An Empirical Investigation into the Effects of a Bond Fund Segregation Policy – Evidence from Taiwan

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ABSTRACT

This paper investigates the effects of a bond segregation policy in Taiwan. Our empirical findings show that the OS&OP ratio decreases below 30% after the year 2007, while the RP ratio and the ST-D ratio increase. In addition, the scale of bond fund sales also decreases. We further conclude that all the ratios present significant differences after 2007 by using the student-t pair test. We apply five widely used copula functions to understand the correlation between these ratios and the mean return rate of the net value. The results find that all the ratios have a positive correlation with the mean return rate except the RP ratio. The volatility of return also decreases no matter in a historical or GARCH model. Lastly, the VaR decreases after carrying out the policy. The OS&OP ratio has a positive correlation with the VaR over the full time period of January 2001 to June 2010. As a consequence, this means that the OS&OP ratio is the key factor for bond funds.

Keywords: Fund Segregation Policy, Quasi Money Market Fund, Bond Fund, Copula Function
JEL classification: G20, C12, C13

1. INTRODUCTION

In Taiwan's bond market the growth in bond funds with structured notes can be pinpointed to factors such as a low interest rate environment, lackluster stock market performance, rapid growth in the scale of local bond funds, and a steep yield curve.[1] However, bond funds focus on pursuing short-term high returns and increasing their scale by investing in structured products with poor liquidity. The problem arises when bond funds allow clients to redeem and take their proceeds the next day, engendering a liquidity divergence between the bond funds' own assets and those offered to clients and increasing the funds' liquidity risks.

[1] In Taiwan, the aggregate amount of bond funds rose from NT$777.4 billion in December 2000 to NT$2.4 trillion by May 2004.

Starting from 2004 the Federal Reserve of the United States consecutively raised the Federal funds rate, causing price drops for many inverse floating-rate notes and range accrual notes due to their lower returns, but then in 2008 lowered the rate. Unfortunately, these products were very illiquid and it was difficult to correctly evaluate their prices, with there being almost no secondary market. Hence, fund managers had to sell such notes at tremendous losses when investors asked for a large amount of redemption, resulting in a market panic and even bringing about systematic risk. Although the local regulation for strengthening bond fund management outlined major management issues, the scarce liquidity resulting from large holdings of structured notes still triggered significant redemptions upon Union Investment Trust and Tai-Yu Investment Trust in Taiwan in July 2004.[2] In order to avoid risk, Taiwan's Financial Supervisory Commission (FSC) decided to carry out a bond segregation policy before the end of 2006. The system split up bond funds into fixed income bond funds and quasi money market bond funds.

Most studies in the bond fund literature focus on funds' performances, credit quality, and value at risk (VaR). Some previous research studies such as Blake, et al. (1993) used linear and non-linear models to examine bond funds' performances. Elton et al. (1995) first developed and tested the relative pricing models (based on the Arbitrage Pricing Theory, or APT) to explain the expected returns and performance of bond funds. These two research studies concluded that active funds do not outperform passive benchmarks. Detzler (1999) evaluated the performance of active global bond mutual funds and found no support of superior fund performance net of expenses against a wide range of benchmarks. Some papers used Capital Asset Pricing Model (CAPM) to evaluate the performance of bond funds. Such as Gallagher and Jarnecic (2002) who examined the investment performance of active Australian bond funds and the impact of investor fund flows on portfolio returns. Their paper evaluated the performance of actively managed Australian bond funds, using both unconditional and conditional performance evaluation techniques, and assessed the impact of flow on retail bond fund performances.

Only Morey and O'Neal (2006) examined the portfolio credit quality holding and daily return patterns for bond mutual funds. They found that bond funds on average hold significantly more government bonds during disclosure than during non-disclosure. Chen et al. (2010) considered nine common factors and measured the timing ability and performance of bond mutual funds. They concluded that timing ability generates non-linearity in fund returns as a function of common factors, but there are several non-timing-related sources of non-linearity.

As mentioned above, we do not find any study in the literature on a bond fund policy. In order to reduce the risk of bond funds, Taiwan's FSC decided to conduct a bond fund segregation policy before the end of 2006. We aim to look into the effectiveness of this segregation policy. Hence, the study empirically investigates the effect of the policy through the ratio test, volatility test, student-t pair test, VaR, and copula rank correlation test.

Our empirical study's dataset consists of monthly outright sell (OS) & outright purchase (OP), repurchase agreement (RP), short-term deposit (ST-D), and the scale of bond fund sales. The net

[2] On July 12, 2004, Union Securities Investment Trust's "Union Win-win Bond Fund" disposed of its corporate bonds (range accrual notes), financial debentures (inverse floating-rate notes) and convertible bonds - a move that incurred losses, lowered its NAV, and caused tremendous amounts of redemption.

value of bond funds comes from daily data. The sample period for the study covers ten years, from January 2001 to June 2010, containing a total of 32 bond funds.

We find that the bond segregation policy is indeed more effective for reducing risk. The proof is from the OS&OP ratio decreasing below 30% after 2007, the RP ratio and ST-D ratio increasing, and the scale of bond fund sales decreasing. We conclude that all the ratios have significant differences after 2007 through the student-t test. In addition, the results show that all the ratios have a positive correlation with the mean return rate, except the RP ratio due to the copula function. The volatility of return and VaR also decrease no matter in the historical or GARCH model. The OS&OP ratio has a positive correlation with the VaR over the full time period of January 2001 to June 2010. The remainder of the paper is organized as follows. Section 2 takes a brief review of the copula function. Section 3 provides our empirical results. Section 4 is conclusion and remarks.

