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An Empirical Analysis of Financial Risk Tolerance and Demographic Factors of Business Graduates in Pakistan

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ABSTRACT

The purpose of this empirical study was to investigate whether financial risk-tolerance differs among business graduates in Pakistan based on their demographic factors (i.e., gender, age, education, experience, income, saving, location, and occupation). This study has tested the financial risk-tolerance scale developed by Grable and Lytton (1999) to empirically measure the different dimensions of financial risk. The study employed a quantitative approach to a multinomial logistic regression model and an online questionnaire tool for the primary data collection. The well-designed questionnaires were distributed among business graduates through online media. The empirical findings of the study depicted a significant positive effect from all the demographics against financial risk-tolerance. Specifically, the results showed that male business graduates having more income and savings, those with more education qualifications and also older graduates are positively related to financial risk-tolerance. However, the relationship between financial risk-tolerance and experience level of individuals was found negative and insignificant, and the same result between the two variables can be confirmed by the findings of the correlation analysis. Furthermore, the parametric study showed that geographical differences exist among business graduates in terms of financial risk-tolerance attitudes.

Keywords: Risk Tolerance, Demographic Factors, Financial Risk, Multinomial Logistic Regression, Cross Regions JEL Classifications: G1, G32, G41

1. INTRODUCTION

Financial risk-tolerance is generally described as the maximum amount of outcome a person is inclined to accept when making a financial decision. It plays a fundamental role in each households' optimal portfolio decisions. It is also considered a key factor in regulating various government policies linked to consumer risks concerning financial decisions. A financial planner's capability to knob risks may be generally associated with investor demographic features viz. gender, age, income, time horizon, investment knowledge, education level, liquidity needs, location, portfolio size, and attitude towards price fluctuations (Fredman, 1996). It has been extensively recognized that for financial planners, it is crucial to make an endeavor to empirically calculate every investor's financial risk-tolerance level using a subjective approach (Mittra, 1995).

The study of (Copeland et al., 2005) in his book entitled, "Financial Theory and Corporate Policy," enumerate individuals on the basis of risk aptitudes, thus the scope of risk in the field of finance theory can never be denied. Thus, viewing the subject area in more detail, the study started from individual perspectives with their insight in terms of the financial risk-tolerance (FRT) in order to get benefit from the observed association of the risk-tolerance and expected returns. The underlying study considers the FRT as an issue of deep concern given by (Grable, 2000; Grable and Lytton, 1999; Hallahan

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et al., 2004; and O'Neill, 2000). The FRT is considered as the major contributor in a portfolio performance (Brinson et al., 1995). Risk tolerance is considered as the absorbing volatility and the variation in returns as per the study of (Grable, 2000; Grable et al., 2004; and Hallahan et al., 2004). The study of financial-risk can be studied deeply by considering the demographic features of an individual, such as qualification, income, and employment status (Grable, 1997). Similarly, (Graham et al., 2002) and (Lovris et al., 2008) also addressed that age, income, and gender of an individual are the significant characteristics to investigate the FRT; whereas, (Joo and Grable, 2004; Laroche et al., 2001; and Pålsson, 1996) stressed the effects of social and demographic characteristics on the financial risk-tolerance of individuals. Another important research study conducted by Sweet (2013) concluded that age, income, gender, years to retirement, education, ability to tolerate risk, and cash flow needs, etc. are important demographic characteristics determining the appropriate risk-tolerance of clients.

Grable and Lytton (1998) have further updated the existing list to the eight most extensively suggested and researched demographic aspects that are typically treated to be the most compelling characteristics for classifying investor risk-tolerance, e.g., gender, age, occupation, self-employment, marital status, income, education, and race. These demographic characteristics of individuals were reliant on risk predicting heuristics introduced in a research study by (Roszkowski, 1992). These are the risk predicting heuristics which are extensively considered to separate individuals into low, average, and high-risk scales. However, there is still no final consensus among researchers and the apparent controversy continues with regard to the best demographic factors as predictors of FRT (e.g., Gilliam et al., 2010; Grable and Lytton, 1998).

The empirical model presented in the study carried out by (Grable and Lytton, 1998) reveals the contributory role of investor FRT as captured by various demographics; however, the controversy has not yet been resolved. If definite demographics can be related to FRT, these aspects may serve as an appropriate arrangement for arranging individuals into risk-tolerance benchmarks. For reliable techniques for measuring financial risk-tolerance is developed by financial advisors; however, many researchers rely on other assessment techniques, which are not appropriately calculated FRT (Grable and Lytton, 1999a). Besides, the financial analysts suggest there is little empirical research consisting of the continued implications of these features as effective determinants (Grable and Lytton, 1999a). Because of the non-availability of a welldesigned risk-tolerance measurement technique and the general use of heuristics by financial experts, the authors believe there is a need for a financial advisor to get a better understanding of the association between risk levels and demographics so as to better guide their clients (Gilliam et al., 2010; Grable and Lytton, 1999a). This can be handled by exploring if demographics have a connection to an individual's FRT, and which characteristics are more valid in predicting that association.

In Pakistan, it had been of immense consideration that how business graduates' preference for risk because business orientation is very important for their successful career. The reason is that business graduates are future financial advisors (business leaders) who will invest with a specific approach by utilizing the financial knowledge, skills, and clear understanding. Unfortunately, in Pakistan, this research area has not yet been attracted the attention of financial economists, financial advisors, and financial analysts. Accordingly, the primary ambition of this study is to fill the existing research gap and to investigate the relationship between FRT and various demographic factors in selecting business graduates in order to rescue them in inappropriate decisions.

