Scientific Research Publishing

Open Journal of Social Sciences, 2021, 9, 478-498
https://www.scirp.org/journal/jss
ISSN Online: 2327-5960
ISSN Print: 2327-5952

Family Wealth Accumulation and Fiscal Prudence among China's Young Adults: Between the Privileged and the Common

Muyan Xie

International School, Wuxi Big Bridge Academy, Wuxi, China
Email: 1756314803@qq.com

How to cite this paper: Xie, M. Y. (2021). Family Wealth Accumulation and Fiscal Prudence among China's Young Adults: Between the Privileged and the Common. *Open Journal of Social Sciences, 9,* 478-498.
https://doi.org/10.4236/jss.2021.99035

Received: August 31, 2021
Accepted: September 19, 2021
Published: September 22, 2021

Abstract

Young adults in middle class Chinese families are seeing increased access to their family's wealth. With the growing ubiquity of digital payments and consumer goods, they are spending at an ever increasing rate. But for young adults from less privileged financial backgrounds, high disposable incomes and glamorous shopping items may be out of reach. This paper is designed to analyze the development of financial literacy among all groups of young adults in China and assess the rationality of their financial behavior. I sought to determine the correlations between financial literacy, family income and fiscal prudence. I applied methods like OLS regression, entropy weight model and significance test to establish firm correlations. I hypothesized children of wealthier families would behave in a more financially reasonable way as they tend to have access to more education and general financial information. Thus, I would test using initial hypothesis that more privileged children will react and shop more prudently, which is further proved in the sections below.

Keywords

Financial Literacy, Financial Behavior, Wealth Accumulation, Chinese Young Adults

1. Introduction

Booming economies and rapid societal development have raised concern in China for the financial responsibility of the next generation. Some citizens believe parents and access to information play a large role in determining financial literacy rate of young adults and their spending patterns.

In the research, we are trying to figure out the possible relationship between financial literacy and fiscal prudence, or spending prudence, among Chinese young adults. By doing so, we can better understand the usefulness of financial education in guiding young adults' behaviors and pave way for future buildup of the problem.

2. Literature Review

Throughout the researches area, the most related paper to our topic here should the paper Financial Prudence among Young (Pillai, Carlo, & D'souza, 2012), in which they discussed about financial prudence of the youth through second hand data and pure theoretical assumptions.

This paper is going to significantly build upon that one by utilizing quantifiable indices and use precise and statistically significant samples.

In New Adolescent Money Attitude Scales: Entitlement and Conscientiousness (Beutler & Gudmunson, 2012), the authors tried to provide the spending behaviors of the young with psychological reasons, including theory of planned behaviors.

Also, previous studies have tried to figure out gender differences in the financial literacy rates and the gender differences in its effectiveness in influencing the youth's prudence (Sharif, 2020). In this paper, we are going to pool the two genders together for the fact that the respondents to the questionnaire are halved through gender and sex is not a major concern here if we are designing to link spending behaviors with financial literacy rates.

Here I will try to take that into account in explaining my own results too.

3. Data

3.1. Collection

Several measures were taken to avoid selection bias in the survey results. As we assume young adults from less wealthy families have less access to online polls, I fixed the number of respondents in each income group. Moreover, the survey was launched to the public during the Chinese Spring Festival, 2021, at which time most young adults are relatively free and willing to respond. We finally collected 137 samples from targets whose self-reported family income is less than 50,000 yuan per year and 372 samples from families above that threshold.

The questionnaire was carefully worded to avoid response bias. We formatted the questionnaire as shown in the appendix, which tried to eliminate bias and quantify the metrics.

The survey was conducted both online and offline. Leveraging my access to my fellow students, I first distributed the survey to my club members in School Economics Club. I then launched the questionnaire to the Internet and received hundreds of responses.

3.2. Exploration

After collecting the results, I tried to quantify all the responses. Questions 1 and 10 focus the respondent's family income overview and should be treated as basic demographic information. Questions 2 to 6 test the respondent's level of financial literacy. Questions 7 to 9 are designed to assess the prudence of the respondent's financial behaviors.

As we can categorize the questions into 3 types, I generate three separate indices named *FLR*, *FBR* and *FWAL*, representing for Financial Literacy Rate, Financial Behavior Rationality and Family Wealth Accumulation Level.

In the sensitivity analysis, we will directly put the raw data of all the question answers in the Financial Literacy assessment areas into the model as independent variables to eliminate the error that can be generated during the entropy weight defined procedure.

4. Statistical Models

Survey Responses Indices

As we may discern from the questionnaire attached in the appendix, the questions have defined correct answers and defined indicator of goodness[1].

We then define the variables *FLR*, *FBR*, and *FWAL* based on these questions. *FLR* is more like a test score. Based on the correctness of the answers to the Financial Literacy questions, we can define them as a quiz. In order to ensure to eliminate the luck part (those who choose by random and get the question right), I add in the following algorithm as shown in Equation (1):

$$S_e = 0 = \frac{1}{I} \times W + \frac{I-1}{I} \times D \tag{1}$$

S_e stands for the expected score of a single question if the respondent simply guesses it. I stands for the number of items for selection in the question. W stands for the score awarded for a correct answer. D stands for the score awarded for an incorrect answer.

Here we set the winning points to be 4. I is question specific, indicating that D is also specific to the question. For example, question 3 has three items to be chosen and only one correct answer. 4 points are won for a correct answer and 2 are deducted for an incorrect answer. Thus, the expected score is 0.

Therefore, we can discern that those who only guess all the questions will get an expected score of 0.

We should also consider the difficulty of each question. It is thus reasonable that we should use the Entropy Weight Model, as going to be explained in the next subsection.

Then we need to determine the value of *FBR* for each sample. *FBR* is defined as the rationality of the financial behavior of the respondent. Questions 7 to 9 account for the assessment of this variable. These questions has unlimited num-

[1]This means that as the responses' numerical values go down or up, it is clear whether the responses are good or bad, within a general trend.

ber of possible answers and are defined all as Minimal Indicators[2]. Because we want to see an index in traditional sense, we process each response in for *FBR* as shown in Equation (2):

$$x'_j = M_j - x_j \tag{2}$$

And we will define M_j in Equation (3):

$$M_j = \max_{1 \le i \le n} \{a_{ij}\} \tag{3}$$

where M_j is simply the largest value in the column.

After the process, we can discern that smaller the original value is, the larger the final value will be, satisfying to our requirement.

We can see that due to the fact that all the responses are of different dimensions and magnitudes, we need to eliminate these impacts. We then will conduct the normalization for the indicators of *FBR*, as shown in Equation (4).

$$a_{ij}^* = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{n} a_{ij}^2}} \left(i = 1, 2, \cdots, n, 1 \le j \le m\right) \tag{4}$$

After these processes, the variables can be changed from minimal indicators to larger indicators and then to indicators of equatable magnitude.

Next, we will again use Entropy Weight Model in order to settle down the weight of each factor to minimize the importance of the less varied determinants while magnify the importance of the more varied ones.

