

On Performance and Persistence of Mutual Funds in
China

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Abstract

The mutual fund market in China is still very young. The first mutual fund in China came out in 1991, but it was not until the beginning of 21st century that the market began to flourish, with a fast-growing number of funds and increasing assets under management (AUM). However, there is still little existing research on Chinese mutual fund investment behavior. This research aims to evaluate the performance and analyze their investment approaches it relates to.

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Introduction and Hypothesis

Mutual funds are a very important component in the US Financial System. Based on the data collected by the 2015 Investment Company Fact Book, “Altogether, 43 percent of U.S. households—or about 53.2 million—owned mutual funds in mid-2014, [...]” (114). By 2016, there were altogether 16 trillion US dollars under mutual fund management. These numbers show that mutual funds are widely held by US households and have long been a common investment choice for them. Compared to the US, China’s mutual fund market is still in its beginning. During the past two decades, the Chinese mutual fund market has developed to

include over 3,000 funds and with 8 trillion RMB of AUM, but there is a lack of literature analyzing their performance systematically. This is what motivates us to pursue this topic.

Moreover, simply knowing whether their returns exceed the market portfolio is not enough. It is necessary to look into investment styles of mutual fund managers in order to identify the sources of mutual fund performance. This research estimates various models to see how mutual fund returns vary across different market segments. Specifically, we examine stock markets, bond markets, size premium markets and market timing segments. We begin by looking at how different types of mutual funds, such as equity, hybrid and bond funds, invest differently in stock market and bond market. The study also estimates more complex models to see how mutual fund managers invest in small cap or large cap stocks and how they are able to capture market uprisings.

Methodology

The research goes from macro-level analysis to more micro-level results and from basic models to more sophisticated ones. To be exact, this research is conducted in terms of four phases, each focusing on different methodologies.

Phase 1: An historical overview of the Chinese mutual funds market to find out how mutual funds have been developing since 1991. The overview includes which types of funds are dominant in the market and which ones are developing most rapidly. We are also interested in identifying different patterns in the number of funds and AUM separated by different fund types. To investigate the mutual fund market in more detail, we also calculate summary

statistics for multiple fund characteristics separated by fund types and understood how they have been changing over time.

Phase 2: Evaluate fund performance with the basic two-factor regression model as follows:

$$r - r_f = \alpha + \beta_s(r_s - r_f) + \beta_b(r_b - r_f) + \varepsilon$$

r : return on each single mutual fund

r_f : risk-free return

r_s : stock market index return

r_b : bond market index return

We construct this two-factor model to reveal the fundamental investment structure of mutual funds. Based on special Chinese market conditions, most Chinese mutual funds use a portfolio of stock index and bond index as benchmark, as stated in their contracts. The stock beta, β_s , and bond beta, β_b , reveals funds' sensitivity to the stock market risk and the bond market risk respectively, which further explains how much stocks and bonds are in the fund portfolio.

The study takes several stock indexes as potential candidate, such as CSI 300 or CSI 500 and it uses All Bond Index as bond market portfolio. These decisions are made based on our initial investigation on multiple mutual fund contracts that these indexes are used the most as their official benchmarks, and thus, may have enough significance in determining fund returns.

Moreover, we further estimate the model on different time periods, i.e. 18 months and 36 months aiming to find whether excess return upon market persists in longer periods.

Phase 3: We proceed by looking at how mutual funds take advantage of size premium with the extended model:

$$r - r_f = \alpha + \beta_s(r_s - r_f) + \beta_{SML}(SML) + \beta_b(r_b - r_f) + \varepsilon$$

SML: small cap – large cap stock. It counts for the size premium portfolio.

The model is inspired by Cahart's (*On persistence in mutual fund performance* 1997) four-factor model and Fama-French (*Industry costs of equity* 1997) three-factor model. We make the same assumption as the two papers that small cap stocks tend to have a higher return because they are less differentiated. Therefore, if there is a swap-away from broad market index to this factor, we can conclude that fund returns are high because they take advantage of investing in more small cap stocks.

Based on the model, we then conduct multiple tests by changing the size premium index SML. We test whether funds gain profit from size premium of CSI 300 or CSI All Share Index. Furthermore, we also separate the national index to see if more size premium effects exist in the Shanghai stock market or in the Shenzhen stock market.

Phase 4: Another interesting phenomenon worth exploring is fund managers' ability to capture market timing patterns, which means whether they can react promptly to market rises and drops and gain profit from it. The model is as follows:

$$r - r_f = \alpha + \beta_s(r_s - r_f) + \beta_{s^+}(r_s - r_f)^+ + \beta_b(r_b - r_f) + \beta_{b^+}(r_b - r_f)^+ + \varepsilon$$

$(r_s - r_f)^+$: positive part of stock market premium. More precisely, it can be calculated by

$(r_s - r_f) \cdot 1\{r_s > r_f\}$ ($1\{r_s > r_f\}=1$ when $r_s > r_f$ and $=0$ otherwise).

$(r_b - r_f)^+$: constructed using the same technique as above

As shown in the equation, we have the β_s as the regular market beta to measure manager's volatility to the market when market is down and β_{s+} to measure manager's **increment** beta when market goes up. Thinking it through in more detail, if β_{s+} equals to zero, fund return is only affected by its systematic risk with the market, which is reflected by the regular market beta β_s ; if β_{s+} is positive, there exists more beta when market goes up, which indicates that fund managers intentionally increase holding more stock when the stock market goes up, and thus generate more returns.

Phase 5: All the models mentioned in Phase 2 to Phase 4 are estimated on every piece of mutual fund with full return series in a given time period. For example, if there are altogether 2000 mutual funds, 2000 regressions are trained for each model. We have cross-sectional summary statistics for important regression characteristics, including intercept, coefficients, Standard Errors, t-statistics and adjusted R-squared. 18-month we chose was from Jan 2015 to June 2016 and the 36 month from June 2013 to June 2016.

Data

Time Period Selection:

All data downloaded date from 1990 to 2016. The year, 1990, is chosen based on the issuance of first mutual fund in China. The study utilizes Wind Database in China to collect all the data, as it contains most of the data necessary for this study.

Data Categories:

In the light of above methodology, I collect data consisting of the following parts:

1. Mutual Fund Data:

- a) All historical and latest mutual fund basic information: security code, name, issuing year, delisting year, fund type (equity, hybrid, bond, money market, alternative or QDII).
- b) AUM time series for each fund
- c) Return time series of each fund

2. Market Index Data: benchmark index data as mentioned in the model above, summarized below:

- a) Risk-free Rate: One-year Deposit Rate
- b) Stock: China Securities Index: CSI 100, 200, 300, 500, All Share; Shanghai Stock Exchange: SSE 100, Small Medium, Composite; Shenzhen Stock Exchange: 100, Medium Small and Innovative, Composite
- c) Bond: CSI All Bond Index

Challenges with collection of data:

1. Mutual fund Data:

- a) It took me several attempts to successfully download the whole set of all mutual fund on Wind Database because of database's complicated categorical structure.

2. Market Index Data:

- a) The figure on the Internet only contains one-year deposit rate change in infrequent time intervals and I have to change this kind of discrete data to time series monthly return data using the formula $\sum r_y/360$ for each month. The daily deposit rate is determined by the latest changing date before this date.
- b) CSI 300, CSI 500 and All Bond Index are all daily return series. I changed daily return to monthly return using compounding rate $\prod(1 + r_d) - 1$.

Results

Historical Trend

My first attempt is to figure out how mutual fund market as a whole developed. I first looked at historical change of different types of mutual funds in terms of both number of funds and their Assets under Management (as shown in Figure 1 and 2 in Appendix I).

As in Figure 1, even though the first mutual fund was issued in 1991, the number of mutual funds stays the same in a very low level before the 21st century. However, it started to increase very quickly at the beginning of 21st century. Especially since 2006, there was a clear rapid growth. This finding reiterates the argument mentioned above as in Introduction that Chinese mutual fund market doesn't start developing until 21st century.

Fund AUM follows the same general historical pattern as seen in Figure 2. However, when looking at year 2016, fund type distribution patterns in terms of fund number and fund AUM are very different. In one single bar in both Figure 1 and 2, the lengths of different color sub-bars show different market share for different fund types. If one sub-bar is long, this fund types occupies more in mutual fund market. As a result, we may first notice that

hybrid funds lead the market in terms of quantity (in Figure 1), while it only ranks second in terms of fund AUM. Money market funds, surprisingly, obtain the most amount of AUM (in Figure 2). However, Money Market Funds are not large in number. There are far less money market funds than hybrid, bond and equity funds. Hence, undoubtedly, the prevailing type of fund in China is hybrid, obtaining a high rank in terms of both quantity and AUM. Since hybrid funds invest in similar financial instruments as equity and bond funds, I decide to include all three types in my analysis.

Fundamental Fund Characteristics

The study follows by giving cross-sectional summary statistics of basic fund characteristics in order to analyze fund market conditions from different aspects in different categories. The summary statistics is given by important descriptive statistical data., i.e. mean, SD, skew, min, max, median and 5%th, 25%th, 75%th and 95%th percentile, for equity, hybrid and bond funds respectively. To give more vivid representation for distributions, this study includes box plots in Appendix I, aiming to give a more intuitive representation of cross-sectional distribution.

