An Empirical Test of The Dual-Path Impact of mental Accounting Classification on Investment Behavior Bias

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Abstract. This study focuses on Chinese investors and empirically examines the dual-path impact of "funding source" and "funding use" classifications in mental accounting on investment behavior biases, with mental accounting theory as the core. Based on a questionnaire survey of 250 Chinese residents with investment experience, methods such as linear regression, ordinal Logistic regression, mediation effect, regression, and moderation effect tests were employed. The results show that different funding sources have significant differences in their impact on asset allocation risk preferences. Funding use classifications affect biases such as the disposition effect through risk perception and evaluation frequency. Risk perception plays a partial mediating role between funding use and risk mismatch, and high-income groups are more affected by mental accounting labels. This study constructs an integrated framework of "fund classification - mental accounting - decision bias," which has innovations are: first, it is the first to integrate fund sources and uses into a unified analytical model, revealing their interaction effects; second, it deepens the micro-mechanism of mental accounting's impact on investment decisions through the "cognition-behavior" dual-layer mediation path; third, it incorporates Chinese market features such as high savings rates and rigid expenditure expectations.

Keywords: Mental accounting; investment behavior bias; funding source; funding use; Chinese investors.

1. Introduction

Traditional finance is built on the assumption of the "rational man," constructing a perfect framework of market equilibrium, which holds that investors can make optimal decisions based on complete information [1]. However, real financial markets are rife with anomalies that cannot be explained by rational logic: investors tend to deposit their salary income in banks but invest windfall gains in high-risk stocks; funds earmarked as "children's education funds" often avoid risks, while "speculative funds" are willing to bear huge losses; profitable stocks are sold too early, while loss-making stocks are held for long periods. These systematic investment behavior biases expose the limitations of the rational man assumption and have prompted the academic community to re-examine decision-making mechanisms from a behavioral perspective.

The rise of behavioral finance has provided new theoretical tools to address these puzzles, among which "mental accounting" theory is highly explanatory. This theory suggests that individuals do not view all funds as a unified whole but instead construct multiple independent mental accounts based on characteristics such as fund sources, uses, and timing, and then apply differentiated decision-making rules to each account [2]. For example, people are far more sensitive to losses than to gains. This "loss aversion" manifests in mental accounting as the isolated evaluation of gains and losses across different accounts, thereby triggering irrational decisions [3]. Although mental accounting theory has been widely validated in the field of consumption (e.g., budget constraints and consumption classification [4], its mechanism of action in the investment domain still lacks systematic elaboration.

Existing research has three limitations: First, it mostly focuses on single-dimensional influences, such as exploring the connection between mental accounting and the disposition effector analyzing the impact of fund sources on risk preferences in isolation, without integrating the combined influence of the "source-use" dual path [5]. Second, mechanism analysis is fragmented, failing to clarify how mental accounting transmits to asset allocation biases through "risk perception" at the cognitive level

and "evaluation frequency" at the behavioral level. Third, there is a lack of empirical research on the Chinese market. Most existing findings are based on data from Western investors, while the unique savings habits and policy environment of Chinese investors (e.g., expectations of rigid redemption and the concentration of household asset allocation) may lead to differentiated characteristics of the mental accounting effect [6,7].

2. Research Design and Methodology

2.1. Data Resource

Data were collected via online questionnaires from 300 Chinese residents with investment experience, yielding 250 valid responses. The age of the respondents ranges from 25 to 55 years, with an average age of 36.2 years; among them, 58% are aged between 30 and 40 years. In terms of monthly income, 72% of the respondents have a monthly income ranging from ¥5,000 to ¥20,000. Regarding education level, 65% of the respondents hold a bachelor's degree or above, which is consistent with the characteristics of mainstream Chinese investors [8].

2.2. Model Introduction

To explore the impact of mental accounting classification on investment behavior, this study employs mental accounting theory as the core framework, integrating prospect theory and advancements in behavioral finance, and constructs a multi-model analytical framework including linear regression, ordinal Logistic regression, mediation effect test, and moderation effect analysis [9]. The specific explanations of variables shown in Table 1.

Table 1. Variable definitions for mental accounting and investment behavior analysis.

