THE EFFECT OF PORTFOLIO MANAGERS' PAST EXPERIENCE ON THEIR PERFORMANCE

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ABSTRACT

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Understanding where the mutual fund returns come from may be advantageous to construct a portfolio of managers for a fund. This paper uses mutual fund performance data in China market from 2001 to 2018 to study whether differences in manager's former working experience affect their performance. After regressions and bootstrap tests, there come some conclusions: managers who starting careers as buy-side industry and sell-side macro analysts generate significant excess returns of 0.4% and 0.6%. What's more, there is no evidence that portfolio managers have market-timing abilities. Last but not least, industry groups show larger portions of return from small-cap stocks and growth stocks. Specifically, buy-side industry group shows superior ability in picking up promising small-cap stocks, and sell-side industry group tends to pay most attention to and invest more in growth stocks.

BIOGRAPHICAL SKETCH

Xinran Xu, born in Jiangsu Province, China, after completing her undergraduate degree in Renmin University in 2017, came to Cornell to study for MS of Applied Economics and Management in the Finance concentration. With several analyst internships and ongoing full-time position as a buy-side analyst, she is interested in how portfolio manager's former working experience affect their performance.

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CHAPTER1

INTRODUCTION

Portfolio manager position, usually calling for a rich experience in equity research, is always a later stage for a professional working in the financial services industry. A portfolio manager manages one or multiple accounts, picking stocks and consistently rebalancing, trying to ultimately generate better returns by adjusting the portfolio by rational evaluation of the market. Extensive studies are researching what factors affect the performance and where the return comes from. Since all portfolio managers have pre-working experiences, such as buy-side analysts or sell-side analysts, I would like to investigate whether different prior working experience plays a significant role in their investment abilities.

LITERATURE REVIEW

1.1 Measuring stock picking and market timing

A famous study by J Treynor, K Mazuy (1966), named “Can mutual funds outguess the market”, talks about how to measure stock picking ability and market timing ability. It’s already a well-known metric of alpha for measuring stock picking ability. About the “outguess” for market timing, the authors define it as evidence: “the volatility of the fund was higher in years when the market did well than in years when the market did poorly.” To account for this, Treynor and Mazuy add a quadratic item to the traditional CAPM model—square of market premium. This suggests that the return should have a non-linear relationship with the market trend.

Moreover, another study by Henriksson and Merton (1981) also pays attention to how to measure market timing. Similarly, they introduce an add-on factor—max {0, market premium} to the traditional CAPM equation. To test the significance of the market timing ability, the coefficient of this item is essential. Although adding these into CAPM seems easy from the angle of mathematics and econometrics, they are of great importance in quantifying the market timing ability.

1.2 Carhart model

The traditional Capital Asset Pricing Model (CAPM) uses only the market premium. Fama and French (1992 & 1993) extend the conventional model by adding two more factors –size effect (SMB, small-cap minus big cap) and value effect (HML, high book-to-market minus low book-to-market). The model is a significant breakthrough in evaluating manager performance. Later, Carhart (1997) further extends the Fama-French three-factor risk model by adding a momentum factor, capturing Jegadeesh and Titman's (1993) one-year momentum anomaly. In detail, the momentum factor (UMD, winners minus losers) is calculated as subtracting the equal-weighted average of the lowest performing firms from the equal-weighted average of the highest performing firms, lagged one month.

1.3 Backgrounds and characteristics effects

A rich literature has shown that portfolio managers' specific characteristics may impact the fund's performance. Golec (1996) examines mutual fund managers' characteristics on their portfolio performance, risk, and fees, and attributes great performance (risk and fees considered simultaneously) to younger age, longer time of managing the fund and advanced degrees like MBA. Chevalier and Ellison (1999) also focuses on the educational background but attributes better fund performance to attending a higher-SAT undergraduate institution. Gottesman and Morey (2006) later focus on education background's effect as well, to compensate for Golec and Chevalier and Ellison, this paper considers both SAT score and GMAT score, and specifically find the significance of a top-ranked MBA program after adjusting for survivorship bias. Moreover, Chartered Financial Analyst (CFA) and a Ph.D. degree are proven to be unimportant in contributing to better mutual fund performance. Cohen, Frazzini, and Malloy (2008) pays attention to portfolio managers' networking and finds that the portfolio performs better when they are connected to corporate boards through education networks.

Later there begin to be some literature talking about mutual fund portfolio manager's former working experiences. Cici (2014) investigates and confirms that industry experiences outside of the asset management career do play an essential role in helping portfolio managers pick stocks from familiar areas and generate high returns.

1.4 Mutual fund studies with a focus on China market

In China, although the development of the mutual fund market traced the western world, some studies stress relevant problems and contribute to the literature. Wang (2002) studies whether the mutual fund managers in China show market timing ability, he used TM-FF3 and HM-FF3 model (which are combinations of TM/HM model and

Fama-French three-factor model). The two models are built to simultaneously incorporate different risks (size, value) and market timing effects. Finally, he concludes that these mutual funds lack market timing ability.

About how the characteristics play a role, Chen and Cao (2006) focuses on the psychological factors' effects—how their confidence affect their returns and concluded that if a portfolio manager has had many failure or success in the past, it will make him or her pessimistic or overconfident, finally leading to a poor performance. Peng (2005) and Li et al. (2006) looks into whether age, tenure, degree matters and concludes that younger portfolio managers working in the same asset management firm for a longer time will produce better performance. Besides, Peng (2005) ends that most portfolio managers have stock picking abilities but barely any market timing talents.

This study contributes to the literature as follows: First, in the western world studies are talking about performance differences between managers starting the career as an industry analyst or macro analyst but none about China market. This study further distinguishes between buy-side and sell-side since their working environment and performance incentives differ a lot. Second, the study tailors the model to fit China market where momentum should be significant because of lots of individual investors and a much less efficient mechanism—Combination model of Carhart and TM/HM factor is testified, referred as Carhart-TM and Carhart-HM in the following.

CHAPTER 2

DATA

We use criterions to screen out our target mutual funds, and then further get the portfolio managers' information. After another screening to select single managed period, then we extract the corresponding returns during the periods. Details on the datasets are provided below.

