of diversification within the most diversified group is 0.0008. By comparison, in high volatility years (the last column of Table 6), a gradually downward pattern for the diversification effect is quite similar to funds operating during low market volatility years. However, the turning points in sign for the diversification effect differ from each other. According to Table 6, funds should hold about 31 stocks to be well diversified when the stock market is volatile, but this number becomes around 26 stocks if the stock market is relatively stable. Therefore, this finding confirms that stock market volatility moderates the effect of diversification on fund performance.

In empirical research on the stock market, several studies have detected a negative relationship between market return and volatility. The findings here and a previous subsection of this paper are in accordance, meaning that the benefit of diversification is higher under lower and more volatile market conditions. Hence, managers should hold more stocks to realize well-diversified portfolios under those conditions.

3.3.3 What can managers do under a crisis?

To examine whether the relation between fund diversification and performance is independent of great crises, we further compare the marginal effects of diversification on inefficiency effect during non-crisis and crisis years. This study first sorts all funds by the number of holdings deciles. The second criterion, whether or not that year presents a crisis event, is used to class funds into non-crisis or crisis years. This paper considers two cases that classify the different non-crisis and crisis groups. Case 1 defines 2008 as the only one crisis year, because a global and dramatic financial crisis occurred that year. In 2008 Taiwan's stock market dropped more than 60 %, resulting in a severe negative hit on the mutual fund industry. Nevertheless, in case 2 the crisis year group involves 2001 as well as 2008, because they are the only 2 years that Taiwan had negative GDP growth since the 1950s.

Table 7 gives the means of the marginal effect of diversification for each group. Regarding case 1, the optimal number of holdings is around 26–28 stocks when the market is not under crisis. However, the optimal number of holdings becomes about 31 stocks if the market confronts a crisis. This means that the benefit of diversification is enhanced and the number of stocks needed to achieve a well-diversified portfolio should increases when market is under a crisis. Based on this result, we suggest that managers should increase the number of stocks in their portfolios for a maximum of 31 stocks to cut down on unsystematic risks.

Table 7 Marginal effect of diversification: non-crisis versus crisis years ($\times 10^{-2}$)

Deciles	Case 1		Case 2	
	Non-crisis	Crisis	Non-crisis	Crisis
1—focused	−0.133***	−0.138	−0.150***	−0.092*
2	−0.050***	−0.075	−0.074***	−0.006
3	−0.018**	−0.109***	−0.024**	−0.028*
4	−0.013	−0.055	−0.021*	−0.010
5	0.010*	0.019	0.005	0.003
6	0.016***	0.006	0.015***	0.016*
7	0.025***	0.028**	0.024***	0.032***
8	0.039***	0.041***	0.039***	0.041***
9	0.043***	0.060***	0.042***	0.062***
10—diversified	0.079***	0.071***	0.079***	0.073***
Total	−0.002	0.003	−0.004	0.006

Case 1 considers only the financial crisis in 2008 as the crisis year group; Case 2 includes two economic recessions in 2001 and 2008 as the crisis year group

***, **, and * Statistical significance at 0.01, 0.05, and 0.10 levels, respectively

With respect to case 2, this paper adopts the two economic recessions in 2001 and 2008 as crisis years. According to Table 7, however, there is no difference in the diversification effect between the non-crisis and crisis year groups. In fact, the stock market recovered and rose about 15 % from a severe plunge after 2000. Therefore, we conclude that the change in the benefit of diversification is directly driven by the stock market conditions, not by the macro-economic conditions. One possible explanation is that the variance–covariance matrix of a portfolio varies with stock market volatility, the average correlation between all pairs of stocks, and the average volatility of all individual stocks according to Pollet and Wilson's (2010) model. Another reason is that although the stock market and economic conditions are not independent, the stock market condition is a leading indicator for the business cycle. Hence, the benefit from diversification might not be directly affected by the macro-economic condition.