As for *FWAL*, we will define it as a row matrix with two columns. The first column will contain a value of 0 or 1. 0 indicates that the respondent's family earn an income less than 50,000 RMB per year and should be classified in the less privileged group, as indicated by the Chinese Communist Party's 5 Years' Targets. 1 means that the income is more than 50,000 RMB annually and should be treated as wealthy. The second value is the percentage income increase of the family, being treated as the wealth accumulation increasing rate of the family. For a better illustration we will use the following Differential Equations, where *W* stands for the wealth occupied by the family:

$$V_n = \frac{\mathrm{d}W}{\mathrm{d}t}, Ar = \frac{\mathrm{d}W}{\mathrm{d}t} - 2\% \tag{5}$$

We define V_n as the nominal increasing rate of wealth. The accumulation rate *Ar*, on the other hand, should be defined as the increase in purchasing power over time, equaling V_n-CPI of the country. We will set the CPI for China as 2%.

In one word, for *FWAL*, the first column indicates which group, G_c or G_p, the respondent should be in with G_c refers to a common family while G_p refers to a wealthy family as defined by annual income.

Entropy Weight Model

Entropy characterizes the level of disorder and, to a large extent, the amount of information in a given system. In this case, the more randomness a variable displays, the higher its entropy and the faster its entropy increases, and so grows

[2]This means that as the responses going smaller and smaller, the better the response is.

the amount of information we can extract from this variable.

The entropy weight method uses this principle to calculate weighting for different variables based on the entropy of their distributions. A larger variance or entropy generally means a larger weight. In the extreme case, if all values for a index are identical, then it does not matter what the value is, and we should give it zero weight.

TOPSIS Analysis

After getting all the needed indicator values for *FLR* and *FBR*, we can use the TOPSIS method to comprehensively evaluate each sample get their relative wellness.

We can get the best response group combination and the worst group combination, and evaluate using Kendall's tau distance model (Jahanshahloo, Lotfi, & Izadikhah, 2006):

$$\begin{aligned} D_i^+ &= \sqrt{\sum_{j=1}^{m} w_j \left(Z_j^+ - z_{ij}\right)^2} \\ D_i^- &= \sqrt{\sum_{j=1}^{m} w_j \left(Z_j^- - z_{ij}\right)^2} \end{aligned} \tag{6}$$

We can thus use the final evaluation equation:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{7}$$

The return value should be a value between 0 and 1.

Ordinary Least Square Regression Model

After obtaining the desired values for analysis, we sought out to determine correlation between one or more independent variables and one dependent variable. For convenience and other concerns defined *FLR*, we can simply use the two variable Ordinary Least Square Regression Model for *FLR* and *FBR*.

Now we will articulate our formulas for this model.

First, the general formula for OLS is shown in Equation (8):

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i \tag{8}$$

where y_i is the response variable; β are the unknown variables; x_i are the independent variables and ε_i is the unobserved error.

Significance Test Model

Next we should concentrate on the comparison between two income groups, G_c and G_p.

The two samples' indices are *FLR* and *FBR*. To compare the two groups of pair values, we can simply use the Two Sample T-test.

To begin with, we will check whether each group satisfies the requirement for analysis using this method.

The samples can be treated as random for all respondents as the questionnaires are randomly selected. The sample is done without replacement. Luckily we should assume the sample size is far less than 10% of the whole population. Also the sample sizes are bigger than 30 for both samples. We thus satisfy the random and normal requirements.

As the true standard deviation of both income groups for *FLR* and *FBR* is unknown, we can use the sample standard error as a close approximation.

5. Model Results

We can compile all the calculated information for the entropy weight model into Figure 1 and Figure 2.

After getting the weights, we are able to use TOPSIS Method to evaluate. For brevity, the final results are available in the appendix. We display some examples of the values as classified by G_c and G_p in Figure 3.

Then we came to our OLS Regression Model. The model produced the following parameters, as shown in Table 1.

From the outcomes we can see that the regression model can only explain 14.72% of the observed values. However, the model is still functional because the F test shows that $F = 87.524$ with $p = 0.000 < 0.05$, meaning that *FLR* definitely will affect *FBR* values.

The interpreted formula can be expressed as:

$$\widehat{FBR} = 0.84 - 0.296FLR \tag{9}$$

indicating a negative and significant relationship between the two variables, contradicting our assumption that as FLR increases, FBR will increase.

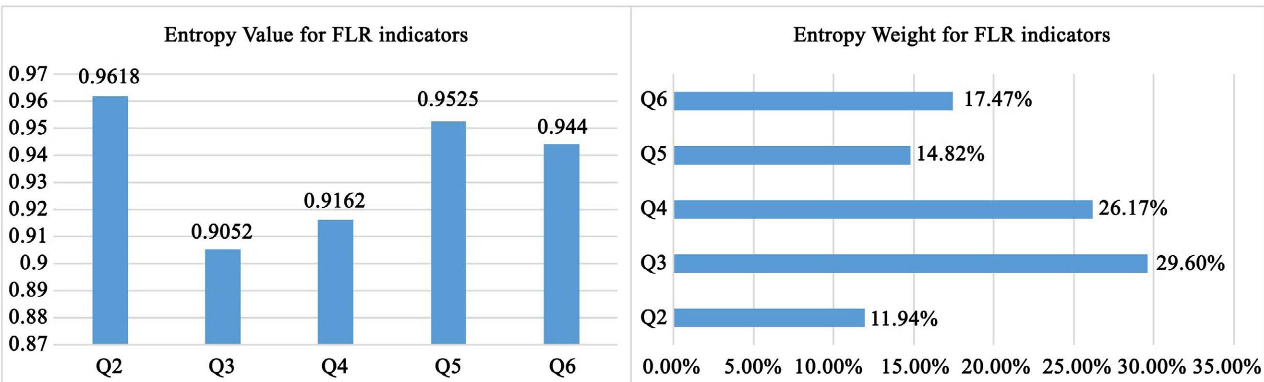


Figure 1. Entropy results for FLR.

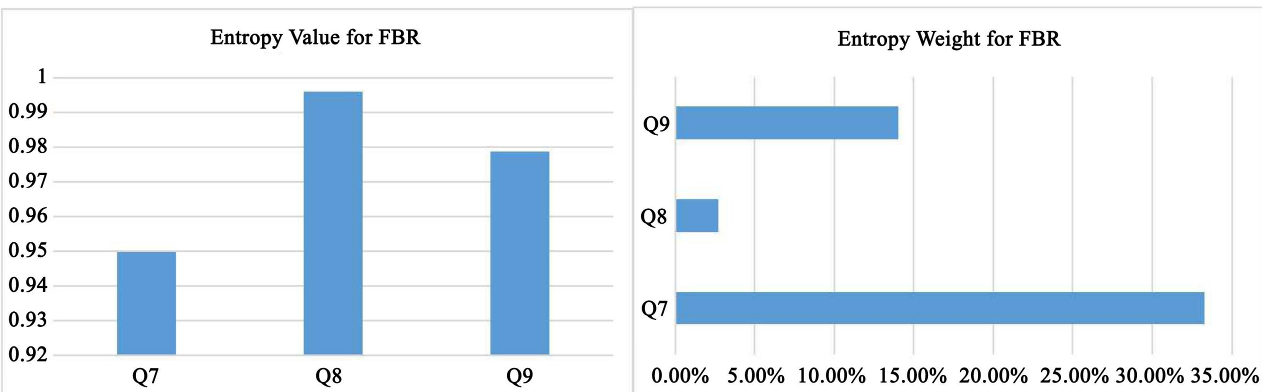


Figure 2. Entropy results for FBR.

