Does gender and family income impact stock trading of B-School students? Findings from a stock simulation exercise

Abstract

Educators across the globe utilise online stock market simulation games to introduce students to trading in the stock market. The primary objective of the simulation exercise is to expose students to the practical application of financial theories on fundamental analysis, stock selection, building an optimal portfolio, monitoring the risk-return characteristics, and continuously improving the portfolio based on changing realities. This paper utilizes the trading data from a simulation exercise conducted by a leading B-school in India. The exercise was conducted as part of Security Analysis and Portfolio Management (SAPM) course offered by the B-school. The objective of the paper is to understand the role of gender and family income in the trading patterns of students in the simulation exercise. The paper covers 163 students who were part of the simulation exercise in 2019. The results indicate that male students trade more aggressively than female students, both in terms of number of trades and the number of companies traded. However, the female students reported higher stock trading performance, measured in stock returns. This is observed to be true at all the quartiles, with the largest magnitude of the difference in the mid-quartiles. The study also indicates that the students from wealthier families perform better than those from poorer backgrounds. However, family income is an insignificant differentiating factor. Further, regression analysis indicates that gender is a significant determinant of stock returns. Based on these findings, the authors argue that gender has a significant role in the stock trading performance of B-schoolers. The paper contributes to the field of behavioural finance, especially on the literature of gender and performance in financial markets.

Keywords: stock market simulation; investment behaviour; investment decisions; gender diversity; income; behavioural finance

1. Introduction

In graduate and undergraduate schools across the globe, there is a tendency to deliver economics and finance-related subjects through traditional lecture (Becker & Watts, 1995; Siegfried, Saunders, Stinar, & Zhang, 1996). The popularity of lecture format in higher education is attributed to its efficiency despite rising criticisms against the format (Renner, 1993). However, the lecture mode is not suitable for technical subjects as the individual difference in learning pace becomes prominent in the case of more difficult courses (Cashin, 1985). For technical subjects, experiential learning is reported to offer a significant improvement in the effectiveness of learning, compared to lecture-intensive delivery (Herz & Merz, 1998; Kolb & Kolb, 2009). In this context, B-schools have been experimenting with varied modes of delivery such as simulations, gamification and case study methodology, for its finance specialization courses (Black, 2000; Kumar & Dash, 2011; Gabula, 2012). This paper utilizes the trading data generated through one of such simulation exercises from a leading B-School in Bangalore, India. The students were required to participate in a mock stock trading platform as part of their elective course on Security Analysis and Portfolio Management (SAPM). The objective of the paper is to understand the impact of gender and family income on the trading pattern of students.

The debate about the differences between men and women in risk tolerance, investment decisions and trading pattern is prevalent in literature (Bajtelsmit & Bernasek, 1996; Barber & Odean, 2001; Eckel & Grossman, Sex differences and statistical stereotyping in attitudes toward financial risk, 2002). The evidences indicate that women exhibit less tolerance to risk and higher aversion to losses than men (Arch, 1993; Byrnes, Miller, & Schafer, 1999). However, there are various studies which oppose these generalizations based on gaps in methodology and biases in sample selection (Schubert, Brown, Gysler, & Brachinger, 1999; Eckel & Grossman, Men, women and risk aversion: Experimental evidence, 2008; Croson & Gneezy, Gender differences in preferences, 2009). Literature also indicates that the difference in behaviour between the two gender depends on the age of the participant with similar trading behaviour exhibited by older men and women (Cheng, Chuang, Wang, & Kuo, 2013). Studies on real gambling environment indicate that women are more risk-averse than men (Sarin & Wieland, 2016). A similar study indicates that women participate lesser in trading and hence have lesser exposure to financial knowledge which would make them hesitant to take larger risks, compared to men (Almenberg & Dreber, 2015). The controversy surrounding existing studies on gender differences in investment and stock trading raise the need for further studies in different contexts, to understand whether the differences in trading pattern between the genders remain consistent. In this context, we intend to contribute to this debate by understanding the difference in the trading pattern between male and female B-school students that participated in the simulation exercise.