4 Conclusions

Previous studies have used simulated portfolios or real mutual fund portfolios to investigate the benefit of diversification, but our paper considers that the effect of diversification is time-varying and market-depended, which may be the reason for the controversial findings in the literature. To deal with this consideration, we apply a frontier-based efficiency measure, the stochastic frontier approach, to evaluate fund performance and to explore the effect of diversification on fund underperformance. Moreover, this study adopts Wang's (2002) SFA model to estimate the marginal effect of diversification. It is expected that one can find the non-monotonic and non-linear effect of diversification, which can provide more insights for fund managers as well as investors.

The empirical results indicate that a concentration strategy is not appropriate for managers in Taiwan after controlling some fund characteristics. It presents that relatively diversified funds are more efficient than relatively focused funds, but the benefit from diversification disappears or becomes negative when a fund holds too large a number of different stocks. According to the non-monotonic effect of diversification, this paper suggests the optimal number of holdings is around 26–28 stocks and the optimal percentage of top 10 holdings is about 51–54 % in general.

To examine whether the relation between fund diversification and performance is independent of market conditions, this paper further compares the marginal effect of diversification on inefficiency effect under three market condition variables: market return, market volatility, and crisis. Our findings reveal that the benefit of diversification increases within lower market return and higher market volatility conditions, meaning that the number of stocks needed to achieve a well-diversified portfolio increases under those market conditions. In addition, a stock market crisis, such as the global financial crisis in 2008, can enhance the benefit of diversification. Compared to non-crisis years, managers should increase the number of stocks in their portfolios for a maximum of 31 stocks. Finally, we consider that the change in the effect of diversification is directly driven by the stock market condition and not by the macro-economic condition.

There are some aspects that can improve our study in future works: first, this research applies the marginal effect on fund inefficiency to explore the market-dependent diversification effect. Wang (2002) also provides an estimation of the marginal effect on the variance of inefficiency effect (u_{it}). Perhaps future studies can examine whether or not a diversification strategy could improve the stability of fund performance. Second, in terms of a traditional return-risk relationship, this paper proves that this SFA measure is a standardized Sharpe ratio (but adjusts statistical noises). Some studies recently have developed portfolio evaluation models based on higher-order moments. For instance, Brandouy et al. (2010) consider not only the mean–variance approach, but also mean–variance–skewness as well as mean–variance–skewness-kurtosis models. Hence, we suggest that future works can expand our study to general moment portfolio models, and then one can examine whether our conclusions are consistent through an extended approach.

Acknowledgments The authors are indebted to two anonymous referees and an editor of this journal for their valuable comments. Professor Hung-Jen Wang kindly provides an example file of maximum likelihood estimation coding, which is of great help. Jin-Li Hu thanks Taiwan's National Science Council (NSC101-2410-H-009-044) for financial support.

Appendix

In fact, it is difficult to derive the marginal effect of number of holdings on the expectation of fund efficiency, that is $\partial E(e^{-u_{it}})/\partial$N_HOLD. Therefore, we try to graph $E(e^{-u_{it}})$ and the number of holdings through a simulation approach. Our simulation steps are represented as the follows.

1. The first step is to compute the population mean efficiency, i.e., $E(e^{-u_{it}})$. Battese and Coelli (1988) present the close form of the mean efficiency if inefficiency effects are positively i.i.d. truncated normal random variables, meaning that $u \sim N^+(\mu, \sigma_u^2)$. Then the following mean efficiency can be derived:

$$E(e^{-u}) = e^{-\mu+\sigma_u^2/2}\left\{\frac{1-\Phi[\sigma_u-(\mu/\sigma_u)]}{1-\Phi(-\mu/\sigma_u)}\right\}. \quad (5)$$

It is straightforward for our study to extend above estimator under an assumption that $u_{it} \sim N^+(\mu_{it}, \sigma_{it}^2)$.

2. Regarding to the pattern of $E(e^{-u_{it}})$, we compute $E(e^{-u_{it}})$ by varying N_HOLD and holding other variables at the sample means. Note that Eq. 5 indicates that $E(e^{-u})$ is independent of the inputs, implying that the mean efficiency is a function of *Z*s. Therefore, we hold all *Z*s at the sample means except for N_HOLD, and then compute $E(e^{-u_{it}})$ by varying N_HOLD from 1 to 100. Accordingly, we graph the mean efficiency against N_HOLD = 1–100 as the following Fig. 2 shows.

