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Fund Returns and Net Redemptions under Incomplete Information in China

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ABSTRACT

This paper delves into the nonlinear flow-performance curve under incomplete information both theoretically and empirically. We find positive slope and negative convexity in the curve of China. These results imply that funds with bad performances are more heavily punished with outflows, compared with the reward to funds with good performances.

1. Introduction

The relation between fund return and net redemption is highly controversial. Some scholars verify a straightforward investment strategy, notably, to buy winners and sell losers. Others argue that this simple investment strategy may not be capable of generating sustainable profitability from following three perspectives: persistence of performances of open-end funds (Carhart, 1997);. ex post examination of effective investment (Elton et al. 2003; Nanda et al., 2004); and ex ante effective investment models (Palomino and Uhlig, 2007; Dangl et al., 2008). These studies shed lights on the complicated investment behavior than previously supposed.

In the real world, the relation seems even more intricate. In mature market like the U.S., the flow-performance curve is far from positive linearity, often convex (Barber et al., 2000). In China, the fund market has seen redemption puzzle (Lu et al., 2007), where funds with top performance have experienced striking high net redemptions. Some studies simply attribute the occasional spurious puzzle to the irrational investment behaviors of

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fund investors, while we try to explain the phenomenon with incomplete information and rational investors. We are highly skeptical that the behavior effect are strong and freaked enough to drive investors to drop the best funds and meanwhile maintain the others.

Following Palomino and Uhlig (2007), we build a dynamic game-theoretic model between fund investors and fund managers with incomplete information, which suggests that the relation between fund returns and redemption decisions can be nonlinear. To verify the implications of the model we apply fixed effect and quantile regression on the panel daily data of 47 funds from 2004 to 2010. The empirical results confirm positive slope and negative convexity of flow-performance curve in China. These findings indicate that despite the anecdotal evidence on the redemption puzzle, funds with higher returns on average experience higher fund inflows; besides, investors tend to punish bad funds than reward good funds in China, and Chinese fund market are more punishment-oriented than incentive-driven.

Our research complements existing literature by explaining the redemption puzzle from a longer period. To our knowledge, we are the first to use long daily data of open-end funds in China to study the properties of flow-performance curve. In addition, our research contributes to the understanding of the relation between fund returns and net redemption from the aspect of incomplete information and rational investors.

2. Dynamic Game between Investors and Managers under Incomplete Information

Following Palomino and Uhlig (2007), we build the dynamic Bayesian game between fund investors and fund managers. We identify the three categories in each of which investors prefer funds with different return intervals, depending on the ex ante expected return of funds relative with that of stock market.

2.1 Assumptions

We assume two types of funds, index funds (henceforth IF) and actively managed funds (henceforth AMF), in the market. The AMF are managed by either a good manager (with binary unconditional probability φ) or a bad one. An investor can not directly observe the quality of the AMF. Instead, he can only infer the manager types based on observed previous performance.

Specifically, we assume that the IF return is μ_0, and the AMF returns R_i are normally distributed:

$$R_i = \mu_i + \sigma_i \varepsilon \text{ , } \varepsilon \sim N(0;1), i = good, bad; \tag{1}$$

where μ_i denotes the expected returns of AMF with manager i. Without loss of generality, we assume $\mu_{bad} < \mu_0 < \mu_{good}$. Managers can choose risk level, captured by volatility σ_i, but cannot choose expected return, a reflection of their capability.

2.2 Fund Managers' Optimization

Assume the equilibrium risk level is $(\sigma^*_{bad}, \sigma^*_{good})$. The likelihood ratio of investors is,

$$L(R, \sigma^*_{bad}, \sigma^*_{good}) = \frac{P(R \mid \mu_{good})}{P(R \mid \mu_{bad})} = \frac{\sigma^*_{good}}{\sigma^*_{bad}} e^{\frac{(R-\mu_{good})^2}{(2\sigma^*_{good})^2} - \frac{(R-\mu_{bad})^2}{(2\sigma^*_{bad})^2}} \tag{2}$$