Another question of interest to the researchers is whether the family income of students have an important role in the stock trading pattern of students? Does higher income lead to more risk-taking and hence aggressiveness? The limited literature indicates that income has no significant impact on individual investor’s trading behaviour (Chandra, 2009).

Hence, the paper attempts to understand whether gender and income have a significant role in determining the trading pattern and performance of B-school students. The analysis is conducted through ANOVA, CDF and regression. The paper contributes to the existing literature and is relevant to the studies in the field of behavioural finance using primary data collected through experiential trading. Our findings clearly indicate that gender and family income are significant indicators of stock returns. Though male students trade more aggressively than female students, both in terms of number of trades and the number of companies traded, they report lower returns than female students across all quartiles. The study also indicates that the students from wealthier families perform better than those from poorer backgrounds across most of the quartiles.

The paper is structured in five sections, the next section covers a description of theoretical background and literature review, section 3 covers the research methodology, results and discussion are detailed in section 4 followed by conclusion in section 5.

2. Theoretical Background and Literature Review

The theories based on the importance of human rationality in financial decisions was challenged by researchers such as Daniel Kahneman and Amos Tversky (Kahneman, Slovic, Slovic, & Tversky, 1982; Kahneman & Tversky, The psychology of preferences, 1982). The research led by Daniel Kahneman also proposed the "Prospect Theory" which introduced asymmetry between way human brain makes decisions involving gains and losses (Kahneman, Slovic, Slovic, & Tversky, 1982). According to the prospect theory, investors who are risk-averse to investment decisions involving gain could be risk-taking when it involves losses.

The theories on behavioural finance have introduced psychological biases as an influencing factor in investor behaviour (Graham, Harvey, & Huang, 2009). The study concluded that the investor's decision-making process is based on their assessment of individual competence. The findings suggest that men have higher assessment of their competence leading to overconfidence and higher optimism reflected in their investment decisions. Further, larger the portfolio and higher the financial literacy, greater the tendency to be aggressive in their investment.

Further studies attributed the difference in the investor behaviour between the two genders to risk-taking abilities, social preference and reaction to competition (Croson & Gneezy, Gender differences in preferences, 2009). The systematic review conducted to understand role of gender in financial decision-making concludes that women are less willing to compete and is risk-averse. Although the existing literature has attributed the differences to the three factors, the study suggests that the source of these differences were speculative.

Other studies also indicate a significant difference between the two genders in risk-based investment (Arch, 1993; Byrnes, Miller, & Schafer, 1999; Barber & Odean, 2001). However, contrasting views have been developed by researchers such as Schubert according to whom the two genders made identical decisions when presented as investment and insurance options, indicating no significant impact of gender (Schubert, Brown, Gysler, & Brachinger, 1999). According to this research, the gender difference in investment decisions under the influence of risk are contextual. Similar studies also indicate that when the level of risk involved was not presented to the investors, there were no significant difference between the behaviour of two genders (Sarin & Wieland, 2016).

Eckel and Grossman contribute to the lack of compatibility between the findings of existing studies to the difference in the framing of the problem in terms of potential payoffs and risks involved (Eckel & Grossman, Men, women and risk aversion: Experimental evidence, 2008). Recent studies also indicate that though women are more averse to losses than men, they want to gain as badly as men (Wieland, Sundali, Kemmelmeier, & Sarin, 2014; Braga & Fávero, 2017). Based on studies conducted in the Brazilian stock market, Almenberg and Dreber attributed the risk aversion of women to their lower participation in stock market and financial knowledge (Almenberg & Dreber, 2015).

The competence theory proposed by Graham (Graham, Harvey, & Huang, 2009) propose that higher income would enhance the confidence of the investor, indicating that there is a possibility in different trading behaviour based on income levels. However, the limited literature indicates that income has no significant impact on individual investor's trading behaviour (Chandra, 2009).

