Received: 12 August 2022 | Revised: 29 May 2023 | Accepted: 14 September 2023

DOI: 10.1111/irfi.12433

ORIGINAL ARTICLE

INTERNATIONAL REVIEW OF FINANCE WILEY

Cognition ability, financial advice seeking, and investment performance: New evidence from China

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Funding information
Fundamental Research Funds for the Central Universities, Grant/Award Number: JBK2304106; Shandong Provincial Natural Science Foundation, Grant/Award Number: ZR2023QG005; National Natural Science Foundation of China, Grant/Award Number: 72002116

Abstract

This paper examines how cognitive ability affects households' demand for financial advice and whether households with financial advisors reap better investment returns in China. Using data from the nationally representative China Household Finance Survey (CHFS) and China Family Panel Studies (CFPS), we find that math ability (i.e., one domain of cognitive ability) has a significant and negative effect on households' propensity to hire financial advisors, whereas the impact of verbal ability (i.e., another domain of cognitive ability) on seeking financial advice is insignificant. The analysis also suggests that the influence of cognitive limitation is larger for less educated and financially literate households. We conduct a regression discontinuity based on the Huai River policy, supporting the causal influence of cognitive ability on financial advice seeking. Furthermore, we find no evidence that financial advice improves investors' investment performance.

KEYWORDS
cognition ability, financial advisors, investment performance

JEL CLASSIFICATION
D12, D14, G11, G14

1 | INTRODUCTION

Previous literature has documented that cognitive limitation is associated with inferior financial behaviors and poor financial outcomes, such as behavioral anomalies (Benjamin et al., 2013; Dohmen et al., 2010; Frederick, 2005), a lack of stock market participation (Christelis et al., 2010; Grinblatt et al., 2011), and poor investment performance (Grinblatt et al., 2012; Kuo et al., 2014). Financial advice may be a remedy to correct for the negative effect of low cognitive ability, because many studies have shown that unbiased financial advice improves investors' portfolio performance (Von Gaudecker, 2015), portfolio diversification (Kramer, 2012; Lu et al., 2020), and help in overcoming consumer behavioral biases (Bergstresser et al., 2009; Gennaioli et al., 2015; Hoechle et al., 2017). A natural question to ask is whether investors with low cognitive abilities seek the support of financial advisors. This question is of importance to improve the well-being of low cognitive able individuals and the wealth distribution among retail investors.

Furthermore, a sequencing question arises over whether hiring financial advisors necessarily helps consumers improve investment performance. While some studies find a positive effect of financial advisors on investors' investment returns because of advisors' expertise (Bhattacharya et al., 2012; Von Gaudecker, 2015), others find that advisors hurt investors' investment performance due to agency problems between advisors and customers (Hackethal et al., 2012; Hoechle et al., 2017; Parker et al., 2012). Thus, if retail investors with lower cognitive abilities are more likely to seek financial advice, and if financial advisors, who are supposed to help consumers correct for cognitive biases, are subject to a conflict of interest, it calls for more attention and action from regulators to better protect consumers' well-being. This issue is of concern because it provides insights to the development of investment advisory industry in many countries, particularly in emerging economics such as China, whose investment advisory market is not as well-established as those in developed countries.

This article investigates how cognitive ability affects households' demand for financial advice and whether households with financial advisors reap better investment returns. Using data from the nationally representative China Household Finance Survey (CHFS) and China Family Panel Studies (CFPS), we first examine the influences of math ability and verbal ability, which are two domains of cognitive ability, on financial advice-seeking behavior, respectively.[1] We find that math ability has a significant and negative effect on households' propensity to hire financial advisors, whereas the impact of verbal ability on seeking financial advice is insignificant. Specifically, our analysis suggests that one standard deviation increase in math ability corresponds to a 114.95 basis-point decrease in the probability of hiring a financial advisor. The results are robust to replacing the financial advisor variable by whether the household follows the financial advisor's recommendation when choosing stock (or fund) to invest. In addition, we find that the influence of cognitive limitation is larger for less educated and financially literate households.

To further explore the causal inference of cognitive ability on households' financial advice-seeking behavior, we conduct a novel regression discontinuity (RD) estimation using a quasi-experiment with the Huai River heating policy. The Huai River heating policy generates exogenous variations in air pollution across the Huai River line (Chen et al., 2013). Moreover, some studies have shown that air pollution impairs individuals' cognitive ability in verbal and math tests (Chen et al., 2018; Zhang et al., 2018). Consequently, the policy generates an exogenous shock on cognitive ability, providing us with an opportunity to conduct RD analysis to identify the causal impact of cognitive ability. After controlling for social demographic variables, the results from RD analysis also support the causal influence of cognitive ability on demand for financial advice.

Moreover, we employ an ordered Probit model to explore whether financial advisors improve households' investment performance. We find no evidence that financial advice leads to higher returns in stock or fund investment. The results are also robust to (1) measuring investment performance by whether the stock (fund) investment earns positive profits, and (2) addressing the problems of sample selection bias and reverse causality by propensity score matching method.

Our study contributes to the literature in several ways. First, our study complements the prior literature on who seeks financial advice. Previous literature on the determinants of financial advice-seeking behavior has mainly focused on social and demographic variables, such as age, gender, education, marital status, income/wealth (Bhattacharya et al., 2012; Bluethgen et al., 2008; Calcagno & Monticone, 2015; Guiso & Jappelli, 2006; Hackethal et al., 2012; Hung & Yoong, 2013). Some studies also analyze additional factors, such as overconfidence, financial trust, financial literacy, and risk tolerance (Burke & Hung, 2021; Gennaioli et al., 2015; Hanna, 2011; Kramer, 2016; Von Gaudecker, 2015). However, relatively few studies have investigated the impact of cognitive ability on propensity to seek advice except for Kramer (2016) and Kim et al. (2019). Using the sample of Dutch retail investors, Kramer (2016) finds that cognitive ability does not affect advice seeking. Kim et al. (2019) explore the impact of cognition on older Americans' demand for financial advice. Our work contributes to this strand of literature in two ways. First, unlike Kramer (2016), we find that more cognitive able investors are less likely to seek financial advice. Second, since older people are quite different from the general population, our study differs from Kim et al. (2019) by extending the sample to general population.

Second, our paper also adds to the literature on whether financial advisors improve financial performance. There is still no consensus in the literature over the question. While some studies find a positive impact of financial advisors on clients' investment performance (Bhattacharya et al., 2012; Von Gaudecker, 2015), others find that financial advisors hurt (Carlin & Manso, 2011; Hackethal et al., 2012; Hoechle et al., 2017; Mullainathan et al., 2012; Stoughton et al., 2011), again others find no impact (Kramer, 2016). Moreover, the voluminous body of the literature is based on developed countries, such as the United States and Germany. Their conclusions may not be directly applicable to other cultural and political settings, such as China. Although Lu et al. (2020) find that investment advisors promote investors' investment diversification, further research is needed because the ultimate goal of hiring financial advisors is to obtain higher returns. Our study extends prior research by examining the impact of financial advisors on clients' investment returns in China.

Finally, our work provides insights for building well-functioning financial advice industry and designing related regulations in China and similar emerging economies. In developed countries like United States and Germany, more than 70% of investors seek advice from financial advisors (Bluethgen et al., 2008; Hung & Yoong, 2013). However, according to the China Household Finance Survey (CHFS), only 1.6% of households hire financial advisors, which is quite low when making international comparisons. Our study provides a possible explanation for this anomaly. Although financial advisors can promote investors' portfolio diversification (Lu et al., 2020), we find that financial advisors do no improve clients' investment return in China. Thus, in emerging economies, policymakers should design effective consumer financial protection regulations and devise mechanisms to correct for asymmetric information between investors and financial advisors.

The remainder of the paper is organized as follows. Section 2 qualitatively describes the relation among cognition ability, financial advice seeking, and investment performance. Section 3 presents data and summary statistics. Section 4 reports the main results, robustness checks, and additional analysis. Section 5 concludes.

2 | LITERATURE BACKGROUND: COGNITIVE LIMITATION, FINANCIAL ADVICE SEEKING, AND INVESTMENT PERFORMANCE

2.1 | Relationship between cognitive limitation and financial advice seeking

The literature has suggested that poor cognitive abilities are associated with low capabilities to acquire and interpret information, to perform numerical calculations, to read, and to recall, and behavioral biases, such as excessive trading and holding local stocks (Christelis et al., 2010; Korniotis & Kumar, 2013; Kuo et al., 2014; Spaniol & Bayen, 2005). In addition, all these have a negative effect on financial decision making and financial outcomes. For example, Agarwal and Mazumder (2013) find that low cognition leads to mistakes in credit card or home loan decisions. Kuo et al. (2014) find that lower cognitive able investors suffer greater losses in their investment.

However, retail investors may response to cognition limitation by seeking financial advice from professional advisors for two reasons. First, financial advisors have a solid financial education, an information lead, and access to required resources, such as data collecting and analyzing systems (Calcagno & Monticone, 2015; Fischer & Gerhardt, 2007). Consequently, financial advisors can improve financial behaviors, such as promoting portfolio diversification (Kramer, 2012; Lu et al., 2020; Von Gaudecker, 2015), reducing the home bias (Kramer, 2012), and reducing the disposition effect (Shapira & Venezia, 2001). Second, some studies reveal that individuals with lower cognitive ability are less aware of advisors' moral hazard (Hackethal et al., 2010; Inderst & Ottaviani, 2012; Stoughton et al., 2011), suggesting that low cognition investors are more likely to hire financial advisors. Thus, we expect a positive relationship between cognitive limitation and financial advice seeking.

2.2 | Relationship between financial advice and investment performance

There is no consensus on whether financial advisors improve or worsen investment performance. On the one hand, some studies argue that financial advisors hurt retail investors' investment returns either because of conflict of interest due to remuneration structures or asymmetric information between advisors and investors (Carlin & Manso, 2011; Hoechle et al., 2017; Iannicola & Jonas, 2010; Stoughton et al., 2011). If financial advisors are compensated through fees and commissions, their advice may be biased (Gennaioli et al., 2015; Inderst & Ottaviani, 2012). In addition, biased advice could cause mis-selling of financial product (Inderst & Ottaviani, 2009), induce excessive trading excessive trading (Mullainathan et al., 2012; Shapira & Venezia, 2001), and taking excessive risks (Piccolo et al., 2016), which ultimately harms the clients' behalf. Recent empirical evidence supports that advised investors achieve lower net returns than independent investors (Hackethal et al., 2012; Hoechle et al., 2018).