The rest of this study will proceed as follows: the "Literature review" section reviews the empirical literature. The "Data description" section deals with the sampling procedure, data collection technique, and variables construction. The "Methodology" section focuses on the analytical framework and estimation strategy. The empirical findings are noted in the "Empirical results" section. The "Conclusion and Implications" section summarizes the whole study.

2. LITERATURE REVIEW

A number of empirical works have extensively analyzed demographic factors related to financial risk-tolerance. Baker and Haslem (1974) conducted a study to find out the impact of investor's socioeconomic characteristics on risk-return and risk preferences. The analysis aptly pointed out that the most important socioeconomic characteristics of individuals that are significantly influencing the common stock risk and return preferences include age, sex, marital status, education, income, and decision orientation; however, occupation and portfolio size have insignificant effects on the targeted aspects. Using the analysis of ANOVA and the linear regression approach, McInish (1982) concluded that age, assets, high-risk portfolio, and the value of common stock were significant determinants of financial risk levels. Using the 1992 Survey of Consumer Finances (SCF), Sung and Hanna (1996) employed the logistic regression model to explore the effects of financial and demographic features on financial risk-tolerance. The empirical analysis included econometrically active 2659 household respondents aged 16-70 years. The results of logistic regression show that age and years to retirement were significantly related to financial risk-tolerance. Liquid and non-liquid assets, self and non-self-employed, education, race, household size, marital status, occupation, and homeownership were insignificantly related to financial risk-tolerance. The study also concluded that femaleheaded households were less risk-tolerant than male-headed households.

Additionally, Grable (2000) investigated the effects of demographic, socioeconomic, and attitudinal factors on financial risk-tolerance by selecting 1075 working employees from South Eastern University, USA. The results of the discriminant analysis showed that financial risk-tolerance in money matters was associated with being male, married, older, professionally employed with higher income, more financial knowledge, more education, and increased economic expectations. Another relevant study conducted by Jianakoplos and Bernasek (2006) decomposed the influences of birth control, chronological order, and calendar year on the age profile of household financial risk-taking activity. The results reported that age was negatively affected the risk-taking

behavior. The findings further revealed that the age-risk profile down from older to younger cohorts. Similarly, (Faff et al., 2009) explored the nonlinear linkage between financial risk tolerance and demographic factors. The testing procedures support the nonlinear role of age, income, and number of dependents on financial risk-tolerance.

In the context of Pakistan, a more recent study by (Shah et al., 2017) tried to investigate the relationship between demographic characteristics and financial risk-tolerance among business students. The correlation analysis reported that the relationship between various demographic factors and financial risk-tolerance was positive and significant, except for occupation. Likewise, the analysis of the simple linear regression model showed that the association between gender, saving, and the location was significant with financial risk-tolerance; however, there was an insignificant relationship found between age, education, experience, income, and occupation with financial risk-tolerance. A most recent and similar study conducted by (Shah et al., 2018) explored the interconnection between demographics and modes of investment. Pearson's correlation analysis showed positive and significant interlinks between saving and investment modes; however, most demographics were not statistically significant in the analysis. The major drawback of these studies is the lack of use of multinomial logistic regression analysis. Therefore, the current study is an in-depth attempt to fill the existing gap found in the finance literature.

3. DATA DESCRIPTION

3.1. Sampling Procedure

This empirical study used the cross-sectional dataset which was collected from six major cities of Pakistan viz. Karachi, Peshawar, Islamabad, Lahore, Quetta, and Chitral covering the time span started from 01 April 2019 to 30 July 2019. The selected convenience sample included business graduate and postgraduate students from six well-established private and public sector universities in the province of Khyber Pakhtunkhwa, Pakistan (n = 382)¹. The original primary dataset was accumulated by forwarding an email with a purpose fulsurvey link to about 200students, wherein 500 questionnaires were distributed manually by personally administering the respondents. All the survey participants were informed through a cover letter and a business graduate communicator. Out of the total 700 respondents, 382 students were randomly picked from the chosen business institutes who appropriately answered financial risk-tolerance

 The selected universities include the University of Swabi; CECOS University, Peshawar; The University of Agriculture (IBMS), Peshawar; Iqra National University, Peshawar; Institute of Management Sciences, Peshawar; and the University of Peshawar (IMS), Peshawar. questions online² ($n_1 = 70$) through the Google Docs website and manually ($n_2 = 312$); whereas, 318 inconveniently filled questionnaires of the survey were discarded from the sample size to avoid misleading regression results.

3.2. Data Collection Instrument

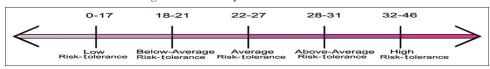
A sampling survey was conducted through a well-structured questionnaire based on a risk scale originally developed by Grable and Lytton (1999), commonly known as the Grable and Lytton risk-tolerance scale (G/L-RTS). Based on the convenient sampling technique, data were manipulated while distributing a questionnaire having 34 questions to all the participants given by Dubinsky and Redilius (1980). Data on socioeconomic, demographic and risk tolerance (RT) measures were designed to elicit a respondent's attitude towards the risk assessment. The questionnaire included 13 risk-tolerance questions similar to those suggested in the 13-Item GL-RTS. To record the level of risktolerance (FRT), five different groups were scaled as suggested by (Nobre et al., 2016), where a business student must fall into one category based on his/her attitude towards the risk. An individual will be considered a lower-risk tolerant if he/she falls in the risktolerance score ranged from 0 to 17, a below-average risk-tolerant if he/she falls in the class ranged from 18 to 21, a moderate-risk tolerant if he/she falls in the category ranged from 22 to 27, an above-average risk-tolerant if he/she lies in the category ranged from 28 to 31; and finally, a student will show high tolerance for risk by taking investment decisions if he/she lies in the class ranged from 32 to 46. However, the introductory questions in the questionnaire were recorded as demographic variables having different categories. The sampling technique used in the current study matched closely with the studies attempted by (Sung and Hanna, 1996; Grable and Lytton, 2001; Gilliam et al., 2010; Nobre et al., 2016; Shah et al., 2017; 2018). The designed risk-tolerance scale is given in Figure 1.