The contrasting views on the importance of gender in financial decision-making motivates the researchers to extend the studies to the specific context of simulation trading of students. The following section details the research methodology.

3. Research Methodology

The simulation exercise administered through a mock-trading platform allowed students to view, analyse and follow the trading of other participants in the group, similar to an actual stock market. A total of 163 (male –83, female – 80) students aged between 21 and 28 (average age: 23.39) participated in the simulation. The participants were provided with an initial capital of INR 500,000 to start trading. The students participated in the simulation exercise for the entire trimester i.e. eight weeks during January – March 2019. As shown in Table 1, the sample considered for study has an equal distribution of male and female students. The finance specialization in MBA is generally preferred by students with under graduate (UG) degree in commerce. The other UG degrees include management, engineering and arts. The family income reported by the students during the time of admission is taken for analysis. Though, the sample has larger proportion of students with commerce background and family income less than INR 500,000, the sample is adequate for further analysis as the smaller groups are more than 30 percent of the sample. The family income in lakhs of Rs. is used for the regression analysis.

Table 1: Classification of the participants

Demographics	Variables	Frequency	% of total
Gender	Male	83	50.92
	Female	80	49.08
Under graduation (UG) specialization	Commerce	105	64.42
	Others	58	35.58
Family Income	<=500,000	107	65.64
	>500,000	56	34.36

The trading characteristics used for analysis include number of companies traded in, number of trades placed (including both buy and sell) and portfolio return obtained during the period. Based on the existing literature, the control variables used are the past academic performance and age of the students. The average of the marks obtained in centralized school examinations, UG and completed trimesters of MBA is used as a measure of past academic performance. The descriptive statistics of the numerical variables used for analysis are provided in Table 2.

Table 2: Descriptive statistics of numerical variables used for analysis

Variables	Minimum	Maximum	Mean	SD
Return	-29.97	16.01	4.44	4.61
Number of companies traded	1.00	77.00	20.39	13.74
Number of trades	1.00	197.00	44.02	39.33
Average marks	62.52	86.38	75.74	4.62
Family income	0	35	6.01	5.68
Age	21	28	23.39	1.36

Statistical tools

We utilize analysis of variance (ANOVA) to identify the difference in trading patterns based on gender, UG specialization and family income. The first step is to understand whether the portfolio returns is significantly different between the groups. Once the group characteristics leading to significantly different portfolio returns are identified, further analysis is conducted to determine the factors contributing to the difference. The number of companies traded in and the number of trades placed are used to explain the difference in portfolio return. Further analysis of the difference in portfolio return is obtained through cumulative distribution function (CDFs) for the different groups.

To understand the factors impacting investment decisions, and hence the returns posted, we adopt a multivariate ordinary least-square (OLS) model. The percentage return obtained by the students during the eight-week trading is used as the dependent variable. Gender and family income are the independent variables considered for the study. The control variables used are age, past academic performance and UG specialization are included as control variables.

We develop the functional form for the above cross-sectional OLS models as:

Portfolio return = *f* (gender, age, average percentage, UG specialization, family income)

$$y_i = \beta_0 + \beta_1\text{*gender dummy} + \beta_2\text{*age} + \beta_3\text{*av. percentage} + \beta_4\text{*commerce dummy} + \beta_5\text{*family income} + e_i$$

where, y_i represents the stock market return, β_1 to β_5 are the coefficients of the model and e_i is the remaining error term.

Regression diagnostics

Prior to building the regression model, correlation matrix is constructed to identify multicollinearity of independent variables. As the independent variables are a combination of numerical and categorical variables, we use Pearson's coefficient for correlation between numerical variables, point biserial correlation for combinations of numerical and categorical variables and Cramer's V for correlation between categorical dummy variables. After building the regression model we check for normality, homoscedasticity and autocorrelation of residuals using PP plot, Breusch Pagan test and Durbin-Watson test, respectively.