2. BRIEF REVIEW of the COPULA MODEL

Over the last few years, the copula function has been widely used in financial econometrics and risk management.[3] For example, Palaro and Hotta (2006) implemented the conditional copula to estimate VaR. Junker et al. (2006) discussed non-linear term structure dependence and risk implication based on the copula function. Hu (2006) proposed a mixed copula model that can capture various patterns of dependence structures. Rodriguez (2007) modeled dependence with switching-parameter copulas to study financial contagion. Chiou and Tsay (2008) addressed a copula-based approach to option pricing and risk assessment. Hsu et al. (2008) proposed copula-based GARCH models for the estimation of futures' optimal hedge ratio. Manner et al. (2009) used copula models with a time-varying dependence structure. Lee and Lin (2010) constructed the copula-based VaR-ARMAX-GJR-GARCH model to examine strategic commodities' co-movements and directional relationships with these variables, as well as estimated the VaR of a gold and silver portfolio.

We first consider the bivariate stochastic process $\{X_{it}\}_{t=1}^{T}$ with $X_t = (\mathrm{X}_{1t}, \mathrm{X}_{2t})'$. Let F $(\mathrm{X}_{1t}, \mathrm{X}_{2t})$ be the joint distribution, and F_i denotes the marginal distribution for $i=1, 2$. By Sklar's Theorem[4] (1959), there then exists a copula function $C(\cdot,\cdot)$: $[0, 1]^2 \rightarrow [0,1]$ mapping the marginal distributions of X_{1t} and X_{2t} to their joint distribution through:[5]

$$F(X_{1t}, X_{2t}) = C(F_1(X_{1t}), F_2(X_{2t})). \tag{1}$$

We assume that the marginal distribution can be modeled parametrically, and thus the probability transform is given by $u_{it} = F_i(X_{it}; \phi_i)$, where ϕ_i is the vector of parameters completely describing

[3] For a complete introduction to copulas, please see Joe (1997) or Nelsen (2006).

[4] Sklar's Theorem is the most important theorem regarding copula functions since it is used in many practical applications.

[5] This class of function is very important, because it permits to define the dependence structure between the margins of a multivariate distribution. Hence, different multivariate marginal distributions will be considered - for example, the Gaussian copula (normal copula), the Student copula, and Archimedean copulas (like Clayton-Copula).

the individual behavior of the series.

The Normal copula is the copula of multivariate normal distribution. It is defined as follows: Assume $X=(X_1,X_2,...,X_n)$ is multivariate normal, if and only if (a) its margins $F_1,...,F_n$ are a normal distribution, and (b) a unique copula function exists,[6] such that:

$$C_R^N(u_1,...,u_n)=\Phi_R(\phi^{-1}(u_1),...,\phi^{-1}(u_n))\,, \tag{2}$$

where Φ_R denotes the standard multivariate normal distribution with correlation matrix R and ϕ^{-1} is the inverse function of standard univariate normal distribution. When n=2, $\rho\in(-1,1)$ is the correlation coefficient, and we can obtain the 2-dimension normal copula function as follows:

$$C\ (u,v,\rho)=\frac{1}{\sqrt{1-\rho^2}}\exp\left(-\frac{\Phi^{-1}(u)^2+\Phi^{-1}(v)^2-2\rho\Phi^{-1}(u)\Phi^{-1}(v)}{2(1-\rho^2)}\right)\exp\left(-\frac{\Phi^{-1}(u)^2\Phi^{-1}(v)^2}{2}\right). \tag{3}$$

By the same concept, the t-copula is the copula function of the multivariate Student's t distribution. Assuming $X=(X_1,X_2,...,X_n)$ is the t-student copula with v degrees of freedom, it can be analytically represented in the following equation:

$$C_{v,R}^t(u_1,...,u_n)=t_{v,\rho}(t_v^{-1}(u_1),...,t_v^{-1}(u_n))\,. \tag{4}$$

For n=2, the t-Student copula has the following analytic form:

$$C_{v,\rho}^t(u,v)=\rho^{-(1/2)}\,\frac{\Gamma(\frac{v+2}{v})\Gamma(\frac{v}{2})}{[\Gamma(\frac{v+1}{v})]^2}\cdot\frac{[1+\frac{\zeta_1^2+\zeta_2^2-2\rho\zeta_1\zeta_2}{v(1-\rho^2)}]^{-\frac{v+2}{2}}}{\prod_{i=1}^{2}(1+\frac{\zeta_i^2}{v})^{-\frac{v+2}{2}}}\,, \tag{5}$$

where $\rho\in(-1,1)$ is the correlation coefficient; Γ_v^{-1} is an inverse of the t distribution with v degrees of freedom; and $\zeta_1=\Gamma_v^{-1}(u)\,,\zeta_2=\Gamma_v^{-1}(v)$.

Another important class of copulas is known as Archimedean copulas. These copulas offer a wide range of applications. An n-dimension copula function is defined as

$$C\left(x_1,\cdots x_n\right)=\Psi^{-1}\left(\sum_{i=1}^{n}\Psi\left(F_i\left(x_i\right)\right)\right), \tag{6}$$

[6] I.e. the normal Copula.

where Ψ : generator function and satisfies $\Psi(1)=0$; $\lim_{x\to 0}\Psi(x)=\infty$; $\Psi'(x)<0$; $\Psi''(x)>0$.

There are then three types of Archimedean copulas functions - namely, Clayton-n-Copula, Gumbel-n-Copula, and Frank-n-Copula functions, respectively.