3.3. Variables Construction

This empirical study includes all those variables in the regression specification which are essentially qualitative in nature and is known as categorical variables, namely financial risk-tolerance, gender, age, education, job experience, income level, saving status, location, and employment status. The regression models which encounter independent variables that are all exclusively qualitative in nature are known as ANOVA (Analysis of Variance) models. ANOVA models are often employed to evaluate the statistical significance of the specific association between the quantitative dependent variable and qualitative independent variables. The purpose of such models is to compare the differences in the average values of two/more categories and is, therefore, more general than

2 https://docs.google.com/forms/d/e/1FAIpQLSeZweQdWI8_dX3CFqOx2 WHIfpk8o_8xQ1TmFT0eYeKNn618TQ/viewform?c=0&w=1.

Figure 1: Grable-Lytton risk-tolerance scale



Source: Author's own illustration, 2019

the t-statistic which can be suggested to compare the means of two categories only.

3.3.1. Dependent variable

The criterion variable in this study is the FRT scores of the business community students. Score categories were determined by evaluating individuals' responses to given questions that appeared their attitude of FRT under the case of different investment avenues. The scores used in the analysis were designed using the FRT levels from the GL-RTS. The respondents willing to take the higher risk were coded 5; whereas, those respondents not ready to take any financial risk under different investment avenues were coded 1. More specifically, the financial risk-tolerance scale is categorized into 5 classifications: (i) 0-17 (low risk-tolerance=1); (ii) 18-21 (below-average risk-tolerance=2); (iii) 22-27 (average risk-tolerance=3); (iv) 28-31 (above-average risk-tolerance=4); and (v) 32-46 (high risk-tolerance=5). Risk-tolerance score levels were reverse coded for the 13 risk-tolerance questions, so that higher risk-tolerance score depicted greater risk-tolerance. Risk-tolerance categories were computed by adding the student scores from the 13 financial risk-related questions.

3.3.2. Demographic variables

A best practice advocates that when risk-tolerance perspectives are quantitatively analyzed, it is necessary to investigate unexplored features that may direct the manner in which individuals frame their risk decisions. Grable (2008) evaluated the influence various socioeconomic plus demographic aspects have in constructing RT assessments. As a matter of fact, the particular factors as predictors taken in this study are gender, age, educational level, job experience, income level, saving status, geographical location, and employment status³. There is a growing quantity of articles demonstrating that gender, age, income, education, location, etc. are significantly associated with risky financial asset ownership, such as (Zhong and Xiao, 1995; Sung and Hanna, 1996; Xiao, 1996; O'Neill et al., 2000; Chaulk et al., 2003; Grable and Lytton 2003; Wang and Hanna, 2007; Shah et al., 2017; 2018). Econometrics reports that the indicator variables viz. gender, sex, and location seem to highly influence the dependent variable and obviously should be incorporated among the regressors in the econometric analysis (Gujarati, 2003). For instance, young males with high income and higher education levels are evidently considered to hold riskier assets (Gilliam et al., 2010).

The existing literature guides us that men tend to be more inclined in taking FR decisions than women (e.g., Bajtelsmit et al., 1999; Halek and Eisenhauer, 2001; Ardehali et al., 2005; Nairn, 2005; Yao and Hanna, 2005; Grable and Roszkowski, 2007; Ganegoda and Evans, 2014). Also, previous articles have concluded that men are more specifically to invest in risky financial assets when controlling for other indicators than women (e.g., Yuh and DeVaney, 1996; Embry and Fox, 1997; Sunden and Surrett, 1998; Zagorsky, 2005). Gilliam et al. (2010) derived that gender differences in RT are consistent across generations while keeping all other household characteristics the same. However, we should expect females to prevail lower risk-tolerance scores than men, irrespective of cultural backgrounds. In our analysis, gender was measured as 1 if a student is male and 0 may indicate a female student. Hence, we expect that: H_{01} : Male business graduates are more risk-tolerant than female business graduates.

Two viewpoints attracted researchers thinking about the association found between RT and age. Many financial advisors and popular press reporters are of the view that an individual's age is inversely associated with RT attitudes (Nairn, 2005; Deaves et al., 2007; Gilliam et al., 2010; Kaczynski et al., 2014). According to these studies, there is the likelihood that as people age grows their tolerance for risk drops as a result. However, current studies criticize this presumed fact. That is, the recent literature is highly supportive of the fact that age vs. risk-tolerance association is often a positive one (Ardehali et al., 2005). Individuals believe that the correlation between age and risk-tolerance is a signal of a shrinking time horizon for old-aged personnel. This undeniable fact may have less to do with an individual's desire to indulge in risky behavior because the individual will not be able to recover the lost assets. Therefore, it is attractive to assume that RT measurement levels vary in comparison to age groups. From the standpoint view of analysis, students' ages were classified into 3 age decades: (i) 18-24 years (=1, 0 otherwise); (ii) 25-40 years (=1, 0 otherwise); and (iii) 41 years and older (=1, 0 otherwise) to reveal the differences in asset holdings across age categories and to capture students' outlook towards risk under different circumstances (e.g., Shorrocks, 1975; Heaton and Lucas, 2000). Prior empirical articles have concluded that age is a predictor of students' savings-investment participation (e.g., Haurin et al., 1996; Ameriks and Zeldes, 2000) with younger students being more probable to take financial risks in pursuit of their monthly or per annum savings and investing goals. The qualitative variable of age takes the artificial value of 1 if a student belongs to a particular group and 0 if he/she does not belong to that category. Though the existing studies have no final consent at this point, this research attempt follows the former argument. Hence, we expect that: H_{02} : The level of risk-tolerance of a student decreases as age goes up.