The results of the analysis are provided in the following section.

4. Results and Discussion

The ANOVA results provided in Table 3 clearly show that the portfolio return is significantly different between male and female groups. In consensus with the existing literature, the results indicate that female students reported an average portfolio return higher than that of the male students (Barber & Odean, 2001). However, the difference in portfolio return for various UG specialization and family income groups is insignificant. The students with commerce background in fact recorded lower portfolio return as compared to other streams. The students from wealthier families reported a higher performance; however, the difference is not significant.

Table 3: Results of ANOVA – Difference between the return by gender, academic background and family income group

Demographics		N	Mean	SD	F-statistic (p-value)
Gender	Male	83	3.72	5.25	4.21 (0.0418**)
	Female	80	5.19	3.73	
Under graduation	Commerce	105	4.21	5.04	0.72 (0.3980)
	Others	9	4.85	3.73	
Family income group	>5 lakhs	56	5.23	3.66	2.54 (0.1130)
	<=5 lakhs	107	4.03	5.01	

**p<0.05

In the next step, we look deeper at the difference in trading behaviour between the two gender groups. We consider the difference in the number of companies traded in and the number of trades placed, including both buys and sells. As the results in Table 4 indicate the two groups based on gender are significantly different on all the factors considered. Though the female students have reported higher portfolio return, the male students are more aggressive traders with higher number of companies traded in and trades placed. According to Barber and Odean, overconfidence male investors trade aggressively which leads to lower net returns (Barber & Odean, 2001).

Table 4: Results of ANOVA – Difference between the trading pattern of male and female students

Variable	Male	Female	F-statistic (p-value)
Portfolio return	3.72	5.19	4.211 (0.042**)
# of companies traded in	22.87	17.83	5.640 (0.019**)
# of trades placed	51.53	36.23	6.373 (0.013**)
# of buys	32.10	23.23	6.943 (0.009***)
# of sells	19.43	13.00	4.593 (0.034**)

**p<0.05; ***p<0.01

Figure 1 shows the cumulative distribution functions of portfolio return for the two genders. The CDF plot and Table 5 indicate that female students outperform male students on every percentile of portfolio return. Further, we also notice that the losses incurred by the female students are lower than that of the male students at the same percentile.

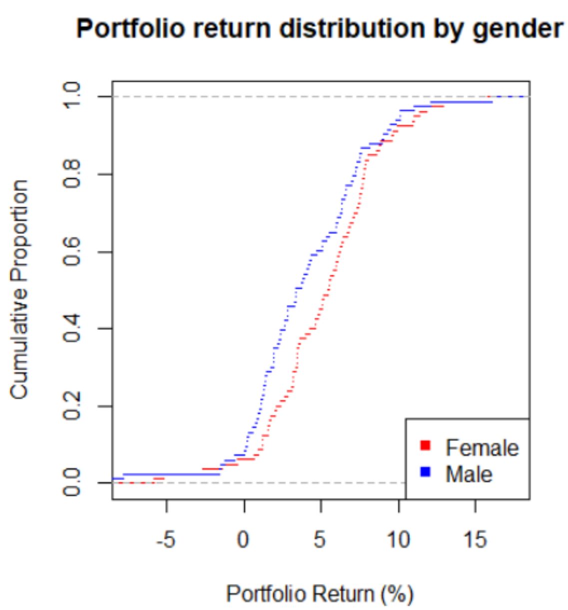

Figure 1: Cumulative distribution function of portfolio return by gender

Table 5: Portfolio return by gender at different percentiles

	5th	10th	25th	50th	75th	95th
Female	-0.48	1.19	3.17	5.46	7.55	9.57
Male	-1.14	0.22	1.35	3.39	6.54	9.05
Difference	0.66	0.97	1.82	2.06	1.01	0.52

Regression results

We proceed to build a regression model to determine whether gender is a significant determinant of portfolio return. Before building the model, we build the correlation matrix to determine multicollinearity of independent variables. As mentioned in the research methodology, we calculate Pearson's coefficient for numerical variables, point biserial for correlation between numerical and categorical variables and Cramer's V for correlation between two categorical variables. The resulting correlation matrix is provided in Table 6.