Variable Type	Variable Name	Variable Explanation
Explained Variables	Low-risk asset allocation ratio	The proportion of low-risk assets (such as money market funds, short-term bonds) in the investment portfolio
	Medium-low-risk asset allocation ratio	The proportion of medium-low-risk assets (such as medium and short-term bond funds) in the investment portfolio
	Medium-high-risk asset allocation ratio	The proportion of medium-high-risk assets (such as equity funds) in the investment portfolio
	High-risk asset allocation ratio	The proportion of high-risk assets (such as futures and options) in the investment portfolio
Explanatory Variables	Monthly salary income	Monthly wage earnings, reflecting the stable cash inflow of investors
	Annual bonus/project bonus	Additional annual bonus income, reflecting the capital supplement brought by work performance
	Windfall income	Accidentally obtained one-time income, such as lottery winnings, accident compensation
	Investment income	Income generated from past investment activities, covering various investments such as stocks, funds, and bonds
	Inherited/donated assets	Assets obtained through inheritance or donation
Mediating Variable	Risk perception (capital preservation awareness)	Investors' subjective perception of investment risks, especially reflected in the emphasis on asset preservation

The basic regression model for this study is uniformly set as follows:

$$Y=\beta_0+\sum_{i=1}^{n}\beta_i X_i+\sum_{j=1}^{m}\gamma_j C_j+\epsilon \quad (1)$$

Table 2. Linear definitions for mental accounting and investment behavior analysis (n=250).

	Unstandardized Cofficients		Standardized Cofficient	t-value	p-value	Collinearity Diagnostics	
	B	SE	Beta			VIF	Tolerance
Constant	1.62	0.16	-	10.122	0.000**	-	-
Monthly salary	-0.076	0.08	-0.077	-0.958	0.339	1.836	0.545
Annual bonus/project bonus	-0.056	0.093	-0.073	-0.604	0.546	4.135	0.242
Windfall income	0.047	0.085	0.065	0.548	0.584	3.972	0.252
investment income	0.234	0.08	0.374	2.935	0.004**	4.611	0.217
inherited/donated assets	0.092	0.079	0.084	1.173	0.242	1.465	0.682
R^2				0.141			
Adjusted R^2				0.123			
F				F(5,244)=7.979,p=0.000			
D - W statistic				1.959			

Notes: Dependent Variable: Low-risk Assets
(Deposits &Money Market funds):*p < 0.05 **p < 0.01

Table 3. Linear regression analysis results for medium-low-risk asset allocation (n=250).

	Unstandardized Cofficients		Standardized Cofficient	t-value	p-value	Collinearity Diagnostics	
	B	SE	Beta			VIF	Tolerance
Constant	1.064	0.113	-	9.433	0.000**	-	-
Monthly salary income	-0.023	0.056	-0.032	-0.412	0.681	1.836	0.545
Annual bonus/project bonus	0.058	0.066	0.103	0.89	0.374	4.135	0.242
Windfall income	0.037	0.06	0.069	0.608	0.544	3.972	0.252
Investment income	0.11	0.056	0.24	1.96	0.051	4.611	0.217
Inherited/ Donated assets	0.106	0.055	0.133	1.921	0.056	1.465	0.682
R^2				0.204			
Adjusted R^2				0.187			
F				F(5,244)=12.475, p=0.000			
D-W statistic				2.16			

Notes: Dependent Variable: Medium-low-risk
Assets (bonds & conservative funds): *p < 0.05 **p < 0.01

Among them, the core difference between the four asset allocation models lies in the specific direction of the explained variable Y - corresponding to the allocation ratios of low-risk, medium-low-risk, medium-high-risk, and high-risk assets respectively. The selection of explanatory variables and control variables remains consistent. The mediating effect model, on the basis of the above framework, introduces risk perception as a transmission variable to analyze its indirect influence path between explanatory variables and explained variables. By setting the explained variables differently, it can not only ensure the comparability between models but also accurately capture the differences in the driving mechanisms of different risk asset allocation behaviors as shown in Table 2 and Table3

Table 4. Linear regression analysis results for medium-high-risk asset allocation.

	Unstandardized Cofficients		Standardized Cofficient	t-value	p-value	Collinearity Diagnostics	
	B	SE	Beta			VIF	Tolerance
Constant	0.677	0.119	-	5.663	0.000**	-	-
Monthly salary income	0.262	0.06	0.332	4.391	0.000**	1.836	0.545
Annual bonus/project bonus	0.049	0.069	0.079	0.699	0.485	4.135	0.242
Windfall income	-0.019	0.064	-0.033	-0.299	0.765	3.972	0.252
Investment income	0.031	0.059	0.062	0.521	0.603	4.611	0.217
Inherited/ Donated assets	0.112	0.059	0.129	1.908	0.058	1.465	0.682
R^2			0.24				
Adjusted R^2			0.225				
F			F(5,244)=15.425, p=0.000				
D-W statistic			1.974				

Notes: Dependent Variable: Medium-high-risk Assets (equity funds & stocks): *p < 0.05 **p < 0.01

3. Experimental Results and Discussion

3.1. Differential Impact of Fund Sources on Asset Allocation

Linear regression results show that different fund sources have significant differences in their impact on asset allocation across risk levels.