On the other hand, since financial advisors care about reputation effects and legal liability (Collins, 2010; Hoechle et al., 2018), they may strive to provide unbiased and suitable advice to their clients. Some empirical studies confirm that unbiased financial advice improves investors' investment returns (Bhattacharya et al., 2012; Von Gaudecker, 2015).

In China, investment advisors usually do not charge fee for their services, whereas they are remunerated by their employers through commissions they generate with their clients (Lu et al., 2020). Consequently, financial advisors may not guide their clients' assets to those with higher fees, but they may encourage their clients to increase trading volumes to earn more commission. Such commission-based financial advice may lead to the mis-selling of financial products and even hurt clients' interests (Gennaioli et al., 2015; Inderst & Ottaviani, 2009, 2012). Thus, we expect that financial advice does not improve investors' investment returns in China.

3 | DATA AND SUMMARY STATISTICS

3.1 | Data and sample

The data for this study comes from several sources. Our first data set is the 2017 China Household Finance Survey (CHFS), which is conducted by the Survey and Research Center for China Household Finance at the Southwestern University of Finance and Economics (SWUFE). Given that CHFS uses a stratified three-stage probability proportion to size random sample design, the 2017 CHFS data is a representative sample (Gan et al., 2014). Specifically, the 2017 CHFS survey covered 29 provinces, 355 counties, and 40,011 households. The data set includes (a) household demographic information, such as household size, household head's gender, age, education, and marriage; (b) financial related information, such as whether hire a financial advisor, income, risk aversion, financial literacy, stock investment return, fund investment return, investment experience; (c) trust on others. It is worth to note that the 2017 CHFS asked respondents to answer the questions according to respondents' facts in 2016.

3.1.1 | Cognitive ability

The mathematical and verbal scores in Health and Retirement Study (HRS) have long been used as indicators of cognitive abilities (e.g., Christelis et al., 2010; Kim et al., 2019). In addition, China Family Panel Studies (CFPS) adapted cognitive abilities related questions from HRS. Thus, we construct measures for cognitive abilities using the CFPS data in 2016, which interviewed 38,121 adult residents across 162 counties in China and is a representative sample (Chen et al., 2018; Zhang et al., 2018). The survey contains a cognitive ability module, including 40 word-recognition questions and two sets of mathematical questions, where each set has 15 questions. All questions are listed in Appendix A. We use the test score of word-recognition questions to measure the verbal dimension of cognitive ability. A larger value of the variable means higher verbal ability. Random draw was used to decide which set of mathematical questions the respondent was going to answer.[2] The CFPS administration argues that we cannot use the number of correct answers as indicator in the analysis, because the two sets of questions are different in terms of difficulty. They suggest that models of item response theory can solve this problem. Thus, CFPS used Rasch model to calculate the score for the math dimension of cognitive ability. Therefore, we use math score derived by Rasch model in our main analysis rather than using the test outcomes of the 15 mathematical questions. A large score of the variable means higher math ability.

Since CHFS and CFPS are different surveys, we merge the data in following way.[3] First, we define variable $cfps_i = 1$ if respondent i participated in CFPS survey, and $cfps_i = 0$ if respondent i participated in CHFS survey. Second, we estimate a Probit model $Probit(cfps_i = 1) = \alpha_1 + \boldsymbol{\alpha}_2 \mathbf{X}_i + \varepsilon_i$, where $\mathbf{X}_i$ include individual i's gender, age, marriage, education, and logarithm of household income. Third, we compute each individual's propensity score to participate CFPS survey. Finally, based on the same city and closest propensity score, we merge cognitive data for the CHFS's household heads with the CFPS survey data. We remove observations with missing values for the key variables or outliers. Consequently, our sample yields 12,899 households in our analysis, covering 242 cities in China.

3.1.2 | City-level macro variables

To control for city-level confounding factors, (a) we collect city-level GDP per capita and total credit level data from CSMAR database, a commonly used database in China. We also collect the number of financial institutions in each city from China Banking and Insurance Regulatory Commission (https://xkz.cbirc.gov.cn/jr/) to somewhat control for the financial supply effect.

Table 1 presents the definitions of the variables used in this study. Our key variables are math ability (*Math*), verbal ability (*Verbal*), financial advisor (*Advisor*), stock return (*Stock_Return*), and fund return (*Fund_Return*). *Math* is the math dimension of cognitive ability, and *Verbal* is the verbal dimension of cognitive ability. *Advisor* indicates whether the household hires a financial advisor in 2016. The stock return (*Stock_Return*), and fund return (*Fund_Return*) measure the household's investment performance.

3.2 | Summary statistics

Panel A of Table 2 reports the summary statistics of the main variables in this study. Panel A reports the statistics of observations, mean, standard deviation, minimum, median, and maximum, including household-level characteristics in A1 and city-level macro variables in A2. From the table, we observe that the mean of *Advisor* is 1.6%, suggesting that only 1.6% of respondents hire financial advisors in 2016. The mean (median) of *Stock_Return* is 3.751 (4, respectively), implying that most retail investors suffer losses in China's stock market. This is consistent with previous

TABLE 1 Variable definitions.

Variables	Description
Advisor	Dummy variable indicating whether the household hires a financial advisor.
Gender	The household head's gender, denoted as 1 for male, 0 otherwise.
Age	The household head's age.
Education	The household head's education level, denoted as 1 for no schooling at all, 2 for primary school, 3 for junior high, 4 for high school, technical secondary school, 5 for junior college, 6 for bachelor's degree, 7 for master's degree, and 8 for doctoral degree.
Marriage	The household head's marriage status, denoted as 1 for married and 0 otherwise.
Household size	The household size.
Trust	The degree of the household's trust on others.
log (Income)	The logarithm of the household's total income (RMB).
Risk aversion	The risk aversion level of the household.[a]
Financial literacy	The household financial literacy measured by correct numbers of the 3 financial related questions on interest rate, inflation, and financial risk.
Stock return	Household's stock return in 2016, denoted as 1 for loss greater than 30%, 2 for loss between 20% and 30%, 3 for loss between 10% and 20%, 4 for loss between 0% and 10%, 5 for break even, 6 for profit between 0% and10%, 7 for profit between 10% and 20%, 8 for profit between 20% and 30%, 9 for profit greater than 30%.
Fund return	Household's fund return in 2016, denoted as 1 for loss greater than 30%, 2 for loss between 20% and 30%, 3 for loss between 10% and 20%, 4 for loss between 0% and 10%, 5 for break even, 6 for profit between 0% and 10%, 7 for profit between 10% and 20%, 8 for profit between 20% and 30%, 9 for profit greater than 30%.
Investment experience	Investment experience measured by years of investment.
Stock advisor	Dummy variable indicating whether the household follows financial advisor's recommendation when choosing stocks to invest in.
Fund advisor	Dummy variable indicating whether the household follows financial advisor's recommendation when choosing funds to invest in.
Math	The math dimension of cognitive ability for the household's head.
Verbal	The verbal dimension of cognitive ability for the household's head.
log (GDP per capita)	Logarithm of GDP per capita (RMB) in the household's city.
log (Number of Financial Institutions)	Logarithm of number of financial institutions in the household's city.
log (Credit)	Logarithm of total credit level (10,000 RMB) in the household's city.

[a]The related question in the survey is: [A4003] Assume you have some assets to invest. Which type of project would you invest in? A. High risk, high return; B. Slightly above-average risk, slightly above-average return; C. Average risk, average return; D. Slightly below-average risk, slightly below-average return; E. Unwilling to take any risk.

studies (Barber et al., 2009; Lu et al., 2020). Similarly, the mean of *Fund_Return* is 4.371, suggesting that most retail investors suffer losses in fund investment.

Moreover, Table 2 also reports the summary statistics of Math test score of the 15 mathematical questions (i.e., Raw Math score), Rasch Math score, and verbal score. We find that individuals correctly answer 7.331 questions out of the 15 mathematical questions and correctly recall 46.99% of the 40 verbal words on average. Furthermore, it indicates that one standard deviation of Rasch Math score is roughly associated with 4.613 points in Math test score of the 15 mathematical questions.

Panel B of Table 2 reports the correlation matrix of the key variables. We find that math ability is negatively correlated with the probability to hire financial advisor. This finding lends preliminary support to the conjecture that

TABLE 2 Summary statistics.

Panel A: Summary statistics of variables[a]

	N	Mean	SD	Min	Median	Max
A1: Household-level characteristics						
Advisor	12,899	0.0160	0.124	0	0	1
Gender	12,899	0.774	0.418	0	1	1
Age	12,899	52.77	13.31	18	53	80
Education	12,899	3.631	1.313	1	3	8
Marriage	12,899	0.877	0.328	0	1	1
Household size	12,899	2.542	0.959	1	2	9
Trust	12,899	2.112	0.902	1	2	5
log (Income)	12,899	11.07	1.310	0.161	11.22	15.43
Risk aversion	12,899	4.009	1.169	1	4	5
Financial literacy	12,899	1.172	0.919	0	1	3
Stock return	1198	3.751	2.266	1	4	9
Fund return	595	4.371	2.205	1	5	9
Investment experience	1614	12.86	7.568	0	11	41
Stock advisor	1637	0.0940	0.292	0	0	1
Fund advisor	660	0.256	0.437	0	0	1
Raw math score	12,899	7.331	4.613	0	7	15
Math score	12,899	507.1	46.49	409	518	584
Verbal score	12,899	4.699	1.865	0	5	10
A2: City-level variables						
log (GDP per capita)	242	10.760	0.506	9.384	10.736	12.028
log (Number of Financial Institutions)	242	5.918	0.880	3.258	5.974	8.291
log (Credit)	242	16.670	1.056	14.789	16.382	20.154

Panel B: Correlation matrix

	Math	Verbal	Advisor	Stock return	Fund return	Financial literacy
Math	1					
Verbal	**0.4581**	1				
Advisor	−**0.0251**	0.0160	1			
Stock return	**0.0514**	0.0058	0.0251	1		
Fund return	**0.0511**	−0.0310	**0.1090**	**0.2555**	1	
Financial literacy	**0.0786**	**0.0619**	**0.0681**	0.0537	**0.0866**	1

Note: This table presents summary statistics of the main variables in this study. Panel A reports the statistics of observations, mean, standard deviation, minimum, median, and maximum, including household-level characteristics in A1 and city-level variables in A2. Panel B presents the correlation matrix of the key variables. In the correlation matrix, coefficients in bold indicate significance at the 5% level.