Table 6: Correlation Matrix – Pearson's, Point biserial and Cramer's V coefficients

	Portfolio return (%)	Gender	Average marks	Commerce Specialization	Family income
Portfolio return (%)	1				
Gender	0.2001	1			
Average marks	0.0035	0.3087	1		
Commerce Spec.	-0.0856	0.0120	-0.0241	1	
Family income	0.1324	0.0720	-0.0379	-0.0837	1

As all the correlation coefficients in Table 6 are between +/-0.5, we proceed with the regression model. The results of the regression model given in Table 7 indicate that gender is a significant determinant of portfolio return. As indicated by the correlation coefficient, the commerce specialization has a negative impact on portfolio return. Though the family income has a positive impact on the portfolio return, the p-value indicates that the variable is not a significant predictor of portfolio return. The model has a low R^2 indicating that we have excluded variables that could be determinants of portfolio return. However, as the objective of this study is to understand the significance of gender as a predictor and not to build a predictive model for forecasting portfolio return, we proceed with the regression diagnostics on the model developed.

Table 7: Regression results

	Dependent variable: Portfolio Return (%)
Gender	1.4121** (0.0498)
Commerce specialization	-0.5824 (0.4363)
Family income	0.0971 (0.1262)
Constant	3.5394** (0.000)
Observations	163
R^2	0.0444
Adjusted R^2	0.0264
Residual Std. Error	4.552 (df = 159)
F Statistic	2.462* (0.0646)

Note: $^{**}p<0.05$; $^{*}p<0.1$

The probability-probability (PP) plot in Figure 2 is a scatter graph showing empirical CDF or portfolio return against that of the sample data. The linearity of the PP plot along with the F statistic and p-value from the regression results, we conclude that the model has a good fit to the observed data.

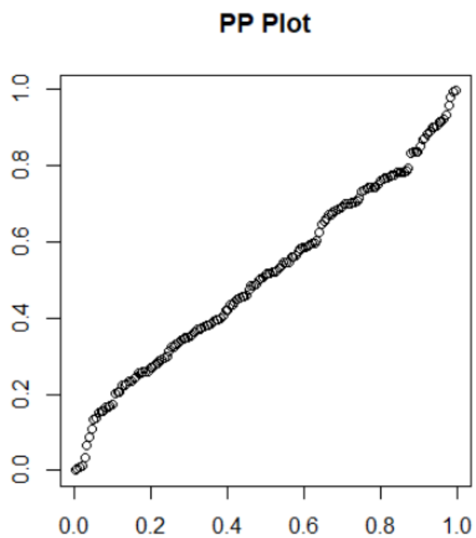

Figure 2: PP-plot to check fit of the model

We check the homoskedasticity and serial autocorrelation of the residuals of the regression model using Breusch-Pagan (BP) test and Durbin-Watson (DW) test, respectively. The results are provided in Table 8. We accept the null hypothesis that the residuals are homoskedastic and that there is no serial autocorrelation.

Table 8: Results of BP test and DW test of residuals

BP Statistic (p-value)	1.5961 (0.6603)
DW Statistic (p-value)	2.0055 (0.5100)

The analysis clearly shows that gender is a significant determinant of portfolio return for the sample of B-School students. Further, family income and educational background of the students are insignificant predictors of portfolio return.

Conclusion

The study is part of the field of behavioural finance, specifically relating to gender and performance in the stock market. The results indicate that there is a significant difference in the trading pattern of male and female students. The evidence obtained from our analysis shows that male students are more aggressive in the market, while the female students trade less frequently. The difference between the two genders is evident in both the number of trades and the number of companies traded in. It is expected that our evidences provide motivation for further research in this area. For further studies, we recommend longitudinal studies on larger samples. Studies could also focus on how the performance changes after acquiring knowledge of the market through the course.