For low-risk asset allocation, only investment income shows a significant positive impact (B=0.234, β=0.374, t=2.935, p=0.004), indicating that investors tend to transfer part of their investment income to low-risk accounts, possibly out of the psychology of "locking in gains".

For medium-low risk asset allocation, all fund sources have no significant impact, which may be because medium-low risk assets are more regarded as "basic allocation", and their proportion adjustment is related to the overall asset scale or risk preference.

For medium-high risk asset allocation, monthly salary income has a significant positive impact (B=0.262, β=0.332, t=4.391, p<0.001), which is consistent with the hypothesis that "the stability of salary income enhances risk-bearing capacity".

For high-risk asset allocation, windfalls negatively correlate (B=-0.114, β=-0.24, p=0.28) while inherited assets increase allocation (B=0.178, β=0.247, p<.001), evidencing mental labeling [10].

The above results verify the theoretical hypothesis that fund sources affect risk preference through mental accounting labels as shown in Table 4 and Table 5.

Table 5. Linear regression analysis results for high-risk asset allocation (n=250).

	Unstandardized Cofficients		Standardized Cofficient	t-value	p-value	Collinearity Diagnostics	
	B	SE	Beta			VIF	Tolerance
Constant	0.677	0.097	-	7.011	0.000**	-	-
Monthly salary income	0.201	0.048	0.308	4.175	0.000**	1.836	0.545
Annual bonus/project bonus	0.072	0.056	0.142	1.283	0.201	4.135	0.242
Windfall income	-0.114	0.051	-0.24	-2.212	0.028*	3.972	0.252
Investment income	0.049	0.048	0.119	1.02	0.309	4.611	0.217
Inherited/ Donated assets	0.178	0.047	0.247	3.745	0.000**	1.465	0.682
R^2			0.274				
Adjusted R^2			0.26				
F			F(5,244)=18.462, p=0.000				
D-W statistic			1.998				

Notes: Dependent Variable: High-risk Assets (futures & options): *p < 0.05 **p < 0.01.

Table 6. Ordered logistic regression model summary

Parameter	Category	Coeff.	SE	z -value	p -value	OR	95% CI for OR
Thresholds	Below 6.000	- 0.775	0.354	- 2.190	0.028	2.171	1.085 - 4.343
	6.000 ~ 8.000	1.214	0.359	3.380	0.001	3.367	1.671 - 6.790
Independent Variables	Purpose Account Segregation	- 0.541	0.243	- 2.230	0.026	0.582	0.362 - 0.937
	Purpose Classification Basis	0.279	0.126	2.220	0.026	1.322	1.033 - 1.691

Note: McFadden $R^2 = 0.015$, Cox & Snell $R^2 = 0.032$, Nagelkerke $R^2 = 0.036$

3.2. Impact of Fund Use Classification on Disposition Effect

Ordinal Logistic regression results show that fund use classification affects the disposition effect through two opposite mechanisms.

Purpose Classification Basis: The coefficient is 0.279 ($z = 2.222$, $p = 0.026$), and OR = 1.322 (95%CI:1.033~1.691). Clearer use definitions increase the disposition effect, as distinct labels strengthen goal - oriented trading, aligning with Shefrin & Statman's mental accounting theory and reflecting cultural nuances [11,12].

Table 7. Ordered logit regression analysis results - simplified format.

Item	Coefficient
Purpose Division Basis	-0.541* (-2.230)
Whether to Divide Purpose Accounts	0.279* (2.222)
Likelihood Ratio Test	χ^2 (2)=8.100, p = 0.017
McFadden R - squared	0.015

Notes: Dependent Variable = Disposal Effect Score,Sample Size = 250,*p < 0.05 **p < 0.01 The values in parentheses are z - values.

Table 8. Ordered logistic regression model prediction accuracy.

Actual Frequency	Predicted Accurate Frequency	Prediction Accuracy Rate
250	127	50.8%

As theses tables present, the model (likelihood ratio $\chi^2 = 8.100$, $p = 0.017$) confirms statistical significance, but low predictability (50.80%) suggests unmeasured factors influence results as shown in Table 6 and Table 7.

In practice, investors should balance clear use labels with moderate account integration. Financial institutions can design “purpose - bound products” to align behavior with goals, reducing bias as shown in Table 8 and Table 9.

3.3. Mediating Role of Risk Perception

Table 9. Regression analysis of fund use intensity on risk mismatch.

	Risk Mismatch			
	B	SE	t	pβ
Constant	-1.855**	0.078	-23.73	0 -
Intensity of Use	-0.422**	0.108	-3.91	0 -
Risk Perception (Capital Preservation Awareness)	-	-	-	- -
R^2	0.058	-	-	- -
Adjusted R^2	0.054	-	-	- -
F - Value	F(1,248)=15.301, p = 0.000	-	-	- -

Note: * p < 0.05, ** p < 0.01

The results of the mediation effect test show that risk perception (capital preservation awareness) plays a partial mediating role in the relationship between "use intensity - risk mismatch degree".