2.1 Qualified funds

To find the data of mutual funds, I purchased the membership of China Stock Market and Accounting Research Database (CSMAR), which is a leading economic and financial Information provider of China financial market data, to international financial and educational institutions, corporation, institutional investors, investment banks and advisors around the world. In the database, I went directly to the mutual fund data part and did some screening as following to acquire the suitable funds.

First, since I intend to find the effects of former experiences on portfolio managers' fund performance, autonomy must be given when portfolio managers select stocks. So several criterions are applied first: 1. they are actively managed; 2. They are not ETFs, or say not index funds which only adjust the weight to duplicate the index.

Then, of course, to measure portfolio managers' ability in choosing stocks, I eliminated funds which constitute of bonds, or to say, all the funds selected are purely stock funds. What's more, I only included the funds which invest in China domestic stock market—excluding "QDII" (qualified domestic institutional investors) which invests in other countries. Last, since there was a series of great reforms after 1998, and the first open-ended mutual fund "Hua An Chuang Xin" was founded in Sep 2001, my list only includes the funds which operate after 2001.

To sum up, my chosen stocks are actively managed equity funds after September 2001, limited in China's stock market, not index or ETF. By this selection process, I got the list of fund IDs.

2.2 Portfolio managers

After getting the list of IDs of funds, portfolio managers' backgrounds can be attained. That is using the IDs to extract the portfolio managers who managed or are managing those funds. Relevant information obtained includes the service start date, the service end date, gender, working experiences, degree attained, etc. To ensure the abundance and consistency of samples of later regression, I used the service end date, and the service start date to calculate the duration of their managing funds then removed those with a period less than 24 months.

Last but not least, since my intention is to investigate the effect of experience on funds' performance, so when processing the service period of these managers, combined with the IDs of funds, if there are overlaps in the time periods of two or more managers managing the same funds, I just removed all the managers and corresponding periods.

Thus after the step, for each managing period of one fund, the returns are only attributable to each single portfolio manager.

Finally, after acquiring the list of portfolio managers, according to their former experiences and backgrounds, I divided them into four categories: buy-side industry, buy-side macro, sell-side industry, and sell-side macro. Primarily this classification is determined by their first job. Only if their first jobs couldn't be grouped into these four categories, second jobs will be a reference. The way I use the first job as the criterion because I think how a portfolio manager is cultivated from the beginning of his or her financial career is crucial. Also, one thing to note, their working years is not reflected in classification, since I intend to see how each group together as a portfolio perform in the market.

2.3 Returns and factors

After I got the list of funds and service periods, I can get the return data, also from the CSMAR database. The returns data is shown as “Return NAV”, the return of net asset value.

Since I would like to see where the difference in return performance comes from, I’d rather use a factor model to capture the return. After the literature review, I decided that Carhart four-factor model which includes market risk premium, size premium (SMB, small-cap minus big cap), book-to-market factor (HML, high book-to-market minus low book-to-market), momentum factor. Moreover, since the elements are calculated with different combinations of markets, to ensure the factors are suitable for my research, the set derived by A Stock Market and Growth Enterprise Market are chosen because B Stock Market is specially designed for foreign investors.

After gathering and sorting all the data, the statistics summary shows the total return as a whole and returns by category:

Table 2. 1: Summary statistics

				Percentile				
	N	Mean	STD	1%	25%	50%	75%	99%
Return (%)	9,039	0.43%	7.77%	-25.11%	-2.87%	0.62%	3.91%	20.48%
Return by category (%)								
buy-side industry	1,337	0.53%	8.16%	-27.53%	-2.68%	0.53%	3.85%	25.78%
buy-side macro	4,785	0.39%	7.68%	-25.54%	-2.93%	0.60%	3.86%	19.85%
sell-side industry	1,121	0.48%	7.76%	-24.83%	-2.76%	0.61%	3.92%	21.68%
sell-side macro	1,717	0.42%	7.72%	-24.49%	-2.88%	0.72%	4.12%	19.70%
MKT (%)	205	0.64%	8.02%	-21.94%	-4.74%	0.88%	4.66%	22.35%
SMB (%)	205	0.80%	5.16%	-12.84%	-2.20%	0.75%	3.64%	11.57%
HML (%)	205	0.27%	3.15%	-9.10%	-1.42%	0.38%	2.07%	7.86%
UMD (%)	205	0.48%	4.95%	-11.25%	-2.55%	0.64%	3.46%	12.04%

In general, the mean monthly return of all single-managed equity mutual funds between 2001 and 2018 is 0.43%. Compared with the overall mean return, different categories show nuances: buy-side industry analysts show the highest 0.54%, with the most substantial standard deviation. Moreover, the sell-side industry analysts follow, showing a monthly return of 0.48% with relatively smaller volatility of 7.76%. Higher risks accompany higher yields. Last are sell-side macro analysts and buy-side macro analysts, producing a monthly return of 0.42% and 0.39%. Overall, however, differences between groups of analysts are not notable.

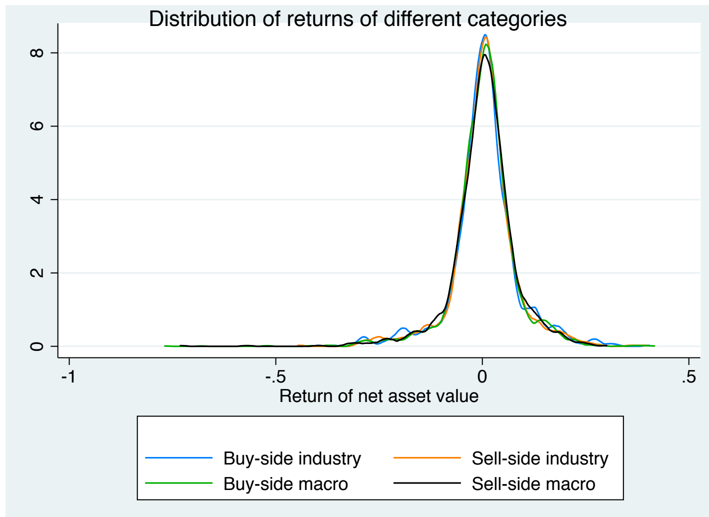

Figure 2. 1: Distribution of returns of different categories

From the graph, we could see that the returns for all four categories are normal distributions, which is consistent with the common assumption of return in finance. Looking into the four categories' analysts, it's evident that both buy-side macro and sell-side macro analysts produce yields that are negatively skewed, while buy-side industry and sell-side industry groups don't. To briefly summarize, analysts who began as an industry equity analyst may show greater ability in generating better returns.