Year of Existence

Summary Statistics	Count	Mean	STD	Skew	Min	5% Percentile	25% Percentile	Median	75% Percentile	95% Percentile	Max
Equity	1039	3.25	3.33	2.15	0.0027	0.54	1.26	1.71	4.39	12.10	15.01
Hybrid	1986	3.04	3.54	1.48	0.0027	0.10	0.68	1.35	4.33	11.01	15.03
Bond	1365	2.82	2.49	1.33	0.0027	0.09	0.67	2.67	3.78	7.93	13.94

Table 1: Cross-sectional Summary Statistics for Fund Year of Existence

In the table above, we can clearly see that the average lifespan of one mutual fund is around 3 years, no matter whether it's an equity, hybrid or bond fund. By taking a closer look

at the distribution, equity funds are more left skewed, which means there are more equity funds with a shorter lifespan. This fact may be due to the higher risk that equity funds are exposed to.

Assets Under Management

Summary Statistics	(in millions RMB)	Count	Mean	STD	Skew	Min	5% Percentile	25% Percentile	Median	75% Percentile	95% Percentile	Max
Equity	2015/6/30	734	2720	6464	5.21	0.6733	26	154	609	2238	11652	56044
	2016/6/30	900	1103	2688	4.72	0.2658	9	60	225	770	5230	26854
Hybrid	2015/6/30	1114	2730	3267	1.92	0.0280	60	368	1439	3893	10158	25564
	2016/6/30	1709	1153	2610	10.94	0.0001	2	121	475	1396	4193	45083
Bond	2015/6/30	845	558	1130	10.24	0.2437	11	76	238	598	2346	22519
	2016/6/30	1070	876	1720	6.88	0.0000	7	81	319	921	3419	30032

Table 2: Cross-sectional Summary Statistics for Fund AUM ending June 2015 and 2016

We further investigate on fund AUM in two dimensions. The chronological dimension includes data from two time points, semi-annual ending in 2015 and 2016, due to our interest in how AUM changes in time. The categorical dimension is split by fund types as usual. We began the analysis by looking at summary statistics in June 2015. Equity and hybrid funds have a similar mean to AUM. However, even though equity funds are much smaller in number, they have a much higher variability. Since equity funds are more left skewed, there are more small equity funds, but there are also several very large-AUM equity funds that draw the average AUM up. One hypothesis is that the equity fund market obtains a complex market condition. Small-AUM funds may be products in small, informal fund companies having very different investing strategies. Bond funds have the smallest mean and SD, which shows that the bond market is a relatively stable market with less outliers.

When we compare the AUM change between June 2015 and 2016, we can witness an increasing number of funds and a decreasing mean and standard deviation in both equity and

hybrid funds. However, the reason for this phenomenon is very different between equity and hybrid Funds. Equity funds had a decrease in all percentiles and also a decreasing skewness. This shows a clear trend that a large amount of money moves out of the equity fund market even though the number of equity funds increases. One empirical hypothesis is that because of two significant Chinese stock market crashes (one in July 2015 and the other in Jan 2016), equity funds were affected most and had a poor performance. Generally, people tend to move away from high-risk assets to more secure ones when the market is undergoing a poor performance.

Hybrid funds, on the other hand, are very different. Skewness of Hybrid Fund AUM is increasing tremendously, bringing the distribution significantly to left. This most likely reveals that, in 2016, there are many newly-issued hybrid funds. Thus, the hybrid fund market was growing in 2016 because people saw many opportunities there.

Finally, Bond Funds are still different from these two. They increase in mean and Standard Deviation steadily. It means that bond funds are developing steadily in the year 2015 with more people investing in them.

Mutual Fund Performance

This study is then followed by running different models mentioned in the Methodology section. This section summarized the statistical findings and empirical reasons for each model. The study began by comparing results for the fundamental two-factor model in 18-month and 36-month period. It follows by conducting research on whether fund managers

take advantage of size premium in stocks and market timing with more factors added to the equation.

When looking at all the test results below, we first checked its significance. The general significance can be revealed by Adjusted R-squared. Then we look closer at the attributes interested by either comparing its mean and Standard Error or checking its t-statistics. If mean is much larger than Standard Error or if t-statistics are large enough, we can conclude that the test on this attribute is significant enough. Unless clearly noted, all the implications below are based on this assumption.

Two Factor Model – 18M vs. 36M

Summary Statistics	Count	Mean	Mean SE	STD	Skew	Min	5% Percentile	25% Percentile	Median	75% Percentile	95% Percentile	Max	
Equity	Alpha	431	0.0113	0.0133	0.0134	0.5541	-0.0423	-0.0021	0.0029	0.0084	0.0193	0.0336	0.0883
	Stock Beta	431	1.0541	0.1311	0.6092	0.7987	-0.0026	-0.0003	0.8544	1.0093	1.2182	2.2507	4.1196
	Bond Beta	431	0.1174	1.5539	1.0859	2.5079	-3.6931	-1.4126	-0.3743	0.0764	0.4736	1.4031	10.2420
Hybrid	Alpha	766	0.0229	0.0165	0.0131	0.0952	-0.0125	0.0037	0.0131	0.0225	0.0322	0.0443	0.0584
	Stock Beta	766	0.9510	0.1623	0.4050	-0.9774	-0.0445	0.0562	0.8217	1.0463	1.2276	1.4279	1.7979
	Bond Beta	766	-0.5289	1.9236	0.9646	-0.4821	-4.2152	-2.2545	-1.1336	-0.4299	0.1057	0.9184	2.0567
Bond	Alpha	753	0.0031	0.0037	0.0068	-7.6126	-0.0904	-0.0031	0.0019	0.0034	0.0053	0.0100	0.0159
	Stock Beta	753	0.0964	0.0367	0.1923	4.7215	-0.0553	-0.0117	0.0019	0.0200	0.1230	0.4319	2.0021
	Bond Beta	753	0.5185	0.4352	0.4386	-0.2129	-2.4910	-0.1040	0.2755	0.5455	0.7460	1.1832	2.6840

Table 3: 18-month Two-factor Regression Model Result

Summary Statistics	Count	Mean	STD	Skew	Min	5% Percentile	25% Percentile	Median	75% Percentile	95% Percentile	Max	
Equity	Alpha	278	0.0055	0.0066	2.3761	-0.0218	-0.0055	0.0031	0.0050	0.0081	0.0143	0.0657
	Stock Beta	278	0.8552	0.4505	2.3830	-0.0014	-0.0003	0.7840	0.8722	0.9375	1.5456	4.8524
	Bond Beta	278	0.3135	0.3799	1.5557	-0.6554	-0.0936	0.0389	0.2250	0.4836	1.1351	2.2414
	Alpha SE	278	0.0074	0.0064	2.6522	0.0000	0.0001	0.0034	0.0058	0.0102	0.0199	0.0585
	Stock Beta SE	278	0.0844	0.0733	2.6522	0.0006	0.0011	0.0382	0.0662	0.1159	0.2271	0.6660
	Bond Beta SE	278	0.7853	0.6820	2.6522	0.0052	0.0102	0.3560	0.6165	1.0792	2.1137	6.1989
	t-statistic for Alpha	278	4.1782	10.0328	3.0573	-1.3094	-0.4102	0.5676	1.0268	1.7048	31.9914	60.7357
	R-squared Adj	278	0.6603	0.3073	-1.0567	-0.0600	-0.0336	0.5110	0.7827	0.9161	0.9672	0.9714
	Hybrid	Alpha	581	0.0087	0.0068	0.2108	-0.0108	-0.0024	0.0043	0.0088	0.0134	0.0196
Stock Beta		581	0.7034	0.2143	-1.2585	-0.0135	0.1726	0.6344	0.7409	0.8266	0.9793	1.2240
Bond Beta		581	0.5712	0.5754	0.2876	-1.2290	-0.3239	0.2055	0.5467	0.8989	1.6053	2.4776
Alpha SE		581	0.0112	0.0041	-0.2407	0.0001	0.0036	0.0085	0.0115	0.0139	0.0174	0.0234
Stock Beta SE		581	0.1271	0.0465	-0.2407	0.0012	0.0406	0.0966	0.1309	0.1588	0.1980	0.2659
Bond Beta SE		581	1.1829	0.4324	-0.2407	0.0115	0.3778	0.8992	1.2181	1.4778	1.8426	2.4754
t-statistic for Alpha		581	0.9531	1.5186	14.7459	-2.2385	-0.1938	0.3874	0.8090	1.2616	2.4148	31.9403
R-squared Adj		581	0.4554	0.1618	0.3142	-0.0576	0.2083	0.3545	0.4401	0.5454	0.7672	0.9282
Bond		Alpha	443	0.0029	0.0034	0.4003	-0.0094	-0.0020	0.0013	0.0029	0.0044	0.0079
	Stock Beta	443	0.1230	0.1956	2.3905	-0.1005	-0.0210	-0.0001	0.0626	0.1462	0.5879	0.9817
	Bond Beta	443	0.8415	0.3944	3.5668	-0.0335	0.3515	0.6450	0.7980	1.0034	1.4757	5.2683
	Alpha SE	443	0.0026	0.0023	2.3845	0.0000	0.0006	0.0012	0.0018	0.0029	0.0093	0.0137
	Stock Beta SE	443	0.0293	0.0266	2.3845	0.0005	0.0074	0.0139	0.0207	0.0334	0.1054	0.1555
	Bond Beta SE	443	0.2723	0.2480	2.3845	0.0049	0.0688	0.1298	0.1925	0.3111	0.9812	1.4475
	t-statistic for Alpha	443	1.7809	2.4406	4.8870	-3.2105	-0.7493	0.7651	1.5735	2.4322	3.8812	21.8148
	R-squared Adj	443	0.4751	0.1705	-0.2624	-0.0596	0.1864	0.3660	0.4813	0.5943	0.7217	0.9709

Table 4: 36-month Two-factor Regression Model Result

Two-factor model result

We first look at result of two-factor model in the 18-month period and particularly look at the alpha, stock beta, bond beta the model estimates for equity, hybrid and bond funds.