Educational qualification of students is considered as the number of years of formal university education, having two classes, i.e., graduate education and postgraduate education. The graduatelevel of education included all those students who were enrolled in B.Com and BBA (Honors) degrees bearing 13-16 years of education. Whereas, the postgraduate level of education composed of all those students who were enrolled at M.Com, MBA, MS/M. Phil. and Ph.D. degrees having at least 16 years of education. Educational attainment levels of students were controlled by selecting a dichotomous variable, coded as 0 if the business student had an educational qualification of undergraduate and as 1 if the student had an education at the postgraduate level. In previous research, it was observed that the educational level of students was found to be a predictor of savings and retirement planning behavior (e.g., Yuh and DeVeney, 1996; and Springstead and Wilson, 2000). Maccrimmon and Wehrung (1986) in their study concluded that a higher level of education encourages a student to take ahigher financial risk. Likewise, other empirical studies derived the fact that the higher levels of education are closely

³ All the considered independent variables in this study are cases for crosssectional analysis.

connected with a higher level of FRT (e.g., Lee and Hanna, 1991; Sung and Hanna, 1996; Grable and Lytton, 1999a; 1999b; Grable, 2000; and Al-Ajmi, 2008). Hence, this trend leads us to formulate the null hypothesis as: H_{30} : Business graduates who have higher education tend to have a higher level of risk-tolerance.

Income is measured as the total income of a respondent earned from all earning sources per annum calculated in Pakistan's currency. Previous studies indicated that compared to men; females usually have lower annual incomes and apparently are more riskaverse. The financial planners suggested that men had higher annual incomes and exhibited greater FRT, and this outcome is in line with the study conducted by Kannadhasan (2015) stated that people with higher income levels have sufficient resources to fulfill their basic commitments. If an investor has more liquid money in hand, so he/she may have greater potential over the risk occurring in the future. (Hallahan et al., 2003; Grable et al., 2006 and Thanki, 2015) noted that high-income people have financial funds to tackle losses, yielding risky investment decisions. These results are also found in the studies handled by Sulaiman (2012) and Thanki (2015) who say that income level has a significant influence on FRT. To notice this result, the annual income of students is divided into 5 income categories: (i) students with <Rs. 100,000/ year (=1, 0 otherwise); (ii) Rs. 100,000 to Rs. 200,000/year (=1, 0 otherwise); (iii) Rs. 200,001 to Rs. 300,000/year (=1, 0 otherwise); (iv) Rs. 300,001 to Rs. 400,000/year (=1, 0 otherwise); and (v) those students with over Rs.400,000/year (=1, 0 otherwise). Hence, we can formulate the null hypothesis as: H_{40} : The level of risk-tolerance increases with the increase in the level of income of business graduates.

Evidence depicts that another demographic feature that seems to affect the FRT is the individual's occupation. Scholars have concluded that individuals working in professional occupations exhibit more risk-tolerant than those people engaged in nonprofessional occupations (Grable and Lytton, 1998). Nonetheless, Sung and Hanna (1996) showed that there was no such significant influence of occupation status on financial risk-tolerance. Grable and Lytton (1998) showed that factors responsible for occupational status as well as self-employment have been notable in differentiating between levels of FRT. It is noticed that businessmen and other business organizers probably tend to higher levels of risk-seeking than those employers who just earning monthly basis salary or wages on a daily basis. This situation compels the world scholars to examine the occupation status in research works that investigates the person's attitude of risk tolerance. However, there is a final conclusion among authors that self-employed workers are more likely to have an increased level of FRT as compared to salaried workers (Haliassos and Bertaut, 1995). For such intention, 4 groups are marked to indicate students' employment status: (i) student is employed in a private organization (=1, 0 otherwise); (ii) student is working in a public sector organization (=1, 0 otherwise); (iii) student is self-employed or in business partnership (=1, 0 otherwise); and (iv) student is an employee of someone else (=1, 0 otherwise). Hence, we expect that: H₅₀: Self-employed business graduates tend to have an increased degree of risk-tolerance than salaried graduates.

Saving is the difference between income and consumption of a person (Browning and Lusardi, 1996). The human ability to tolerate the financial risk depends on the consumer's financial wealth (i.e., investment and saving). More saving of individuals tends to increase investment pattern which leads to high financial risk. In our study, saving is considered in the percentage form which is categorized into 5 choices: (i) saving <5% of income (=1, 0 otherwise); (ii) 5-10% of income (=1, 0 otherwise); (iii) 11-20% of income (=1, 0 otherwise); (iv) 21-30% of income (=1, 0 otherwise); and (v) above 30% of income (=1, 0 otherwise). Hence, we expect that: H_{60} : Risk-taking behavior of business graduate increases with saving.