Upon the previous return R, investors use the Bayesian rule to compute the conditional probability of a good manager as

$$\begin{aligned} P(\mu_{good} \mid R) &= \frac{P(R \mid \mu_{good}) P(\mu_{good})}{P(R \mid \mu_{good}) P(\mu_{good}) + P(R \mid \mu_{bad}) P(\mu_{bad})} \\ &= \frac{\varphi}{\varphi + (1-\varphi) L(R, \sigma^*_{good}, \sigma^*_{bad})} \end{aligned} \tag{3}$$

The managers' objective is to maximize the probability, and

$$\underset{\sigma_i}{Max}\ P(\mu_{good} \mid R) \Leftrightarrow \underset{\sigma_i}{Min}\, L(R, \sigma^*_{good}, \sigma^*_{bad}) \tag{4}$$

To reach a solution, we have

$$\frac{\delta L(R, \sigma^*_{good}, \sigma^*_{bad})}{\delta \sigma^*_{good}} = \left(\frac{1}{\sigma^*_{bad}} - \frac{(R-\mu_{good})^2}{\sigma^*_{bad} \sigma^{*2}_{good}} \right) e^{\frac{(R-\mu_{good})^2}{(2\sigma^*_{good})^2} - \frac{(R-\mu_{bad})^2}{(2\sigma^*_{bad})^2}} = 0$$

$$\frac{\delta L(R, \sigma^*_{good}, \sigma^*_{bad})}{\delta \sigma^*_{bad}} = \left(\frac{\sigma^*_{good} (R-\mu_{bad})^2}{\sigma^{*4}_{bad}} - \frac{\sigma^*_{good}}{\sigma^{*2}_{bad}} \right) e^{\frac{(R-\mu_{good})^2}{(2\sigma^*_{good})^2} - \frac{(R-\mu_{bad})^2}{(2\sigma^*_{bad})^2}} = 0$$

Given $\sigma^*_i > 0$, the optimization is

$$\sigma^*_{good} = \left| R - \mu_{good} \right|, \sigma^*_{bad} = \left| R - \mu_{bad} \right| \tag{5}$$

Rational investors acknowledge this, and the posterior probability in Equation (3) is

$$P(\mu_{good} \mid R) = \left. \frac{\varphi}{\varphi + (1-\varphi) L(R, \sigma^*_{good}, \sigma^*_{bad})} \right|_{\sigma^*_i = \left| R-\mu_i \right|} \tag{6}$$

2.3 Fund Investors' Optimization

Rational investors invest in an AMF rathen than an IF only when

$$E\mu_{active} = P(\mu_{good} \mid R) \times \mu_{good} + P(\mu_{bad} \mid R) \times \mu_{bad} > \mu_0$$

This is equivalent to

$$P(\mu_{good} \mid R) > \frac{\mu_0 - \mu_{bad}}{\mu_{good} - \mu_{bad}} = \tau \tag{7}$$

Plugging Equation (6) into (7), we have

$$\left. \frac{\varphi}{\varphi + (1-\varphi) L(R, \sigma^*_{good}, \sigma^*_{bad})} \right|_{\sigma^*_i = R-\mu_i} > \tau$$

i.e., $L(R,\sigma^*_{good},\sigma^*_{bad})\big|_{\sigma^*_i=|R-\mu_i|} = \dfrac{|R-\mu_{good}|}{|R-\mu_{bad}|} < \dfrac{\varphi(1-\tau)}{\tau(1-\varphi)}$

(8)

Let $\lambda = \dfrac{\varphi(1-\tau)}{\tau(1-\varphi)}$, then Equation (8) is equivalent to

$$\lambda|R-\mu_{bad}| > |R-\mu_{good}| \tag{9}$$

Equation (9) equals $\lambda^2(R-\mu_{bad})^2 > (R-\mu_{good})^2$. After simplifying this equation, we can deduce that the return of the AMF must satisfy,

$$G(R) = (\lambda^2-1)R^2 + 2(\mu_{good}-\lambda^2\mu_{bad})R + (\lambda^2\mu^2_{bad}-\mu^2_{good}) > 0 \tag{10}$$

The discriminant for Equation (10) is

$\Delta = 4(\mu_{good}-\lambda^2\mu_{bad})^2 - 4(\lambda^2-1)(\lambda^2\mu^2_{bad}-\mu^2_{good}) = \lambda^2(\mu_{good}-\mu_{bad})^2 > 0$.