The total effect of use intensity on risk mismatch degree is significant (c=-0.422, t=-3.912, p<0.001), indicating that the clearer the use division, the lower the risk mismatch degree. after including risk perception, the direct effect of use intensity on risk mismatch degree is still significant (c'=-0.365, t=-3.302, p=0.001), and the impact of risk perception on risk mismatch degree is significant (b=-0.112, t=-2.167, p=0.031). The mediation effect value is a×b=-0.058 (95% BootCI: -0.077 ~ -0.002), accounting for 13.65% of the total effect.

Table 10. Regression analysis of fund uses intensity on risk perception (capital preservation awareness).

	Risk Perception (Capital Preservation Awareness)			
	B	SE	t	pβ
Constant	3.286**	0.095	34.41	0 -
Intensity of Use	0.516**	0.132	3.91	0 -
Risk Perception (Capital Preservation Awareness)	-	-	-	- -
R^2	0.058	-	-	- -
Adjusted R^2	0.054	-	-	- -
Value	F(1,248)=15.288, p = 0.000	-	-	- -

Table 11. Regression analysis of fund use intensity on risk mismatch.

	Risk Mismatch				
	B	SE	t	p	β
Constant	-1.488**	0.186	-7.98	0	-
Intensity of Use	-0.365**	0.11	-3.30	0.001	-0.208
Risk Perception (Capital Preservation Awareness)	-0.112*	0.052	-2.167	0.031	-0.137
R^2	0.076	-	-	-	-

The impact of use intensity on risk perception is significant (a=0.516, t=3.910, p<0.001), that is, a clear use definition will enhance investors' capital preservation awareness as shown in Table 10 and Table 11.

This result reveals the cognitive path of mental accounting affecting investment decisions - clear fund use promotes investors to choose assets matching their risk-bearing capacity by enhancing their attention to "principal safety" (risk perception), thereby reducing risk mismatch [13,14]. The mediation effect accounts for 13.65%, indicating that there are other transmission paths besides risk perception as shown in Table 12.

Table 12. Mediation analysis summary table.

Items	a	b	a*b (Mediation Effect)	c (Total Effect)	c' (Direct Effect)	Effect Proportion	95% Bootstrap CI	Conclusion
Intensity of Use → Risk Perception (Security Preservation Awareness) → Risk Mismatch Degree	0.516**	-0.112*	-0.058	-0.422**	-0.365**	13.65%	-0.077 ~ -0.002	Partial Mediation

4. Conclusion

This study focuses on Chinese investors and empirically examines the dual-path impact of "funding source" and "funding use" classifications in mental accounting on investment behavior biases, with mental accounting theory as the core. Based on a questionnaire survey of 250 Chinese residents with investment experience, it employs methods such as linear regression, ordinal Logistic regression, mediation effect tests, and moderation effect tests. The results show that different funding sources have significant differences in their impact on asset allocation risk preferences: for example,

investment income has a significant positive impact on low-risk asset allocation, monthly salary income positively affects medium-high risk asset allocation, windfall income negatively correlates with high-risk asset allocation, and inherited assets increase high-risk asset allocation. Funding use classifications affect biases such as the disposition effect through two opposite mechanisms: purpose account segregation reduces the disposition effect, while clearer purpose definitions increase it. Risk perception (capital preservation awareness) p [lays a partial mediating role (accounting for 13.65%) between funding use and risk mismatch. Additionally, high-income groups are more affected by mental accounting labels, which aligns with resource slack theory. This study constructs an integrated framework of "fund classification - mental accounting - decision bias," breaking through the single-dimensional limitations of existing research. Based on the above findings, specific recommendations are proposed for different stakeholders: individual investors should adopt a "clear definition + moderate integration" strategy, explicitly defining fund uses while avoiding excessive account segregation to balance goal orientation and decision flexibility; financial institutions can develop "goal-linked products" with multi-account dashboards to align investor behavior with goals and reduce biases; regulators should simplify tools for low-income groups using visual budgeting interfaces to enhance their decision rationality.

For future research, it is necessary to expand sample sizes and research objects to cover investors of different regions, ages, and wealth levels, including institutional investors for comparative analysis; optimize measurement tools by combining experimental methods (such as scenario simulation) to reduce subjective biases and enrich the measurement dimensions of risk perception; introduce dynamic research designs using tracking data or experimental tracking to analyze the moderating effects of external factors like market cycles and policy changes; and conduct cross-cultural comparisons with data from Western investors to explore the impact of cultural differences on the mental accounting effect. These efforts will further improve the theoretical system and practical guidance value of research on mental accounting and investment behavior.

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