Experience depicted the number of years individuals worked in different types of organizations. The review of literature guides us that the precipitating factor of experience affected the degree of risk-tolerance among people. That is, individuals with the least experience are having a less risky portfolio, which will earn the lowest returns. This means that the inexperienced people exercise more caution in making investment decisions due to their low risk-tolerance which will surely affect the returns negatively. Therefore, the experience level of students is divided into 5 categories to investigate the effect of experience on the level of financial risk-tolerance: (i) <1 year (=1, 0 otherwise); (ii) 1-2 years (=1, 0 otherwise); (iii) 3-4 years (=1, 0 otherwise); (iv) 5-6 years (=1, 0 otherwise); and (v) 7 years and above (=1, 0 otherwise). Hence, expect that: H_{70} : Risk-taking behavior of business graduates decreases with the level of experience.

Interestingly, the location is selected as a proxy for geographical differences which is also a key demographic determinant that has been widely examined in studies on the FRT. The theory guides us that the decision-making by investors for taking a risk is highly concerned with the differences in their region of residence. Statman (2008) reported that the possibility of taking financial risk changes across geographical locations. For instance, the author observed that in China businessmen are highly willing to earn income and investment gamble subjected to those investors living in Japan, Switzerland, Italy, and Germany. Other authors also remarked that much of the difference in investor's motivation to take financial risk is probably due to the location differences (Cole, 1996). Therefore, the different locations to which people belongs is categorized into 6 options: (i) Karachi (=1, 0 otherwise); (ii) Quetta (=1, 0 otherwise); (iii) Peshawar (=1, 0 otherwise); (iv) Lahore (=1, 0 otherwise); (v) Islamabad (=1, 0 otherwise); and (vi) Chitral (=1, 0 otherwise). Hence, we expect that: H_{so} : Risktaking behavior of business graduate changes with the difference in location.

4. METHODOLOGY

4.1. Analytical Framework

This research attempt has derived its theoretical framework from the financial management framework which was introduced by (Leimberg et al., 1993) in the textbook entitled, "The Tools and Techniques of Financial Planning". The authors proposed a conceptual layout which is mainly focusing on the association between the FRT of investors and the key demographics viz. income, expenditure, financial well-being, etc. Later on, Grable (1997) also encourages the researchers across the globe to conduct studies that how certain demographic attributes affect the financial behavior of individuals and investors in general, and the financial risk-tolerance in specific. For such analysis, Grable and Lytton (1999) originated and tested an FRT scale in their published article that has since been extensively applied by consumers, educators, financial advisors, and world researchers to investigate an individual's willingness to engage in risky financial behavior. To measure the FRT, the authors presented a 13-item FRT scale that has been referenced in hundreds of research articles across the globe.

When the GL-RTS for the 1st time published online, there were very few publicly available techniques for measuring the FRT. This measure was the first to produce risk scale reliability and validity estimates. In recent times, financial advisors usually practice the measure when they are interested in providing extensive planning services as a method to gauge and recognize their client's risk attitudes before allocating client assets. While for customers, the GL-RTS are frequently used to know their own attitude to take financial risks and inspect investment preferences. This study is using the GL-RTS (1999) to evaluate the cross-sectional differences that exist among various business institutes of Pakistan in terms of FRT attitudes. Therefore, we incorporate the modeling framework utilized in prior studies such as (Grable and Lytton, 1999; Gilliam et al., 2010; Kannadhasan, 2015; Kuznaik et al., 2015; Nobre et al., 2016; Shah et al., 2017; 2018) for exploring the association between FRT and demographics. After deeply reviewing the scholarly works on the risky financial behavior of investors, the ongoing study proposes the theoretical model depicted in Figure 2.

The general functional form of the proposed model in the current analysis is given in Equation 1.

$$FRT_{i} = f(GEN_{i}, AGE_{i}, EDUC_{i}, EXPER_{i},$$

$$INCM_{i}, SAV_{i}, LOC_{i}, OCUP_{i})$$
(1)

In Equation 1, FRT, GEN, AGE, EDUC, EXPER, INCM, SAV, LOC, and OCUP stands for financial risk-tolerance, gender, age, educational level, job experience, income level, saving status, geographical location and category of occupation, respectively. In order to quantitatively capture a categorical attribute with multiple possibilities in a regression model like the case here, it is mandatory to create dummy variables for each category minus 1. The categorical variable assumes the artificial value of 1 if a specific attribute is present in the given category and 0 otherwise. Specifically, if a categorical variable has J categories⁴, then we need to introduce (J-1) dummy variables to fully capture all the information given by a qualitative variable. For instance, since the categorical variable "occupation" has four different possibilities, we encountered only three dummies for this specific variable in our proposed multiple regression model. However, if we consider all four dummy variables for the above-mentioned variable at the same time and space, we will experience perfect multicollinearity since $D_1+D_2+D_3+D_4=1$ and hence; all the dummy variables will shape an exact linear relationship with the intercept term (β_0) of the econometric model. In Econometrics, this situation is called the dummy variable trap. This is a situation in which two or more than two qualitative variables are perfectly correlated with each other⁵. That is, the scenario indicates that one independent variable can be predicted from the other variables. This situation leads to problems with understanding which independent variable contributes to the explanation of the response variable and technical issues in estimating a multinomial logistic regression.

To circumvent the issue of dummy variable trap, the fundamental guideline is that for each categorical variable the number of dummy variables used must be 1< the total number of possible groups of that variable. The category for which no dummy variable is created is called the reference group. Such a group is kept as a benchmark category because the researchers do all kinds of

5 In the presence of perfect multicollinearity, the research software will signal a response message to the author saying that the given data matrix is singular. Hence, if somebody else wants to run the regression, the computer software will refuse to run the OLS regression.