And two solutions to $G(R)=0$ are respectively

$$R_1 = \frac{\mu_{good}+\lambda\mu_{bad}}{1+\lambda}, R_2 = \frac{\mu_{good}-\lambda\mu_{bad}}{1-\lambda} \tag{11}$$

2.4 Return Intervals for Investors

Figure 1 shows the shape of $G(R)$ and return intervals chosen by investors in three cases as λ varies.

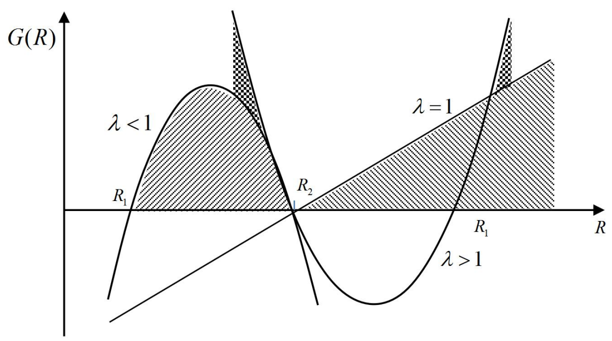

Figure 1. Return Intervals Chosen by Investors Based on λ

A. If $\lambda > 1$

This means $\varphi > \tau$, which intuitively implies that the prior probability of good manager is higher than the proportion of the return difference between IF and bad AMF to the return difference between good and bad AMF. And the economic meaning is that randomly investing in AMF gains more than IF (with $\mu_{good} > \mu_{bad}$, we get $\varphi\mu_{good}+(1\text{-}\varphi)\mu_{bad} > \lambda\mu_{good}+(1\text{-}\lambda)\mu_{bad} = \mu_0$)

The parabola, $G(R)$, now opens up and R_2 and R_1 satisfy $R_2 < \mu_{bad} < R_1 < \mu_{good}$. Investors prefer funds with returns falling in $(-\infty, R_2)\cup(R_1,+\infty)$,. Even if the fund returns pretty low previously, there is a chance that the AMF is still good. And a good manager tend to choose high risk (prestn far away from μ_{good}) while the bad choose low risk. All these factors compensate the low historical return and make investment in such an AMF profitable Similar induction holds for high historical return.

B. If $\lambda = 1$

This means that $\varphi = \tau$ and the returns of randomly investing in an AMF and IF are equal. In this vein, $G(R)$ degenerates to a straight line and rational return interval is $(\frac{\mu_{good}+\mu_{bad}}{2}, +\infty)$.

C. If $0 < \lambda < 1$

This means $\varphi < \tau$ and randomly investing in an AMF is unprofitable. The parabola, $G(R)$ now opens down and R_2 and R_1 satisfy $\mu_{bad} < R_1 < \mu_{good} < R_2$. In this case, Investors choose AMF with returns satisfying $R \in (R_1, R_2)$. Intuitively, the low possibility of good AMF make it unprofitable to investing in AMF even if the previous return is high, regardless of the low risk taking of good fund and the otherwise high risk taking of bad fund sequently.

Under incomplete information, rational investors will choose high performing funds if $\lambda = 1$, and won't respond linearly to the returns of AMF elsewhere. To summarize, the return intervals chosen by investors are respectively,

$$\begin{cases} R \in (-\infty, R_2)\cup(R_1,+\infty), & \lambda > 1 \\ R \in (\frac{\mu_{good}+\mu_{bad}}{2}, +\infty), & \lambda = 1 \\ R \in (R_1, R_2), & 1 > \lambda > 0 \end{cases} \tag{12}$$

3. The Effect of Fund Returns on Net Redemptions

Bailey et al. (2011) figure out that net redemption decisions of investors are determined by market news, tax rates, fund family, behavioral and demographic characteristics of investors, and other factors than solely by fund returns Different from their research, we also incorporate the influence of asset allocation, including both asset proportion and investment concentration, which is believed to proxy for the unobserved fund risk level and manager ability. More specifically, the asset proportion in the funds reveals the risk level of funds and the investment concentration is closely related to the fund managers' ability.