Figure 2 sketches the relationship between the mean efficiency and the number of holdings. It presents a clear inverse U-shape relation, indicating that this relation is non-monotonic and exhibits a optimal number of holdings. As we hold other *Z*s at the sample means, the optimal number of holdings is equal to 19.

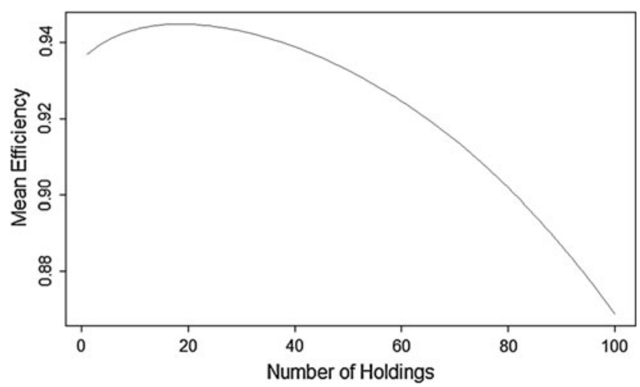

Fig. 2 Relationship between $E(e^{-u_{it}})$ and N_HOLD

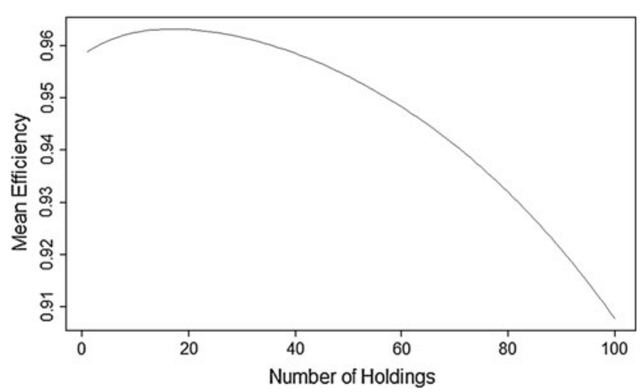

Fig. 3 Relationship between $E(e^{-u_{it}})$ and N_HOLD with higher fund size and invested share

With respect to the effect of market conditions on $\partial E(e^{-u_{it}})/\partial$N_HOLD, we can change the levels of some *Z*s and graph the mean efficiency against N_HOLD, again. It is reasonable that fund size (TNA) and invested share (INVEST) will increase as the stock market performs well (Pollet and Wilson 2008). Hence, we hold EXP and OTC at the sample means and let TNA and INVEST are equal to the sample means plus half of a standard deviation.

Figure 3 presents the pattern of $\partial E(e^{-u_{it}})/\partial$N_HOLD with a higher INVEST. It still shows a clear inverse U-shape relation between the mean efficiency and the number of holdings. However, the optimal number of holdings becomes 17, implying that the diversification benefit in a better market condition is lower than that in a worse market condition. Therefore, we conclude that the findings of $\partial E(e^{-u_{it}})/\partial$N_HOLD and $\partial E(u_{it})/\partial$N_HOLD are similar. That is, N_HOLD presents a non-monotonic effect on the mean efficiency and the inefficiency term. We can also find out the optimal number of holdings. However, the suggested optimal numbers of holdings are not identical between two measures (i.e., $\partial E(u_{it})/\partial$N_HOLD suggests the optimal number of holdings is around 26–28). There are two possible explanations for this discrepancy. First, the relation between $\partial E(e^{-u_{it}})/\partial$z and $\partial E(u_{it})/\partial$z is not necessarily monotonic. Second, we do not derive the close form of $\partial E(e^{-u_{it}})/\partial$z but sketch $E(e^{-u_{it}})$ against N_HOLD to demonstrate this marginal effect. As mentioned above, we hold other *Z*s at sample means in order to calculate $E(e^{-u})$ with a given N_HOLD. However, Wang (2002) derives the close form of $\partial E(u_{it})/\partial$z which uses all *Z*s at the observed values for each observation. Hence, it is not surprising that the implied optimal numbers of holdings are not exactly identical.