Group Common Report					
Sample	FLR	FBR	Sample	FLR	FBR
1	0.656	0.842	16	0.493	0.785
2	0.645	0.88	17	0	0.944
3	0.269	0.89	18	0.253	0.928
4	0.269	0.944	19	0.344	0.875
5	0.269	0.88	20	0.427	0.956
6	0.435	0.875	21	0.515	0.628
7	0.731	1	22	0.515	0.928
8	0.269	0.875	23	0.355	0.928
9	0	0.865	24	0.632	0.956
10	0.656	0.928	25	0.427	0.89
11	0.269	0.944	26	0.573	0.88
12	0.737	1	27	0.656	0.754
13	0.545	0.88	28	0	0.561
14	0.368	0.88	29	0.515	0.865
15	0.269	0.89	30	0.253	0.944

Group Previleged Report					
Sample	FLR	FBR	Sample	FLR	FBR
138	1	0.51	153	1	0.408
139	0.731	0.45	154	1	0.488
140	0.565	0.563	155	1	0.611
141	0.545	0.59	156	0.565	0.324
142	1	0.563	157	0.573	0.563
143	0.485	0.674	158	0.632	0.475
144	0.632	0.776	159	0.731	0.728
145	4	0.401	160	1	0.466
146	0.493	0.638	161	0.568	0.538
147	0.747	0.331	162	1	0.403
148	0.545	0.499	163	0.632	0.604
149	1	0.373	164	0.545	0.654
150	0.493	0.59	165	1	0.674
151	0.731	0.564	166	0.632	0.663
152	0.737	0.403	167	0.545	0.364

Figure 3. Entropy results for FBR.

Table 1. OLS regression results.

Items	Coef	Std. Err	t	p	R^2	Adjusted R^2	F
Constant	0.84	0.02	41.811	0.000**	0.147	0.146	F (1, 507) = 106.246, $p = 0.000$
Variable	−0.296	0.029	−10.308	0.000**	0.147	0.146	F (1, 507) = 106.246, $p = 0.000$

The p-value for the variable coefficient is 0.000, which is within a significance level as strict as 0.01, demonstrating that the negative correlation is almost certain.

Next, we will first compare the sample distribution in G_c and G_p.

We will use the two sample T-test for significance. The results are in Table 2.

Also we tested *FBR* in Table 3.

6. Sensitivity Analysis I

Wary of the low R^2 value for the OLS regression model, I decided to do a sensitivity analysis on it. This procedure includes testing the accountability of *FBR* on each respondent without the intermediate calculation of *FLR*.

The model shows the following results in Figure 4.

With these adjustments, R^2 is now higher and still shows an indication of correlation in terms of the F score.

7. Extension

7.1. Reflection

7.1.1. Results Deviation and Conformation

Deviation: The model results deviate from our expectations. We *cannot* confirm that:

OLS Regression Results (n=509)

	Coef	Std. Err	t	p	R^2	$Adj\ R^2$	F
Const.	0.786	0.012	65.042	0.000**	0.26	0.253	F (5, 503) = 41.620, p = 0.000
Q2	−0.01	0.002	−4.105	0.000**			
Q3	−0.008	0.002	−3.275	0.001**			
Q4	−0.007	0.003	−2.501	0.012*			
Q5	−0.022	0.003	−6.915	0.000**			
Q6	−0.012	0.003	−3.564	0.000**			

Depedent Variable: FBR

D-W Value: 1.608

* p<0.05 ** p<0.01

Figure 4. OLS model output.

Table 2. T-test result for FLR in two groups.

t	p-value	Df
−14.4079	0.000	294.778

Table 3. T-test result for FBR in two groups.

t	p-value	Df
25.5381	0.000	278.564

1) Young Adults living in privileged wealthy families will conduct more rationally in financial behaviors than the young from the common backgrounds.

2) Financial Literacy Rate will necessarily increase rationality of financial behaviors.

Conformation: However, one of the t-tests confirms the following hypothesis:

1) Young Adults living in privileged wealthy families have higher financial literacy rate than those in the common families.

We can aggregate the findings in one chart as in **Figure 5**.

The difference between the two groups' two indices is clear.

Suspect: Some people may suggest that the wealth accumulation rate, *Ar*, will decrease the financial prudence of young adults. For responsibility, I will picture both variables in **Figure 6**.

Verification: For clarity, we will show the results of the tests only:

From this chart we can discern that *Ar*, the J in the chart, has no defined relationship with *FBR*.

7.1.2. Lurking Variables

Of common sense, increasing financial literacy will definitely increase one's financial rationality. This leads us to wonder about the existence of lurking variables in this research.

We cannot conduct a controlled experiment in this area. Thus the most reasonable statistical account may be the following variables:

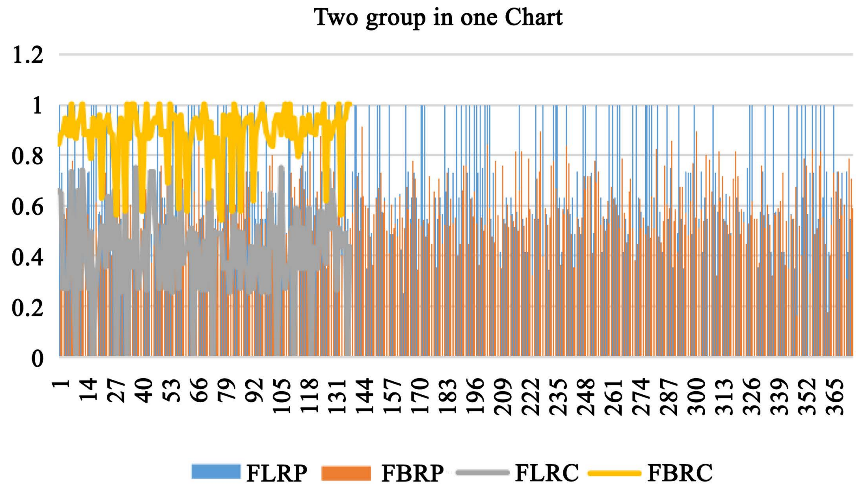


Figure 5. Group overall results.