Alpha: All funds result in a positive alpha, which means that they all generate positive excess returns compared to benchmark portfolio. Comparing across funds, hybrid funds have the best performance with the highest alpha, while bond funds have the lowest. Bond funds are not performing very well as they have more number of funds with a negative alpha. If we look deeper into the distribution, while equity and hybrid funds have similar average performances, they are quite different across the whole distribution. Equity funds have a higher standard deviation and a higher range. This implies that equity fund investment is “high risk, high return” style, while hybrid funds are a more “risk-averse” option.

Stock Beta: Fund sensitivity to the stock market index is reasonable and easy to interpret. Equity funds attain the highest stock beta, which follows by hybrid funds. This corresponds with the portion of investment in stock markets. Bond funds have a very low stock beta, which means that they rarely invest in any stocks. Distribution-wise, equity funds have the highest standard deviation, which means that they have very different strategies in investing in stock markets. Some hypotheses include that some companies choose more risky stocks, while others choose more conservatively.

Bond Beta: Some interesting findings come out when doing the bond beta analysis for the 18-month period. Hybrid funds appear to have a negative bond beta, as if they are using

bonds to leverage stocks. Even though hybrid funds are obliged to hold a long position in both equity and bond by Chinese regulation, this result exhibits a different behavior. One hypothesis of this strange effect is too much noise in such a short time period. We further verify this hypothesis by estimating the model in 36-month period. The new test result shows that hybrid funds actually act in accordance with regulation. This new result also reveals that bond funds have a mean of near 1 on bond beta, which corresponds to their prescribed investment strategies as bond funds. Hybrid funds have a lower bond beta, equity fund have the lowest, which can all be explained by their prescribed investment strategies.

Model Comparison

1. The 36-month model appears to be more accurate than the 18-month model. The longer time period rules out some of the potential effects of noise in regression results. The 36-month model generally has a less standard deviation and less standard error for all terms and the distribution is certainly more compact.
2. The 36-month model generates less excess return, which shows that it is hard for mutual fund managers to sustain their fund performance for a longer period of time.
3. There are still problems in both models. We can see that the standard error for both alpha and bond beta are relatively large. A large standard error in bond beta may result from a strong correlation between the stock market and the bond market so that most bond risk has already been explained by stock factor.

4. A large standard error for alpha may imply that there are still other factors influencing the fund performance that is not yet capture in the two-factor model. I then conduct further test on more complex models to find out more factors affecting excess returns.

Size Market

CSI 300 as market index

$$r - r_f = \alpha + \beta_s(CSI300 - r_f) + \beta_{SML}(CSI200 - CSI100) + \beta_b(AllBondIndex - r_f) + \varepsilon.$$

Summary Statistics		Count	Mean	STD	Skew	Min	5% Percentile	25% Percentile	Median	75% Percentile	95% Percentile	Max
Equity	Alpha	278	0.0054	0.0066	2.3992	-0.0222	-0.0056	0.0031	0.0050	0.0079	0.0137	0.0662
	CSI 300	278	0.9005	0.4632	1.9046	-0.0017	-0.0005	0.8502	0.9095	0.9471	1.7050	4.7122
	CSI SML	278	0.4252	0.6443	0.7859	-1.3146	-0.3526	-0.0021	0.2918	0.8478	1.6213	2.6295
	Bond	278	0.1437	0.3306	1.7578	-1.0687	-0.2735	0.0034	0.1265	0.2455	0.5969	2.2328
	Alpha SE	278	0.0049	0.0047	5.9364	0.0000	0.0001	0.0027	0.0040	0.0058	0.0121	0.0581
	CSI 300 SE	278	0.0562	0.0546	5.9364	0.0006	0.0011	0.0314	0.0460	0.0668	0.1399	0.6714
	CSI SML SE	278	0.0908	0.0883	5.9364	0.0009	0.0018	0.0507	0.0743	0.1079	0.2261	1.0850
	Bond SE	278	0.5166	0.5020	5.9364	0.0052	0.0102	0.2886	0.4227	0.6138	1.2857	6.1706
	t-statistic for Alpha	278	4.5197	9.9501	3.0528	-1.7341	-0.7318	0.9237	1.5570	2.1228	32.0777	61.1982
	R-squared Adj	278	0.7990	0.2935	-2.3098	-0.0914	-0.0368	0.8265	0.9122	0.9489	0.9690	0.9775
Hybrid	Alpha	581	0.0084	0.0068	0.2030	-0.0112	-0.0027	0.0039	0.0084	0.0130	0.0192	0.0316
	CSI 300	581	0.7988	0.2414	-1.3787	-0.0138	0.1794	0.7253	0.8429	0.9392	1.1097	1.3284
	CSI SML	581	0.8944	0.4467	-0.3612	-0.3692	0.0718	0.6260	0.9524	1.2113	1.5770	2.0478
	Bond	581	0.2141	0.5188	0.0931	-1.6339	-0.6306	-0.1143	0.1966	0.5226	1.0709	1.8007
	Alpha SE	581	0.0071	0.0023	-0.0533	0.0001	0.0031	0.0056	0.0072	0.0086	0.0107	0.0141
	CSI 300 SE	581	0.0825	0.0264	-0.0533	0.0012	0.0363	0.0652	0.0835	0.0989	0.1234	0.1632
	CSI SML SE	581	0.1333	0.0427	-0.0533	0.0020	0.0587	0.1054	0.1350	0.1598	0.1994	0.2638
	Bond SE	581	0.7581	0.2426	-0.0533	0.0112	0.3340	0.5996	0.7677	0.9091	1.1339	1.5001
	t-statistic for Alpha	581	1.3432	1.6916	11.2302	-2.2355	-0.3656	0.5375	1.2476	1.8872	3.2690	32.8930
	R-squared Adj	581	0.7515	0.1394	-2.5696	0.0021	0.4429	0.7285	0.7886	0.8275	0.8813	0.9284
Bond	Alpha	443	0.0029	0.0034	0.4228	-0.0095	-0.0021	0.0013	0.0029	0.0044	0.0079	0.0193
	CSI 300	443	0.1274	0.1968	2.4086	-0.0898	-0.0156	0.0011	0.0660	0.1606	0.6496	0.9951
	CSI SML	443	0.0413	0.1323	-0.4342	-0.7009	-0.1279	0.0043	0.0340	0.0829	0.2404	0.6874
	Bond	443	0.8251	0.3851	3.3597	-0.0290	0.3527	0.6168	0.7781	0.9796	1.4922	5.0536
	Alpha SE	443	0.0024	0.0022	2.4477	0.0000	0.0006	0.0011	0.0017	0.0028	0.0086	0.0124
	CSI 300 SE	443	0.0280	0.0255	2.4477	0.0005	0.0072	0.0132	0.0199	0.0320	0.0998	0.1433
	CSI SML SE	443	0.0452	0.0412	2.4477	0.0009	0.0117	0.0214	0.0321	0.0518	0.1613	0.2317
	Bond SE	443	0.2572	0.2346	2.4477	0.0050	0.0664	0.1216	0.1828	0.2944	0.9173	1.3175
	t-statistic for Alpha	443	1.8518	2.4537	4.6361	-3.4848	-0.7685	0.8087	1.6577	2.5970	4.1582	21.6038
	R-squared Adj	443	0.5268	0.1671	-0.6809	-0.0617	0.2487	0.4259	0.5469	0.6461	0.7601	0.9701

Table 6: Regression Result for Size Premium Test on CSI 300

Based on the above result, the most general conclusion we can get is that there exists a size effect in returns in CSI 300, fund managers for all three types of funds are able to capture this excess return generated by small stocks' excess return than large stocks when the market goes up. When compared with the two-factor model, there is a clear swap-away from market

portfolio to size premium market. This indicates that fund managers have the ability to capture this size premium effect. More precisely, they can actively invest in small stocks when small stocks are generating a higher return.

When we compare alpha with previous two-factor model, we witness a swap-away from broad market to size premium market, which means alpha in this model is lower than that in two-factor model. This phenomenon represents that some of fund managers' excess returns can be explained by this size premium effect.