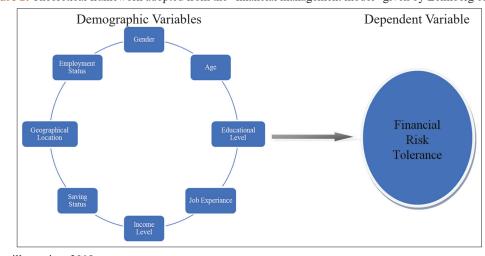


Figure 2: Theoretical framework adopted from the "financial management model" given by Leimberg et al. (1993)

Source: Author's own illustration, 2019

⁴ J is the number of groups of the dummy variable included in the regression model.

comparisons in relation to this category. However, the selection of the control group is strictly up to the investigator. In certain cases, the choice of the comparison category is dictated by the definite problem at the researcher's hand. Interestingly, if we change the omitted category of a qualitative variable, the estimation results will definitely change as a result, because now all comparisons are made in relation to that new category. Certainly, this shift in the category will not change the overall conclusion of the analysis.

The second convenient approach to avoid the dummy variable trap is to allow as many dummy variables as the number of possibilities of that qualitative variable by suppressing an intercept term from the regression model. In such cases, we will take the expectation of the regression model in order to interpret the regression coefficients. That is, without the intercept term and introducing a dummy variable for each class, we get directly the mean values of the multiple categories. There is a long debate among the researchers on the topic that which is a convenient way to circumvent the dummy variable trap. Kennedy (1998) narrated that most researchers across the globe find the regression model with an intercept term more suitable between the above two stated ways as it allows the researchers to solve more easily the questions in which they usually have the more interest, such as, whether or not the categorization of dummy variables make a difference, and if yes, by how much.

Considering the second case, we develop the following multiple linear regression model to fully capture a qualitative characteristic is expressed as given in Equation 2.

$$FRT_{i} = \beta_{0} + \beta_{1}SEXM_{i} + \beta_{2}AGE_{2i} + \beta_{3}AGE_{3i} + \beta_{4}EDUC_{2i} + \beta_{5}EXPER_{2i} + \beta_{6}EXPER_{3i} + \beta_{7}EXPER_{4i} + \beta_{8}EXPER_{5i} + \beta_{9}INCM_{2i} + \beta_{10}INCM_{3i} + \beta_{11}INCM_{4i} + \beta_{12}INCM_{5i} + \beta_{13}SAV_{2i} + \beta_{14}SAV_{3i} + \beta_{15}SAV_{4i} + \beta_{16}SAV_{5i} + \beta_{17}LOC_{2i} + \beta_{18}LOC_{3i} + \beta_{19}LOC_{4i} + \beta_{20}LOC_{5i} + \beta_{21}LOC_{6i} + \beta_{22}OCUP_{2i} + \beta_{23}OCUP_{3i} + \beta_{24}OCUP_{4i} + \varepsilon_{i}$$
(2)

Where:

 FRT_i = The financial risk-tolerance score

- $\beta_0^{=}$ An intercept term of the model which displays the mean value of the base category or which represents the average value for the variable of interest (*FRT_i*), when the explanatory variables (*X_i*)=0
- X_i = The list of all explanatory variables of the regression model (i.e., demographic variables)⁶
- β_i = The impact of the qualitative characteristic represented by the dummy variable or the differential intercept coefficients⁷
- $\varepsilon_i^{=}$ The stochastic disturbance term which represents the deviations, where $E(\varepsilon_i | X_i) = 0$ and $Var(\varepsilon_i | X_i) = \delta^2$.
- *i*= The number of cross-sections, where i=1,2,3,...,382.

We have created the following dummies (D_i) in the above multiple linear regression model.

$$SEXM = \begin{bmatrix} 1 & if male \\ 0 & if female \end{bmatrix}$$
(3)

$$SEXF = \begin{bmatrix} 1 & if \ female \\ 0 & if \ male \end{bmatrix}$$
(4)

Where SEXF defines the base category in this special case.

$$AGE_{1} = \begin{bmatrix} 1 & for 18 to 24 \\ 0 & otherwise \end{bmatrix}$$
(5)

$$AGE_2 = \begin{bmatrix} 1 & for \ 25 to \ 40 \\ 0 & otherwise \end{bmatrix}$$
(6)

$$AGE_{3} = \begin{bmatrix} 1 & for more than 40 \\ 0 & otherwise \end{bmatrix}$$
(7)

Where AGE_1 defines the comparison category in this special case.

$$EDUC_{1} = \begin{bmatrix} 1 & if undergraduate only \\ 0 & otherwise \end{bmatrix}$$
(8)

$$EDUC_2 = \begin{bmatrix} 1 & if \ postgraduate \ only \\ 0 & otherwise \end{bmatrix}$$
(9)

Where $EDUC_1$ defines the benchmark category in this special case.

$$EXPER_{1} = \begin{bmatrix} 1 \text{ if less than 1 year} \\ 0 \text{ otherwise} \end{bmatrix}$$
(10)

$$EXPER_{2} = \begin{bmatrix} 1 \text{ if } 1 \text{ to } 2 \text{ years} \\ 0 \text{ therwise} \end{bmatrix}$$
(11)

$$EXPER_{3} = \begin{bmatrix} 1if \ 3to \ 4 \ years \\ 0 \ otherwise \end{bmatrix}$$
(12)

$$EXPER_4 = \begin{bmatrix} 1if \ 5 to \ 6 \ years \\ 0 \ otherwise \end{bmatrix}$$
(13)

$$EXPER_{5} = \begin{bmatrix} 1 \text{ if 7 years and above} \\ 0 \text{ otherwise} \end{bmatrix}$$
(14)

Where $EXPER_1$ defines the control category in this special case.

$$INCM_{1} = \begin{bmatrix} 1 \text{ for less than } Rs.1lac \\ 0 \text{ otherwise} \end{bmatrix}$$
(15)

$$INCM_{2} = \begin{bmatrix} 1 \text{ for } Rs.1 \text{ lac to } Rs.2 \text{ lac} \\ 0 \text{ otherwise} \end{bmatrix}$$
(16)

⁶ The independent variables are a mixture of binary/dichotomous variables, trichotomous variables, and polychotomous variables.