3.1 Variables and Data

In this paper, we employ several redemption indicators as dependent variables, including net purchase amount (*NPA*), net purchase ratio (*NPR*), and purchase to redemption ratio (*PRR*) for robustness. The most important independent variable is undoubtedly the fund returns. Other important independent variables include asset allocation indicator measured with asset proportion and investment concentration, which are also directly observable like *NGR* and may signal other properties of the fund managers. Asset proportion characterizes asset diversification, measured by *SAR* and *CAR*. Investment concentration signals hidden information about investment strategies and manager ability, measured by *SFR* and *IFR*. The calculation method of the variables are shown in Table~.

variables	*Calculation method*
NPA	daily purchasing amount minus the redemption amount
NPR	NPA divided by net fund value
PRR	daily purchasing amount divided by the redemption amount
NGR	growth rate of net value
SAR	stock value held by fund divided by total asset value
CAR	cash held by fund divided by total asset value
SFR	top-ten-stock value held by the fund divided by the total asset value
IFR	top-three-industry value held by the fund divided by the total asset

To lower the confounding influence of the fund market structure①, we restrict our sample to stock funds and partial stock funds②. We select as our sample a total of 47 stocks and partial stock funds listed in the open-end fund market in China from the second quarter of 2004 to the second quarter of 2010We exclude the trading data of the first quarter of listed funds for that redemptions are abnormally high shortly after the funds are listed. Some firm-level specific factors may still exert influence on the redemption behavior, and therefore, we apply following fixed effects model in this paper③.

$$NPA_{it} = \beta NGR_{it} + \gamma_1 SAR_{it} + \gamma_2 CAR_{it} + \gamma_3 SFR_{it} + \gamma_4 IFR_{it} + c_i + \varepsilon_{it} \tag{13}$$

3.2 The First-order Effect

Table 1 shows the first-order effects of fund returns on net redemption, which present two appealing results:

First, the significantly positive coefficients of NGR indicate that the increase of return of the funds overall induces more net purchase from the investors, and the results are robust with NPA reflecting the absolute value of net purchase, NPR reflecting the relative purchase, and PRR reflecting trading activity. Therefore, in overall open-end fund market in China, higher returns tend to increase cash inflow to the funds. In other words, we don't observe the "redemption puzzle" on individual fund level.

Table 1. Regression Results of the Fixed Effects Models

	NPA	*NPR*	*PRR*
NGR	15997483*** (0.0001)	2.1913*** (0.0000)	0.0125*** (0.0000)
SAR	14335877*** (0.0038)	1.3066** (0.0175)	0.0046*** (0.0003)
CAR	72360806*** (0.0000)	7.1763*** (0.0000)	0.0144*** (0.0000)
SFR	-20708328*** (0.0050)	-2.1342*** (0.0092)	-0.0035* (0.0625)
IFR	1.95E+09*** (0.0024)	130.6255* (0.0671)	0.2744* (0.0923)
R^2	0.12	0.13	0.18
Prob(F)	0.0000	0.0000	0.0000
DW	1.9892	2.0566	1.9475

Notes: The cells show coefficients with robust standard errors in parentheses. *, ** and *** denote significance at 10%, 5% and 1% level, respectively.

Second, the asset allocation demonstrate a significant impact on investors' redemption The coefficients on *SAR*, *CAR*, *SFR*, and *IFR* are distinguishable from zero, indicating that they do make a difference to net cash-flows to the funds. In terms of asset proportion, the positive coefficients on both *SAR* and *CAR* show that investors are in favor of funds with more stocks and cash assets in hand, which may result from investors' preference for higher professionalization and liquidity. Nonetheless, *SFR* is negatively correlated with redemptions whereas *IFR* is on the contrary positively related to redemptions. This suggests that investors hope that the funds invest in some particular industries but not in few specific stocks in the industry

3.3 The Second Order Effect

To verify the non-linear relation between returns and net redemptions put forward in our game model, we conduct an quantile regression (Carhart, 1997), which is applicable by our daily data.