(1) Clayton-n-Copula function: when $\alpha > 0$,

$$C(u_1,...,u_n)=\left[\sum_{i=1}^{n} u_i^{-\alpha}-n+1\right]^{-1/\alpha} \tag{7}$$

(2) Gumbel-n-Copula function: when $\alpha > 1$

$$C(u_1,\ldots,u_n)=\exp\left[-\left(\sum_{i=1}^{n}(-\ln u_i)^{\alpha}\right)^{1/\alpha}\right] \tag{8}$$

(3) Frank-n-Copula function: when $\alpha > 0$, $n > 3$

$$C(u_1\ldots u_n)=-\frac{1}{\alpha}\ln\left\{1+\frac{\prod_{i=1}^{n}\left(e^{-\alpha u_i}-1\right)}{\left(e^{-\alpha_i}-1\right)^{n-1}}\right\}. \tag{9}$$

We further use the Kendall tau (τ) coefficient to calculate the rank correlation coefficient of operation events-pair. It is a non-parametric statistic used to measure the association or statistical dependence between two measured quantities. For a pair (u, v), we can construct a two-dimension copula C and obtain the Kendall tau as equation (10):

$$\tau=4\iint C(u,v)\,dC(u,v)-1. \tag{10}$$

3. EMPIRICAL RESULT ANALYSIS

As described above, this article investigates the effect of a bond segregation policy in Taiwan. The dataset hence consists of bond funds that were issued in Taiwan. For the purpose of comparison, the sample period for the study covers ten years, from January 2001 to June 2010. Table 1 presents a total of 32 bond funds' name, their trading code, and their initiation date. The data were obtained from the Taiwan Economic Journal (TEJ) database.

Table 1. Basic descriptions of the bond funds

Code	Name of Bond Fund	Initiation Date	Code	Name of Bond Fund	Initiation Date
UI02	Union Bond	1999/9/30	DF02	The Forever Bond Fund	1996/10/15
TR02	Manulife Wan Li Bond Fund	1999/9/9	JF78	JF (Taiwan) First Bond Fund	1996/10/15
BR02	Primasia Paoyen Bond	1999/9/7	TS06	Shinkong Chi-Shin Fund	1996/9/3
TC18	IBT 1699 Bond Fund	1999/6/7	FP07	Fubon Chi-Hsiang Bond Fund	1996/6/14
CP12	PCA Well Pool Fund	1998/12/23	CA02	Capital Safe Income Bond Fund	1996/5/18
AP02	Manulife Wan Li Bond Fund	1998/11/5	ML04	Prudential Financial Bond Fund	1996/5/17
DS02	Truswell Bond Fund	1998/10/28	YC03	Hua Nan Phoenix Bond Fund	1996/2/6
AI03	PineBridge Taiwan Giant Fund	1998/9/7	CS03	Invesco ROC Bond Fund	1995/11/9
TC02	IBT Ta-Chong Bond Fund	1998/6/22	CI08	HSBC NTD Money Management Fund	1995/11/2
GC02	SinoPac Bond Fund	1998/6/19	IC27	ING Taiwan Bond Fund	1995/10/21
FH02	Fuh-Hwa Bond Fund	1998/5/28	KY02	Polaris De-Li Bond Fund	1995/9/21
JS02	Jih Sun Bond Fund	1997/10/3	PS04	UPAMC James Bond Fund	1995/6/16
NC10	NITC Taiwan Bond Fund	1997/3/7	JF75	JF Taiwan Bond	1995/6/15
YT08	Yuanta Wan-Tai Bond Fund	1997/2/19	NC06	NITC Bond	1994/4/12
TI03	TIIM Bond Fund	1997/2/13	TS01	ShinKong High Yield	1994/1/31
CI10	HSBC NTD Money Management Fund 2	1996/10/17	0008	ING Taiwan Income Fund	1991/12/6

Note: The code represents the bond fund's trading code, respectively.

Table 2 reports the descriptive statistics of the average ratios of OS&OP, RP, and ST-D, and the scale of bond fund sales for before and after the bond segregation policy was set up. The OS ratio is 41.6535% before 2007 and decreases to 16.7258% after 2007, except for the Truswell Bond Fund (43.9369%) (see also Figure (1a)). This average ratio is less than 30% and satisfies the regulation of the bond segregation policy. We further see the RP ratio is 32.058% before 2007 and increases to 37.219% after that year (see also Figure (1b)). It implies that the bond funds increase their RP ratio after the segregation policy. However, the variation is not large. The notable ratio is the short-term deposit. The purpose of the bond segregation policy is to allow the bond funds to transfer over to becoming quasi money market funds. This kind of fund must maintain a low risk profile by trading some short-term financial instruments such as bond repurchase agreements, commercial bills, etc. From Table 2, we see the short-term deposit ratio is only 23.1675% before 2007 and decreases to 40.2448% (see also Figure (1c)). This change is very large. The last column is the scale of bond fund sales, which decrease after 2007. The scale is NT$36.548 million before carrying out the bond segregation policy and decreases to NT$21.66 million. The variation explains that investors do not like to trade low yielding quasi money market bonds. Thus, the scale of bond fund sales decreases after the policy (see also Figure (1d)).

Table 2. Summary statistics of bond funds - OS&OP, RP, S-CD, and the Scale of bond fund sales

	Panel A: before after segregation policy				Panel B: after after segregation policy			
	OS ratio	RP ratio	ST-D	Scale* (NT$ million)	OS ratio	RP ratio	ST-D	Scale* ((NT$ million)
Mean	41.6535	32.0580	23.1675	**36.548**	16.7258	37.2190	40.2448	**21.660**
Std	50.2431	43.9369	34.9089	**502.431**	43.9369	34.9089	50.2431	**439.369**
Max	50.2431	43.9369	34.9089	**502.431**	43.9369	34.9089	50.2431	**439.369**
Min	29.9414	16.6440	10.5039	**299.414**	16.6440	12.7574	29.9414	**166.440**
Skewness	-0.3693	0.3693	0.1385	**4.553**	1.9301	-0.4373	-1.4705	**9.709**
Kurtotsis	1.9151	2.3391	2.6361	**24.033**	8.6460	3.4477	4.5610	**33.317**
J-B	2.2969	1.2447	0.2789	**15.802**	2.2969	1.2447	0.2789	**15.802**

Note: 1.*Scale means the scale of bond fund sales.