References

Almenberg, J., & Dreber, A. (2015). Gender, stock market participation and financial literacy. *Economics Letters , 137*, 140-142.

Arch, E. C. (1993). Risk-taking: a motivational basis for sex differences. *Psychological reports , 73* (1), 3-11.

Bajtelsmit, V. L., & Bernasek, A. (1996). Why do women invest differently than men? *Financial Counseling and Planning , 7*.

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The quarterly journal of economics , 116* (1), 261-292.

Becker, W., & Watts, M. (1995). Teaching tools: Teaching methods in undergraduate economics. *Economic Inquiry , 33* (4), 692-700.

Black, C. (2000). Finance Education: An Experiential Approach in an Open Learning Environment. *Industry and Higher Education , 14* (5), 305-3016.

Braga, R., & Fávero, L. P. (2017). Disposition effect and tolerance to losses in stock investment decisions: An Experimental Study. *Journal of Behavioral Finance , 18* (3), 271-280.

Byrnes, J. P., Miller, D. C., & Schafer, W. D. (1999). Gender differences in risk taking: a meta-analysis. *Psychological bulletin , 125* (3), 367.

Cashin, W. E. (1985). *Improving Lectures. Idea Paper No. 14.*

Chandra, A. (2009). Individual investors' trading behavior and the competence effect. *IUP Journal of Behavioral Finance , 6* (1), 56.

Cheng, Y. H., Chuang, S. C., Wang, S. M., & Kuo, S. Y. (2013). The effect of companion's gender on impulsive purchasing: the moderating factor of cohesiveness and susceptibility to interpersonal influence. *Journal of Applied Social Psychology , 43* (1), 227-236.

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic literature , 47* (2), 448-74.

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic literature , 47* (2), 448-74.

Eckel, C. C., & Grossman, P. J. (2008). Men, women and risk aversion: Experimental evidence. *Handbook of experimental economics results , 1*, 1061-1073.

Eckel, C. C., & Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and human behavior , 23* (4), 281-295.

Gabula, A. (2012). Experiential learning in management education. *Journal of Applied Management and Investments , 1* (3), 319-325.

Graham, J. R., Harvey, C. R., & Huang, H. (2009). Investor competence, trading frequency, and home bias. *Management Science , 55* (7), 1094-1106.

Herz, B., & Merz, W. (1998). Experiential learning and the effectiveness of economic simulation games. *Simulation & Gaming , 29* (2), 238-250.

Kahneman, D., & Tversky, A. (1982). The psychology of preferences. *Scientific American , 246* (1), 160-173.

Kahneman, D., Slovic, S. P., Slovic, P., & Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases.* Cambridge university press.

Kolb, A. Y., & Kolb, D. A. (2009). The learning way: Meta-cognitive aspects of experiential learning. *Simulation & gaming , 40* (3), 297-327.

Kumar, S., & Dash, M. K. (2011). Management education in India: trends, issues and implications. *Research Journal of International Studies , 18* (1), 16-26.

Renner, P. (1993). *The art of teaching adults.* Vancouver, British Columbia: Training Associates.

Sarin, R., & Wieland, A. (2016). Risk aversion for decisions under uncertainty: Are there gender differences? *Journal of Behavioral and Experimental Economics , 60*, 1-8.

Schubert, R., Brown, M., Gysler, M., & Brachinger, H. W. (1999). Financial decision-making: are women really more risk-averse? *American economic review , 89* (2), 381-385.

Siegfried, J., Saunders, P., Stinar, E., & Zhang, H. (1996). Teaching tools: How is introductory economics taught in America? *Economic Inquiry , 34* (1), 182-192.

Wieland, A., Sundali, J., Kemmelmeier, M., & Sarin, R. (2014). Gender differences in the endowment effect: Women pay less, but won't accept less. *Judgment & Decision Making , 9* (6).