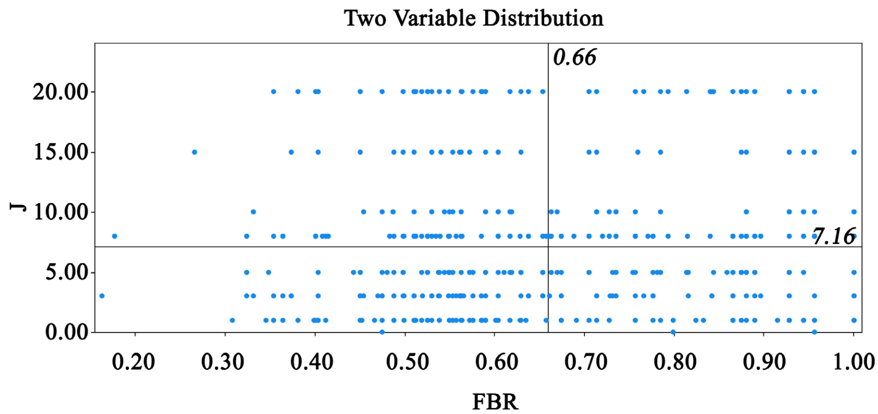


Figure 6. Two variable distributions.

1) Households that can provide decent financial literacy education environment will have more stimuli to urge the young to conduct irrational purchases.

2) Parents in lower income households may offer less financial support for their children, thus prohibiting them from making financially irresponsible purchases.

It is a pity, but we cannot get conduct a controlled experiment due to time, financial and moral restrictions.

7.2. Psychological Explanation

Even though statistically we are almost done here, we can still account for the observed data using behavior finance and Gestalt Psychology.

7.2.1. Marginal Utility Theory

Excessive spending does not necessarily imply irrationality on the part of the consumer. Instead, we may consider that the consumer is rather buying "unnecessary" items in pursuit of a sense of fulfillment. In this sense, it is rightful that we should introduce the Marginal Utility Theory in Microeconomics. According to Marginal utility theory, "Utility is an idea that people get a certain level of satisfaction/happiness/utility from consuming goods and service" and "Marginal utility is the benefit of consuming an extra unit".

Thus we can propose our theory:

- Marginal Utility Per Dollar for children of upper income households is less than for those of the middle and lower class backgrounds.
- To achieve the same amount of utility, young adults of wealthy households will purchase more.
- Necessary purchases for an individual have an identical dollar value regardless of his or her financial background.
- And thus the privileged young will purchase more "unnecessary" goods.

Still, unfortunately, it is only our postulation and cannot be verified using substantial statistics. However, the following suppositions can have some kind of supporting evidence.

7.2.2. Access to Confusing Purchasing Chances

Another factor we must consider is the effect of easy purchases and confusing advertisements.

We will set the following variables to quantify our assumption. Let T_i be the temptation coefficient of the product. P_i represents the probability of getting confused and buying the product, which depends on both FLR and T_i.

To simplify the model, we set three temptations of different degrees, being mild temptation, intermediate temptation and high temptation respectively. The consumer passes through these temptations daily, as demonstrated in Figure 7.

We set here that N1, N2, N3 should be 3, 2 and 1 respectively for young adults in wealthy families and will be 2, 1 and 0 for young adults in the less privileged families for their lack of access to such temptations in their living environment.

We are able to measure the effect of the differences in temptation coefficient for products and the number of temptations in the following simulations 7.3.

7.2.3. Theory of Planned Behaviors

By the concept of TPB, current behaviors are determined by past experiences and interactions. The young adults might base their purchasing behaviors on observed behavior of their parents. We could investigate the purchasing behavior of various parents and observe whether or not that correlates with the observed behavior of their children. Unfortunately, this research will have to be left to further surveys (Icek Ajzen, 2011).

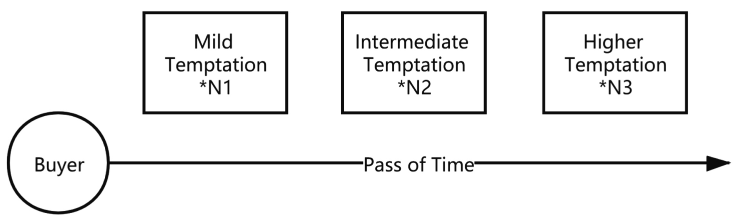


Figure 7. Flow chart of temptations.

7.3. Statistical Simulation

Monte Carlo Simulation

Monte Carlo simulation is actually a general reference to an idea. As long as a large number of random samples are used when solving a problem, and then probabilistic analysis is performed on these samples, the method of predicting the results can be called a Monte Carlo method.

The idea for this model is that we will conduct numerous trials to simulate the process of living for the two groups and determine the average rate of purchasing unnecessary items.

Markov Chain Simulation

In the real world, there are many such phenomena: Under the condition that a certain system has known the current situation, the future state of the system is only related to the present, and the past history is not directly related. The mathematical model describing this kind of random phenomenon is called the Markov model.

In this situation, we will set an additional intermediate calculation in the program. This intermediate is affected by the former purchase of the day and will lower the probability of being lured by the same kind or higher level or temptation. An illustration is given below in Figure 8.

The equation form of the Markov Chain Model is:

$$P\left\{\xi_{n+1}=j \mid \xi_n=i, \xi_{n-1}=i_{n-1}, \cdots, \xi_1=i_1\right\}=P\left\{\xi_{n+1}=j \mid \xi_n=i\right\} \tag{10}$$

For clarity, the coding will be available in the appendix and the next section will present the model results directly.

7.4. Models Results

Table 4 is the summary of a simulations run for 1,000,000 iterations.[3]:

We can see our models do confirm that advertisements and easy access to payment is a factor in affecting *FBR*.

7.5. Additional Researches

To completely utilize my data, I conducted the following procedure. For brevity, I will present the statistical methods and results only briefly.

Population Estimation: Using a 99% confidence interval, we can state that we are we are 99% sure that the true population value for *FLR* and *FBR* will be contained by Table 5.

Differences with Confidence: 99% confidence intervals for the difference of the means of the indicators of both groups can be expressed, as shown in Table 6.

Table 4. Monte carlo results.

Stat.	G_c Irrational Rate	G_p Irrational Rate
Mean	14.57/100	9.87/100
Variation	0.78/100	0.98/100

[3]We automatically use the *FLR* acquired in the survey as parameters in the program; Temptation rates are set different for two groups, being 3:2:1 and 2:1:0 respectively. Other factors are set equal.

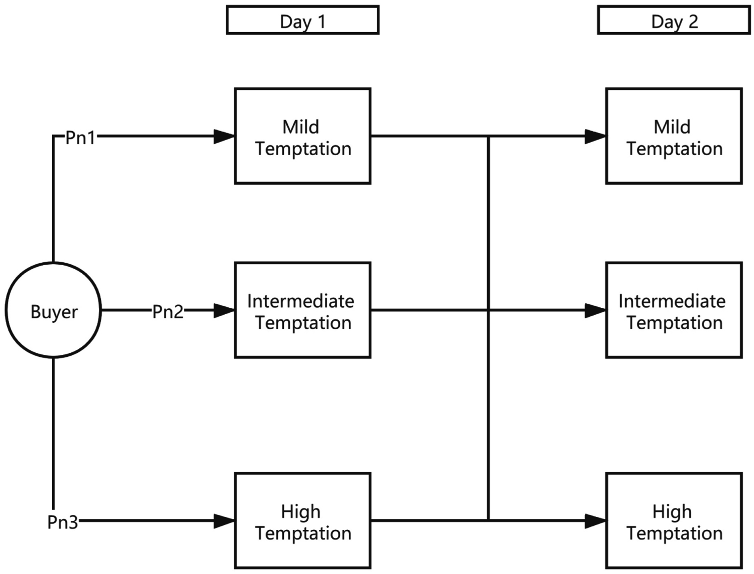


Figure 8. Flow chart of TPB.