[a]There are two reasons for the reduced sample size for stock return, fund return, investment experience, stock advisor, and fund advisor. First, many Chinese households did not invest in stock or funds. Second, some respondents were unaware of these variables or did not answer the related questions, resulting in missing values.

TABLE 3 Impacts of math ability and verbal ability on propensity to seek financial advice.

	(1)	(2)	(3)	(4)	(5)	(6)
Math	−0.0188***	−0.0147**			−0.0169**	−0.0146*
	(0.0065)	(0.0071)			(0.0075)	(0.0080)
Verbal			0.0176	0.0045	0.0099	0.0002
			(0.0144)	(0.0169)	(0.0170)	(0.0191)
Gender		−0.0488		−0.0492		−0.0488
		(0.0735)		(0.0735)		(0.0735)
Age		−0.0018		−0.0018		−0.0018
		(0.0025)		(0.0025)		(0.0025)
Education		0.0760**		0.0795***		0.0760**
		(0.0297)		(0.0278)		(0.0295)
Marriage		−0.2355**		−0.2357**		−0.2355**
		(0.0957)		(0.0957)		(0.0957)
Household size		−0.0546		−0.0541		−0.0545
		(0.0382)		(0.0383)		(0.0383)
Trust		0.0744**		0.0744**		0.0744**
		(0.0356)		(0.0355)		(0.0356)
log (Income)		0.2696***		0.2686***		0.2697***
		(0.0582)		(0.0581)		(0.0582)
Risk aversion		−0.1196***		−0.1194***		−0.1196***
		(0.0251)		(0.0252)		(0.0251)
Financial literacy		0.0623*		0.0627*		0.0623*
		(0.0341)		(0.0341)		(0.0341)
log (GDP per capita)		0.2902***		0.2889***		0.2902***
		(0.1037)		(0.1038)		(0.1038)
log (Number of Financial Institutions)		−0.0126		−0.0132		−0.0126
		(0.0760)		(0.0760)		(0.0759)
log (Credit)		0.0204		0.0213		0.0204
		(0.0616)		(0.0618)		(0.0616)
Constant	−3.1146***	−8.7246***	−2.2855***	−8.5134***	−3.0687***	−8.7237***
	(0.3379)	(1.0831)	(0.0756)	(1.0084)	(0.3527)	(1.0911)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,899	12,899	12,899	12,899	12,899	12,899
Pseudo R^2	0.0042	0.1468	0.0016	0.1466	0.0044	0.1468

Note: This table presents the effects of math ability and verbal ability on households' financial advice seeking behavior. Columns (1) and (2) report the impact of math ability on the propensity of seeking financial advice with the following specification: $Probit(Advisor_{ij}) = \alpha + \beta_1 Math_i + \gamma \mathbf{X}_{ij} + \varepsilon_{ij}$, where $Advisor_{ij}$ is the dependent variable, measured as whether the household *i* in city *j* hired a financial advisor in 2016. $Math_i$ is the math dimension of cognitive ability for household *i*. The vector $\mathbf{X}_{ij}$ contains control variables, including household head's gender, age, education level, marriage status, household size, trust on others, logarithm of the household total income, risk aversion, financial literacy, household's city-level logarithm of GDP per capita, logarithm of number of financial institutions, and logarithm of total credit level. ε_{ij} is the i.i.d. error term. Columns (3) and (4) present the results of the following specification: $Probit(Advisor_{ij}) = \alpha + \beta_2 Verbal_i + \gamma \mathbf{X}_{ij} + \varepsilon_{ij}$, where $Verbal_i$ is the verbal dimension of cognitive ability for household *i*. Columns (5) and (6) present the results of the following specification: $Probit(Advisor_{ij}) = \alpha + \beta_1 Math_i + \beta_2 Verbal_i + \gamma \mathbf{X}_{ij} + \varepsilon_{ij}$. Columns (1), (3), and (5) report baseline results, whereas columns (2), (4), and (6) include control variables. All models control for city fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

cognitive ability might decrease the demand for financial advice. However, we do not find any significant correlation between verbal ability and propensity to seek financial advice. Moreover, we find that the correlation between *Advisor* and *Stock_Return* is insignificant, suggesting that hiring financial advisor does not improve stock investment performance. In addition, *Advisor* is positively correlated with *Stock_Return*. Due to other confounders, these results from correlation analysis are preliminary. Thus, we conduct further analysis in following section.

4 | MAIN RESULTS

4.1 | Cognitive limitation and financial advice seeking

4.1.1 | Regression analysis

This subsection studies how cognitive ability affects household's demand for financial advice. We first present our empirical model and then provide estimation results.

To test the relation between cognitive ability and financial advice seeking, we set up the following model:

$$Probit\left(Advisor_{ij}\right) = \alpha + \beta_1 Math_i + \boldsymbol{\gamma}\mathbf{X}_{ij} + \varepsilon_{ij}, \tag{1}$$

$$Probit\left(Advisor_{ij}\right) = \alpha + \beta_2 Verbal_i + \boldsymbol{\gamma}\mathbf{X}_{ij} + \varepsilon_{ij}, \tag{2}$$

where *i* represents the household, and *j* is the household's city. $Advisor_{ij}$ is the dependent variable, measured as whether the household *i* in city *j* hired a financial advisor in 2016. $Math_i$ and $Verbal_i$ are the math and verbal dimensions of cognitive ability for household *i*, respectively. Following the literature (Calcagno & Monticone, 2015; Hung & Yoong, 2013; Kramer, 2016), $\mathbf{X}_{ij}$ is a vector of control variables, including household head's gender, age, education level, marriage status, household size, trust on others, logarithm of the household total income, risk aversion, financial literacy, household's city-level logarithm of GDP per capita, logarithm of number of financial institutions, and logarithm of total credit level. The models also control for city-fixed effects. ε_{ij} is the i.i.d. error term.

Table 3 presents the estimation results of Equations (1) and (2). Columns (1) and (3) show the base line results without control variables, whereas Columns (2) and (4) include control variables. Since math and verbal are two dimensions of cognitive ability (Smith et al., 2010), we examine the impacts of math ability and verbal ability on household financial advice-seeking behavior, respectively. Specifically, Columns (1) and (2) report the effect of math ability on households' propensity to seek financial advice. The results show that the coefficients on *Math* are negative and statistically significant. The point estimate in Column (2) suggests that one standard deviation increase in math ability (i.e., 4.613 points increase in correctly answering of the 15 mathematical questions) corresponds to a 114.95 basis-point decrease in the probability of hiring a financial advisor.[4] Columns (3) and (4) indicate that verbal ability does not affect the households' propensity to hiring financial advisor. Moreover, we also include both *Math* and *Verbal* in one model. Columns (5) and (6) report the results of the following specification: $Probit\left(Advisor_{ij}\right) = \alpha + \beta_1 Math_i + \beta_2 Verbal_i + \boldsymbol{\gamma}\mathbf{X}_{ij} + \varepsilon_{ij}$. To exclude multi-collinearity problem, we calculate the variance inflation factor (VIF). The maximum and mean VIF are 1.90 and 1.35, respectively, indicating that the model does not suffer from multi-collinearity problem. In Columns (5) and (6), the results show that previous conclusions still hold.

There are two interpretations for previous findings. First, people with greater math ability are more patient and hence less likely to make mistakes in financial decisions. Thus, those with greater math ability are less likely to hire financial advisors, who can provide rational and professional investment advice. Second, math ability is directly related to the ability to understand financial concepts and to analyzing financial information and data (Agarwal & Mazumder, 2013). Therefore, relative to verbal ability, math ability has a more profound impact on financial advice seeking behavior.

Moreover, the coefficients on other variables are reasonable. For example, education level is positively related to propensity to hiring financial advisors, which is consistent with previous studies (Chatterjee & Zahirovic-Herbert, 2010; Collins, 2012). Marriage status is negative correlated with advice seeking, which is consist with study by Gutierrez et al. (2011). In addition, we find no significant difference by gender, age, household size, and financial literacy, which is consistent with study by Hung and Yoong (2013) and Kim et al. (2019).

One concern arises over the differences between *Math* and educational level when it comes to measure cognitive ability. First, Agarwal and Mazumder (2013) and Christelis et al. (2010) argue that education is not a well proxy of cognitive abilities. They point out that even after taking education into account, cognitive abilities vary across individuals, cities, and countries. For example, using the OECD Program for International Student Assessment (PISA), Hanushek and Woessmann (2012) find that among 15 years olds with the same level of schooling there is large international variability in mathematical and science test scores. Second, to exclude the multi-collinearity problem between *Math* and education, we calculate the variance inflation factor (VIF). The maximum and mean VIF are 1.90 and 1.35, respectively, indicating that the model does not suffer from multi-collinearity problem. Moreover, from Columns (5) and (6) in Table 3, we can find that, after controlling education, the impact of Math is still significant. Thus, education may not be a good proxy of math. And higher education does not necessarily mean a higher level of *Math* result.

In summary, this analysis shows that those with greater math ability are less likely to have a financial advisor. However, verbal ability does not affect households' financial advice-seeking behavior.

4.1.2 | Robustness check

In the previous analysis, we have so far investigated the effect of cognitive ability on whether households hire financial advisors. However, hiring a financial advisor does not mean that the household follows the recommendations of the advisor (Stolper & Walter, 2017). To address this concern, we follow Bhattacharya et al. (2012) and replace the financial advisor variable in the main analysis by whether the household follows financial advisor when choosing stock (or fund) to invest in. According to the 2017 CHFS questionnaire, we employ the following question to construct *Stock_advisor*: "[D3111f] How do you choose which stock to invest in? 1. Fundamental analysis; 2. Technological analysis; 3. Economic hot spots; 4. Introduction by relatives and friends; 5. Recommendations from the Internet and cell phones; 6. Consultation of professionals and institutions (financial advisor, investment advisor, financial institutions); 7777. Others (Please specify)". *Stock_advisor* equals 1 if the respondent chooses 6; 0 otherwise. According to the 2017 CHFS questionnaire, we employ the following question to construct *Fund_advisor*: "[D5108ba] How does your household choose which fund to invest in? 1. Fund performance; 2. Professional ability of fund manager; 3. Introduction by relatives and friends; 4. Recommendations from the Internet and cell phones; 5. Consultation of professionals and institutions (financial advisor, investment advisor, financial institutions); 7777. Others (Please specify)". *Fund_advisor* equals 1 if the respondent chooses 5; 0 otherwise.