CHAPTER 3

EMPIRICAL FRAMEWORK

As mentioned in the literature review, to disintegrate the fund return, researchers always use risk factor model like Fama-French model or Carhart model, which are both extensions of CAPM. Also, to account for market timing ability, TM model and HM model could be used to reflect a non-linear relationship between excess return and market premium. Moreover, some researchers used TM-FF3 and HM-FF3, simultaneously taking different risks and non-linear market timing ability into consideration.

From my point of view, the momentum factor is vital for China stock market. As known to all, in China stock market, individual investors take up a much higher percentage than the western market where institutional investors dominate. Also, the educational background of individual investors varies, although some can conduct independent, in-depth research about stocks, most end up showing herding effect. Under such circumstances, we include the momentum factor.

To sum up, my primary independent variables are risk factors—size, value, market, momentum, and also a non-linear item—TM and HM model. In mathematical formula,

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta1_{i,t}SMB_t + \beta2_{i,t}HML_t + \beta3_{i,t}MKT_t + \beta4_{i,t}UMD_t + \gamma_{i,t}f(MKT_t) + \varepsilon_t$$

On the left-hand side, it represents the excess return of mutual fund—return of fund i in month t minus risk-free rate. On the right-hand side of the equation, all the factors—SMB, HML, MKT, UMD are unique in each month t. The item to catch non-linear relationship—f(MKT) will either be TM model (MKT^2) or HM model (max {MKT, 0}).

Back to the topic, since I would like to focus on different groups of mutual fund managers, after sorting into the four groups (buy-side industry, buy-side macro, sell-side industry, and sell-side macro), at each month t, I constructed a portfolio for each group. For example, take an average of all buy-side industry managers in month t as the $R_{i,t}$ in the equation. Ideally, each month from 2001 to 2018, there are four return numbers. But as mutual funds are open and closed at times, some data are missing.

CHAPTER 4

EMPIRICAL RESULTS

Table 4. 1: Regression results for Carhart-TM and Carhart-HM model

	buy-side industry		buy-side macro		sell-side industry		sell-side macro	
VARIABLES	return1	return1	return2	return2	return3	return3	return4	return4
mkt	0.808***	0.817***	0.684***	0.734***	0.695***	0.689***	0.678***	0.771***
	(0.0302)	(0.0544)	(0.0274)	(0.0506)	(0.0220)	(0.0333)	(0.0270)	(0.0499)
smb	0.224***	0.225***	0.103**	0.103**	0.192***	0.191***	0.035	0.035
	(0.0630)	(0.0631)	(0.0495)	(0.0496)	(0.0425)	(0.0425)	(0.0485)	(0.0485)
hml	-0.334***	-0.334***	-0.287***	-0.289***	-0.407***	-0.407***	-0.295***	-0.296***
	(0.0913)	(0.0917)	(0.0816)	(0.0816)	(0.0672)	(0.0671)	(0.0802)	(0.0802)
umd	0.110***	0.111***	0.168***	0.167***	0.200***	0.199***	0.115***	0.113**
	(0.0395)	(0.0392)	(0.0450)	(0.0452)	(0.0343)	(0.0342)	(0.0443)	(0.0445)
gmkt_tm	-0.071		-0.272		0.033		-0.431**	
	(0.2390)		(0.1980)		(0.1510)		(0.1940)	
gmkt_hm		-0.016		-0.098		0.009		-0.180**
		(0.0884)		(0.0838)		(0.0625)		(0.0822)
Constant	0.004*	0.004	0.003	0.004	0.001	0.001	0.005*	0.007**
	(0.0023)	(0.0029)	(0.0026)	(0.0034)	(0.0020)	(0.0026)	(0.0026)	(0.0034)
Observations	104	104	205	205	130	130	196	196
R-squared	0.917	0.917	0.781	0.781	0.926	0.926	0.785	0.785

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4. 2: Multi-collinearity test

Variable	VIF	1/VIF	Variable	VIF	1/VIF
mkt	3.5	0.2857	smb	3.31	0.302134
gmkt_hm	3.47	0.288484	hml	3.23	0.309492
smb	3.31	0.301729	umd	1.1	0.908908
hml	3.26	0.306894	gmkt_tm	1.09	0.917133
umd	1.08	0.923097	mkt	1.08	0.92407
Mean VIF	2.92		Mean VIF	1.96	

For each group, the regression has been done both on Carhart-TM model and Carhart-HM model. Multi-colinearity test has been passed—no VIF value bigger than 10. Basically, the coefficients for the same variable are similar within each group, with coefficients of TM and HM factor differing. Generally, the R-squared of these regressions is all above 0.75, suggesting the combination model works well for the sample mutual fund return data in China in statistics.

Firstly, for the Carhart Alpha (expressed as “constant” in the chart), compared with sell-side industry mutual fund managers who seem not to show stock-picking abilities, those who begin their career as buy-side industry analysts significantly generate an excess return of 0.4%. When it comes to macro analysts, sell-side macro portfolio managers exhibit superior stock-picking abilities significantly with an excess return of 0.5% under TM model and 0.7% under HM model.

When looking at the coefficients of TM and HM factors, it’s surprising that sell-side macro managers have the significantly lowest negative ones. As mentioned in the construction of f(MKT), the factors are either MKT^2 or max {0, MKT}, thus reflecting that sell-side macro managers show poor market timing abilities in avoiding loss and achieving returns. For other groups, however, the coefficients are not significant. This implies that adding a non-linear factor into Carhart model is called into question. Later a single Carhart model would be run as a comparison.

Moreover, one thing worth notice is that industry managers, compared with other groups, generate significantly bigger returns from SMB factor, that is return of small-cap companies minus big-cap companies. Moreover, the buy-side industry group has the highest estimate. This may reflect that, when beginning a career in a relatively more value-investing oriented environment, these managers show greater abilities in discovering the discrepancies in intrinsic value and market price of small-cap stocks, which gain less attention and coverage than hot tickers.