Table 5. Population estimation.

group	99% Confidence Interval	ME	n
Overall *FLR*	(0.581495,0.636505)	0.027505	509
Overall *FBR*	(0.637684,0.680316)	0.021316	509
G_c *FLR*	(0.369271,0.448729)	0.039729	137
G_c *FBR*	(0.855555,0.906445)	0.025445	137
G_p *FLR*	(0.652735,0.711265)	0.029265	372
G_p *FBR*	(0.55928,0.59472)	0.01772	372

Table 6. CI estimation.

Name	99% Confidence Interval	ME
G_c *FLR* − G_p *FLR*	(−0.338868, −0.241132)	0.048868
G_c *FBR* − G_p *FBR*	(0.288845, 0.331155)	0.021155

7.6. Sensitivity Analysis II

We will vary the temptation rates in the simulation in order to test the sensitivity and significance of the tests.

Trail one: G_p 3:3:3 G_c 2:2:1,

Trial two: G_p 3:3:2 G_c 2:2:2.

The results show the same pattern as that in the previous tests, making *FBR* indicators lower for G_p than G_c.

8. Suggestions

No matter what the reason is, young adults from higher income households demonstrate more "irrational" shopping behavior. From the results of our statistical simulation, we can suspect that if we can change some of the variables in the test, the results can be improved. Sensitivity Analysis II was highly suggestive of our original hypotheses.

From these, we can propose the following suggestions to fight the observed lack of fiscal prudence of China's young adults:

- Scrutinize advertisements,
- Offer more financial education to further increase the Financial Literacy Rate,
- Limit young adults' access to online payment methods.

9. Conclusion

This article contains a plethora of statistical analyses. For brevity, lots of obscured and unnecessary procedures have been eliminated. However, to summarize the findings, we have included this chapter.

9.1. Outcomes

First of all, from the OLS and F test, we can see that the correlation between *FLR* and *FBR* is weak and possibly even unexpectedly negative.

Furthermore, young adults from less affluent households demonstrate an increased scrutiny of nonessential purchases when compared to their wealthier counterparts, as indicated in the significance test.

Finally, young adults from wealthier background have higher financial literacy rates than those from less privileged ones.

9.2. Suggestions

Some of our proposals for the cause of the unexpected results are not fit for implementation or need a further independent research to confirm. However, using statistical simulation methods, we have confirmed that advertisements and easy access to payment methods do increase a young adult's theoretical likelihood of buying irresponsibly.

We thus propose that advertising should be further controlled to limit its sensational effects and that parents should limit their children's access to mobile payments methods like Alipay in China.

Finally, we can see that financial literacy rate still plays a large role in determining the prudence of an individual's spending behavior. For this reason, we as a society should continue to increase the availability of and access to financial education for all adults in China.

Special Thanks

This article is inspired by my Counselors, Erte Li at Wuxi Big Bridge Academy. He gave me phenomenal ideas and corresponding action guidelines. This paper could not have been realized without his help.

Thanks to those who responded to the questionnaires. It's you who help to understand the financial behaviors now in China.

Acknowledgements

The survey that provided the data for analysis was conducted by an investigation group lead by the author, Muyan Xie, at Wuxi Big Bridge Academy International School Economics Club. As the president of the club, Muyan Xie leads his team to disseminate the survey. This paper was written solely by Muyan Xie.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Ajzen, I. (2011). The Theory of Planned Behaviour: Reactions and Reflections. *Psychology & Health, 26,* 1113-1127. https://doi.org/10.1080/08870446.2011.613995

Beutler, I. F., & Gudmunson, C. G. (2012). New Adolescent Money Attitude Scales: Entitlement and Conscientiousness. *Journal of Financial Counseling and Planning, 23,* 14. https://search.ebscohost.com/login.aspx?direct=true&db=psyh&AN=2013-08936-002&site=ehost-live&scope=site

Jahanshahloo, G. R., Lotfi, F. H., & Izadikhah, M. (2006). An Algorithmic Method to Extend TOPSIS for Decision-Making Problems with Interval Data. *Applied Mathematics and Computation, 175,* 1375-1384. https://doi.org/10.1016/j.amc.2005.08.048

Pillai, K. R., Carlo, R., & D'souza, R. (2012). Financial Prudence among Youth. *Journal of Contemporary Management Research, 6,* 52-68. https://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=90299646&site=ehost-live&scope=site

Sharif, S. P. et al. (2020). Gender Differences in Financial Literacy and Financial Behaviour among Young Adults: The Role of Parents and Information Seeking. *Journal of Family and Economic Issues, 41,* 672-690. https://doi.org/10.1007/s10834-020-09674-z

Appendices

Questionnaire

本问卷针对是中国户籍的13到20岁青年。
This survey is targeted toward young adults between 13 to 20 years old with Chinese Passport.

- 我满足条件参加啦！
  Yes, I am qualified!
- 我好像不能参加诶。
  Sorry, but I am not qualified.

1. 请问您的家庭年收入为多少人民币？本问卷不记名，请放心作答。
What is your family yearly income in yuan? This questionnaire is anonymous, please feel free to answer.

- 0 - 50000
- 50000+

以下为一个小测验，请作答。
Below is a small quiz, please help us answer it.

2. 请问投资银行和商业银行是一样的嘛?
Is investment bank the same as commercial banks?

- 是的
  Yes
- 不是的
  No

3. 请问下面哪个最接近中国的银行的不定期存款利率?
Which of rate is the closest to interest rate of deposits in Chinese banks?

- 0.3% 每年
  0.3% per year
- 5% 每年
  5% per year
- 8% 每年
  8% per year

4. 请问降准指的是什么?
What does lowering reserve requirement means?

- 调低中央银行的资金储备量
  Lowering Central Bank's amount of preparation reserve
- 调低所有银行的资金储备率
  Lowering all banks' rate of preparation reserve
- 调低所有银行的准备利润率
  Lowering all banks' rate of preparation interest
- 调低所有证券交易所得开会金额要求
  Lowering all stock exchanges' account setup capital requirement

5. 请问以下哪个组合中两个物品的价格走势会大概率相反?
Which of the following pairs will have the two items' price developing at an opposite direction?

- 黄金和股市
  Gold and Stocks
- 黄金和石油
  Gold and Oil
- 房价和股市
  Houses and Stocks

6. 请问Beta（在股市中）指的是什么?
What does Beta stands for in stock markets?