⁷ Such coefficients depict us by how much the numerical value of the constant term that takes the value of 1 differs from the intercept value of the group taken as a reference.

$$INCM_{3} = \begin{bmatrix} 1 \text{ for above } Rs.2 \text{ lac to } Rs.3 \text{ lac} \\ 0 \text{ otherwise} \end{bmatrix}$$
(17)

$$INCM_{4} = \begin{bmatrix} 1 \text{ for above } Rs.3lac \text{ to } Rs.4lac \\ 0 \text{ otherwise} \end{bmatrix}$$
(18)

$$INCM_{5} = \begin{bmatrix} 1 \text{ for more than } Rs.4lac \\ 0 \text{ otherwise} \end{bmatrix}$$
(19)

Where $INCM_1$ defines the omitted category in this special case.

$$SAV_1 = \begin{bmatrix} 1 \text{ for less than 5\%} \\ 0 \text{ otherwise} \end{bmatrix}$$
(20)

$$SAV_2 = \begin{bmatrix} 1 \text{ for } 5\% \text{ to } 10\% \\ 0 \text{ otherwise} \end{bmatrix}$$
(21)

$$SAV_3 = \begin{bmatrix} 1 \text{ for } 11\% \text{ to } 20\% \\ 0 \text{ otherwise} \end{bmatrix}$$
(22)

$$SAV_4 = \begin{bmatrix} 1 \text{ for } 21\% \text{ to } 30\% \\ 0 \text{ otherwise} \end{bmatrix}$$
(23)

$$SAV_{5} = \begin{bmatrix} 1 \text{ for above } 30\% \\ 0 \text{ otherwise} \end{bmatrix}$$
(24)

Where SAV_1 defines the referent category in this special case.

$$LOC_{1} = \begin{bmatrix} 1 \text{ if the student belongs to Karachi} \\ 0 \text{ otherwise} \end{bmatrix}$$
(25)

$$LOC_{2} = \begin{bmatrix} 1 \text{ if the student belongs to } Quetta \\ 0 \text{ otherwise} \end{bmatrix}$$
(26)

$$LOC_{5} = \begin{bmatrix} 1 \text{ if the student belongs to Islamabad} \\ 0 \text{ otherwise} \end{bmatrix}$$
(27)

$$LOC_{4} = \begin{bmatrix} 1 \text{ if the student belongs to Lahore} \\ 0 \text{ otherwise} \end{bmatrix}$$
(28)

$$LOC_{5} = \begin{bmatrix} 1 \text{ if the student belongs to Islamabad} \\ 0 \text{ otherwise} \end{bmatrix}$$
(29)

$$LOC_{6} = \begin{bmatrix} 1 \text{ if the student belongs to Chitral} \\ 0 \text{ otherwise} \end{bmatrix}$$
(30)

Where LOC_1 defines the base category in this special case. And finally:

$$OCUP_{1} = \begin{bmatrix} 1 \text{ if private sector employed} \\ 0 \text{ otherwise} \end{bmatrix}$$
(31)

$$OCUP_{2} = \begin{bmatrix} 1 if \ public \ sector \ employed \\ 0 \ otherwise \end{bmatrix}$$
(32)

$$OCUP_{3} = \begin{bmatrix} 1 \text{ if self} - \text{employed or partner} \\ 0 \text{ otherwise} \end{bmatrix}$$
(33)

$$OCUP_4 = \begin{bmatrix} 1 & if other kind of employed \\ 0 & otherwise \end{bmatrix}$$
(34)

Where *OCUP*₁ being the omitted category in this special case.

4.2. Estimation Strategy

When there is no logical or natural ordering that exists among the categories of a polychotomous dummy variable appear as a target variable in the model, multinomial logistic regression is considered an effective estimation strategy for handling such types of commuting choices. The technique of a multinomial logistic model can be performed to quantitatively analyze such kinds of multi-category classifications. The polytomous logistic regression model is a straightforward classification approach that generalizes the logistic regression model to multi-category problems. Softmax regression models empirically estimate the association between explanatory variables and a multiple ranked unordered outcome in question. In our analysis, the outcome variable is the polychotomous dummy variables which compute the financial risk-tolerance score having 5 alternatives.

The multinomial logit model considers a linear predictor function to clearly predict the probability that a sampling unit *i* have nominal response K, of the form given in Equation 35.

$$f(K,i) = \beta_{0,k} + \beta_{1,k} X_{1,k} + \beta_{2,k} X_{2,k} + \beta_{3,k} X_{3,k} + \dots + \beta_{N,k} X_{N,k}$$
(35)

Where $OCUP_1$ is the parameter estimate connected with the N^{th} independent variable and the K^{th} nominal response. As we know that the parameter estimates and the independent variables are normally arranged into vectors of size N+1, so that the linear predictor function can be expressed in a more compact manner as:

$$f(K,i) = \beta_k X_i \tag{36}$$

Where:

- β_{μ} = A set of parameter estimates associated with nominal response K, and,
- nt variables connected X = A row vector (i.e. a set with observation i).

For the financial risk-tolerance with K categories, this requires the calculation of K-1 equations, each equation for one dummy

variable relative to a particular baseline⁸, to investigate the association between the FRT score and the explanatory variables of the regression model.