2.P-value is the probability that the data come from the normal distribution, according to the Jarque -Berra normality test.

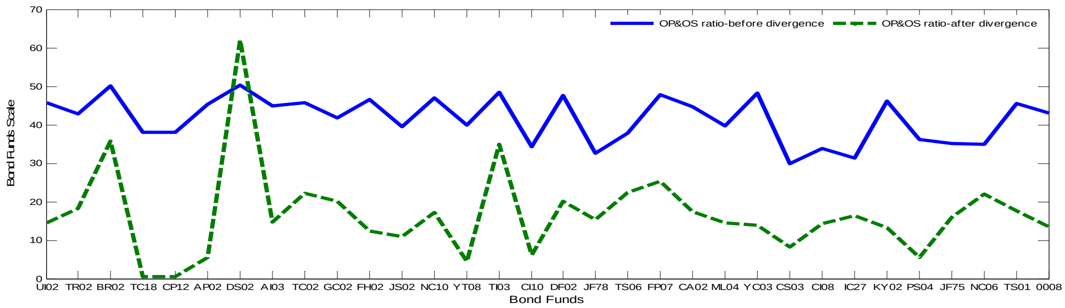

Figure (1a). Variation of OP&OS ratio - before and after bond segregation policy

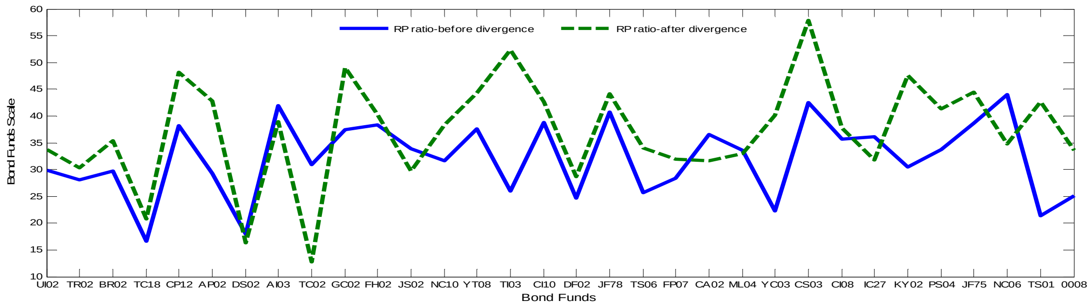

Figure (1b). Variation of RP ratio - before and after bond segregation policy

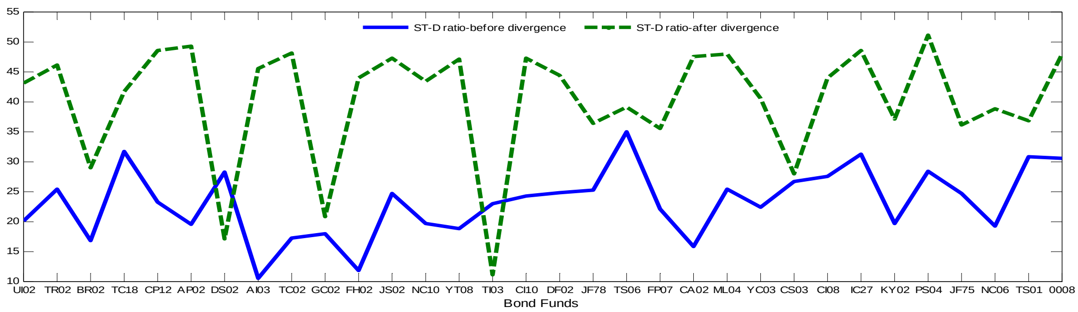

Figure (1c). Variation of ST-D - before and after bond segregation policy

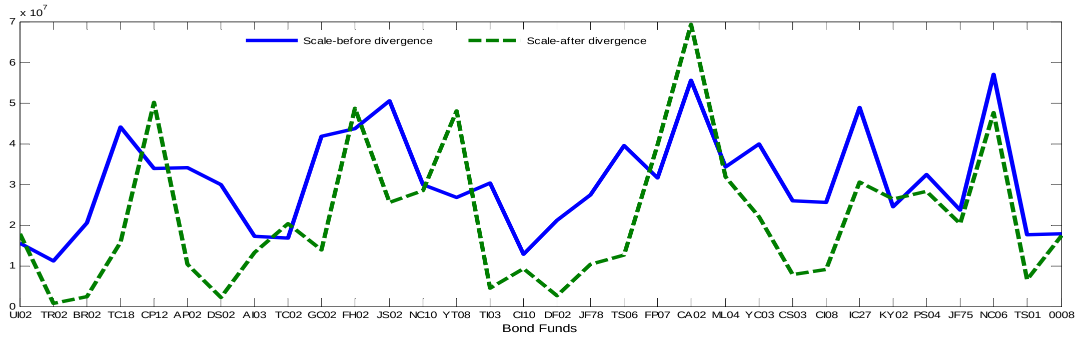

Figure (1d). Variation of the scale of bond fund sales - before and after bond segregation policy

For a significance comparison, we further test these ratios with student-t pair test. The null hypothesis is Ho: The difference in the OS&OP (RP, ST-D) ratio or the scale of bond fund sales is not significant before and after the bond segregation policy. Table 3 reports the results. The first row is t statistics, the second row is degrees of freedom (dof), and the last row is p-value. We find that all the p-values are significant at the 1% significance level. This also means that the ratios show a significant difference after carrying out the segregation policy since 2007.