The results are presented in Table 4 and do not alter our conclusions, which those with greater math ability are less likely to seek financial advice. Moreover, we find that verbal ability is negatively related to financial advice-seeking in stock investment, whereas no difference in fund investment. This finding is intuitive, because verbal ability is directly related to the ability to read and to understand related financial reports—all of which are arguably very important for picking stocks.

In addition, another concern is about the interpretations on the negative relationship between math ability and financial advice seeking.[5] First, households who do not seek financial advices might be the case that they are financial advice providers, who also get high scores on "Math." Second, households who do not seek financial advices might be the case that they do not need to, because they can get recommendations through word of mouth or through their friends. To address these problems, we conduct two robustness checks. In the first robustness check, we removed observations whose occupations are financial related and then re-estimated the model. In the second

TABLE 4 Impacts of cognitive ability on whether households follow financial advisors' suggestions.

	(1) Stock_advisor	(2) Stock_advisor	(3) Fund_advisor	(4) Fund_advisor
Math	−0.0175**		−0.0192**	
	(0.0081)		(0.0089)	
Verbal		−0.3082***		0.1202
		(0.1239)		(0.1314)
Gender	−0.2208**	−0.2209**	−0.3591***	−0.3607***
	(0.1006)	(0.1007)	(0.1225)	(0.1222)
Age	−0.0114***	−0.0109***	0.0022	0.0021
	(0.0040)	(0.0039)	(0.0046)	(0.0046)
Education	0.0282	0.0440	0.1190**	0.1168**
	(0.0431)	(0.0414)	(0.0495)	(0.0474)
Marriage	0.1621	0.1505	0.1872	0.1872
	(0.1685)	(0.1688)	(0.1930)	(0.1931)
Household size	−0.0291	−0.0298	−0.0012	−0.0007
	(0.0627)	(0.0625)	(0.0743)	(0.0745)
Trust	0.0099	0.0111	−0.0247	−0.0242
	(0.0545)	(0.0543)	(0.0641)	(0.0639)
log (Income)	0.0529	0.0482	0.0432	0.0437
	(0.0601)	(0.0597)	(0.0673)	(0.0674)
Risk aversion	−0.0016	−0.0024	0.0785	0.0786
	(0.0361)	(0.0363)	(0.0506)	(0.0505)
Financial literacy	0.0586	0.0592	−0.0342	−0.0336
	(0.0504)	(0.0503)	(0.0653)	(0.0657)
log (GDP per capita)	−0.1609	−0.1564	−0.0254	−0.0266
	(0.1602)	(0.1606)	(0.1974)	(0.1979)
log (Number of Financial Institutions)	0.0252	0.0225	−0.0613	−0.0607
	(0.1302)	(0.1306)	(0.1569)	(0.1572)
log (Credit)	0.0844	0.0840	0.1464	0.1468
	(0.1016)	(0.1020)	(0.1225)	(0.1223)
Constant	−1.8685	−1.3829	−3.8042**	−3.9011**
	(1.3801)	(1.2826)	(1.8549)	(1.7361)
City fixed effects	Yes	Yes	Yes	Yes
Observations	1637	1637	660	660
Pseudo R^2	0.0283	0.0293	0.0363	0.0363

Note: This table reports the results of estimating Equations (1) and (2) when the financial advisor variable is replaced by whether the household follows financial advisor when choosing stock (or fund) to invest in. All models include the following control variables: household head's gender, age, education level, marriage status, household size, trust on others, logarithm of the household total income, risk aversion, financial literacy, household's city-level logarithm of GDP per capita, logarithm of number of financial institutions, and logarithm of total credit level. All models control for city fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

robustness check, we removed observations (1) who get advices from relatives and friends, and (2) who get recommendations from the Internet and cell phones. The estimation results are shown in Table 5. We can find that our conclusion still holds.

A final concern is related to the merged data. Math and verbal cognition scores are extracted from CFPS, and then merge into the household-level data in CHFS. Although both data sets are representative, one might doubt whether the two data sets can be appropriately combined in this manner. To address this concern, we aggregate both CFPS and CHFS data at city-level average, and then merge the data at city levels. With the merged data, we re-estimate the models. The results are reported in Table 6. We can find that the conclusion remains unchanged.

4.1.3 | Addressing endogeneity concerns

Our previous findings may suffer from endogeneity problems because cognition may be correlated with some unobservable personal traits (e.g., financial anxiety), which could affect the demand for financial advice (Kim et al., 2019). These concerns could impair the causal interpretation. Due to data limitation, we cannot follow Kim

TABLE 5 Robustness check: considering financial occupation and other advice sources.

	(1)		(2)	
	Coef.	SE	Coef.	SE
Math	−0.0153**	0.0072	−0.0161*	0.0092
Verbal	−0.0007	0.0196	−0.0119	0.0214
Gender	−0.1029	0.0736	−0.1148	0.0798
Age	−0.0016	0.0026	−0.0012	0.0028
Education	0.0678**	0.0301	0.0739**	0.0329
Marriage	−0.1765*	0.1007	−0.2097**	0.1065
Household size	−0.0514	0.0387	−0.0356	0.0422
Trust	0.0689*	0.0366	0.0819**	0.0388
log (Income)	0.2694***	0.0602	0.2796***	0.0692
Risk aversion	−0.1126***	0.0257	−0.1249***	0.0281
Financial literacy	0.0728**	0.0348	0.0957**	0.0375
log (GDP per capita*)*	0.3152***	0.1084	0.2450**	0.1131
log (Number of Financial Institutions)	−0.0071	0.0787	0.0180	0.0860
log (Credit)	0.0093	0.0627	0.0392	0.0698
Constant	−8.9034***	1.1491	−9.0247***	1.2395
City fixed effects	Yes	Yes	Yes	Yes
Observations	12,714		12,019	
Pseudo R^2	0.1406		0.1626	

Note: This table reports the estimation results of estimating $Probit(Advisor_{ij}) = \alpha + \beta_1 Math_i + \beta_2 Verbal_i + \gamma \mathbf{X}_{ij} + \varepsilon_i$. Column (1) shows the results when we removed observations whose occupations are financial related. Column (2) displays the results when we removed observations (1) who get advices from relatives and friends and (2) who get recommendations from the Internet and cell phones. All models include the following control variables: household head's gender, age, education level, marriage status, household size, trust on others, logarithm of the household total income, risk aversion, financial literacy, household's city-level logarithm of GDP per capita, logarithm of number of financial institutions, and logarithm of total credit level. All models control for city fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 6 Robustness check: city-level evidence.

	(1)	(2)	(3)
Math	−0.0051**		−0.0073**
	(0.0026)		(0.0032)
Verbal		−0.0051	−0.0062
		(0.0031)	(0.0047)
Gender	0.0170	0.0183	0.0186
	(0.0137)	(0.0142)	(0.0144)
Age	0.0001	0.0002	0.0002
	(0.0002)	(0.0003)	(0.0003)
Education	0.0041	0.0045	0.0039
	(0.0044)	(0.0040)	(0.0045)
Marriage	−0.0179	−0.0127	−0.0113
	(0.0217)	(0.0221)	(0.0236)
Household size	−0.0026	−0.0042	−0.0045
	(0.0036)	(0.0038)	(0.0040)
Trust	0.0011	0.0022	0.0023
	(0.0046)	(0.0049)	(0.0051)
log (Income)	0.0168***	0.0161***	0.0165***
	(0.0055)	(0.0057)	(0.0054)
Risk aversion	0.0002	−0.0013	−0.0011
	(0.0034)	(0.0034)	(0.0034)
Financial literacy	0.0051	0.0070	0.0073
	(0.0086)	(0.0088)	(0.0088)
log (GDP per capita*)*	−0.0018	−0.0021	−0.0024
	(0.0075)	(0.0074)	(0.0075)
log (Number of Financial Institutions)	0.0153**	0.0147**	0.0149**
	(0.0071)	(0.0071)	(0.0070)
log (Credit)	0.0006	0.0007	0.0004
	(0.0034)	(0.0035)	(0.0035)
Constant	−0.0844	−0.0775	−0.1125
	(0.0910)	(0.0579)	(0.1025)
Observations	242	242	242
Pseudo R^2	0.0667	0.0777	0.0792

Note: This table reports the estimation results using city-level data. We aggregate both CFPS and CHFS data at city-level average, and then merge the data at city levels. All models include the following control variables: city-level average household head's gender, age, education level, marriage status, household size, trust on others, logarithm of the household total income, risk aversion, financial literacy, household's city-level logarithm of GDP per capita, logarithm of number of financial institutions, and logarithm of total credit level. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

et al. (2019) to use vision dysfunction as an instrumental variable for cognitive ability. Instead, we employ a novel regression discontinuity (RD) estimation based on the Huai River heating policy to identify the causal impact of cognitive ability on households' propensity to hire financial advisors.

In China, the average January temperature is approximately 0°C along the Qinling Mountains and Huai River line. Therefore, the Chinese government used the line to establish a heating system, which provides winter heating only for homes and offices in northern China (i.e., north of the Qinling Mountains and Huai River line) between November 15 and March 15 each year. In contrast, such winter heating is not extended to areas in southern China. The heating system is mainly operated via coal heating plants, which are technically inefficient and hence release air pollutants. Consequently, the policy has led to a discontinuity in air pollution on the two sides of the Qinling Mountains and Huai River line.

Some studies have shown that air pollution impairs individuals' cognitive ability in verbal and math tests (Chen et al., 2018; Zhang et al., 2018). Thus, the Huai River heating policy would lead to a discontinuity in cognitive ability on the two sides of the Huai River line. If cognitive ability has a causal impact on financial advice seeking behavior, there should also have a discontinuity in demand for financial advice on the two sides of Huai River line.