CSI All Share as market index

$$r - r_f = \alpha + \beta_s(CSIAllShare - r_f) + \beta_{SML}(CSI500 - CSI300) + \beta_b(AllBondIndex - r_f) + \varepsilon.$$

Summary Statistics	Count	Mean	STD	Skew	Min	5% Percentile	25% Percentile	Median	75% Percentile	95% Percentile	Max	
Equity	Alpha	278	-0.0003	0.0084	0.4769	-0.0355	-0.0124	-0.0034	0.0009	0.0032	0.0090	0.0653
	CSIAllShare	278	0.8880	0.4546	1.8122	-0.0016	-0.0003	0.8371	0.8969	0.9402	1.6975	4.5719
	CSI SML	278	-0.1735	0.5657	-1.0127	-4.1892	-0.9357	-0.5408	-0.1950	0.1781	0.7286	1.2787
	Bond	278	0.1109	0.3117	1.6089	-0.9738	-0.2730	-0.0337	0.0508	0.2143	0.6901	1.8261
	Alpha SE	278	0.0049	0.0048	6.0961	0.0000	0.0001	0.0031	0.0039	0.0056	0.0124	0.0588
	CSIAllShare SE	278	0.0551	0.0533	6.0961	0.0006	0.0011	0.0347	0.0437	0.0625	0.1390	0.6593
	CSI SML SE	278	0.0794	0.0768	6.0961	0.0008	0.0016	0.0500	0.0630	0.0901	0.2005	0.9510
	Bond SE	278	0.5126	0.4959	6.0961	0.0052	0.0103	0.3230	0.4069	0.5819	1.2945	6.1393
	t-statistic for Alpha	278	3.3423	10.1376	3.0012	-2.9892	-1.7193	-0.6890	0.1996	1.3055	31.4428	60.1304
	R-squared Adj	278	0.7997	0.2960	-2.3373	-0.0913	-0.0503	0.8335	0.9108	0.9491	0.9616	0.9648
Hybrid	Alpha	581	-0.0008	0.0074	0.0529	-0.0226	-0.0132	-0.0062	-0.0006	0.0040	0.0107	0.0262
	CSIAllShare	581	0.8024	0.2444	-1.3568	-0.0167	0.1727	0.7269	0.8447	0.9479	1.1211	1.3247
	CSI SML	581	0.3089	0.3221	-0.3229	-0.7293	-0.2792	0.1013	0.3327	0.5331	0.7955	1.1973
	Bond	581	0.2570	0.5296	0.1377	-1.5551	-0.6078	-0.0693	0.2276	0.5642	1.1557	1.9457
	Alpha SE	581	0.0067	0.0021	0.0016	0.0001	0.0032	0.0054	0.0068	0.0080	0.0100	0.0143
	CSIAllShare SE	581	0.0748	0.0233	0.0016	0.0012	0.0358	0.0602	0.0757	0.0893	0.1117	0.1606
	CSI SML SE	581	0.1079	0.0337	0.0016	0.0018	0.0517	0.0868	0.1092	0.1288	0.1611	0.2317
	Bond SE	581	0.6968	0.2173	0.0016	0.0114	0.3336	0.5606	0.7047	0.8317	1.0399	1.4957
	t-statistic for Alpha	581	0.0570	1.8019	9.8545	-4.3433	-1.8104	-0.8351	-0.0927	0.6840	2.3354	32.1698
	R-squared Adj	581	0.7809	0.1435	-2.7392	-0.0207	0.4604	0.7634	0.8206	0.8608	0.9025	0.9356
Bond	Alpha	443	0.0023	0.0040	0.1991	-0.0146	-0.0038	0.0007	0.0024	0.0041	0.0075	0.0210
	CSIAllShare	443	0.1253	0.1940	2.4171	-0.0905	-0.0151	0.0007	0.0628	0.1581	0.6541	0.9801
	CSI SML	443	-0.0405	0.1552	-2.6955	-0.8990	-0.3651	-0.0583	0.0032	0.0371	0.1030	0.3339
	Bond	443	0.8175	0.3793	3.4411	-0.0313	0.3402	0.6108	0.7778	0.9783	1.4387	5.0395
	Alpha SE	443	0.0025	0.0022	2.4608	0.0000	0.0006	0.0012	0.0018	0.0028	0.0088	0.0126
	CSIAllShare SE	443	0.0275	0.0250	2.4608	0.0005	0.0070	0.0131	0.0197	0.0314	0.0984	0.1412
	CSI SML SE	443	0.0396	0.0361	2.4608	0.0008	0.0101	0.0189	0.0284	0.0453	0.1419	0.2036
	Bond SE	443	0.2558	0.2329	2.4608	0.0050	0.0653	0.1221	0.1831	0.2926	0.9162	1.3144
	t-statistic for Alpha	443	1.5714	2.4927	4.3772	-4.0915	-1.2662	0.3783	1.4271	2.3899	3.8491	21.2549
	R-squared Adj	443	0.5281	0.1676	-0.6759	-0.0639	0.2524	0.4291	0.5513	0.6422	0.7709	0.9703

Table 6: Regression Result for Size Premium Test on CSI All Share

When we choose the market index to be a broader range of stocks, i.e. CSI All Share, the result is very different from that of CSI 300. One significant difference is that there is a significant drop in coefficients on the size factor. Equity funds even end up in a negative size premium market beta, meaning that equity fund managers still invest in large stocks even though small stocks have higher excess returns. One possible reason for this difference is that even though CSI 200 is the smaller fraction in CSI 300, they are still relatively large stocks compared to stocks in CSI 500, which is the smaller-cap fraction of CSI All Share index. This is a clear indication that fund managers still prefer relatively large or medium-size stocks. They cannot take that much risk by investing in stocks with very small capitalization. We can then conclude that mutual fund investments are relatively risk-averse, even though they sacrifice the potentials of excess return from small-cap stocks when market goes up.

Shanghai & Shenzhen Composite Index as market index

$$\begin{aligned}
 r - r_f = & \alpha + \beta_{SSE}(SSEComposite - r_f) + \beta_{Shen}(ShenComposite - r_f) \\
 & + \beta_{SSESML}(SSEMediumSmall - SSE100) \\
 & + \beta_{ShenSML}(ShenMedSmallInnovation - SSE100) + \beta_b(AllBondIndex \\
 & - r_f) + \varepsilon
 \end{aligned}$$

Summary Statistics		Count	Mean	STD	Skew	Min	5% Percentile	25% Percentile	Median	75% Percentile	95% Percentile	Max
Equity	Alpha	278	0.0035	0.0118	3.7313	-0.0308	-0.0102	-0.0024	0.0031	0.0091	0.0173	0.1265
	SSE Composite	278	0.4234	0.5650	-0.4505	-1.6904	-0.5847	0.0048	0.4323	0.8242	1.1881	2.1573
	Shen Composite	278	0.5365	0.7045	2.4256	-0.3780	-0.1726	0.0098	0.3380	0.8307	1.7517	5.6400
	SSE SML	278	-0.2387	0.4083	-2.2357	-3.4186	-0.7886	-0.3755	-0.2161	-0.0448	0.3112	1.1482
	Shen SML	278	-0.3468	0.5559	-7.8132	-7.4549	-0.9600	-0.4714	-0.3387	-0.0087	0.1414	0.2914
	Bond	278	-0.0391	0.2816	0.9130	-1.0663	-0.3971	-0.1864	-0.0533	0.0553	0.4506	1.3858
	Alpha SE	278	0.0046	0.0045	5.6500	0.0001	0.0001	0.0027	0.0036	0.0055	0.0121	0.0539
	SSE Composite SE	278	0.2199	0.2155	5.6500	0.0025	0.0050	0.1307	0.1722	0.2610	0.5777	2.5668
	Shen Composite SE	278	0.2187	0.2143	5.6500	0.0024	0.0050	0.1300	0.1713	0.2596	0.5746	2.5528
	SSE SML SE	278	0.3206	0.3141	5.6500	0.0036	0.0073	0.1905	0.2510	0.3804	0.8421	3.7412
	Shen SML SE	278	0.1653	0.1619	5.6500	0.0018	0.0037	0.0982	0.1294	0.1962	0.4342	1.9291
	Bond SE	278	0.4689	0.4594	5.6500	0.0052	0.0106	0.2787	0.3671	0.5564	1.2316	5.4719
	t-statistic for Alpha	278	4.2800	9.7579	2.8684	-2.8523	-1.6788	-0.4850	1.3782	3.6698	29.9148	58.6234
	R-squared Adj	278	0.8141	0.2984	-2.3699	-0.1242	-0.0493	0.8575	0.9317	0.9568	0.9730	0.9776
Hybrid	Alpha	581	-0.0012	0.0085	0.0877	-0.0246	-0.0150	-0.0071	-0.0012	0.0046	0.0129	0.0262
	SSE Composite	581	-0.1269	0.3499	0.2331	-1.2202	-0.6728	-0.3614	-0.1226	0.0682	0.5416	1.1108
	Shen Composite	581	0.9666	0.4662	-0.3406	-0.4199	0.1144	0.6781	1.0235	1.2936	1.6610	2.2400
	SSE SML	581	0.0446	0.4676	0.3047	-1.3835	-0.6897	-0.2534	0.0289	0.3089	0.8805	1.5325
	Shen SML	581	-0.1960	0.2613	0.3615	-0.9274	-0.6131	-0.3846	-0.2076	-0.0213	0.2261	0.8939
	Bond	581	0.1511	0.5454	0.1351	-1.6586	-0.6933	-0.1956	0.1212	0.4711	1.0948	1.8339
	Alpha SE	581	0.0063	0.0020	0.2043	0.0001	0.0032	0.0051	0.0062	0.0075	0.0096	0.0144
	SSE Composite SE	581	0.3006	0.0939	0.2043	0.0055	0.1508	0.2450	0.2957	0.3573	0.4548	0.6839
	Shen Composite SE	581	0.2990	0.0934	0.2043	0.0055	0.1500	0.2436	0.2941	0.3553	0.4524	0.6801
	SSE SML SE	581	0.4381	0.1368	0.2043	0.0080	0.2198	0.3571	0.4311	0.5208	0.6630	0.9968
	Shen SML SE	581	0.2259	0.0706	0.2043	0.0041	0.1133	0.1841	0.2223	0.2685	0.3419	0.5140
	Bond SE	581	0.6408	0.2001	0.2043	0.0118	0.3215	0.5222	0.6305	0.7617	0.9696	1.4579
	t-statistic for Alpha	581	0.0017	1.9209	7.0934	-4.4190	-2.1440	-1.0658	-0.2035	0.8762	2.6231	30.4943
	R-squared Adj	581	0.8058	0.1512	-2.8916	-0.0899	0.4574	0.7919	0.8504	0.8872	0.9221	0.9522
Bond	Alpha	443	0.0028	0.0045	1.6427	-0.0122	-0.0032	0.0008	0.0024	0.0045	0.0085	0.0286
	SSE Composite	443	0.0333	0.1331	1.0131	-0.7195	-0.1352	-0.0234	0.0065	0.0728	0.2833	0.6643
	Shen Composite	443	0.1016	0.1809	2.9727	-0.1277	-0.0514	0.0037	0.0489	0.1268	0.4560	1.2718
	SSE SML	443	0.0028	0.1760	1.4208	-0.7553	-0.2103	-0.0865	-0.0279	0.0694	0.3343	0.9815
	Shen SML	443	-0.0670	0.1423	-2.7041	-0.8321	-0.3839	-0.0896	-0.0292	0.0040	0.0586	0.2042
	Bond	443	0.7878	0.3675	3.4428	-0.0265	0.2720	0.5954	0.7635	0.9562	1.3343	4.9259
	Alpha SE	443	0.0025	0.0023	2.4768	0.0001	0.0007	0.0012	0.0018	0.0029	0.0090	0.0126
	SSE Composite SE	443	0.1207	0.1097	2.4768	0.0024	0.0322	0.0577	0.0863	0.1382	0.4284	0.6020
	Shen Composite SE	443	0.1201	0.1091	2.4768	0.0024	0.0321	0.0574	0.0858	0.1375	0.4260	0.5987
	SSE SML SE	443	0.1760	0.1599	2.4768	0.0035	0.0470	0.0841	0.1257	0.2015	0.6244	0.8774
	Shen SML SE	443	0.0907	0.0824	2.4768	0.0018	0.0242	0.0434	0.0648	0.1039	0.3220	0.4524
	Bond SE	443	0.2574	0.2338	2.4768	0.0051	0.0687	0.1231	0.1839	0.2947	0.9132	1.2833
	t-statistic for Alpha	443	1.6553	2.4615	4.1298	-3.8651	-1.2408	0.4286	1.5074	2.4702	4.1013	20.6328
	R-squared Adj	443	0.5206	0.1712	-0.6738	-0.1337	0.2375	0.4147	0.5405	0.6412	0.7685	0.9687