Table 3. Student's pair t-test results

	OP & OS ratio	RP ratio	ST-D	Scale*
t statistic	14.0226	3.2548	8.4153	3.6660
dof	31	31	31	31
p-value	0.0000***	0.0027***	0.0000***	0.0009***

Note: 1. Pair t test includes the OP&OS ratio (before) vs. OP&OS ratio (after); RP ratio (before) vs. RP ratio (after); ST-D (before) vs. ST-D (after); the scale of bond fund sales (before) vs. Scale (after).

2. *Scale means the scale of bond fund sales.

3.dof is degrees of freedom.

4. *** denotes significant at the 1% significance level.

We also apply the five copula functions mentioned above to observe the rank correlation between the OS&OP ratio, RP ratio, ST-D ratio, and the scale of bond fund sales factors with the mean return of bond funds, respectively. The copula function used here includes the normal copula, student t copula, Clayton copula, Gumbel copula, and Frank copula. Panels A, B, C, and D in Table 4 report the four factors' results for the full period, respectively. Kendall's tau value is the rank correlation, LL is the log-likelihood value of the copula estimation, and AIC (Akaike, 1974) and BIC (Schwarz, 1978) are also criteria. From panel A, we see the Gumbel copula function fits very well before the bond segregation policy. Kendall's tau is 0.1525, which means that the OS&OP ratio is positive with a mean return rate of bond funds. This also explains that bond funds have a high OS&OP ratio and yield, and so they are more attractive for investors, yet a high return implies high risk. By contrast to the OS&OP ratio, Kendall's tau between the RP ratio and the mean return of bond funds is negative, implying that a higher (lower) RP ratio will decrease (increase) the mean return rate of bond funds. As to ST-D, Kendall's tau is positive, but it is small. This explains that the ST-D has a low yield and risk. The last factor is the scale of bond fund sales, showing a positive rank correlation. The reason is that a high yield bond fund is more attractive.

Figures (4a) to (4b) also exhibit the four factors to mean returns for the 32 bond funds. It is not difficult to understand the relationship from the variation of these figures.

Table 4. Kendall's tau of copula functions

	Normal Copula	Student t Copula	Clayton Copula	Gumbel Copula	Frank Copula
Panel A: OS&OP ratio vs. mean return rate of bond funds					
Kendall's tau	0.1472	0.1509	0.1939	0.1525	0.1378
LL	-3.1882	-3.3048	-1.2173	-1.0468	-1.3082
AIC	-6.1717	-6.5949	-2.4046	-1.5276	-1.8551
BIC	-6.1683	-6.5841	-2.3826	1.5208	-1.8103
Panel B: RP ratio vs. mean return rate of bond funds					
Kendall's tau	-0.2111	-0.2733	-0.2457	-0.3868	-0.2353
LL	-1.7926	-4.5433	-4.5432	-2.3225	-2.1326
AIC	-3.6055	-9.1127	-6.5443	-4.5999	-4.2251
BIC	-3.6205	-9.1317	-6.5365	-4.5669	-4.1244
Panel C: ST-D ratio vs. mean return rate of bond funds					
Kendall's tau	0.1638	0.2027	0.1703	0.1778	0.1606
LL	-1.0716	-1.1135	-1.1132	-1.0957	-0.8553
AIC	-2.1272	-2.2074	-2.2007	-2.1153	-1.6183
BIC	-2.1155	-2.1931	-2.1819	-2.0596	-1.5507
Panel D: Scale vs. mean return rate of bond funds					
Kendall's tau	0.2163	0.2621	0.1923	0.2352	0.2112
LL	-1.8832	-1.9449	-1.3787	-1.9507	-1.5558
AIC	-3.7456	-3.8649	-2.7277	-3.8196	-2.9884
BIC	-3.7304	-3.8466	-2.7059	-3.7597	-2.8980

Note: AIC (Akaike, 1974) is defined as $AIC(M)$ = -2 LL + 2T; where LL is the log-likelihood value of the copula estimation, and T is the number of parameters in the copula model. BIC is Bayesian information criterion, (Schwarz ,1978).