The RD econometric models to test the impact of the Huai River heating policy on cognitive ability and financial advice-seeking are shown as follows:

$$Math_{ij} = \alpha_0 + \alpha_1 D(North)_j + f(R_j) + \boldsymbol{\alpha}_2 \mathbf{Z}_i + u_j + \varepsilon_{ij} \tag{3}$$

$$Verbal_{ij} = \beta_0 + \beta_1 D(North)_j + f(R_j) + \boldsymbol{\beta}_2 \mathbf{Z}_i + u_j + \varepsilon_{ij} \tag{4}$$

$$Probit(Advisor_{ij}) = \gamma_0 + \gamma_1 D(North)_j + f(R_j) + \boldsymbol{\gamma}_2 \mathbf{X}_i + u_j + \varepsilon_{ij} \tag{5}$$

where $Math_{ij}$ and $Verbal_{ij}$ are math ability and verbal ability in household i's city j, respectively. $Advisor_{ij}$ refers to whether household i in city j hires a financial advisor in 2016. The dummy variable $D(North)_j$ indicates whether city j is located above the Huai River line. R_j (i.e., "Distance" in Table 7) is the centered standardized assignment variable, which is subtracting Huai River's latitude from the city j's latitude. As a result, the coefficients of $D(North)_j$ captures the jump in dependent variables across the cut-off. $f(R_j)$ is a K-order polynomial function of R_j: $f(R_j) = \sum_{k=1}^{K} \left[\theta_k R_j^k + \lambda_k D(North)_j * R_j^k\right]$. The terms $\theta_k \cdot R_j^k$ are to capture the linear and nonlinear trends over R_j. And other terms $\lambda_k \cdot D(North_j) \cdot R_j^k$ are to capture the trend differences over R_j on both sides of the Huai River. Lee and Lemieux (2010) point out that the polynomial function $f(R_j)$ can improve the precision of estimating the treatment effect. The vector $\mathbf{Z}_i$ contains variables that affect cognitive ability, including gender, age, education level, marriage, household size, and the logarithm of household income. Similar to Equations (1) and (2), $\mathbf{X}_i$ is a vector of control variables affecting financial advice-seeking. The models also control for province fixed effects u_j, which capture some confounding factors, such as different provinces with different educational systems.[6] The RD design requires correctly specifying $f(R_j)$. First, following Gelman and Imbens (2019), we use linear or quadratic polynomials, i.e., $K = 1$ or $K = 2$. Second, following Chen et al. (2013), we restrict the cities to within 5° latitude of the Qinling Mountain and Huai River line, i.e., $|R_j| \le 5°$. We also provide robustness checks based on $|R_j| \le 8°$.

Table 7 reports the results from the estimation of Equations (3)–(5). We focus on the linear ($K = 1$) specification. Columns (1) and (2) indicate that the Huai River heating policy has worsened the math ability and verbal ability of households in cities in North China. Our estimation indicates that, across Huai River (from Southern side to Northern side), there are a 14.353 points sharp drop in Rasch Math score (i.e., about 1.42 points drop in raw math score) and a 0.6827 points sharp drop in Verbal score. This finding is consistent with previous literature (Chen et al., 2018; Zhang et al., 2018). Column (3) reports the result of Equation (5) for the demand for financial advice. Column (3) suggests that, relative to residents in South China, the Huai River heating policy increases households' propensity to hire financial advisors in North China. This impact is nontrivial. The jump across the river in Column (3) implies that, compared with households in South China, the probability for those in North China to hire financial advisors rises by 21.6%.

TABLE 7 RD analysis based on the Huai River heating policy.

	Linear form, bandwidth = 5°			Linear form, bandwidth = 8°			Quadratic from, bandwidth = 5°		
	Math (1)	Verbal (2)	Advisor (3)	Math (4)	Verbal (5)	Advisor (6)	Math (7)	Verbal (8)	Advisor (9)
North	−14.3530***	−0.6827*	7.1740***	−27.8781**	−0.9479**	3.1958***	−20.8521***	−0.2107*	7.2318**
	(4.0802)	(0.3773)	(2.1061)	(13.5428)	(0.4576)	(1.0904)	(6.1376)	(0.1208)	(3.5151)
Distance	−9.3746	−0.2679***	−0.1781	8.5398	−0.2926**	0.2684*	−29.2144**	−0.1352	−1.2539***
	(6.2295)	(0.0903)	(0.3314)	(7.4578)	(0.1409)	(0.1470)	(13.7854)	(0.1553)	(0.3737)
*North*distance*	1.4115	−0.2119**	0.0196	−5.4751	−0.3118**	−0.0207	6.2545	−0.7668***	1.0853**
	(1.6551)	(0.1070)	(0.1301)	(9.7984)	(0.1399)	(0.0765)	(5.7055)	(0.2331)	(0.4746)
Distance^2							−8.2456**	−0.0232	−0.2208***
							(3.7666)	(0.0317)	(0.0612)
*North*distance*^{2}							3.3715***	−0.0049	0.1255
							(1.1065)	(0.0466)	(0.0929)
Gender	3.4160**	−0.0221	0.1186	3.8176***	−0.0631	0.0064	3.3933**	−0.0218	0.1191
	(1.3839)	(0.0571)	(0.1206)	(1.1099)	(0.0462)	(0.0881)	(1.3844)	(0.0571)	(0.1206)
Age	−0.3588***	−0.0066***	−0.0070*	−0.3375***	−0.0072***	−0.0055*	−0.3565***	−0.0065***	−0.0070*
	(0.0494)	(0.0020)	(0.0036)	(0.0388)	(0.0016)	(0.0030)	(0.0494)	(0.0020)	(0.0036)
Education	13.2643***	0.3587***	0.1054***	12.5530***	0.3300***	0.0867**	13.2566***	0.3584***	0.1064***
	(0.5328)	(0.0216)	(0.0382)	(0.4288)	(0.0175)	(0.0339)	(0.5329)	(0.0216)	(0.0381)
Marriage	−0.2903	−0.0165	−0.2568*	−0.0669	0.0078	−0.2675**	−0.3114	−0.0168	−0.2561*
	(1.9386)	(0.0808)	(0.1460)	(1.5254)	(0.0632)	(0.1148)	(1.9394)	(0.0809)	(0.1462)
Household size	0.4340	0.0022	−0.0201	0.2923	−0.0101	−0.0073	0.4448	0.0025	−0.0199
	(0.6861)	(0.0270)	(0.0566)	(0.5653)	(0.0225)	(0.0490)	(0.6864)	(0.0270)	(0.0565)
log (Income)	4.3098***	0.1410***	0.1974**	3.8888***	0.1022***	0.2253***	4.3206***	0.1413***	0.1965**
	(0.5296)	(0.0211)	(0.0899)	(0.4322)	(0.0178)	(0.0708)	(0.5300)	(0.0211)	(0.0895)
Trust			0.0791			0.0769*			0.0787
			(0.0540)			(0.0426)			(0.0540)

(Continues)

TABLE 7 (Continued)

	Linear form, bandwidth = 5°			Linear form, bandwidth = 8°			Quadratic from, bandwidth = 5°		
	Math (1)	Verbal (2)	Advisor (3)	Math (4)	Verbal (5)	Advisor (6)	Math (7)	Verbal (8)	Advisor (9)
Risk aversion			−0.1388***			−0.0965***			−0.1390***
			(0.0340)			(0.0288)			(0.0338)
Financial literacy			0.0448			0.0875**			0.0445
			(0.0481)			(0.0398)			(0.0482)
log (*GDP* per capita)			0.1347			0.2678			0.1348
			(0.2603)			(0.2119)			(0.2609)
log (Number of Financial Institutions)			−0.0950			0.0055			−0.0838
			(0.1981)			(0.1623)			(0.2022)
log (Credit)			0.1528			0.0886			0.1433
			(0.1763)			(0.1494)			(0.1769)
Constant	477.0958***	4.3905***	−6.9587***	484.2834***	4.4607***	−9.1662***	474.2396***	4.3057***	−6.9521***
	(11.0298)	(0.4220)	(2.1198)	(7.1088)	(0.2982)	(1.5836)	(11.4317)	(0.4342)	(2.1809)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5837	5387	5387	9030	9030	9030	5837	5837	5837
Pseudo/Adjusted R^2	0.1099	0.0549	0.1724	0.1011	0.0476	0.1578	0.1101	0.0550	0.1725

Note: This table reports the estimation results of RD regressions.
$Math_{ij} = \alpha_0 + \alpha_1 D(North)_j + f(R_j) + \boldsymbol{\alpha}_2 \mathbf{Z}_i + u_j + \varepsilon_{ij}$,
$Verbal_{ij} = \beta_0 + \beta_1 D(North)_j + f(R_j) + \boldsymbol{\beta}_2 \mathbf{Z}_i + u_j + \varepsilon_{ij}$,
$Probit(Advisor_{ij}) = \gamma_0 + \gamma_1 D(North)_j + f(R_j) + \boldsymbol{\gamma}_2 \mathbf{X}_i + u_j + \varepsilon_{ij}$.
Here $Math_{ij}$ and $Verbal_{ij}$ are math ability and verbal ability in household *i*'s city *j*, respectively. $Advisor_{ij}$ refers to whether household *i* in city *j* hires a financial advisor in 2016. The dummy variable $D(North)_j$ indicates whether city *j* is located above the Huai River line. R_j (i.e., "Distance" in Table 7) is the centered standardized assignment variable, which is subtracting Huai River's latitude from the city *j*'s latitude. We set $|R_i| \leq 5°$ and $|R_i| \leq 8°$, respectively. $f(R_j)$ is a *K*-order polynomial function of R_j: $f(R_j) = \sum_{k=1}^{K} \left[\theta_k R_j^k + \lambda_k D(North)_j * R_j^k\right]$. We use linear ($K = 1$) and quadratic ($K = 2$) specifications in this table. The vector $\mathbf{Z}_i$ contains variables that affect cognitive ability, including gender, age, education level, marriage, household size, and the logarithm of household income. Similar to Equations (1) and (2), $\mathbf{X}_i$ is a vector of control variables affecting financial advice-seeking. The models also control for province fixed effects u_j. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We conducted two tests to verify the robustness of our RD results. First, we test the sensitivity of the choice of bandwidth. We implement the RD design with bandwidths of 8. Second, we explore the robustness of the results to a quadratic ($K = 2$) specification to implement the RD design. As shown in Table 7, we find that the conclusions remain unchanged.

Theoretically, it is supposed that the negative effects on cognitive ability would be more salient for older individuals because their air pollution exposure would be longer. This point provides an opportunity to strengthen our argument. To verify this point, we add interaction term of "$D(North)_j$ and age" into Equations (3) and (4). The estimation results are shown in Table 8. We can find that the negative effect of the policy on math ability is larger for older individuals, while the effect of the policy on verbal ability does not differ by age.