To check whether the Carhart-TM/HM model is appropriate in analyzing China mutual fund market, regressions for four groups are run with results shown in the chart.

Table 4. 3: Regression results for single Carhart model

VARIABLES	buy-side industry meanreturn1	buy-side macro meanreturn2	sell-side industry meanreturn3	sell-side macro meanreturn4
mkt	0.809***	0.685***	0.693***	0.680***
	(0.0301)	(0.0274)	(0.0206)	(0.0273)
smb	0.225***	0.105**	0.191***	0.0385
	(0.0627)	(0.0496)	(0.0423)	(0.0490)
hml	-0.336***	-0.292***	-0.408***	-0.303***
	(0.0906)	(0.0817)	(0.0668)	(0.0810)
umd	0.112***	0.176***	0.198***	0.129***
	(0.0385)	(0.0447)	(0.0331)	(0.0443)
Constant	0.004*	0.001	0.001	0.002
	(0.0020)	(0.0023)	(0.0017)	(0.0023)
Observations	104	205	130	196
R-squared	0.917	0.779	0.926	0.780

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4. 4: Adjusted R-square of Carhart-TM/HM model and Carhart model

	buy-side industry		buy-side macro		sell-side industry		sell-side macro	
Adjusted R-squared (TM,HM model)	0.9131	0.9131	0.7757	0.7751	0.9235	0.9234	0.7796	0.7794
Adjusted R-squared (Single Carhart)	0.9139	0.9139	0.7747	0.7747	0.9240	0.9240	0.7750	0.7750

As known, to effectively see whether adding variables improve the explanatory power, adjusted R-squared applies. From the comparison, we can see that, for buy-side industry group and sell-side industry group, single Carhart model is slightly better. The reason may be that mutual fund portfolio managers beginning as an industry analyst typically cannot generate an excess return by pre-evaluating market trends. Adding the non-linear item into the regression equation adversely affects explanatory power.

When looking at the results of the single Carhart regression, the Carhart alpha 0.4% is still significant for the buy-side industry group. Also, same as in the Carhart-TM/HM model, for the factor—SML, buy-side industry portfolio managers show superior talents in picking up valuable small-cap stocks. Moreover, the value factor—HML, shows some points as well. If we compare the better fits as discussed before, buy-side industry and sell-side industry portfolio managers separately have value factor coefficients as -0.336 and -0.408, while buy-side macro and sell-side macro groups show -0.289 and -0.296. Again, the value factor attributes return to growth stocks to some degree. Industry groups as a whole are better at selecting premium growth stocks. When it comes to the question that why sell-side managers have a higher coefficient (abstract value), from my experiences in the real world, sell-side analysts issue amounts of reports frequently, daily reports, weekly reports, monthly reports and in-depth reports for both industry and individual companies. Also, because of the particularity of sell-side analysts, teams are competing with each other, trying to differentiating themselves from others. Accordingly, singularity and novelty become crucial points when they issue reports. Thus, the number of reports and pursuit of specialty together give sell-side analysts more exposure in growth stocks, which are usually “hot tickers”. Of course, new ideas will be transferred to interested buy-side analysts as soon as possible, but time lag exists, so is the tiny difference.

To sum up, for each of the four groups of mutual fund portfolio managers, we did two regressions: single Carhart model and its combination with TM/HM factor, which is a non-linear market factor. Thus the conclusive table is as following:

Table 4. 5: Regression results of conclusive models

VARIABLES	buy-side industry	sell-side industry	buy-side macro		sell-side macro	
	return1	return3	return2	return2	return4	return4
mkt	0.809***	0.693***	0.684***	0.734***	0.678***	0.771***
	(0.0301)	(0.0206)	(0.0274)	(0.0506)	(0.0270)	(0.0499)
smb	0.225***	0.191***	0.103**	0.103**	0.0345	0.0347
	(0.0627)	(0.0423)	(0.0495)	(0.0496)	(0.0485)	(0.0485)
hml	-0.336***	-0.408***	-0.287***	-0.289***	-0.295***	-0.296***
	(0.0906)	(0.0668)	(0.0816)	(0.0816)	(0.0802)	(0.0802)
umd	0.112***	0.198***	0.168***	0.167***	0.115***	0.113**
	(0.0385)	(0.0331)	(0.0450)	(0.0452)	(0.0443)	(0.0445)
gmkt_tm	N/A	N/A	-0.272		-0.431**	
			(0.198)		(0.194)	
gmkt_hm	N/A	N/A		-0.0976		-0.180**
				(0.0838)		(0.0822)
Constant	0.004*	0.001	0.003	0.004	0.005*	0.007**
	(0.0020)	(0.0017)	(0.0026)	(0.0034)	(0.0026)	(0.0034)
Observations	104	130	205	205	196	196
R-squared	0.917	0.926	0.781	0.781	0.785	0.785

From our initial regressions:

1) After comparing the adjusted R-squared, it’s reasonable to decide that for industry groups, single Carhart model is better; while for macro groups, the Carhart-TM and

Carhart-HM suit well (momentum factors are all statistically significant, proving that in China market Carhart model works better than Fama-French model);

2) As for the Carhart alpha, significant coefficients are 0.4% of buy-side industry in single Carhart model and 0.5% and 0.7% of sell-side macro group in Carhart-TM/HM model;

3) But for market timing, for macro managers, there is no evidence of positively taking advantage of market timing ability. It's quite surprising that sell-side macro group even significantly do poorly reflected by negative coefficients of the non-linear market factor, -0.4 and -0.2 separately under Carhart-TM and Carhart-HM;

4) For size factor SMB and value factor HML, industry groups have larger coefficients. Notably, buy-side industry group shows superior ability in picking up promising small-cap stocks, and sell-side industry group tends to pay most attention to and invest more in growth stocks.

CHAPTER 5

ROBUSTNESS TEST

Although the results seem to coincide with our intuition generally, further tests should be done to prove their soundness and do some extra explanations for unsolved questions. As published by Bradley Efron in "Bootstrap methods: another look at the jackknife" (1979), similar with Kosowski, Timmermann, White, and Wermers (2006), Cao et al. (2013), a bootstrap analysis will be used, which relies on random sampling with replacement.