References

Annaert J, van den Broeck J, Vander Vennet R (2003) Determinants of mutual fund underperformance: a Bayesian stochastic frontier approach. Eur J Oper Res 151:617–632

Battese GE, Coelli TJ (1988) Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. J Econom 38:387–399

Brandouy O, Briec W, Kerstens K, Van de Woestyne I (2010) Portfolio performance gauging in discrete time using a Luenberger productivity indicator. J Bank Finance 34:1899–1910

Campbell JY, Lettau M, Malkiel BG, Xu Y (2001) Have individual stocks become more volatile? An empirical investigation of idiosyncratic risk. J Finance 56:1–44

Choi YK (2006) Relative portfolio performance evaluation and incentive structure. J Bus 79:903–921

Cuthbertson K, Nitzsche D, O'Sullivan N (2008) UK mutual fund performance: skill or luck? J Emp Finance 15:613–634

Domian DL, Louton DA, Racine MD (2003) Portfolio diversification for long holding periods: how many stocks do investors need? Stud Econ Finance 21:40–64

Domian DL, Louton DA, Racine MD (2007) Diversification in portfolios of individual stocks: 100 stocks are not enough. Finance Rev 42:557–570

Evans JL, Archer SH (1968) Diversification and the reduction of dispersion: an empirical analysis. J Finance 23:761–767

Fabozzi FJ (1999) Investments management. Prentice Hall, Englewood Cliffs

Ferson WE, Schadt RW (1996) Measuring fund strategy and performance in changing economic conditions. J Finance 51:425–461

Habib MA, Ljungqvist A (2005) Firm value and managerial incentives: a stochastic frontier approach. J Bus 78:2053–2093

Ibbotson RG, Kaplan PD (2000) Does asset allocation policy explain 40, 90, or 100 percent of performance? Finance Anal J 56:26–33

Kacperczyk M, Sialm C, Zheng L (2005) On the industry concentration of actively managed equity mutual funds. J Finance 60:1983–2011

Kaushik A, Barnhart SW (2009) Do mutual funds with few holdings outperform the market? J Asset Manag 9:398–408

Kothari SP, Warner JB (2001) Evaluating mutual fund performance. J Finance 56:1985–2010

Kumbhakar S, Lovell CAK (2000) Stochastic frontier analysis. Cambridge University Press, New York

Lai HP, Huang CJ (2010) Likelihood ratio tests for model selection of stochastic frontier models. J Prod Anal 34:3–13

Lo AW (2002) The statistics of Sharpe ratios. Finance Anal J 58: 36–52

Newbould GD, Poon PS (1993) The minimum number of stocks needed for diversification. Finance Pract Educ 3:85–87

Newbould GD, Poon PS (1996) Portfolio risk, portfolio performance, and the individual investor. J Invest 5:72–78

Pollet JM, Wilson M (2008) How does size affect mutual fund behavior? J Finance 63:2941–2969

Pollet JM, Wilson M (2010) Average correlation and stock market returns. J Finance Econ 96:364–380

Ramos SB (2009) The size and structure of the world mutual fund industry. Eur Finance Manag 15:145–180

Santos A, Tusi J, Da Costa N Jr, Da Silva S (2005) Evaluating Brazilian mutual funds with stochastic frontiers. Econ Bull 13:1–6

Sapp T, Yan X (2008) Security concentration and active fund management: do focused funds offer superior performance? Finance Rev 43:27–549

Shawky HA, Smith DM (2005) Optimal number of stock holdings in mutual fund portfolios based on market performance. Finance Rev 40:481–495

Statman M (1987) How many stocks make a diversified portfolio? J Finance Quant Anal 22:353–364

Statman M (2004) The diversification puzzle. Finance Anal J 60: 44–53

Wang HJ (2002) Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. J Product Anal 18:241–253