Table 7: Regression Result for Size Premium Test on Shanghai & Shenzhen Composite Index

The study then continues by finding how mutual fund investments differ between the Shanghai and the Shenzhen stock market, which are known to be the two biggest public stock markets in China. Based on the results in Table 7, equity fund investment on both stock markets is similar to prior test with CSI All Share. There are negative coefficients on both size markets. Because we are using Medium & Small stock indexes, the conclusion is that fund managers do not invest in those small stocks.

On the other hand, hybrid funds yield a different result. While hybrid funds still invest in large stocks in the Shenzhen market, they tend not to take advantage of the size premium effect in the Shanghai market. This finding hypothesizes the general investment behavior of

hybrid fund managers, which they tend to trust the growth of small stocks in the Shanghai market over the Shenzhen market. Such a strange phenomenon drives me to think further for more hypotheses to explain this effect.

Another hypothesis is that the Shanghai and the Shenzhen market have a high correlation with each other so that one coefficient contains the effects on both markets and makes the other coefficient insignificant. This hypothesis is supported by the large Standard Error for both the Shanghai and the Shenzhen market SML coefficients. This hypothesis is further tested by the correlation matrix as shown below.

Correlation Matrix	SSE Composite	Shen Composite
SSE Composite	1	0.8376
Shen Composite	0.8376	1

Table 8: Correlation Matrix for SSE and Shenzhen Composite Index

Based on the correlation matrix, there does exist a strong correlation between SSE Composite Index and Shenzhen Composite Index. It means that in most cases, these two indexes grow and drop together. Therefore, this later hypothesis is proved correct and it is actually of minor significance to see the difference of investment behavior in two similar-behaving indexes.

Market Timing

Using the methodology mentioned in Phase 3, we then measure how well fund managers react in accordance with market performance and make smart decisions by investing more when the market condition is good. The specific model used is as follows:

$$r - r_f = \alpha + \beta_s(CSI300 - r_f) + \beta_{s^+}(CSI300 - r_f)^+ + \beta_b(AllBondIndex - r_f) + \beta_{b^+}(AllBondIndex - r_f)^+ + \varepsilon$$

Summary Statistics		Count	Mean	STD	Skew	Min	5% Percentile	25% Percentile	Median	75% Percentile	95% Percentile	Max
Equity	Alpha	278	0.0155	0.0191	3.2031	-0.0098	-0.0031	0.0031	0.0098	0.0246	0.0483	0.1859
	CSI300	278	1.1001	0.6177	0.8234	-0.0049	-0.0014	0.8417	1.0234	1.3597	2.4690	3.8441
	CSI300+	278	-0.4327	0.6717	-0.3523	-2.6167	-1.7362	-0.8759	-0.3384	0.0037	0.4272	2.8348
	Bond	278	-0.0852	2.1443	10.1396	-6.5575	-2.0713	-0.8242	0.0137	0.3791	1.4080	30.3739
	Bond+	278	0.7046	3.8531	-9.7537	-53.3460	-2.1587	-0.1868	0.3756	2.1266	4.3525	11.4937
	Alpha SE	278	0.0148	0.0127	2.8114	0.0001	0.0002	0.0072	0.0119	0.0200	0.0391	0.1177
	CSI300 SE	278	0.1546	0.1326	2.8114	0.0011	0.0022	0.0754	0.1240	0.2088	0.4080	1.2278
	CSI300+ SE	278	0.2174	0.1864	2.8114	0.0016	0.0032	0.1061	0.1743	0.2936	0.5736	1.7260
	Bond SE	278	1.7589	1.5083	2.8114	0.0131	0.0256	0.8581	1.4099	2.3753	4.6408	13.9647
	Bond+ SE	278	3.0040	2.5759	2.8114	0.0223	0.0437	1.4655	2.4079	4.0567	7.9257	23.8494
	t-statistic for Alpha	278	2.3011	4.5112	2.9505	-1.1487	-0.3306	0.4704	1.0407	1.5341	14.4477	27.2822
	t-statistic for CSI300+	278	-1.1985	2.2072	0.4695	-5.0097	-3.9071	-3.0310	-1.8866	0.6027	2.7684	3.9159
	t-statistic for Bond+	278	0.1671	0.7107	-0.4932	-2.2368	-1.0543	-0.3068	0.2147	0.6686	1.2782	1.6738
	R-squared Adj	278	0.7016	0.2957	-1.4888	-0.0863	-0.0409	0.5905	0.8143	0.9197	0.9657	0.9702
Hybrid	Alpha	581	0.0349	0.0187	0.0975	-0.0085	0.0039	0.0221	0.0355	0.0476	0.0661	0.0915
	CSI300	581	1.2275	0.4418	-0.9235	-0.0637	0.1643	1.0506	1.2853	1.5151	1.8161	2.2302
	CSI300+	581	-0.8911	0.4818	0.3189	-2.3283	-1.5845	-1.2313	-0.9337	-0.5907	-0.0051	0.4652
	Bond	581	0.6013	1.6106	0.2316	-4.6048	-1.8444	-0.4215	0.5484	1.5656	3.4758	5.6059
	Bond+	581	-0.1410	2.9067	-0.2201	-9.7040	-5.1387	-1.8254	-0.1162	1.7223	4.0813	11.2540
	Alpha SE	581	0.0223	0.0079	-0.2200	0.0002	0.0076	0.0174	0.0229	0.0274	0.0345	0.0465
	CSI300 SE	581	0.2325	0.0824	-0.2200	0.0025	0.0796	0.1818	0.2388	0.2857	0.3594	0.4848
	CSI300+ SE	581	0.3268	0.1158	-0.2200	0.0035	0.1119	0.2556	0.3357	0.4016	0.5052	0.6816
	Bond SE	581	2.6441	0.9368	-0.2200	0.0283	0.9050	2.0681	2.7165	3.2494	4.0877	5.5146
	Bond+ SE	581	4.5156	1.5999	-0.2200	0.0484	1.5456	3.5319	4.6393	5.5494	6.9811	9.4179
	t-statistic for Alpha	581	1.5380	0.8265	5.6964	-1.4058	0.4343	1.1276	1.5521	1.9216	2.4852	13.9875
	t-statistic for CSI300+	581	-2.5254	1.1827	1.6306	-4.7493	-3.9445	-3.2714	-2.7890	-2.0877	-0.0507	3.2436
	t-statistic for Bond+	581	-0.0115	0.6903	0.1151	-2.1535	-1.1668	-0.4241	-0.0196	0.4114	1.1058	3.2259
	R-squared Adj	581	0.5387	0.1492	-0.4359	-0.0596	0.2919	0.4555	0.5405	0.6280	0.7850	0.9305
Bond	Alpha	443	0.0044	0.0066	2.5315	-0.0146	-0.0022	0.0009	0.0028	0.0060	0.0170	0.0464
	CSI300	443	0.1354	0.2287	2.7274	-0.1149	-0.0184	0.0070	0.0414	0.1534	0.6732	1.3166
	CSI300+	443	-0.0158	0.1568	0.7067	-0.6210	-0.2493	-0.0656	-0.0245	0.0293	0.2084	0.7572
	Bond	443	0.9765	0.9372	2.4793	-0.9760	0.0274	0.5050	0.7702	1.1299	3.1082	6.3116
	Bond+	443	-0.2540	1.5009	-2.1740	-8.3506	-3.4339	-0.4298	0.0517	0.4206	1.3449	5.2211
	Alpha SE	443	0.0055	0.0050	2.4221	0.0001	0.0014	0.0026	0.0038	0.0064	0.0193	0.0300
	CSI300 SE	443	0.0577	0.0525	2.4221	0.0011	0.0143	0.0273	0.0401	0.0667	0.2013	0.3127
	CSI300+ SE	443	0.0811	0.0738	2.4221	0.0015	0.0202	0.0384	0.0564	0.0937	0.2830	0.4396
	Bond SE	443	0.6565	0.5973	2.4221	0.0123	0.1631	0.3104	0.4565	0.7584	2.2895	3.5568
	Bond+ SE	443	1.1212	1.0201	2.4221	0.0209	0.2786	0.5302	0.7796	1.2953	3.9100	6.0745
	t-statistic for Alpha	443	0.8412	1.1994	3.8876	-2.3373	-0.5440	0.2779	0.8347	1.2797	1.9059	10.8250
	t-statistic for CSI300+	443	-0.2948	1.4294	0.2131	-5.2136	-2.2974	-1.2025	-0.4738	0.6296	2.3844	3.5437
	t-statistic for Bond+	443	0.1384	0.9626	0.4075	-2.5436	-1.2972	-0.5043	0.0790	0.6972	1.9050	3.4819
	R-squared Adj	443	0.4882	0.1735	-0.4356	-0.0773	0.1933	0.3744	0.5157	0.6116	0.7399	0.9696