5.1 Bootstrap test methodology

As mentioned in the former parts, the alpha for buy-side industry and sell-side macro groups are statistically significant—0.4% for buy-side industry and 0.5% and 0.7% of sell-side macro group in Carhart-TM/HM model.

To test whether the alphas are result of these managers' internal skills cultivated and categorized by working experiences or only because of luck or other occasional factors, pseudo returns could be generated. Take sell-side macro group as an example (which better fits into Carhart-TM/HM model):

$$Y_t = \alpha_{i,t} + \beta 1_{i,t} SMB_t + \beta 2_{i,t} HML_t + \beta 3_{i,t} MKT_t + \beta 4_{i,t} UMD_t + \gamma_{i,t} f(MKT_t) + \varepsilon_t \quad (1)$$

After we do the regression, we store all the coefficients ($\hat{\beta}1_i, \hat{\beta}2_i, \hat{\beta}3_i, \hat{\beta}4_i, \hat{\gamma}_{i,t}$), and time series of residuals ($\hat{\varepsilon}_1, \hat{\varepsilon}_2, \hat{\varepsilon}_3, \hat{\varepsilon}_4, \dots \hat{\varepsilon}_t$), where t is the number of monthly observations of sell-side macro group.

Then to do the bootstrap test, as I intend to test the alpha for sell-side macro group, we generate pseudo monthly returns as equation (2) which has no stocking picking ability (i.e., $\alpha_{i,t}$=0):

$$\hat{Y}_t = \hat{\beta}1_{i,t}SMB_t + \hat{\beta}2_{i,t}HML_t + \hat{\beta}3_{i,t}MKT_t + \hat{\beta}4_{i,t}UMD_t + \hat{\gamma}_{i,t}f(MKT_t) + \hat{\varepsilon}_t \tag{2}$$

As the pseudo returns are attained, then we use them to estimate the regression equation (1) and store the new alpha and its t-statistic. By construction, any new alpha should be statistically insignificant because a zero alpha is assumed when generating pseudo numbers.

Repeat the procedures above for N times and we could get the distributions of the new alphas and their t-statistics. Regarding the number of bootstrap simulations, Wilcox (2010) concludes that 599 is recommended for general use. We take an N=1000 to ensure the resampling abundance.

5.2 Test for Carhart alpha for sell-side macro group

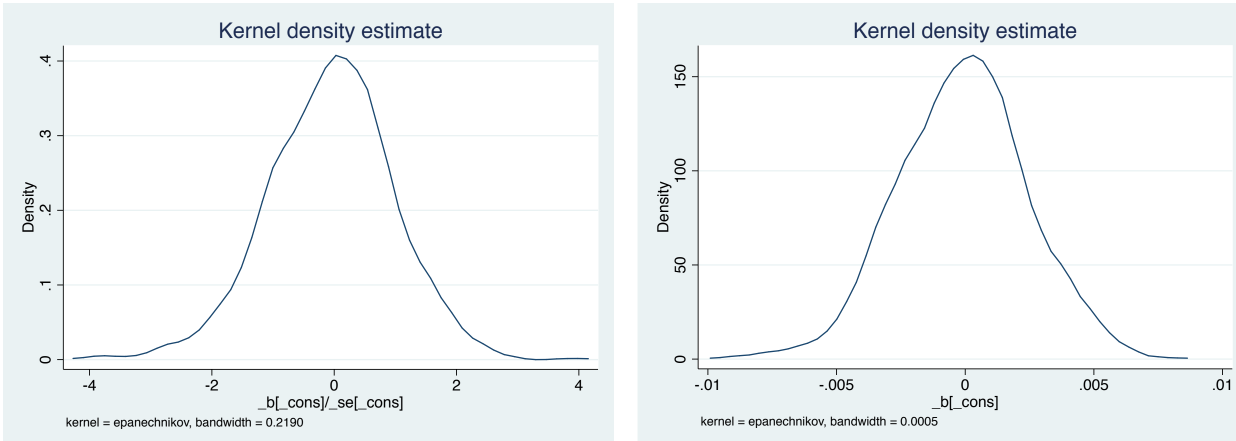

Figure 5. 1: Distribution of t-statistic of alpha and alpha for sell-side macro group – TM model

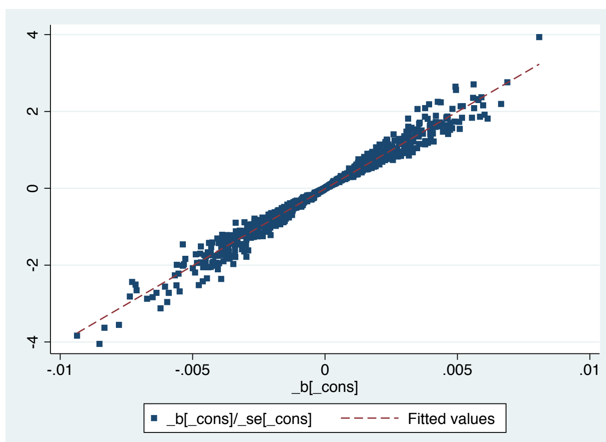

Figure 5. 2: Scatter plot representing correlation between alpha and its t-statistic

As from the several previous graphs, we can see that, first, the distributions of new estimates are not normal distributions, suggesting that the inference drawn from original regressions which based on the “normal distribution assumption” could be doubtful, further confirming the necessity of bootstrap test. Second, the constants (i.e., alphas of the sell-side macro group) are highly correlated with their t-statistics.

Generally, most of the values fell into the area which could not reject the null hypothesis: the constant equals zero. Thus, the original alpha 0.5% has enough explanatory power for this sell-side macro group based on TM model.