4.1.4 | Heterogeneity analysis

The literature has documented the heterogenous effects by gender, age, education, and financial literacy. For example, investors with higher financial literacy can make better use of information (Bucher-Koenen & Koenen, 2015). Thus, financial literacy could substitute for financial advice (Collins, 2012; Hung & Yoong, 2013). As a result, financial literacy can mitigate the low cognitive households' rely on financial advisors. Moreover, male and female investors behave quite different in investment (Barber & Odean, 2001). Thus, we further investigate whether household characteristics could mitigate or exaggerate the effect of cognitive limitation on the propensity to hire financial advisors. Specifically, we separately add the interaction terms of "Math and Gender," "Verbal and Gender," "Math and Age," "Verbal and Age," "Math and Education," "Verbal and Education," "Math and Financial literacy," "Verbal and Financial literacy" into regressions. The estimation results are shown in Table 9. We find that the influence of cognitive limitation is larger for less educated and financially literate households.

Columns (1)–(4) show that the coefficients of the interaction terms "Math and Gender," "Verbal and Gender," "Math and Age," "Verbal and Age" are insignificant. Whereas, Columns (5)–(8) show that the coefficients of the interaction terms "Math and Education," "Verbal and Education," "Math and Financial literacy," "Verbal and Financial literacy" are positive and statistically significant. These results suggest that the impact of cognitive ability on demand for financial advice does not differ by gender and age, and that education and financial literacy could help mitigate the effects of cognitive limitation. We use Column (5) for illustration. It compares the effects of Math on demand for financial advice across different education levels. The positive coefficient on the interaction term "Math and Education" suggests that, holding Math and other variables unchanged, households with higher educational levels are more likely to hire financial advisors than those with lower educational levels. This result is consistent with previous literature (Gerrans & Hershey, 2017; Kramer, 2016; Lachance & Tang, 2012). Because those with higher education levels are better aware of their cognitive limitation and hence more likely to seek for financial advisors' help.

4.2 | Can financial advisors improve investment performance?

4.2.1 | Regression analysis

In this subsection, we explore whether financial advisors could improve investment performance. In our analysis, we use the stock return and fund return to measure the investment performance.

Given that the stock return variable and fund return variable are ordered, we set up the following ordered Probit model:

TABLE 8 Robustness check of RD analysis: difference between older and younger individuals.

	Linear form, bandwidth = 5°		Linear form, bandwidth = 8°		Quadratic from, bandwidth = 5°	
	Math (1)	Verbal (2)	Math (3)	Verbal (4)	Math (5)	Verbal (6)
North	−12.7905**	−0.5765**	−23.1581*	−0.8904**	−15.3258**	−0.1615*
	(6.0173)	(0.2853)	(12.9859)	(0.4149)	(7.4122)	(0.0964)
*North*age*	−0.1692**	−0.0505	−0.1759*	−0.0584	−0.1696**	−0.0499
	(0.0894)	(0.0437)	(0.0708)	(0.0494)	(0.0895)	(0.0436)
Distance	−9.3445	−0.2657***	8.5530	−0.3028**	−28.7497**	−0.1385
	(6.2293)	(0.0803)	(7.4575)	(0.1509)	(13.7840)	(0.1554)
*North*distance*	1.5532	−0.2129**	−5.4923	−0.3131**	6.3012	−0.7634***
	(1.6552)	(0.1070)	(9.7993)	(0.1429)	(5.7073)	(0.2330)
Distance^2					−8.1411**	−0.0240
					(3.7874)	(0.0317)
*North*distance*^{2}					3.0553***	−0.0026
					(1.1081)	(0.0465)
Gender	3.4404**	−0.0204	3.8191***	−0.0620	3.4187**	−0.0200
	(1.3842)	(0.0571)	(1.1097)	(0.0462)	(1.3847)	(0.0571)
Age	−0.3884***	−0.0044*	−0.3416***	−0.0040*	−0.3862***	−0.0044*
	(0.0640)	(0.0026)	(0.0563)	(0.0023)	(0.0640)	(0.0026)
Education	13.2785***	0.3576***	12.5539***	0.3293***	13.2709***	0.3574***
	(0.5343)	(0.0216)	(0.4291)	(0.0175)	(0.5345)	(0.0216)
Marriage	−0.3671	−0.0108	−0.0742	0.0134	−0.3879	−0.0113
	(1.9419)	(0.0807)	(1.5289)	(0.0631)	(1.9425)	(0.0808)
Household size	0.4706	−0.0004	0.2949	−0.0120	0.4812	−0.0002
	(0.6877)	(0.0271)	(0.5659)	(0.0226)	(0.6879)	(0.0271)
log (Income)	4.3011***	0.1417***	3.8877***	0.1030***	4.3116***	0.1420***
	(0.5299)	(0.0211)	(0.4324)	(0.0178)	(0.5302)	(0.0211)

TABLE 8 (Continued)

	Linear form, bandwidth = 5°		Linear form, bandwidth = 8°		Quadratic from, bandwidth = 5°	
	Math (1)	**Verbal (2)**	**Math (3)**	**Verbal (4)**	**Math (5)**	**Verbal (6)**
Constant	475.3003***	4.5215***	484.0951***	4.6057***	472.4624***	4.4333***
	(11.3497)	(0.4302)	(7.3769)	(0.3066)	(11.7282)	(0.4415)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5837	5387	9030	9030	5837	5837
Adjusted R^2	0.1100	0.0551	0.1011	0.0480	0.1102	0.0553

Note: This table reports the estimation results of RD regressions.
$Math_{ij} = \alpha_0 + \alpha_1 D(North)_j + \alpha_2 D(North)_j * Age_i + f(R_j) + \boldsymbol{\alpha}_3 \mathbf{Z}_i + u_j + \varepsilon_{ij}$.
$Verbal_{ij} = \beta_0 + \beta_1 D(North)_j + \beta_2 D(North)_j * Age_i + f(R_j) + \boldsymbol{\beta}_3 \mathbf{Z}_i + u_j + \varepsilon_{ij}$.
Here $Math_{ij}$ and $Verbal_{ij}$ are math ability and verbal ability in household *i*'s city *j*, respectively. The dummy variable $D(North)_j$ indicates whether city *j* is located above the Huai River line. The variable $D(North)_j * Age_i$ is the interaction term of $D(North)_j$ and age of household *i*'s head. R_j (i.e., "Distance" in Table 7) is the centered standardized assignment variable, which is subtracting Huai River's latitude from the city *j*'s latitude. We set $|R_i| \le 5°$ and $|R_i| \le 8°$, respectively. $f(R_j)$ is a *K*-order polynomial function of R_j: $f(R_j) = \sum_{k=1}^{K} \left[\theta_k R_j^k + \lambda_k D(North)_j * R_j^k\right]$. We use linear ($K = 1$) and quadratic ($K = 2$) specifications in this table. The vector $\mathbf{Z}_i$ contains variables that affect cognitive ability, including gender, age, education level, marriage, household size, and the logarithm of household income. The models also control for province fixed effects u_j. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 9 Heterogenous cognitive ability effects by household head's gender, age, education, and financial literacy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Math	−0.0166**		−0.0124**		−0.0162***		−0.0138**	
	(0.0083)		(0.0056)		(0.0054)		(0.0065)	
Verbal		0.0111		−0.0361		0.0323		0.0325
		(0.0330)		(0.0609)		(0.0506)		(0.0305)
*Math*Gender*	−0.0002							
	(0.0015)							
*Verbal*Gender*		−0.0087						
		(0.0382)						
*Math*Age*			0.0001					
			(0.0000)					
*Verbal*Age*				0.0008				
				(0.0012)				
*Math*Education*					0.0013***			
					(0.0005)			
*Verbal*Education*						0.0064***		
						(0.0022)		
*Math*Financial literacy*							0.0044*	
							(0.0024)	
*Verbal*Financial literacy*								0.1181**
								(0.0564)
Gender	0.0784	−0.0062	−0.0500	−0.0495	−0.0474	−0.0486	−0.0476	−0.0481
	(0.7721)	(0.2038)	(0.0736)	(0.0736)	(0.0739)	(0.0737)	(0.0735)	(0.0737)
Age	−0.0018	−0.0018	−0.0319	−0.0058	−0.0021	−0.0019	−0.0019	−0.0018
	(0.0026)	(0.0025)	(0.0217)	(0.0063)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Education	0.0760**	0.0796***	0.0770***	0.0812***	0.7589***	0.1098*	0.0762**	0.0797***
	(0.0297)	(0.0278)	(0.0297)	(0.0278)	(0.2364)	(0.0594)	(0.0296)	(0.0278)
Marriage	−0.2359**	−0.2356**	−0.2367**	−0.2365**	−0.2358**	−0.2363**	−0.2355**	−0.2363**
	(0.0958)	(0.0957)	(0.0957)	(0.0957)	(0.0956)	(0.0957)	(0.0957)	(0.0957)

TABLE 9 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Household size	−0.0544	−0.0541	−0.0536	−0.0543	−0.0532	−0.0542	−0.0545	−0.0546
	(0.0382)	(0.0382)	(0.0381)	(0.0383)	(0.0380)	(0.0383)	(0.0383)	(0.0383)
Trust	0.0743**	0.0746**	0.0745**	0.0748**	0.0755**	0.0746**	0.0747**	0.0743**
	(0.0356)	(0.0355)	(0.0357)	(0.0355)	(0.0357)	(0.0355)	(0.0356)	(0.0355)
log (Income)	0.2698***	0.2687***	0.2678***	0.2673***	0.2725***	0.2689***	0.2695***	0.2681***
	(0.0583)	(0.0582)	(0.0580)	(0.0581)	(0.0585)	(0.0582)	(0.0581)	(0.0581)
Risk aversion	−0.1196***	−0.1194***	−0.1196***	−0.1190***	−0.1193***	−0.1194***	−0.1198***	−0.1198***
	(0.0251)	(0.0252)	(0.0252)	(0.0252)	(0.0251)	(0.0252)	(0.0251)	(0.0252)
Financial literacy	0.0625*	0.0627*	0.0631*	0.0623*	0.0642*	0.0627*	0.2864	0.1509*
	(0.0341)	(0.0342)	(0.0342)	(0.0341)	(0.0342)	(0.0341)	(0.3385)	(0.0829)
log (GDP per capita)	0.2903***	0.2894***	0.2890***	0.2902***	0.2899***	0.2897***	0.2900***	0.2917***
	(0.1036)	(0.1036)	(0.1036)	(0.1037)	(0.1042)	(0.1039)	(0.1037)	(0.1037)
log (Number of Financial Institutions)	−0.0126	−0.0130	−0.0135	−0.0148	−0.0118	−0.0134	−0.0120	−0.0136
	(0.0760)	(0.0760)	(0.0761)	(0.0760)	(0.0762)	(0.0761)	(0.0759)	(0.0761)
log (Credit)	0.0205	0.0211	0.0215	0.0220	0.0205	0.0211	0.0202	0.0210
	(0.0616)	(0.0617)	(0.0617)	(0.0618)	(0.0615)	(0.0617)	(0.0615)	(0.0617)
Constant	−8.8243***	−8.5505***	−7.2517***	−8.3233***	−11.6769***	−8.6420***	−9.0637***	−8.6639***
	(1.2246)	(1.0247)	(1.4488)	(1.0633)	(1.5000)	(1.0579)	(1.2169)	(1.0213)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,899	12,899	12,899	12,899	12,899	12,899	12,899	12,899
Pseudo R^2	0.1468	0.1467	0.1474	0.1469	0.1500	0.1468	0.1470	0.1471