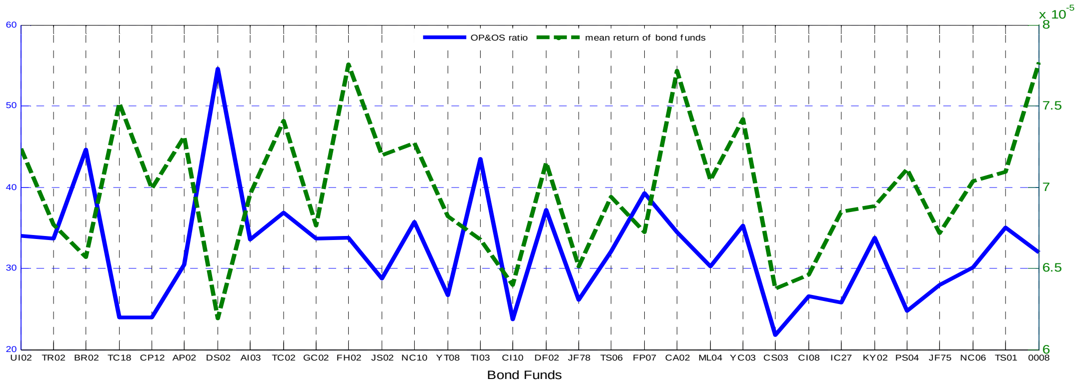

Figure (4a). OS&OP ratio versus mean return rate of bond funds

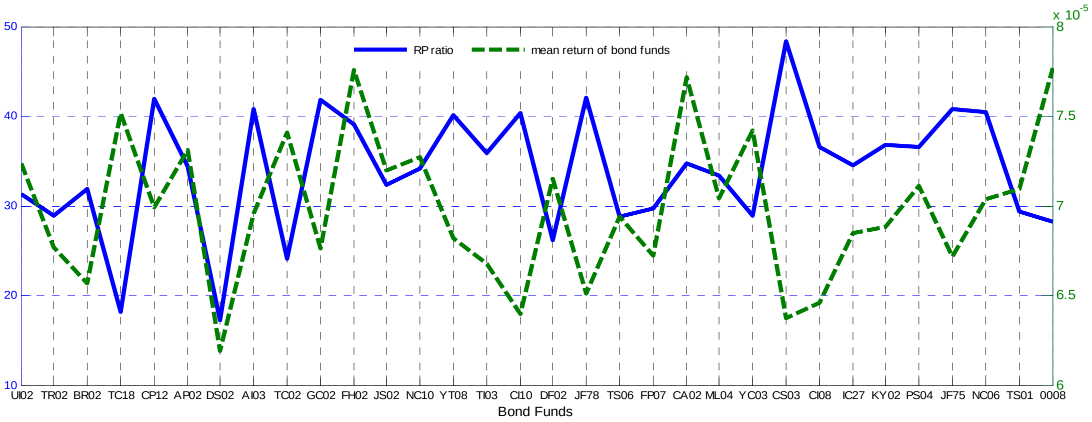

Figure (4b). P ratio versus mean return rate of bond funds

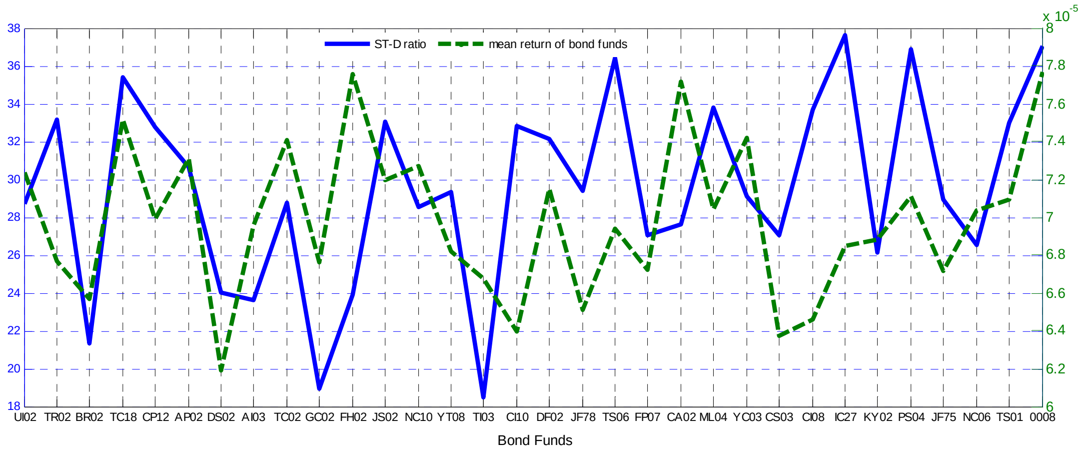

Figure (4c). S -CD ratio versus mean return rate of bond funds

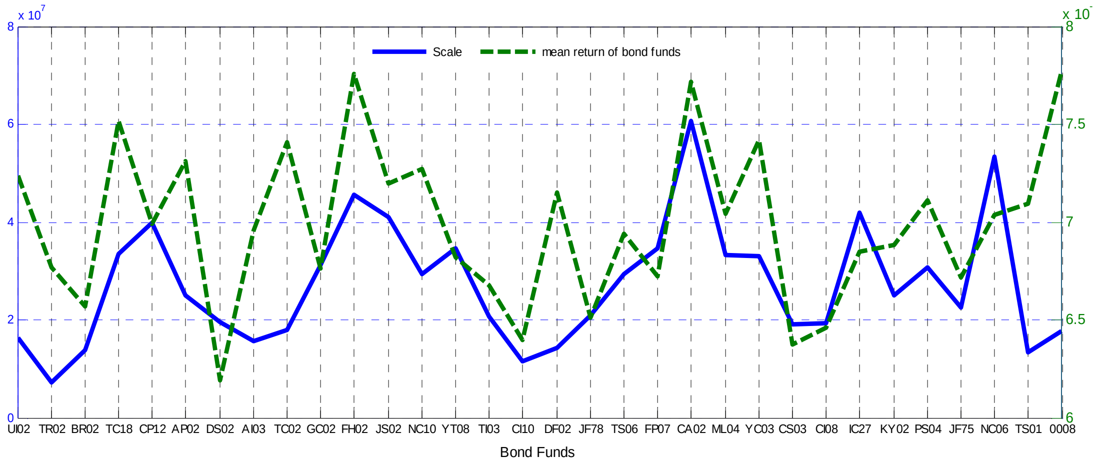

Figure (4d). The scale of bond fund sales versus mean return rate of bond funds

We further investigate the variation of VaR before and after the segregation policy. In the measurement of volatility, we adapt the historical and GARCH (1, 1) models. Table 5 reports all the results. Panel A exhibits the descriptive statistics before the segregation policy. The mean volatility historically is smaller than the GARCH (1,1) model. The result is the same after policy implementation. The most notable information is that the volatility significantly decreases after carrying out the policy. The historical volatility decreases from 0.00008549 to 0.00004203 and from 0.00001492 to 0.00005613 for GARCH volatility. This means that it is efficient for bond funds to reduce their OS&OP ratio and transfer over to quasi money market funds. Figures (5a) and (5b) show the volatility before and after divergence, respectively.