- 风险
  Risk
- 相对价格
  Relative Price
- 股票回本时间
  Time needed for a stock to earn its original value

- 账户的同向方差
  Covariance of a portfolio

7. 请问您在非生活必须品方面的消费频率为什么？金额大概为多少？
What is your frequency of shopping not must-needed items? How much do they sum up?

- ( ) 次/每天
  ( ) times/per day
- ( ) RMB/每天
  ( ) RMB/per day

8. 请问您消费后后悔的频率为多少？
What is your frequency of regretting the shopping you made?

- ( )次/每20次
  ( )times/per 20 times

9. 请问您的后悔的消费的金额大概为多少呢？
What is the amount of the shopping that you regret?

- ( ) RMB/每年
  ( ) RMB/per year

10. 您的家庭的收入在过去三年中提高了多少呢？
On what percentage did your family's income increase in the past three years?

- ( )%

Survey Data Chart

G_c Results

Sample	FLR	FBR
1	0.656	0.842
2	0.645	0.88
3	0.269	0.89
4	0.269	0.944
5	0.269	0.88
6	0.435	0.875
7	0.731	1
8	0.269	0.875
9	0	0.865
10	0.656	0.928
11	0.269	0.944
12	0.737	1
13	0.545	0.88
14	0.368	0.88
15	0.269	0.89
16	0.493	0.785
17	0	0.944
18	0.253	0.928
19	0.344	0.875
20	0.427	0.956
21	0.515	0.628
22	0.515	0.928
23	0.355	0.928
24	0.632	0.956
25	0.427	0.89
26	0.573	0.88
27	0.656	0.754
28	0	0.561
29	0.515	0.865
30	0.253	0.944
31	0.263	0.928
32	0.568	0.576
33	0	1
34	0.455	0.865
35	0.355	1
36	0.355	1
37	0.747	0.956
38	0.269	0.88
39	0.344	0.875
40	0.368	0.576
41	0.493	0.88
42	0.263	1
43	0.565	0.865
44	0.731	0.875
45	0.731	0.928
46	0.565	0.944

Sample	FLR	FBR
47	0.427	0.928
48	0.269	1
49	0.368	0.88
50	0.515	0.89
51	0.269	0.89
52	0.269	0.688
53	0.747	1
54	0.253	0.944
55	0.545	0.956
56	0.515	0.944
57	0.269	0.586
58	0.656	0.956
59	0.368	0.865
60	0.415	0.88
61	0.427	0.576
62	0.488	0.816
63	0.507	0.875
64	0	0.928
65	0.485	0.944
66	0.432	0.928
67	0.269	0.865
68	0.263	0.956
69	0.455	1
70	0.263	0.944
71	0.585	0.628
72	0.656	0.928
73	0	0.793
74	0.493	0.865
75	0.485	0.865
76	0.485	0.586
77	0.485	0.54
78	0.348	0.956
79	0.368	0.88
80	0.368	0.928
81	0.253	0.956
82	0.415	0.576
83	0.565	1
84	0.355	0.956
85	0.493	0.944
86	0.269	0.576
87	0.488	0.875
88	0.355	0.928
89	0.344	0.944
90	0.253	0.928
91	0.435	0.956
92	0.269	0.617

Sample	FLR	FBR
93	0.355	0.88
94	0.515	0.928
95	0.355	0.944
96	0.253	1
97	0.427	0.956
98	0.263	0.89
99	0.253	0.865
100	0.645	0.842
101	0.435	0.833
102	0.512	0.928
103	0	0.956
104	0.355	0.956
105	0.747	0.88
106	0.348	0.956
107	0.269	1
108	0.355	0.875
109	0.368	1
110	0.507	0.865
111	0	0.944
112	0.585	0.865
113	0.573	0.793
114	0.348	0.816
115	0.507	0.944
116	0.348	0.88
117	0.435	0.928
118	0.585	0.956
119	0	0.89
120	0.432	0.89
121	0.355	0.88
122	0.348	0.956
123	0.573	0.928
124	0.573	0.928
125	0.415	1
126	0.368	0.617
127	0.737	0.928
128	0.507	0.865
129	0.656	0.89
130	0.545	0.928
131	0.263	0.928
132	0.507	1
133	0.435	0.561
134	0.455	0.928
135	0.488	0.944
136	0	1
137	0.435	1

DOI: 10.4236/jss.2021.99035

G_p Results

Sample	FLR	FBR
138	1	0.51
139	0.731	0.45
140	0.565	0.563
141	0.545	0.59
142	1	0.563
143	0.485	0.674
144	0.632	0.776
145	1	0.401
146	0.493	0.638
147	0.747	0.331
148	0.545	0.499
149	1	0.373
150	0.493	0.59
151	0.731	0.564
152	0.737	0.403
153	1	0.408
154	1	0.488
155	1	0.611
156	0.565	0.324
157	0.573	0.563
158	0.632	0.475
159	0.731	0.728
160	1	0.466
161	0.568	0.538
162	1	0.403
163	0.632	0.604
164	0.545	0.654
165	1	0.674
166	0.632	0.663
167	0.545	0.364
168	0.415	0.654
169	0.731	0.785
170	0.415	0.735
171	0.545	0.604
172	1	0.553
173	0.568	0.381
174	0.545	0.51
175	1	0.487
176	0.348	0.51
177	0.488	0.549
178	0.747	0.663
179	0.493	0.564
180	0.568	0.563
181	0.488	0.373
182	0.632	0.443
183	0.731	0.563
184	1	0.53
185	0.737	0.757
186	0.632	0.403
187	0.632	0.59
188	0.568	0.844
189	0.415	0.266
190	1	0.498
191	1	0.364
192	1	0.364
193	1	0.45
194	0.415	0.51
195	0.545	0.705
196	0.568	0.475
197	0.737	0.617
198	1	0.771
199	0.737	0.403

Sample	FLR	FBR
200	1	0.512
201	1	0.654
202	0.415	0.53
203	1	0.84
204	0.545	0.55
205	0.747	0.563
206	0.348	0.731
207	0.731	0.572
208	0.545	0.619
209	0.632	0.604
210	0.488	0.51
211	0.545	0.403
212	1	0.705
213	0.737	0.475
214	0.415	0.51
215	1	0.842
216	1	0.604
217	0.731	0.544
218	0.737	0.619
219	1	0.45
220	0.632	0.604
221	1	0.53
222	0.568	0.585
223	1	0.629
224	0.545	0.757
225	0.545	0.735
226	1	0.674
227	0.737	0.553
228	0.656	0.401
229	1	0.364
230	0.545	0.45
231	0.737	0.51
232	0.545	0.654
233	0.545	0.373
234	0.545	0.53
235	1	0.59
236	0.632	0.757
237	0.545	0.799
238	0.632	0.604
239	0.652	0.525
240	0.488	0.498
241	0.545	0.401
242	0.632	0.354
243	0.737	0.585
244	0.493	0.488
245	1	0.499
246	1	0.729
247	0.632	0.585
248	0.348	0.674
249	0.512	0.51
250	0.632	0.705
251	0.747	0.757
252	1	0.663
253	0.737	0.525
254	1	0.629
255	0.545	0.815
256	0.568	0.499
257	1	0.563
258	0.632	0.654
259	0.545	0.557
260	0.747	0.875
261	0.737	0.519