We classify the observations into 7 groups according to the quantiles of the lagged return in the previous day. Weighted averages of the dependent and independent variables in each group are computed to conduct the quantile regression (13). The results where NPA and NPR are employed as dependent variables respectively are shown in Table 2 and Table 3.

The impacts of fund returns on net redemptions of investors are apparently different in different groups. Net redemptions are influenced by the profitability of funds whatever levels the returns are at, although coefficients on NGR in groups High (2), High (3) and Low (3) are negative

① The Chinese fund market consists of four types of funds: stock funds, bond funds, money market funds and hybrid funds. Returns, risks, and investment strategies vary a lot among them and thus investors may respond quite differently.

② Partial stock funds refer to hybrid funds with more than 50% stock asset.

③ We also conduct the Hausman test, the result of which support the application of fixed effect.

Table 2. Results of Quantile Regressions on NPA

	High (1)	High (2)	High (3)	Middle	Low (3)	Low (2)	Low (1)
NGR	15020256*** (0.0027)	-3982721** (0.0366)	-5801712* (0.0952)	20715095*** (0.0004)	-4567113** (0.0425)	20364231** (0.0393)	11165208* (0.0669)
SAR	-2086629 (0.7057)	11101441*** (0.0026)	6115447*** (0.0001)	11347856* (0.0991)	-6503724* (0.0673)	26215558** (0.0259)	12553221 (0.2030)
CAR	12416265** (0.0280)	16811094** (0.0217)	8031948** (0.0421)	9658886*** (0.0000)	11076818 (0.1835)	50697583* (0.0508)	45933941*** (0.0000)
SFR	4343248 (0.6067)	1677585 (0.6813)	4511214 (0.2132)	-25621653** (0.0154)	760207.9 (0.8515)	-30444706* (0.0563)	-11986712* (0.0516)
IFR	8.79E+08 (0.1604)	1.10E+09*** (0.0016)	-7.39E+08 (0.2130)	1.69E+09** (0.0235)	-1.38E+08 (0.6637)	2.89E+09* (0.0542)	3.49E+08 (0.5320)
R^2	0.12	0.19	0.11	0.31	0.10	0.11	0.21
Prob(F)	0.0544	0.0010	0.0807	0.0000	0.1993	0.0407	0.0002
DW	2.0251	2.1578	2.0275	1.9351	2.0682	1.9528	1.998

Table 3. Results of Quantile Regressions on NPR

	High (1)	High (2)	High (3)	Middle	Low (3)	Low (2)	Low (1)
NGR	1.2144*** (0.0003)	-0.2531** (0.0253)	-0.2236** (0.0475)	2.3439*** (0.0003)	-0.3473* (0.0527)	1.8594** (0.0406)	1.6970** (0.0206)
SAR	-0.3946 (0.1029)	0.6751*** (0.0003)	0.0558*** (0.0066)	1.7662*** (0.0040)	-0.0541* (0.0604)	0.4513 (0.3736)	0.6422 (0.1779)
CAR	1.5665*** (0.0059)	0.6900 (0.1218)	0.1888** (0.0790)	8.5660*** (0.0000)	0.6211 (0.3825)	5.7455*** (0.0000)	3.1494** (0.0104)
SFR	0.1729 (0.6099)	-0.4869** (0.0230)	0.0030 (0.1953)	-3.0906*** (0.0000)	-0.3738 (0.3712)	-1.1234* (0.0910)	-0.1200 (0.8495)
IFR	-35.9373 (0.2170)	60.2998*** (0.0007)	21.2185* (0.0912)	139.4713** (0.0173)	-2.5610 (0.9287)	64.2149 (0.3143)	-85.8251 (0.1584)
R^2	0.16	0.17	0.12	0.34	0.10	0.27	0.16
Prob(F)	0.050	0.0029	0.0320	0.0000	0.09273	0.0000	0.0064
DW	2.0576	2.0381	2.0818	2.0163	2.0663	1.9581	2.0386

However, we believe this reflects the rational choice of investors rather than a puzzle. As previous studies find that open-end funds as a whole underperform the market index, λ is larger than 1 in China according to its economic implication, and our dynamic model indicates rational investors will prefer higher return in some situations while lower return in others Therefore, we ascertain that even the occasionally observed “redemption puzzle” may not be an irrational investment behavior in China.