Table 9: Regression Result for Market Timing Test on CSI 300

Table 9 gives the test results on market timing for the above model. The most surprising result is that the coefficients for all three types of funds on market timing factor is negative. This gives the indication that fund managers invest highly when the market falls and step back when market rises. Obviously, this is an irrational action for professional fund managers. One possible hypothesis is that they are doing it unintentionally. Instead, the unsteady market is the one to blame. The fund managers fail to rebalance their investment when the market starts going down. More precisely, they realize the market rise, but as soon as they invest more, the market starts to fall suddenly. This finding implies another investment strategy for fund managers: they tend to buy and hold the stock longer instead of

actively rebalancing the portfolio to invest aggressively during market rise and sell extra stocks during market drops. This can be tested by identifying serial correlation on stock index return series to find whether market rises are always followed by falls in the CSI 300 index. We test serial correlation with the ARIMA model and the results are shown below.

Serial Correlation Test on CSI 300 Returns

In order to run the ARIMA model, we first run the autocorrelation test to determine the most suitable lag.

Autocorrelation Function: C2

Lag	ACF	T	LBQ
1	0.133508	1.18	1.44
2	-0.092003	-0.80	2.14
3	0.005143	0.04	2.14
4	0.039838	0.34	2.28
5	0.045251	0.39	2.45
6	-0.086178	-0.74	3.09
7	0.012196	0.10	3.11
8	0.003603	0.03	3.11
9	-0.222144	-1.89	7.57
10	-0.013819	-0.11	7.59
11	0.041759	0.34	7.75
12	0.043332	0.35	7.93
13	-0.219560	-1.78	12.56
14	-0.183463	-1.20	14.85
15	0.108910	0.84	16.03
16	0.022347	0.17	16.08
17	-0.087537	-0.67	16.86
18	0.042873	0.32	17.05
19	0.212234	1.60	21.82
20	-0.065379	-0.48	22.28

Autocorrelation for C2

Table 10: Autocorrelation function for CSI 300 return

Normally, for lags of 1 to 3, if ACF t-statistics are above 1.25, this lag shall yield significant results and for lags above 3, lag shall be significant when t-statistics reach 2.0. Based on our autocorrelation function, we first find that no lags are significant. However, t-statistics with a lag of 1 is approximate to 1.25. Thus, we then try running the ARIMA model with a lag of 1. After running multiple ARIMA model tests with no difference, first difference and second difference, ARIMA(1,2,1) gives the best result shown below.

```

Final Estimates of Parameters

Type      Coef      SE Coef      T      P
AR  1     -0.3650     0.1104     -3.31  0.001
MA  1      0.9924     0.0649     15.29  0.000
Constant  0.0001293  0.0004945     0.26  0.795

Differencing: 2 regular differences
Number of observations: Original series 78, after differencing 76
Residuals:   SS = 0.700604 (backforecasts excluded)
              MS = 0.009597  DF = 73

Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag        12      24      36      48
Chi-Square 21.8   49.4   73.2   83.5
DF          9      21      33      45
P-Value    0.010  0.000  0.000  0.000

```

Table 11: ARIMA (1, 2, 1) test for CSI 300 return

Based on the ARIMA model result, we can clearly see a negative auto-regression coefficient, which means that stock returns in current period have a reverse relationship with the returns in the previous period. Therefore, the hypothesis where prior-period market rise is often followed by a market fall in current period is thus verified. The real situation, for example, is that if fund managers buy aggressively on stocks in May and hold them to June, this investment generates a negative effect on market timing because of negative auto-correlation of stock market.

Conclusions

We can see that although mutual funds came into Chinese market in 1991, the mutual fund market did not begin to develop rapidly until 2006. However, it now has over 3000 funds managing more than 8 trillion RMB of assets. It also spans a comprehensive range of investment categories, including equity, hybrid, bond, money market, alternative and QDII. Until now, hybrid funds are the most prevalent type of funds in China, ranking first in number of funds and second in assets under management (AUM). Although money market

funds own the most AUM, there are very few money market funds in the market. In this study, we focus on how hybrid funds compare in many aspects with equity and bond funds, which invest in the same financial instruments.

The first empirical finding is that all three types of funds have similar average years of existence of about 3 years. However, there are more equity funds with shorter lifespans, maybe due to more risks involved. AUM analysis reveals similar clues on volatility in equity funds. In June 2015, although equity and hybrid funds have similar average AUM, equity funds have higher variability and more skewness, which shows that there are a number of small equity funds managed by small, informal fund companies. However, this situation changes one year later in June 2016. Equity funds now have less skewness and have less AUM in every percentile, showing that due to volatility in the stock market (two big market downturns in July 2015 and January 2016), people don't want to invest in such high-risk products. On the other hand, hybrid funds have much higher skewness. Many newly-issued hybrid funds have started to gain AUM. People move from equity funds to more secure hybrid funds. In our AUM analysis, bond funds have the least AUM market share but they are still growing steadily.

Next, we analyze the performance of equity, hybrid, bond mutual funds. We estimate fund returns of a two-factor model using stock and bond market index returns and we get some nice results. Equity funds have the highest stock beta, about 0.8, and bond funds have the lowest stock beta of about 0.1, which is consistent with regulations, and lends credibility to our extensive findings. First, greater standard deviation in stock beta for equity funds indicates that equity funds have very different investment strategies that result in very

different returns. Also, comparing alpha results for 18-month and 36-month sample periods, we can conclude that funds cannot sustain in the level of alpha over the longer term, but they are still earning positive excess returns.

Once we establish that funds are actually doing well in this 36-month period, the study continues by testing hypotheses about how funds are earning excess returns. The first question is whether fund managers take advantage of the fact that low-volume stocks generally have greater average return than high-volume stocks. After running multiple tests, the study finds that fund managers attain excess return if we use the CSI 300 as the market index. When we change the market index to the CSI All Share, fund managers surprisingly do not appear to be investing more in small stocks. Given that although the CSI 200 is the smaller fraction of stocks in the CSI 300, they are actually middle-size stocks with higher volume than the CSI 500 (the small fraction of the CSI All Share model). Thus, we conclude that although stocks in small stock indexes may have the greatest excess return, fund managers cannot afford taking on their risk. Instead, their excess returns come largely from middle-size stocks that still have a sufficient return.

Another question is whether fund managers increase return by investing more during market rises, which is called the market timing effect. In fact, our empirical finding suggests us the reverse effect. Because the stock market in China is volatile and market downturns often proceeds market rises, and fund managers fail to rebalance their accounts to avoid bankruptcy, they are only effectively limited to buy and hold strategies, which can make money in terms of market timing effects.

In a nutshell, because of the high volatility in Chinese stock markets, fund managers struggle to increase profits from market timing. And for the same reason, they usually avoid the risk of investing in small stocks. Their excess return, instead, comes from middle-size stocks, which make mutual fund a relatively conservative low-return investment in China.

Reference Papers

Carhart, Mark M. "On persistence in mutual fund performance." *The Journal of finance* 52.1 (1997): 57-82.

Carpenter, Jennifer, Fangzhou Lu, and Robert Whitelaw. "The Real Value of China's Stock Market." (2015): n. pag. Web.

Chi, Yeguang. "Private Information in the Chinese Stock Market: Evidence from Mutual Funds and Corporate Insiders." *By Yeguang Chi :: SSRN*. N.p., 12 Aug. 2016. Web.

Cremers, Martijn, and Antti Petajisto. "How Active Is Your Fund Manager? A New Measure That Predicts Performance." *By Martijn Cremers, Antti Petajisto :: SSRN*. N.p., 21 Mar. 2006. Web.

DANIEL, KENT, MARK GRINBLATT, SHERIDAN TITMAN, and RUSS WERMERS. "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks." *The Journal of Finance*. Blackwell Publishing Ltd, 18 Apr. 2012. Web.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake. "The Persistence of Risk adjusted Mutual Fund Performance." *The Journal of Business*, Apr. 1996. Web. 15 Apr. 2016.