Sample	FLR	FBR
262	0.545	0.72
263	0.348	0.663
264	1	0.498
265	0.545	0.55
266	0.545	0.735
267	1	0.488
268	0.355	0.896
269	0.545	0.635
270	1	0.403
271	0.493	0.776
272	1	0.45
273	0.545	0.45
274	0.348	0.51
275	0.737	0.572
276	1	0.663
277	1	0.714
278	0.731	0.498
279	0.632	0.915
280	0.632	0.638
281	0.568	0.601
282	0.348	0.59
283	1	0.475
284	0.493	0.364
285	0.348	0.566
286	0.632	0.629
287	1	0.67
288	1	0.731
289	0.573	0.572
290	0.632	0.617
291	0.348	0.498
292	1	0.412
293	0.488	0.604
294	0.488	0.51
295	0.632	0.53
296	0.545	0.475
297	0.645	0.638
298	0.427	0.55
299	0.253	0.51
300	1	0.674
301	0.737	0.585
302	0.545	0.53
303	0.632	0.776
304	0.731	0.705
305	0.632	0.345
306	0.545	0.549
307	1	0.519
308	1	0.544
309	1	0.475
310	0.545	0.53
311	0.632	0.714
312	0.263	0.45
313	0.545	0.654
314	0.632	0.354
315	0.545	0.705
316	0.632	0.563
317	0.568	0.45
318	1	0.525
319	0.656	0.728
320	0.747	0.519
321	0.415	0.629
322	0.731	0.53
323	0.415	0.553

Sample	FLR	FBR
324	1	0.401
325	0.632	0.45
326	1	0.661
327	0.355	0.76
328	1	0.757
329	0.731	0.45
330	1	0.629
331	0.632	0.557
332	1	0.654
333	1	0.53
334	0.731	0.364
335	1	0.55
336	0.747	0.498
337	1	0.525
338	1	0.844
339	1	0.59
340	0.545	0.475
341	0.731	0.454
342	0.415	0.776
343	0.545	0.563
344	0.415	0.354
345	0.348	0.757
346	0.545	0.53
347	0.632	0.604
348	0.493	0.512
349	0.632	0.563
350	0.565	0.537
351	0.515	0.814
352	0.573	0.498
353	1	0.661
354	0.545	0.814
355	0.545	0.519
356	0.415	0.553
357	0.415	0.785
358	0.415	0.585
359	0.565	0.324
360	0.737	0.549
361	1	0.705
362	0.545	0.735
363	0.632	0.896
364	1	0.399
365	0.545	0.59
366	0.568	0.525
367	0.344	0.553
368	0.432	0.757
369	1	0.776
370	1	0.67
371	1	0.59
372	0.632	0.364
373	0.415	0.585
374	0.632	0.564
375	1	0.84
376	0.585	0.766
377	0.568	0.488
378	0.632	0.354
379	0.485	0.354
380	0.737	0.55
381	0.545	0.512
382	0.485	0.55
383	1	0.714
384	1	0.663
385	0.632	0.714

Sample	FLR	FBR
386	0.545	0.714
387	0.731	0.412
388	0.493	0.776
389	1	0.691
390	0.632	0.735
391	0.632	0.525
392	0.415	0.557
393	0.545	0.499
394	0.545	0.617
395	1	0.53
396	0.632	0.674
397	1	0.629
398	0.632	0.604
399	1	0.563
400	1	0.51
401	0.415	0.785
402	0.415	0.572
403	0.545	0.454
404	0.485	0.657
405	0.485	0.705
406	1	0.51
407	1	0.381
408	1	0.45
409	0.632	0.629
410	0.573	0.51
411	0.545	0.55
412	1	0.488
413	1	0.519
414	1	0.47
415	1	0.638
416	0.632	0.51
417	0.731	0.824
418	1	0.475
419	0.573	0.452
420	0.415	0.538
421	0.485	0.757
422	1	0.604
423	0.545	0.59
424	0.747	0.859
425	0.355	0.538
426	0.545	0.585
427	0.493	0.415
428	1	0.674
429	0.545	0.674
430	0.348	0.525
431	0.737	0.572
432	0.731	0.483
433	0.731	0.617
434	0.488	0.766
435	1	0.553
436	0.747	0.896
437	0.545	0.51
438	0.737	0.585
439	0.415	0.539
440	0.632	0.799
441	0.545	0.553
442	0.415	0.781
443	0.545	0.654
444	1	0.604
445	0.731	0.324
446	0.573	0.815
447	0.632	0.617

Sample	FLR	FBR
448	0.545	0.714
449	0.545	0.538
450	0.645	0.525
451	0.488	0.638
452	0.493	0.48
453	0.415	0.705
454	1	0.814
455	0.632	0.714
456	0.573	0.488
457	0.545	0.585
458	0.573	0.535
459	0.415	0.45
460	0.747	0.53
461	1	0.563
462	1	0.617
463	0.507	0.549
464	0.415	0.549
465	0.355	0.373
466	0.573	0.757
467	0.737	0.563
468	1	0.51
469	0.545	0.604
470	0.565	0.525
471	0.415	0.324
472	1	0.572
473	0.573	0.563
474	0.488	0.59
475	0.573	0.619
476	0.415	0.728
477	0.415	0.364
478	0.253	0.537
479	1	0.348
480	0.568	0.563
481	0.545	0.549
482	0.348	0.674
483	1	0.163
484	0.355	0.52
485	1	0.401
486	0.632	0.785
487	1	0.757
488	0.568	0.705
489	0.731	0.331
490	1	0.824
491	0.731	0.487
492	1	0.51
493	0.545	0.757
494	1	0.814
495	0.632	0.553
496	1	0.45
497	0.737	0.177
498	0.415	0.403
499	0.632	0.525
500	1	0.728
501	0.545	0.657
502	0.737	0.735
503	0.545	0.629
504	0.731	0.563
505	0.545	0.604
506	0.737	0.308
507	0.415	0.785
508	0.545	0.705
509	0.269	0.59

Coding (With corresponding images)

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
data = pd.read_excel('Final-data.xlsx')
import seaborn as sns
sns.set(font='Times New Roman',font_scale=1.5)
```

```
def cleanB(x):
    if x == 0 :
        return -4
    elif x == 1:
        return 4

def cleanC(x):
    if x == 0 :
        return -2
    elif x == 1:
        return 4

def cleanD(x):
    if x == 0 :
        return -4/3
    elif x == 1:
        return 4

def cleanE(x):
    if x == 0 :
        return -2
    elif x == 1:
        return 4

def cleanF(x):
    if x == 0 :
        return -4/3
    elif x == 1:
        return 4

data['B'] = data['B'].apply(cleanB)
data['C'] = data['C'].apply(cleanC)
data['D'] = data['D'].apply(cleanD)
data['E'] = data['E'].apply(cleanE)
data['F'] = data['F'].apply(cleanF)
```