Note: This table investigates whether household characteristics could mitigate or exaggerate the effect of cognitive ability on household's propensity to hire a financial advisor. we separately add the interaction terms of "Math and Gender," "Verbal and Gender," "Math and Age," "Verbal and Age," "Math and Education," "Verbal and Education," "Math and Financial literacy," "Verbal and Financial literacy" into regressions. The dependent variable is the dummy variable denoted as 1 if the household hired a financial advisor in 2016; 0 otherwise. All models include following control variables: household head's gender, age, education level, marriage status, household size, trust on others, logarithm of the household total income, risk aversion, financial literacy, household's city-level logarithm of GDP per capita, logarithm of number of financial institutions, and logarithm of total credit level. All models control for city fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

$$OProbit\left(Stock\ Return_{ij}\right) = \alpha_0 + \alpha_1 Advisor_i + \boldsymbol{\alpha}_2 \mathbf{X}_i + u_j + \varepsilon_{ij}, \tag{6}$$

$$OProbit\left(Fund\ Return_{ij}\right) = \beta_0 + \beta_1 Advisor_i + \boldsymbol{\beta}_2 \mathbf{X}_i + u_j + \varepsilon_{ij}, \tag{7}$$

where i and j represent the household, and household's city, respectively. $Stock\ Return_{ij}$ and $Fund\ Return_{ij}$, defined in Table 1, are the household i's investment return in stock and fund, respectively. $Advisor_i$ represents whether household i hires financial advisor. The vector $\boldsymbol{X}_i$ contains control variables, including gender, age, education level, marriage, household size, trust on others, logarithm of household income, risk aversion, financial literacy, and investment experience. The models also control for city-fixed effects u_j. ε_{ij} is the i.i.d. error term.

The estimation results of Equations (6) and (7) are reported in Table 10. Columns (1) and (3) present the effect of hiring financial advisors on households' stock return and fund return, respectively. The coefficients on $Advisor_i$ are insignificant, suggesting that hiring financial advisors does not improve household investment performance. Stolper and Walter (2017) argue that financial advice does not translate into sound financial decisions if individuals do not follow the recommendations of their advisors. To address this concern, we replace the key variable $Advisor_i$ in Equations (6) and (7) with *Stock advisor* and *Fund advisor*, respectively. Stock (Fund) advisor defined as whether the household follows the recommendations of financial advisor while choosing stock (fund, respectively). Columns (2) and (4) report the estimation results. We can find that the conclusions remain unchanged.

4.2.2 | Robustness check

Different measurement of investment performance

To further test the robustness of the results in Table 10, we define the stock (fund) return variable by whether the stock (fund) investment earns positive profits. Then we estimate Equations (6) and (7) with Probit models. The estimation results are presented in Table 11. The evidence in Table 11 does not alter our conclusion that financial advisors do not add value to investment performance in China financial market.

Propensity score matching-ordered Probit model

Previous analysis suggests that hiring financial advisors does not improve investment performance. However, this conclusion may encounter two concerns. First, it may suffer from sample selection bias because those hiring financial advisors could be quite different from those who do not hire financial advisors. The second concern is reverse causality. The household will decide whether to hire financial advisors according to its own investment performance. Thus, we follow Heckman et al. (1998) and use propensity score matching (PSM) method to solve the problems of sample selection bias and reverse causality.

Specifically, we first apply a Probit regression model to estimate the probability of hiring a financial advisor on the following variables: gender, age, education, marriage, household size, trust on others, logarithm of household income, risk aversion, financial literacy, and whether accessing internet. Then, we obtain the propensity score from the model and match households using the nearest neighbor matching approach. Following the literature (Wang et al., 2018), we set the radius caliper to be 0.05*standard deviation of the propensity scores. To verify the robustness of the nearest neighbor matching approach, we also conduct kernel matching approach. Finally, we re-estimate Equations (6) and (7) with the matched sample. Table 12 presents the estimation results. We find no evidence that hiring financial advisors improves investment performance. Thus, our main findings remain robust.

TABLE 10 Impact of financial advisor on household investment performance.

	(1) Stock return	(2) Stock return	(3) Fund return	(4) Fund return
Advisor	−0.1315		0.2394	
	(0.1775)		(0.1534)	
Stock advisor		−0.0150		
		(0.1391)		
Fund advisor				0.1994
				(0.1317)
Gender	0.0203	0.0092	0.1481	0.1762
	(0.0903)	(0.0909)	(0.1383)	(0.1405)
Age	0.0010	0.0012	0.0032	0.0019
	(0.0040)	(0.0040)	(0.0062)	(0.0062)
Education	−0.0130	−0.0112	0.0626	0.0550
	(0.0257)	(0.0258)	(0.0411)	(0.0417)
Marriage	−0.1381	−0.1400	−0.0186	−0.0791
	(0.1535)	(0.1536)	(0.2311)	(0.2312)
Household size	−0.0366	−0.0341	0.1473**	0.1475**
	(0.0502)	(0.0500)	(0.0668)	(0.0674)
Trust	0.0171	0.0159	−0.0741	−0.0620
	(0.0479)	(0.0478)	(0.0732)	(0.0752)
log (Income)	0.1089**	0.1068**	0.1692**	0.1735**
	(0.0470)	(0.0470)	(0.0723)	(0.0725)
Risk aversion	−0.0852***	−0.0824**	−0.0071	−0.0249
	(0.0321)	(0.0320)	(0.0576)	(0.0588)
Financial literacy	0.0656	0.0681	0.0660	0.0589
	(0.0468)	(0.0469)	(0.0732)	(0.0737)
Investment experience	0.0244***	0.0243***	−0.0084	−0.0089
	(0.0066)	(0.0066)	(0.0112)	(0.0112)
City fixed effects	Yes	Yes	Yes	Yes
Observations	807	802	375	372
Pseudo R^2	0.0328	0.0321	0.0653	0.0637

Note: This table studies whether hiring financial advisors improve households' investment performance. Model (1) examines the impact of financial advisor on stock return using the following ordered Probit model: $OProbit(Stock\ Return_{ij}) = \alpha_0 + \alpha_1 Advisor_i + \boldsymbol{\alpha_2 X_i} + u_j + \varepsilon_{ij}$, where *Stock Return*$_{ij}$ represents household *i*'s stock return defined in Table 1., *Advisor*$_i$ denotes whether household *i* hires a financial advisor, and vector $\boldsymbol{X_i}$ contains the control variables, including gender, age, education level, marriage, household size, trust on others, logarithm of household income, risk aversion, financial literacy, and investment experience. The model also controls for city fixed effects u_j. Model (3) investigates the effect of financial advisor on fund return using the following model: $OProbit(Fund\ Return_{ij}) = \beta_0 + \beta_1 Advisor_i + \boldsymbol{\beta_2 X_i} + u_j + \varepsilon_{ij}$. Model (2) and (4) replace the key variable *Advisor*$_i$ in Equations (6) and (7) with *Stock advisor* and *Fund advisor*, respectively. Stock (Fund) advisor defined as whether the household follows the recommendations of financial advisor while choosing stock (fund, respectively). Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 11 Robustness check: Changing measurement of investment performance.

	(1) Stock return	(2) Stock return	(3) Fund return	(4) Fund return
Advisor	−0.1105		0.2906	
	(0.2518)		(0.2302)	
Stock advisor		0.0698		
		(0.1809)		
Fund advisor				0.1365
				(0.1740)
Gender	0.0525	0.0525	0.2025	0.2350
	(0.1206)	(0.1209)	(0.1755)	(0.1784)
Age	0.0009	0.0011	0.0049	0.0040
	(0.0054)	(0.0054)	(0.0071)	(0.0071)
Education	−0.0615*	−0.0598	0.0606	0.0551
	(0.0365)	(0.0365)	(0.0510)	(0.0518)
Marriage	−0.1654	−0.1675	0.2472	0.1755
	(0.2013)	(0.2012)	(0.3152)	(0.3093)
Household size	−0.0759	−0.0764	0.0941	0.0994
	(0.0639)	(0.0637)	(0.0803)	(0.0805)
Trust	0.0253	0.0248	−0.0846	−0.0791
	(0.0659)	(0.0660)	(0.0903)	(0.0914)
log (Income)	0.2646***	0.2585***	0.1898**	0.1974**
	(0.0769)	(0.0764)	(0.0952)	(0.0940)
Risk aversion	−0.0525	−0.0486	0.0276	0.0082
	(0.0425)	(0.0426)	(0.0687)	(0.0704)
Financial literacy	0.0364	0.0380	0.0232	0.0267
	(0.0667)	(0.0668)	(0.0903)	(0.0913)
Investment experience	0.0184**	0.0178**	−0.0218	−0.0242
	(0.0083)	(0.0083)	(0.0158)	(0.0159)
Constant	−4.0221***	−3.9724***	−2.6435**	−2.6451**
	(0.9446)	(0.9468)	(1.3436)	(1.3457)
City fixed effects	Yes	Yes	Yes	Yes
Observations	755	751	344	342
Pseudo R^2	0.0649	0.0643	0.1005	0.0975

Note: This table reports the results when we change the measurement of investment performance by whether the stock (fund) investment earns positive profits. The dependent variable is *Stock Return*$_i$ (*Fund Return*$_i$), taking value of 1 if the household stock (fund, respectively) investment earns positive profits, 0 otherwise. All models include household characteristics and city fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5 | CONCLUSION

The increasingly diverse array of complex financial products poses a serious challenge to investors, especially those with low cognitive abilities. Thus, this paper examines whether those with lower cognitive ability are more likely to

TABLE 12 Financial advisor and investment performance: PSM-ordered Probit model.