Let's repeat the process for HM model, and we can get results as following:

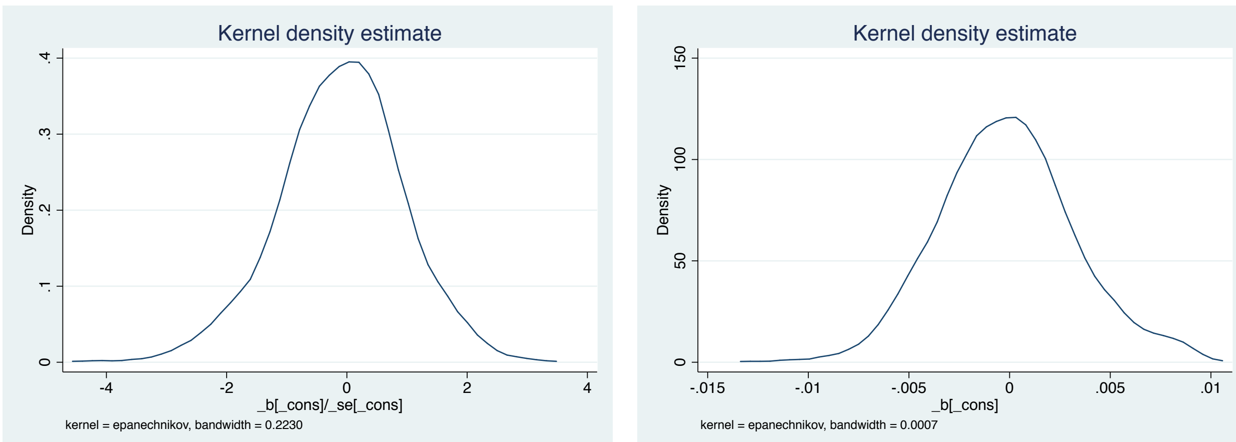

Figure 5. 3: Distribution of t-statistic of alpha and alpha for sell-side macro group – HM model

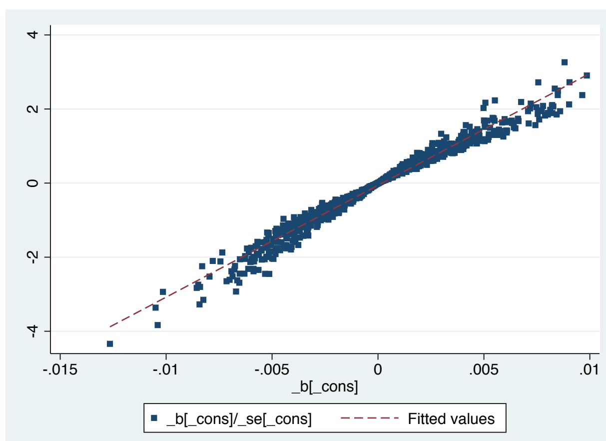

Figure 5. 4: Scatter plot representing correlation between alpha and its t-statistic

Table 5. 1: Summary of Carhart alpha of bootstrap test for sell-side macro group

			Bottom t-statistics			Top t-statistics		
			1%	5%	10%	10%	5%	1%
Carhart Alpha	TM model	t-statistic	-2.722	-1.761	-1.293	1.220	1.601	2.244
		p value	0.010	0.085	0.173	0.189	0.111	0.033
	HM model	t-statistic	-2.717	-1.886	-1.393	1.185	1.613	2.179
		p value	0.010	0.068	0.151	0.197	0.109	0.038

Again, most values are within the range where the null hypothesis could not be rejected. In conclusion, the original Carhart alphas 0.5% and 0.7% under Carhart TM/HM model are not due to luck.

5.3 Test for Carhart alpha for buy-side industry group

As we have seen the highly-similar graphs of coefficients and its t-statistic, next we will just put two graphs—estimates and scatter plots to show whether null hypothesis can be rejected.

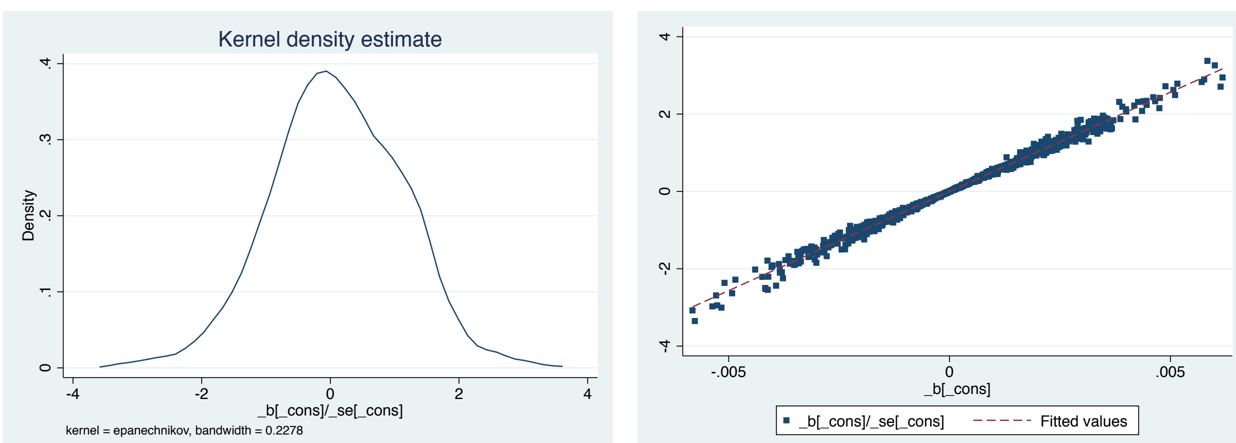

Figure 5. 5: Distribution of t-statistic of alpha and scatter plot for buy-side industry group

From the above graphs and statistics, we only find low p values for top and low-ranked t-statistics, suggesting that throughout the resampled data, a preponderant part indicates that the new alphas are insignificant due to random chance, or say, sampling variation. Instead, the original alpha 0.4% is because of inner talents as in a buy-side industry group of mutual fund portfolio managers.

		Bottom t-statistics			Top t-statistics		
Carhart Alpha		1%	5%	10%	10%	5%	1%
	t-statistic	-2.467	-1.546	-1.128	1.362	1.690	2.464
	p value	0.020	0.121	0.210	0.157	0.096	0.020

Table 5. 2: Summary of Carhart alpha bootstrap test for buy-side industry group

5.4 Test for market-timing factor

As we discuss before, non-linear factors MKT^2 and Max {0, MKT} in TM and HM model represent ability of positively taking advantage of the market trend. The surprising negative coefficient of TM/HM factor shown in sell-side macro group calls for a further test. Again, we do an N=1000 test for these coefficients.