Table 5. Summary statistics of volatility

	Panel A: before policy		Panel B: after policy	
	Historical	GARCH	Historical	GARCH
Mean	8.5485e-005	1.4918e-004	4.2034e-005	5.6137e-005
Std	1.9617e-005	1.7063e-004	1.03386e-005	5.1009e-005
Max	1.7984e-004	0.00103	8.8735e-005	3.2998e-004
Min	7.3457e-005	6.6617e-005	1.79150e-005	2.8229e-005
Skewness	3.9770	4.5987	2.52574	5.0479
Kurtotsis	18.6846	24.30426	14.9833	27.6690
J-B	412.364***	717.9527***	2.25491***	947.3229***

Note: P-value is the probability that the data come from the normal distribution, according to the Jarque-Berra normality test.

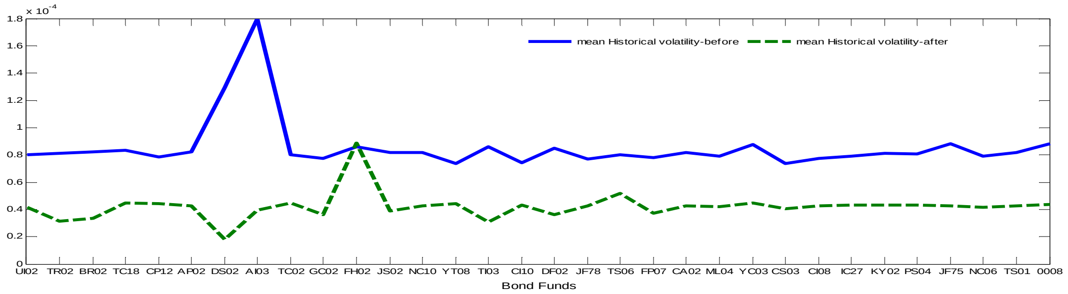

Figure (5a). Historical volatility of net value return - before and after the policy

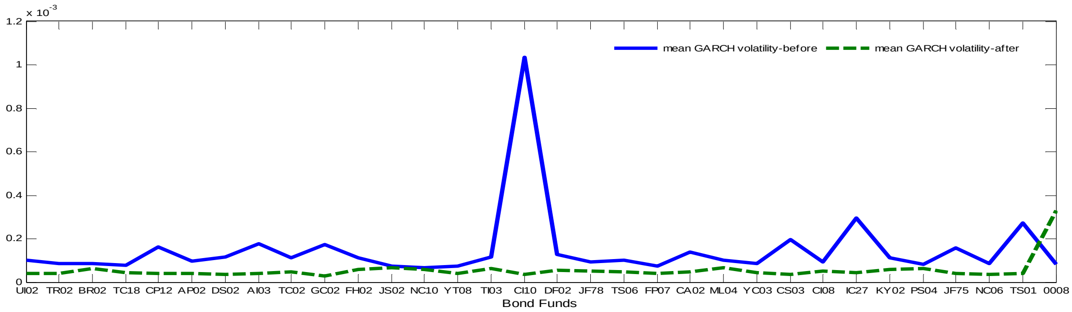

Figure (5b). GARCH volatility of net value return - before and after the policy

Value at Risk (VaR)[7] is a widely used risk measure of the risk of loss on a specific portfolio of financial assets. For a given portfolio, probability, and time horizon, VaR is defined as a threshold value such that the probability that the mark-to-market loss on the portfolio over the given time horizon exceeds this value (assuming normal markets and no trading in the portfolio) at the given probability level.

[7] For details about VaR, see John Hull (2010).

In order to understand the variation of VaR before and after policy implementation, we calculate the historical and GARCH VaR due to the variance-covariance model. Table 6 reports the results. The VaR significantly decreases after the bond fund segregation policy. The historical volatility decreases from 313.7818 to 64.7841 and from 381.9062 to 92.6052 for GARCH VaR. Figures (6a) and (6b) show the variation of the OS&OP ratio versus historical and GARCH VaR over the full time period of January 2001 to June 2010, respectively. We also apply the five copula functions to obtain the rank correlation between the OS&OP ratio and historical VaR and GARCH VaR, respectively. The results tell us that there exists a positive correlation no matter in the historical or GARCH model, implying that the OS&OP ratio is the absolute key factor for bond funds.

Table 6. Summary statistics of VaR

	Panel A: before policy		Panel B: after policy	
	Historical	GARCH	Historical	GARCH
Mean	313.7818	381.9062	64.7841	92.6052
Std	300.3809	349.2460	70.5020	197.0734
Max	1772.2571	2075.2242	418.6445	1152.9274
Min	185.1700	176.3635	32.6211	28.6579
Skewness	3.8225	3.7546	4.1649	5.0910
Kurtotsis	18.6276	18.5062	21.1960	27.9090
J-B	403.5600***	395.7708***	533.9697***	965.5081***

Note: P-value is the probability that the data come from the normal distribution, according to the Jarque -Berra normality test.