	Nearest neighbor matching		Kernel matching	
	Stock return (1)	Fund return (2)	Stock return (3)	Fund return (4)
Advisor	−0.1731	0.2295	−0.1539	0.2457
	(0.1845)	(0.1605)	(0.1780)	(0.1525)
Gender	0.0404	0.1695	0.0478	0.1801
	(0.0961)	(0.1460)	(0.0921)	(0.1388)
Age	0.0001	0.0059	0.0007	0.0064
	(0.0042)	(0.0062)	(0.0041)	(0.0061)
Education	−0.0218	0.0735*	−0.0155	0.0778*
	(0.0272)	(0.0412)	(0.0264)	(0.0406)
Marriage	−0.1520	0.1135	−0.1468	0.0226
	(0.1670)	(0.2490)	(0.1601)	(0.2334)
Household size	−0.0847	0.1153*	−0.0843	0.1301*
	(0.0545)	(0.0700)	(0.0531)	(0.0681)
Trust	0.0532	−0.0561	0.0382	−0.0579
	(0.0521)	(0.0758)	(0.0501)	(0.0745)
log (Income)	0.1398***	0.1761**	0.1297***	0.1543**
	(0.0511)	(0.0828)	(0.0484)	(0.0731)
Risk aversion	−0.1061***	−0.0256	−0.1000***	−0.0233
	(0.0335)	(0.0615)	(0.0327)	(0.0579)
Financial literacy	0.0562	0.0691	0.0425	0.0588
	(0.0488)	(0.0775)	(0.0470)	(0.0732)
Investment experience	0.0299***	−0.0102	0.0265***	−0.0111
	(0.0068)	(0.0122)	(0.0067)	(0.0112)
City fixed effects	Yes	Yes	Yes	Yes
Observations	694	320	734	342
Pseudo R^2	0.0291	0.0493	0.0266	0.0480

Note: This table reports the estimation results of PSM-ordered Probit model. we first apply a Probit regression model to estimate the probability of hiring a financial advisor on the following variables: gender, age, education, marriage, household size, trust on others, logarithm of household income, risk aversion, financial literacy, and whether accessing internet. Then, we obtain the propensity score from the model and match households using the nearest neighbor matching approach. Following the literature (Wang et al., 2018), we set the radius caliper to be 0.05*standard deviation of the propensity scores. To verify the robustness of the nearest neighbor matching approach, we also conduct kernel matching approach. Finally, we re-estimate Equations (6) and (7) with the matched sample. All models include city fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

seek financial advice and whether financial advisors improve clients' investment returns in China. Using data from China Household Finance Survey (CHFS) and China Family Panel Studies (CFPS), we find math ability has a significant and negative effect on households' propensity to hire financial advisors, whereas the impact of verbal ability on seeking financial advice is insignificant. Specifically, our analysis suggests that one standard deviation increase in math ability corresponds to a 114.95 basis-point decrease in the probability of hiring a financial advisor. Furthermore, the regression discontinuity analysis based on the Huai River heating policy support the causal influence of cognitive ability on financial advice-seeking behavior. In addition, we find that the influence of cognitive limitation is larger for less educated and financially literate households. Finally, our analysis shows that financial advisors do not lead to higher returns in stock or fund investment.

Our results have important implications for both policymakers and investors in China and similar emerging countries. On the one hand, regulators and policymakers should design effective interventions to deal with asymmetric information problems in financial advisory markets and to protect customers from potentially exploitive services. For example, advisor ratings can help establish a well-functioning financial advice market.[7] In addition, referring to the European MiFID2 rules and Australia's Corporations Amendment (Future of Financial Advice) Act, policymakers can design similar regulations to encourage the development of high-quality advice services and enact consumer financial protection regulation. On the other hand, investors should take ways to incentivize advisors to provide better recommendations. We find that those with low cognitive abilities are more likely to hire financial advisors, whereas financial advisors do not improve the investment performance, implying that financial advice is not a sufficient remedy for low cognitive able individuals if the advice is biased. Investors can promote unbiased advice either by asking for a second expert's opinion or by monitoring the advisor's activity themselves (Calcagno et al., 2017).

It is also worth to note the limitations of the current study. Since no data set contains both cognitive ability and financial advice seeking at individual level, verbal and math scores were extracted from CFPS, and then merged into the individual data in CHFS. Although both surveys are representative and city-level robustness check does not change the results, it may remain questionable whether the two data sets can be appropriately combined in this manner. Thus, future research can revisit the question if individual data are available.

ACKNOWLEDGMENTS

We gratefully acknowledge the constructive comments from Professors Guanying Huang, Xiangrui Wang, Di Wu, and Shuyu Xue. All errors are our own. The authors acknowledge the financial support from the Fundamental Research Funds for the Central Universities (JBK2304106), Shandong Provincial Natural Science Foundation (ZR2023QG005), and National Natural Science Foundation of China (72002116).

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

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ENDNOTES

[1] Math and verbal skills are two important domains of cognitive ability (Christelis et al., 2010).

[2] In each set of mathematical questions, the questions are sorted in ascending order of difficulty. The test ends when the respondent incorrectly answers three questions in succession. Then the rank of the hardest question an individual can answer is her/his test score.

[3] We would like to thank the anonymous reviewer for the novel merging approach.

[4] It is worth to note that Table 2 only reports the estimation results of Probit model. Here, we calculate the economic consequence based on the marginal effect generated from the estimation results in Table 2.

[5] We would like to thank the anonymous reviewer for reminding us this concern.

[6] We really thank the anonymous reviewer for pointing out this point.

[7] See more details on the website: https://www.afr.com/companies/financial-services/new-quality-of-financial-advice-rating-system-to-probe-licensee-governance-20180730-h13axu.

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How to cite this article: Yang, Z., Gao, J., & Yu, D. (2023). Cognition ability, financial advice seeking, and investment performance: New evidence from China. *International Review of Finance*, 1–30. https://doi.org/10.1111/irfi.12433

APPENDIX A: FORTY WORD-RECOGNITION QUESTIONS AND TWO SETS OF MATHEMATICAL QUESTIONS

1. **Forty words in the verbal test**

LIST A	LIST B	LIST C	LIST D
A01. RICE	B01. STOOL	C01. MOUNTAIN	D01. WATER
A02. RIVER	B02. FOOT	C02. STONE	D02. HOSPITAL
A03. DOCTOR	B03. SKY	C03. BLOOD	D03. TREE
A04. CLOTHES	B04. MONEY	C04. MOTHER	D04. FATHER
A05. EGG	B05. PILLOW	C05. SHOES	D05. FIRE
A06. CAT	B06. DOG	C06. EYE	D06. TOOTH
A07. BOWL	B07. HOUSE	C07. GIRL	D07. MOON
A08. CHILD	B08. WOOD	C08. HOUSE	D08. VILLAGE
A09. HAND	B09. PRIMARY SCHOOL	C09. ROAD	D09. BOY
A10. BOOK	B10. TEA	C10. SUN	D10. TABLE

2. **Two sets of mathematical questions**

(1) **First set**

D201 Please read the number series on the computer screen, and fill in the blank number.
"8…BLANK…12…14"
D202 Please read the number series on the computer screen, and fill in the blank number.
"23…26…30…35…BLANK"
D203 Please read the number series on the computer screen, and fill in the blank number.
"18…17…15…BLANK…8"
D204 Please read the number series on the computer screen, and fill in the blank number.
"6…7…BLANK…9"
D205 Please read the number series on the computer screen, and fill in the blank number.
"6…BLANK…4…3"
D206 Please read the number series on the computer screen, and fill in the blank number.
"5…8…11…BLANK"
D207 Please read the number series on the computer screen, and fill in the blank number.
"BLANK…4…6…8"
D208 Please read the number series on the computer screen, and fill in the blank number.
"1…3…3…5…7…7…BLANK"
D209 Please read the number series on the computer screen, and fill in the blank number.
"18…10…6…BLANK…3"
D210 Please read the number series on the computer screen, and fill in the blank number.
"17…BLANK…12…8"
D211 Please read the number series on the computer screen, and fill in the blank number.
"10…BLANK…3…1"

D212 Please read the number series on the computer screen, and fill in the blank number.
“17…16…14…10…BLANK”
D213 Please read the number series on the computer screen, and fill in the blank number.
“BLANK…20…26…38…62”
D214 Please read the number series on the computer screen, and fill in the blank number.
“5…BLANK…11…19…35”
D215 Please read the number series on the computer screen, and fill in the blank number.
“54…70…BLANK…BLANK…84”

(2) **Second set**

D221 Please read the number series on the computer screen, and fill in the blank number.
“7…10…13…BLANK”
D222 Please read the number series on the computer screen, and fill in the blank number.
“BLANK…13…15…18…22”
D223 Please read the number series on the computer screen, and fill in the blank number.
“18…17…BLANK…12…8”
D224 Please read the number series on the computer screen, and fill in the blank number.
“4…5…6…BLANK”
D225 Please read the number series on the computer screen, and fill in the blank number.
“5…4…3…BLANK”
D226 Please read the number series on the computer screen, and fill in the blank number.
“11…BLANK…15…7”
D227 Please read the number series on the computer screen, and fill in the blank number.
“BLANK…15…13…11”
D228 Please read the number series on the computer screen, and fill in the blank number.
“10…6…3…BLANK”
D229 Please read the number series on the computer screen, and fill in the blank number.
“11…9…6…BLANK”
D230 Please read the number series on the computer screen, and fill in the blank number.
“1…3…9…BLANK”
D231 Please read the number series on the computer screen, and fill in the blank number.
“13…15…19…27…BLANK”
D232 Please read the number series on the computer screen, and fill in the blank number.
“3…3…4…6…6…7…BLANK…BLANK”
D233 Please read the number series on the computer screen, and fill in the blank number.
“6…BLANK…15…27…51”
D234 Please read the number series on the computer screen, and fill in the blank number.
“BLANK…18…24…36…60”
D235 Please read the number series on the computer screen, and fill in the blank number.
“60…33…24…21…BLANK”