Fama, Eugene F., and Kenneth R. French. "Industry costs of equity." *Journal of financial economics* 43.2 (1997): 153-193.

Firth, Michael, Chen Lin, and Hong Zou. "Friend or Foe? The Role of State and Mutual Fund Ownership in the Split Share Structure Reform in China." *By Michael Firth, Chen Lin, Hong Zou :: SSRN*. *Journal of Financial and Quantitative Analysis*, 21 Feb. 2010. Web.

HENDRICKS, DARRYLL, JAYENDU PATEL, and RICHARD ZECKHAUSER. "Hot

Hands in Mutual Funds: Short-Run Persistence of Relative Performance, 1974–1988."

The Journal of Finance. Blackwell Publishing Ltd, 30 Apr. 2012. Web.

Lehmann, Bruce N., and David M. Modest. "Mutual Fund Performance Evaluation: A Comparison of Benchmarks and Benchmark Comparisons." *Stanford Graduate School of Business*. *The Journal of Finance*, June 1987. Web.

Wermers, Russ. "Performance Measurement of Mutual Funds, Hedge Funds, and Institutional Accounts." *Performance Measurement of Mutual Funds, Hedge Funds, and Institutional Accounts / Annual Review of Financial Economics*. Robert H. Smith School of Business, 04 Aug. 2016. Web.

Yao, Yuzuo. "The Core Issues of Open-Ended Funds in China: Conflicts of Interest and Ownership Structure." *By Yuzuo Yao :: SSRN*. N.p., 07 Apr. 2016. Web.

Yuan, R., JZ Xiao, and H. Zou. "Mutual Funds' Ownership and Firm Performance: Evidence from China." *HKU Scholars Hub: Home*. Elsevier BV. The Journal's Web Site Is Located at [Http://www.elsevier.com/locate/jbf](http://www.elsevier.com/locate/jbf), 01 Jan. 1970. Web.

Appendix I: Figures and Tables

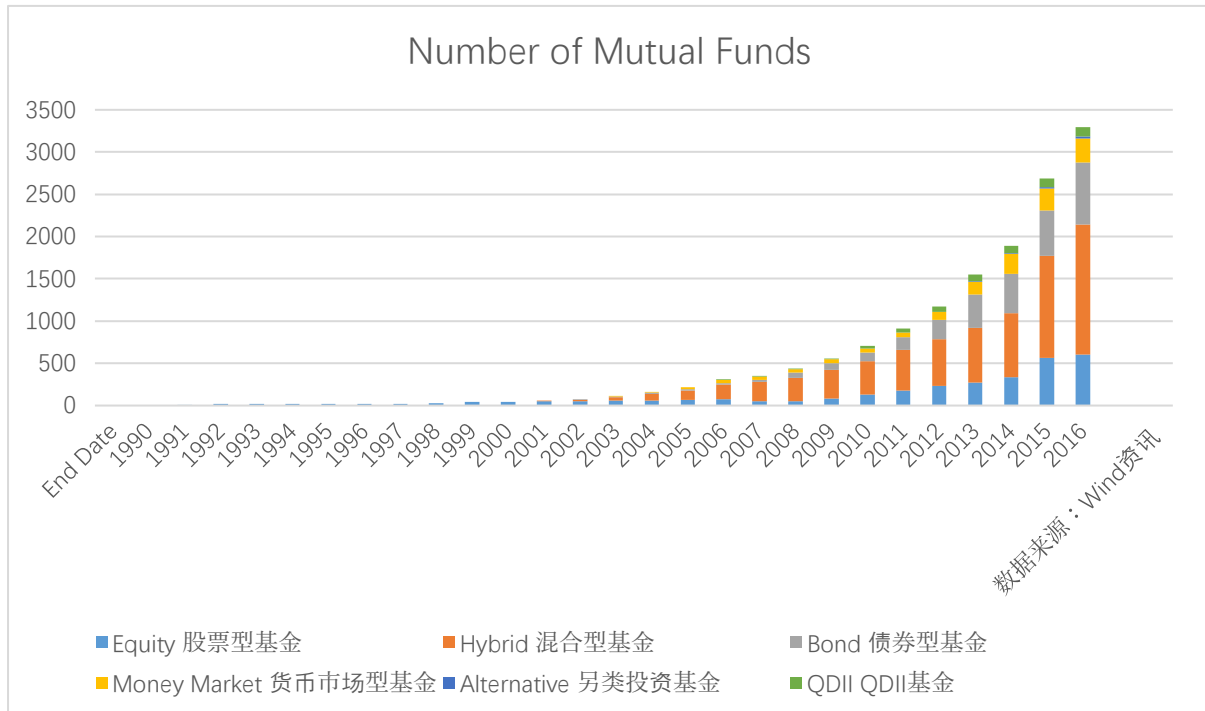


Figure 1: Historical Change of Number of Mutual Fund

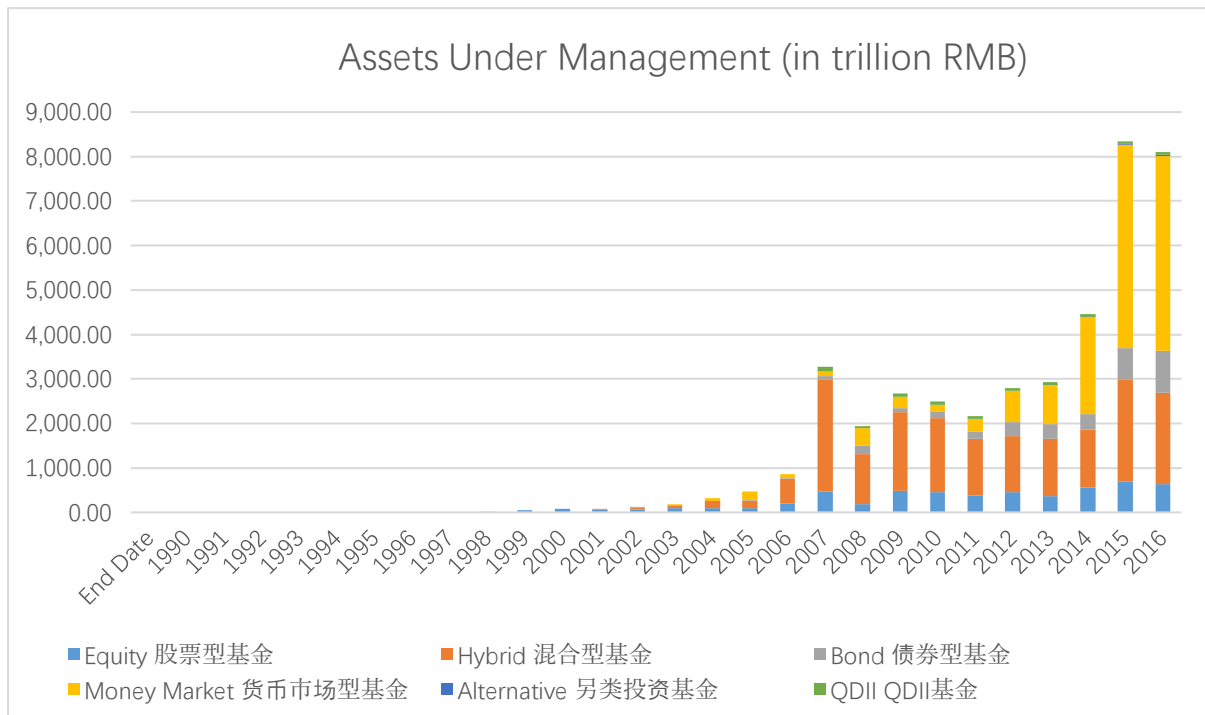


Figure 2: Historical Change of Assets under Management (in trillion dollars)