Nevertheless, the impacts of asset allocation on net redemptions also differs in different groups of funds in the following three aspects. First,, the insignificant coefficients on *SAR* in high(1) and low(1)imply that the fund returns dominate in the net redemption decision-makings and that the asset allocation plays little role in terms of these funds. Second, the coefficients on *CAR* are consistently positive and significant in all cases except Low (3), indicating that higher liquidity of the funds is desired by investors. Third, the impacts of *SFR* and *IFR* on net redemptions varies significantly in the groups.

Table 4. Results of 1/2 Quantile Regressions on NPA

	NGR	SAR	CAR	SFR	IFR	R^2	DW
High（1）	10922721*** （0.0006）	10138265*** （0.0026）	17360723*** （0.0021）	2134690* （0.0813）	1.07E+09*** （0.0012）	0.14	1.9328
Low（2）	16139738*** （0.0017）	23758936*** （0.0057）	57326558*** （0.0052）	-12689237 （0.0106）	1.73E+09*** （0.0035）	0.13	1.9893

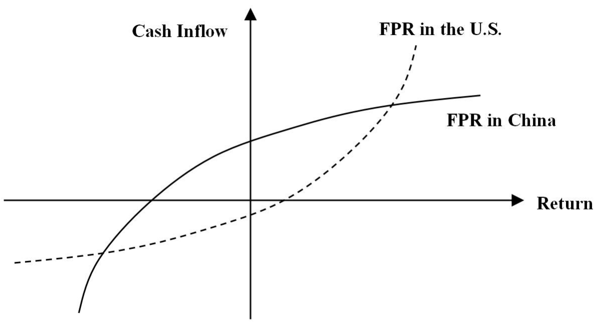

Figure 2. The Flow-performance Relations (FPR) in China and the U.S.

To further examine the convexity in the flow-performance relation in the open-end fund market of China, we run a 1/2 quantile regression on NPA and the results are presented in Table 5.Obviously, the coefficient on NGR in the funds with high returns is less than that in the funds with low returns, i.e., $\left.\frac{\partial flow}{\partial R}\right|_{R\_low} > \left.\frac{\partial flow}{\partial R}\right|_{R\_high}$. Hence we have $\frac{\partial^2 Inflow}{\partial R^2} < 0$, which implies the negative convexity in the flow-performance relation in China. On the contrary, researches on the mutual fund market in the U.S. (Barber et al., 2000) uncover positive convexity in the relation, albeit the impact of return on cash inflows is also non-linear.

The difference between the flow-performance relations in China and the U.S. in Figure 2 indicates that cash inflows are more sensitive to the high returns of funds in the U.S., showing an incentive-driven pattern, while cash outflows are more vulnerable to low returns in China, showing a punishment-oriented pattern. The difference may stem from excessively risk-averse of investors with incomplete information: (1) information disclosure about the asset allocation is not in time in China; (2) the ranking system is in its infancy; and (3) the information transmission mechanism is not well established.

4. Conclusion

In this paper, we first build a theoretical model of the dynamic game between fund investors and fund managers under incomplete information to investigate the relation between fund returns and net redemptions. Then, using the panel data of a total of 47 stock funds and partial stock funds and fixed effects model, we empirically investigate the first-order and second-order effects of the fund returns on net redemptions in the open-end fund market in China.

We find: (1) the Bayesian equilibrium of dynamic game between investors and fund managers verify a nonlinear impact of returns on redemption; (2) the net purchase are positively correlated with the performance and asset allocation of funds in overall market of China; (3) the flow-performance curve is nonlinear and negative convex, which exactly contrasts with the positive convexity in in the flow-performance relation in the U.S. These findings don't provide evidence for redemption puzzle in the overall market of China. Besides, the positive slope and negative convexity of the flow-performance curve demonstrates a punishment-oriented pattern of investment behavior in China.

About the author

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