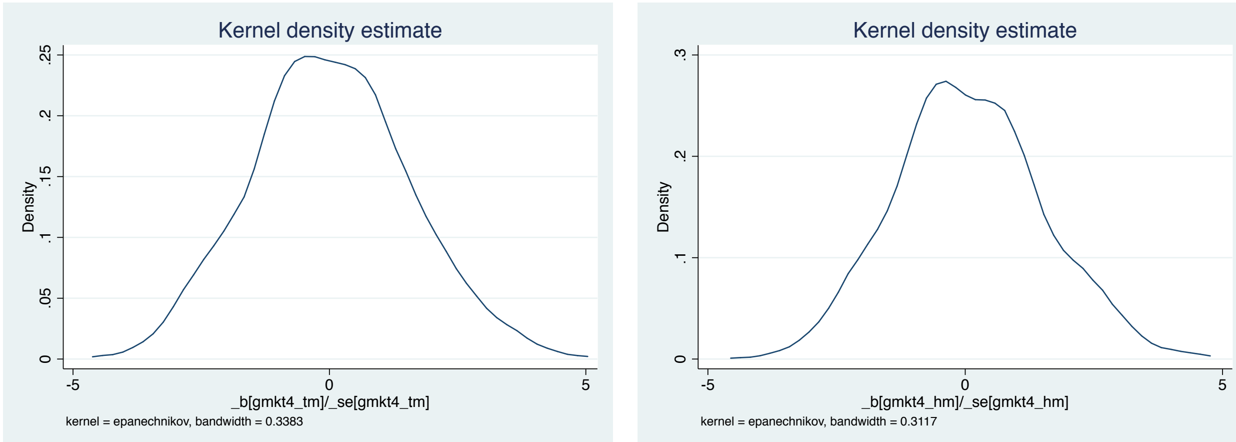

Figure 5. 6: Distribution of t-statistic of TM/HM factor for sell-side macro group

Table 5. 3: Summary of TM/HM factor bootstrap test for sell-side macro group

			Bottom t-statistics			Top t-statistics		
			1%	5%	10%	10%	5%	1%
MKT factor	TM model	t-statistic	-3.309	-2.516	-1.969	2.047	2.641	3.733
		p value	0.002	0.017	0.058	0.050	0.013	0.000
	HM model	t-statistic	-3.075	-2.226	-1.792	2.060	2.553	3.512
		p value	0.004	0.034	0.080	0.048	0.016	0.001

The above statistics show that both top and bottom p-values are relatively smaller compared with tests above for alphas, suggesting the non-linear TM/HM factors are not quite statistically sound, negative market timing ability can be attributed to luck and casualty to some degree. Recalling that although the Carhart-TM/HM model has higher adjusted R-squared, the improvement is quite tiny, say from 77.47% to 77.57%. To this point, we could conclude that the Carhart-TM/HM model is not suitable for mutual fund portfolio managers in China stock market. Alternatively, say the market-timing ability does not exist, and some statistical negative coefficients for the sell-side macro group are likely to be attributed to random chance.

5.5 Test for size factor and value factor

Next we do bootstrap test regarding size factor and value factor in industry groups (both buy-side and sell-side):

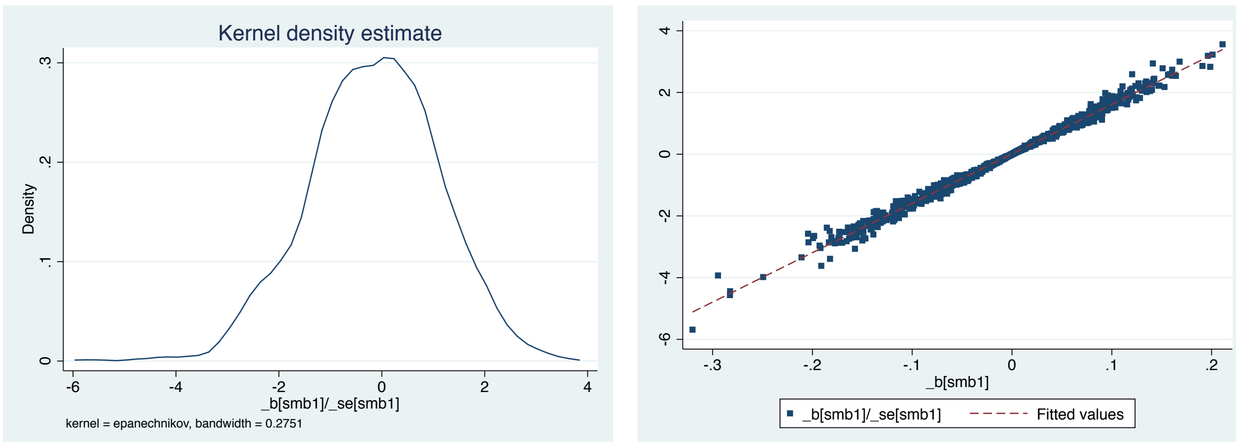

Figure 5. 7: Distribution of t-statistic of size factor and scatter plot for buy-side industry group

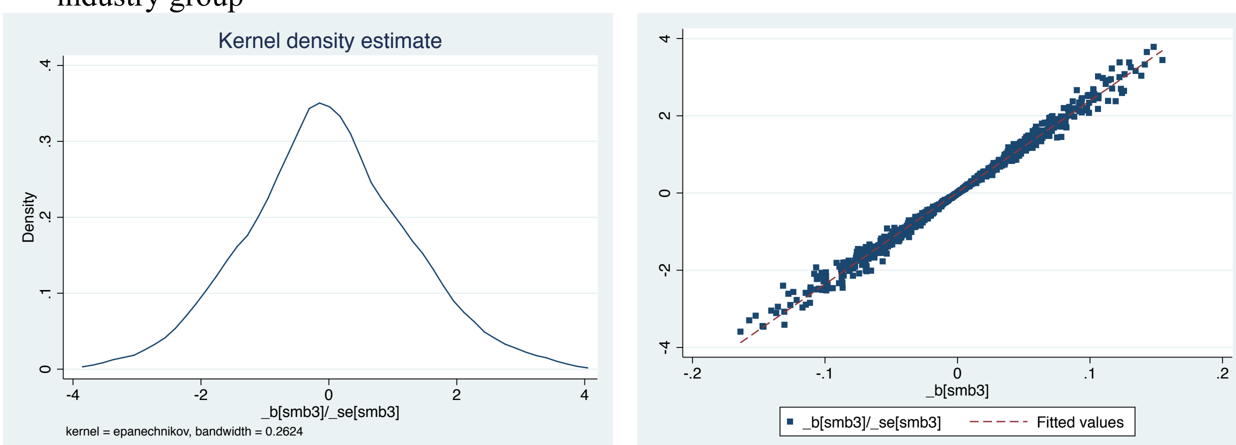

Figure 5. 8: Distribution of t-statistic of size factor and scatter plot for sell-side industry group