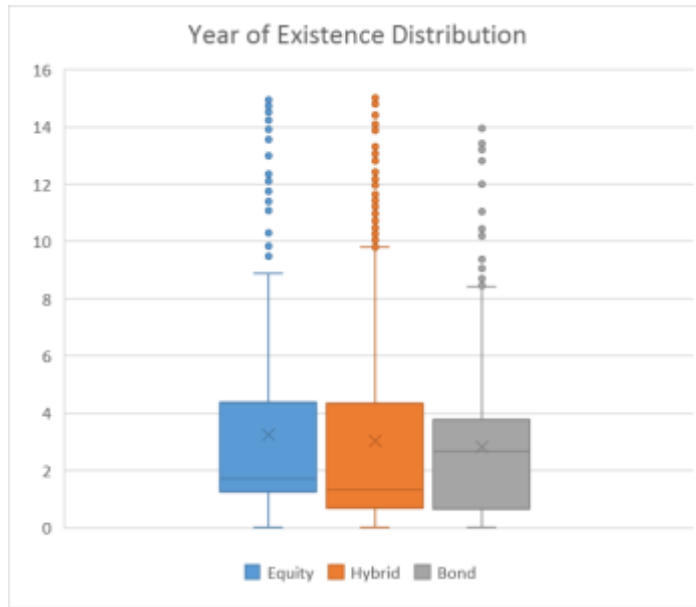


Figure 3: Summary Statistics for Existing Years

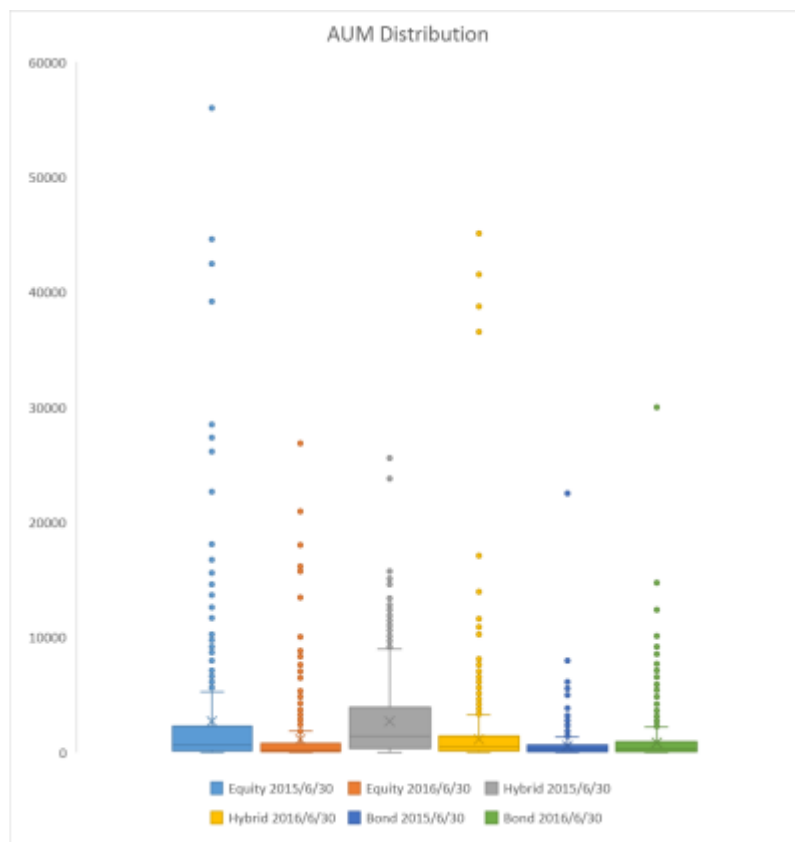


Figure 4: Cross-sectional Statistics for AUM (Asset Under Management)

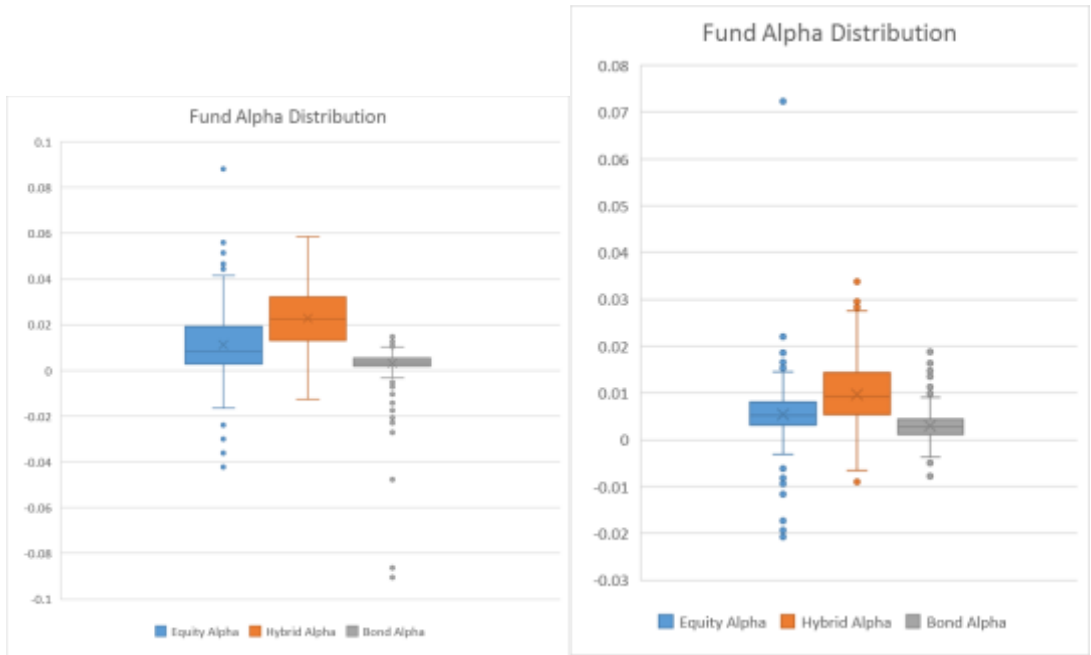


Figure 5: Fund Alpha Distribution for 18-month (left) and 36-month (right)

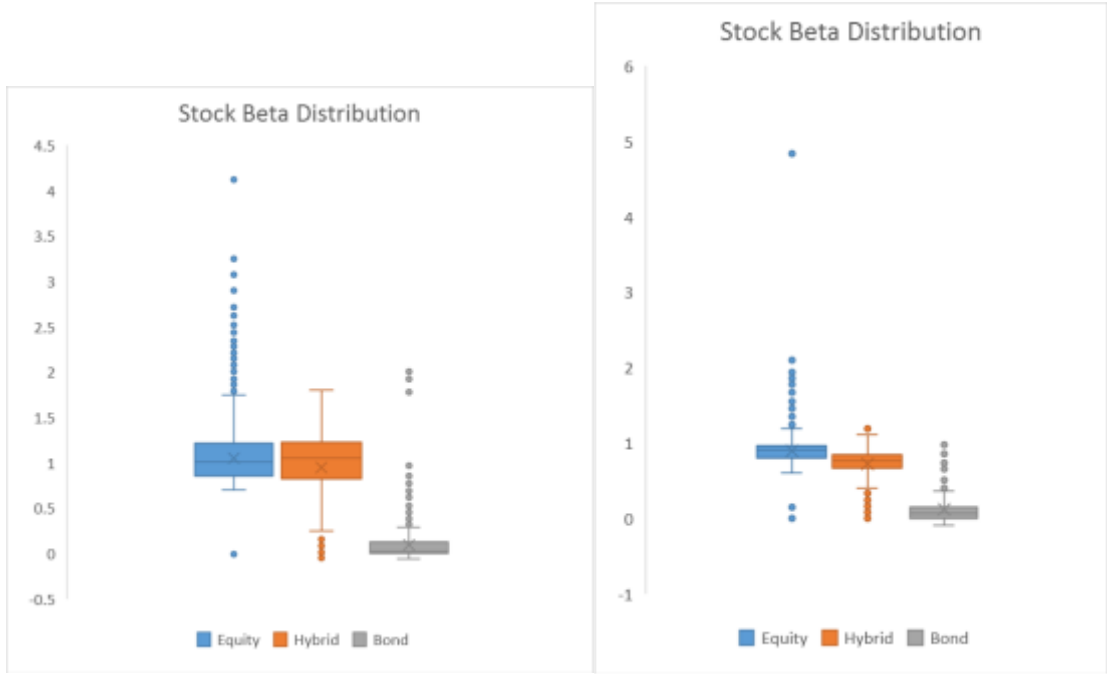


Figure 6: Fund Stock Beta Distribution for 18-month (left) and 36-month (right)

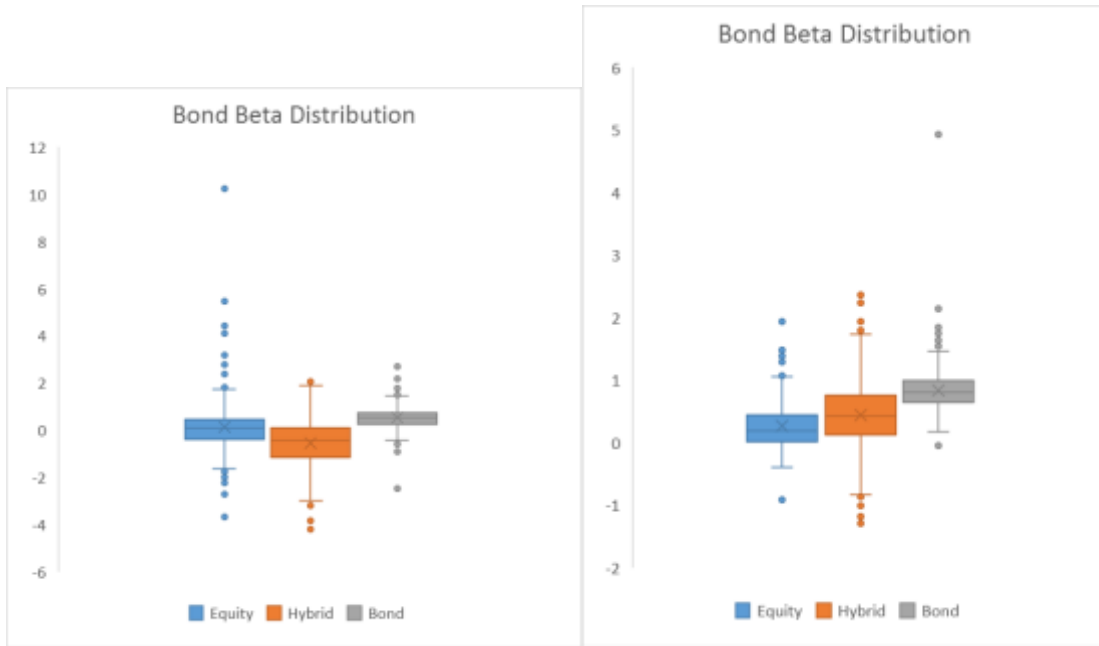


Figure 7: Fund Bond Beta Distribution for 18-month (left) and 36-month (right)