```
def entropy(li):
    li = np.array(li)
    for i in range(li.shape[1]):
        li[:,i] = (li[:,i] - min(li[:,i]))/(max(li[:,i]) - min(li[:,i]))
    m, n = li.shape
    k = 1 / np.log(m)
    yij = li.sum(axis=0)
    pij = li / yij
    test = pij * np.log(pij)
    test = np.nan_to_num(test)
    ej = -k * (test.sum(axis=0))
    wi = (1 - ej) / np.sum(1 - ej)
    return wi
```

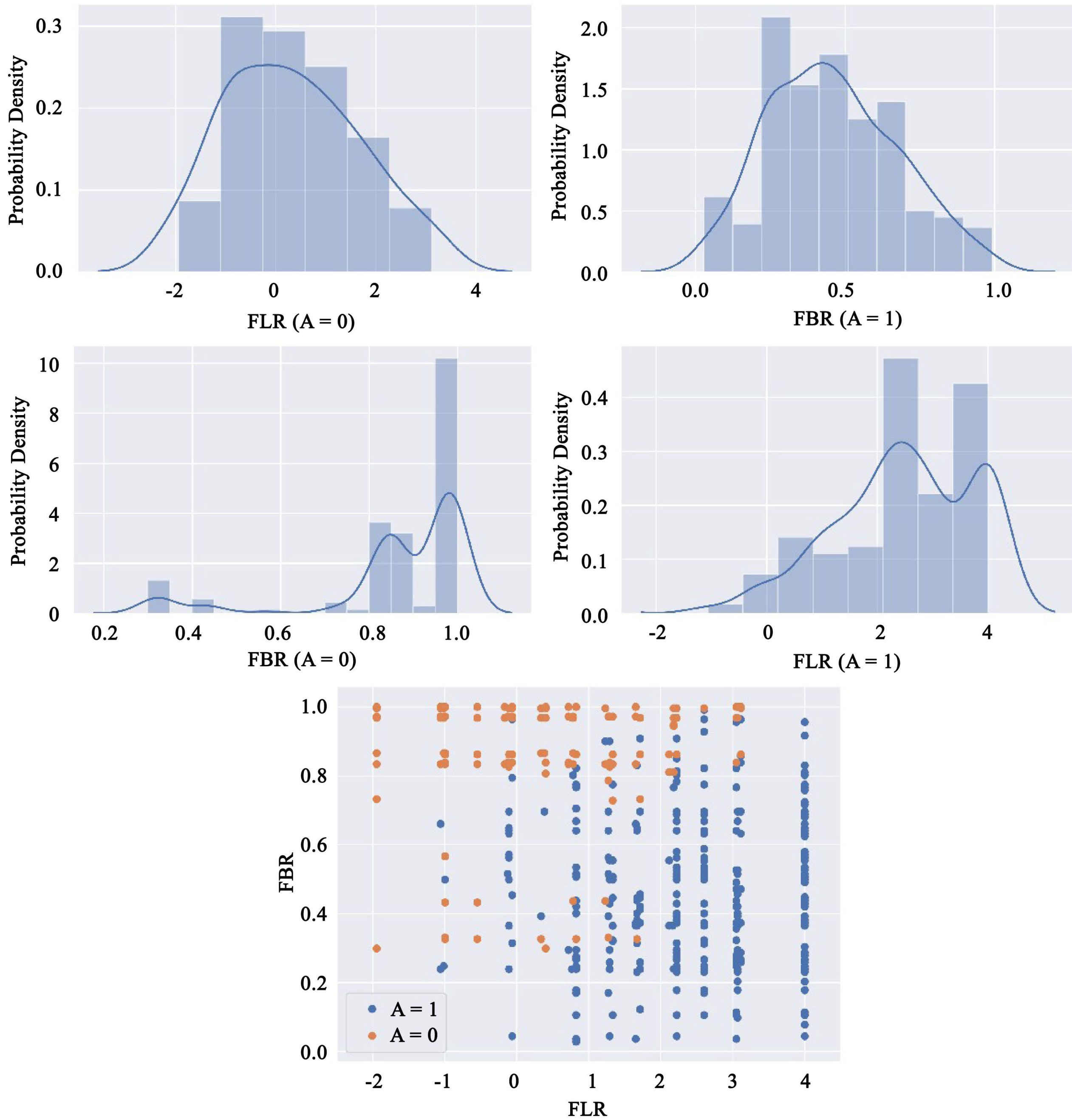
```
li=data[['B','C','D','E','F']]
wi = entropy(li)
data['FLR'] = np.dot(np.array(data[['B','C','D','E','F']]),wi)
```

```
def clean_min_max(x):
    return (max(x) - x)/(max(x)-min(x))
data['G'] = clean_min_max(data['G'])
data['H'] = clean_min_max(data['H'])
data['I'] = clean_min_max(data['I'])
li=data[['G','H','I']]
wi = entropy(li)
data['FBR'] = np.dot(np.array(data[['G','H','I']]),wi)
```

```
plt.figure(figsize=(8,6))
df2 = data[data['A']==1]
plt.scatter(df2['FLR'],df2['FBR'],label = 'A=1')
df1 = data[data['A']==0]
plt.scatter(df1['FLR'],df1['FBR'],label = 'A=0')
plt.xlim([-2.5,4.5])
plt.legend()
plt.xlabel('FLR')
plt.ylabel('FBR')

print('A=0's average value is ',np.mean(df1['FLR']),' Sd is ',np.var(df1['FLR']))
print('A=0's average value is',np.mean(df1['FBR']),'Sd is',np.var(df1['FBR']))
print('A=1's average value is',np.mean(df2['FLR']),'Sd is',np.var(df2['FLR']))
print('A=1's average value is',np.mean(df2['FBR']),'Sd is',np.var(df2['FBR']))
plt.savefig('scatterplot.png',dpi = 800,bbox_inches = 'tight')
```

```
import seaborn as sns
sns.distplot(df2['FLR'])
plt.xlabel('FLR(A=1)')
plt.ylabel('Probability Density')
plt.savefig('FLR(A=1).png',dpi = 800,bbox_inches = 'tight')
sns.distplot(df2['FBR'])
plt.xlabel('FBR(A=1)')
plt.ylabel('Probability Density')
plt.savefig('FBR(A=1).png',dpi = 800,bbox_inches = 'tight')
sns.distplot(df1['FLR'])
plt.xlabel('FLR(A=0)')
plt.ylabel('Probability Density')
plt.savefig('FLR(A=0).png',dpi = 800,bbox_inches = 'tight')
sns.distplot(df1['FBR'])
plt.xlabel('FBR(A=0)')
plt.ylabel('Probability Density')
plt.savefig('FBR(A=0).png',dpi = 800,bbox_inches = 'tight')
data.to_excel('data_with_score.xlsx')
```


Probability Density
FLR (A = 0)
Probability Density
FBR (A = 1)
Probability Density
FBR (A = 0)
Probability Density
FLR (A = 1)
FBR
FLR
A = 1
A = 0