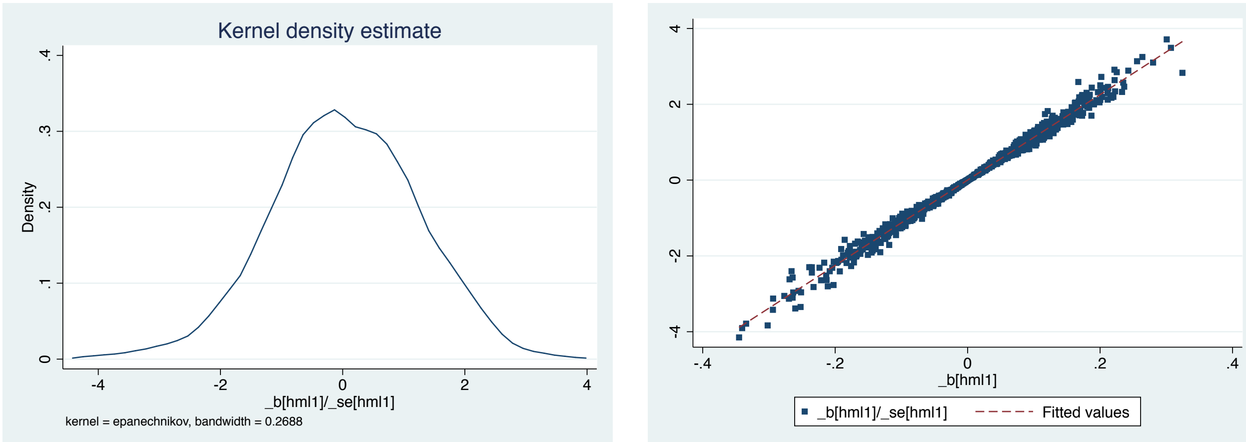

Figure 5. 9: Distribution of t-statistic of value factor and scatter plot for buy-side industry group

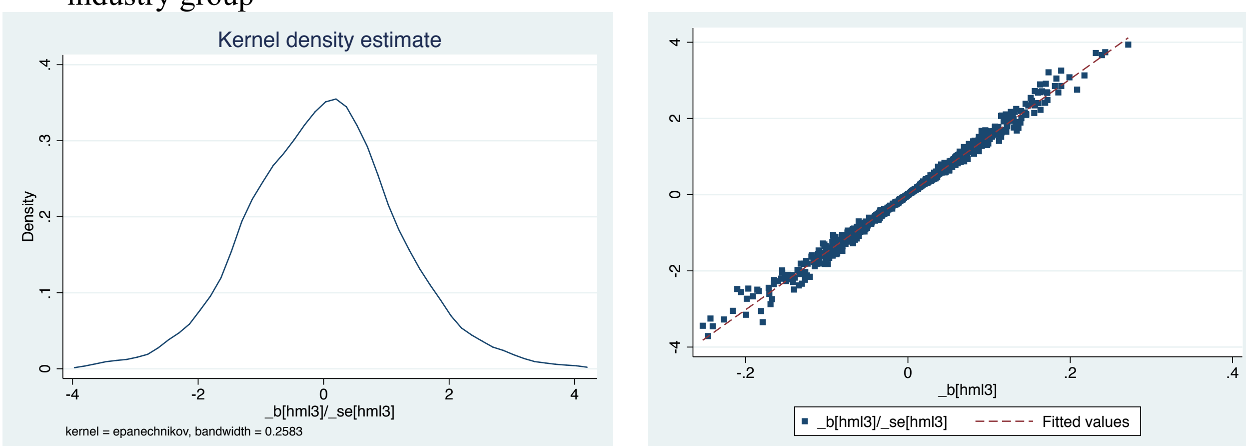

Figure 5. 10: Distribution of t-statistic of value factor and scatter plot for sell-side industry group

Table 5. 4: Summary of SMB and HML factor bootstrap test for buy-side and sell-side industry group

			Bottom t-statistics			Top t-statistics		
			1%	5%	10%	10%	5%	1%
SMB factor	buy-side industry	t-statistic	-3.002	-2.331	-1.776	1.444	1.852	2.594
		p value	0.005	0.028	0.083	0.140	0.072	0.015
	sell-side industry	t-statistic	-2.956	-2.038	-1.612	1.606	2.130	3.058
		p value	0.006	0.051	0.109	0.110	0.042	0.004
HML factor	buy-side industry	t-statistic	-3.079	-1.949	-1.483	1.554	2.026	2.680
		p value	0.004	0.061	0.133	0.119	0.052	0.012
	sell-side industry	t-statistic	-2.811	-1.853	-1.477	1.493	1.966	2.902
		p value	0.008	0.072	0.134	0.131	0.058	0.007

From the above tests, again, looking at the distribution of t-statistics, a preponderant part located in the non-rejective area indicate strong evidence that the observable return generated from small-cap and growth stocks is not attributable to random change. Alternatively, say both buy-side and sell-side industry managers show significant superiority over macro groups in selecting small-cap and growth stocks.

CONCLUSION

Using mutual fund data of China stock market from 2001 to 2018 from CSMAR, we find that, portfolio managers who start a career as buy-side industry and sell-side macro analysts significantly generate excess returns, for about 0.4% and 0.6% on average.

The Carhart-TM/HM model which incorporates non-linear market premium factor seems not to work well in China although there is a statistical improvement to some degree. Single Carhart model works better. Generically, there is no evidence that managers show market-timing ability in any group.

Last but not least, industry groups both buy-side and sell-side significantly generate a bigger proportion of return from small-cap stocks and low book-to-market ratio stocks (growth stocks). Notably, buy-side industry group shows superior ability in picking up promising small-cap stocks, and sell-side industry group tends to pay most attention to and invest more in growth stocks.

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