Table 7. Kendall's tau of copula functions

	Normal Copula	Student t Copula	Clayton Copula	Gumbel Copula	Frank Copula
Panel A: OS&OP ratio vs. VaR_his_all of bond funds					
Kendall's tau	0.2786	0.3186	0.2713	0.2972	0.2914
LL	-3.1680	-3.3649	-2.8679	-3.0481	-2.8563
AIC	-6.3095	-6.6998	-5.6892	-6.0072	-5.5364
BIC	-6.2901	-6.6779	-5.6551	-5.9420	-5.4072
Panel B: OS&OP ratio vs. VaR_GARCH_all of bond funds					
Kendall's tau	0.0330	0.0390	0.0476	0.0928	0.0341
LL	-0.0431	-0.0519	0.2177	-0.3077	-0.0355
AIC	-0.0829	-0.1000	0.4417	-0.5466	-0.0519
BIC	-0.0805	-0.0972	0.4463	-0.4961	-0.0378

Note: AIC (Akaike, 1974) is defined as $AIC(M) = -2\ LL + 2T$; where LL is the log-likelihood value of the copula estimation, and T is the number of parameters in the copula model. BIC is Bayesian information criterion, (Schwarz ,1978).

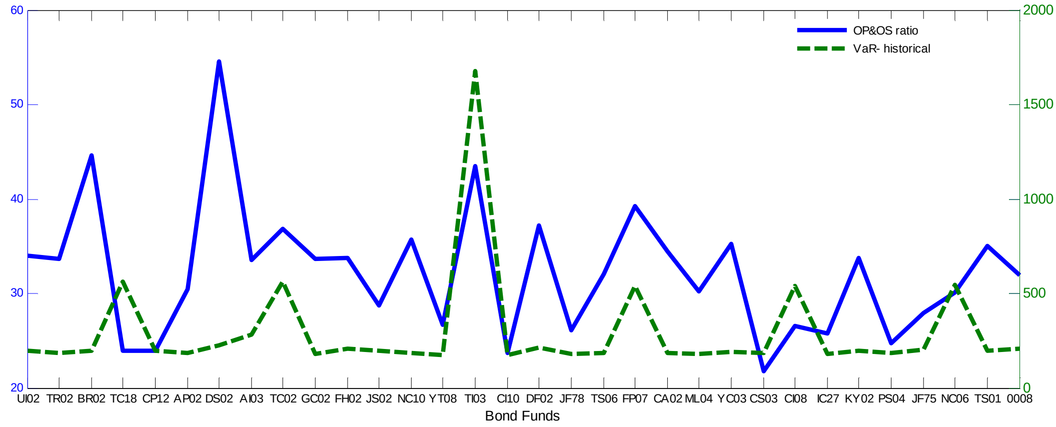

Figure (6a). OS&OP ratio verus VaR_His_all of bond funds

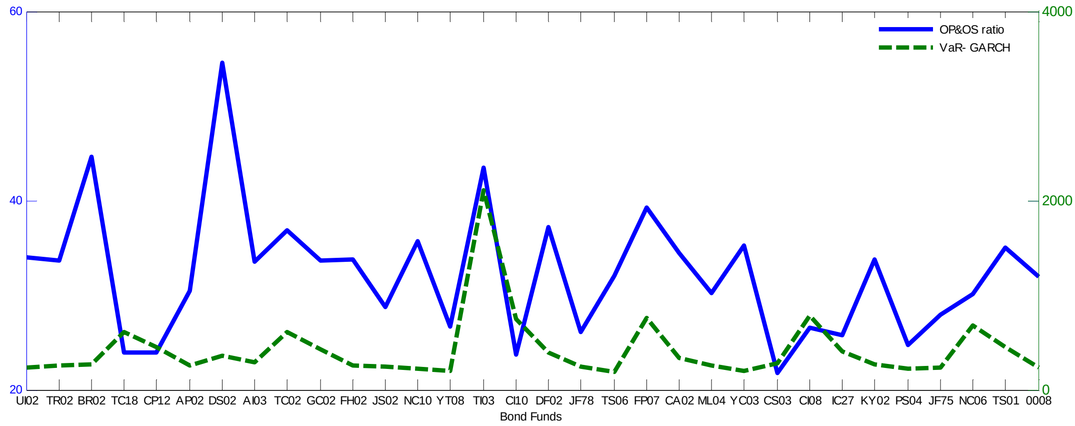

Figure (6b). OS&OP ratio verus VaR_GARCH_all of bond funds

4. CONCLUSION and REMARKS

This article conducts an empirical investigation into the effect from carrying out Taiwan's bond segregation policy. We first focus on the variation of the OS&OP ratio, RP ratio, ST-D and the scale of bond fund sales. We further apply five copula functions to obtain the rank correlation between these ratios and the mean return rate of net value. We also investigate the variation of two volatilities and VaRs before and after the policy.

Our empirical findings show that the OS&OP ratio decreases below 30% after 2007. The RP ratio and ST-D ratio conversely increase, while the scale of bond fund sales also decrease. We then test the significance of these ratios through the student-t pair test. We conclude that all the ratios present a significant difference after 2007. In order to see the correlation between these ratios and the mean return rate of net value, we apply five widely used copula functions. The results find that all the ratios have a positive correlation with the mean return rate except the RP ratio. The volatility of return also decreases no matter in the historical or GARCH model. Lastly, the VaR decreases after carrying out the bond fund segregation policy. The OS&OP ratio has a positive correlation with the VaR, implying that the OS&OP ratio serves as the absolute key factor for bond funds.

After Taiwan's FSC was established in July 2004, it immediately had to deal with a market of scarce liquidity, resulting from large holdings of structured notes that triggered significant redemptions upon Union Investment Trust and Tai-Yu Investment Trust. The authority enhanced the liquidity mechanism, improving valuation measurements and implementing the bond segregation policy. To sum up, we conclude that the bond fund segregation policy significantly reduced the risk for bond funds. In other words, the policy has been effective and successful.

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