Mathematically,

$$ln\left[\frac{\Pr((Y_i = 1|X))}{\Pr((Y_i = K|X))}\right] = \alpha_1 + \beta_1 \cdot X_i^9$$
(37)

$$ln\left[\frac{\left(\Pr(Y_i=2)|X\right)}{\left(\Pr(Y_i=K)|X\right)}\right] = \alpha_2 + \beta_2 \cdot X_i$$
(38)

$$ln\left[\frac{\left(\Pr(Y_i = K - 1)|X\right)}{\left(\Pr(Y_i = K)|X\right)}\right] = \alpha_K + \beta_{K-1}.X_i \quad (39)$$

Taking exponential on both sides of the expressions, and solving for the set of predicting probabilities, we yield,

$$\left(\Pr(Y_i = 1|X)\right) = \left(\Pr(Y_i = K|X)\right)e^{\beta_1 \cdot X_i}$$
(40)

$$\left(\Pr(Y_i = 2|X)\right) = \left(\Pr(Y_i = K|X)\right)e^{\beta_2 \cdot X_i}$$
(41)

$$\left(\Pr(Y_i = K - 1|X)\right) = \left(\Pr(Y_i = K|X)\right)e^{\beta_{k-1} \cdot X_i}$$
(42)

The statistical theory guides us that all K of the predicting probabilities must be equal to unity *i.e.* $\sum_{K=1}^{K-1} (\Pr(Y_i = K | X)) = 1)$, we can write:

$$\left(\Pr(Y_i = K|X)\right) = 1 - \sum_{K=1}^{K-1} \Pr\left(\left(Y_i = k|X\right)\right) = 1 - \sum_{K=1}^{K-1} \Pr\left(\left(Y_i = k|X\right)\right) e^{\beta_k \cdot X_i}$$
(43)

$$\Pr(Y_i = (K|X)) = \frac{1}{1 + \sum_{k=1}^{k-1} e^{\beta_k \cdot X_i}}$$
(44)

Using the above Equation 44, we can easily find out other probabilities of the system as whole:

$$\left(\Pr(Y_{i} = 1|X)\right) = \frac{e^{\beta_{1} \cdot X_{i}}}{1 + \sum_{k=1}^{k-1} e^{\beta_{k} \cdot X_{i}}}$$
(45)

8 Each equation of the system models the odds of a choice relative to a base category.

9 β_1 measures the change in the log odds of Y=1 relative to Y=K associated with a one-unit change in X. And, exponent of β_1 is a relative risk ratio. For instance, if exp $(\beta_1) = 1.1$, then an increase of one unit in X multiplies the odds of Y=1 relative to Y=K by 1.1.

Table 1. Summary of the descriptive statistics

$$\left(\Pr(Y_i = 2|X)\right) = \frac{e^{\beta_2 \cdot X_i}}{1 + \sum_{k=1}^{k-1} e^{\beta_k \cdot X_i}}$$
(46)

$$\left(\Pr(Y_{i} = K - 1|X)\right) = \frac{e^{\beta_{k-1} \cdot X_{i}}}{1 + \sum_{k=1}^{k-1} e^{\beta_{k} \cdot X_{i}}}$$
(47)

Therefore, if the first group is considered as a reference category of a dummy variable; hence, for we can write as:

$$ln\left[\frac{\Pr((Y_i = m|X))}{\Pr((Y_i = 1|X))}\right] = \alpha_m + \sum_{k=1}^k \beta_{mk} X_{ik} = Z_{mi}$$
(48)

For each category of a dummy variable, there will be M-l predicted log odds ratios, one for each group compared to the base group. If m=l, then,

$$ln\left[\frac{\Pr((Y_i = 1|X))}{\Pr((Y_i = 1|X))}\right] = \ln(1) = 0 = Z_{11} \text{ as } \exp(0) = 1.$$

When there are multiple ranked categories (i.e. more than two types of a qualitative variable), manipulating probabilities is comparatively a difficult task when compared with the ordinary logistic regression model. Hence, for m=2, 3, 4, ..., M, we can derive the resulting expression as:

$$(\Pr(Y_i = m | X)) = \frac{\exp(Z_{mi})}{1 + \sum_{k=2}^{M} \exp(Z_{hi})}$$
 (49)

For the base category of a dummy variable, we denote the resulting equation as:

$$\Pr(Y_i(=1|X)) = \frac{1}{1 + \sum_{h=2}^{M} \exp(Z_{hi})}$$
(50)

However, it must be remembered that when M=2, the multinomial logit and logistic regression models become the same.

5. EMPIRICAL RESULTS

5.1. Statistical Analysis

The opening step of the cross-sectional data is to check for the descriptive statistics, which are examined to illustrate the basic traits of the demographic information in research. Such kinds of statistics provide simple summaries about the sample size that have been selected and lots of statistical measures in a very sensible way. Hence, descriptive statistics include three major features of one variable that we tend to look at the dispersion,

Variable	N	Min.	Max.	Mean	S.D ¹⁰	Var.	Skewness K		Kurte	Kurtosis	
							Statistic	S.E	Statistic	S.E	
Risk tolerance	382	1.00	5.00	3.1492	0.90274	0.815	0.089	0.125	-0.043	0.249	

Source: Result extracted from SPSS 24

the central tendency, and the distribution of individual values. The results of descriptive statistics for the FRT categories are reported in Table 1.

Table 1 reports that the value of mean of risk-tolerance is 3.15 with a S.D of 0.90, showing that the students are behaving moderately towards a risk-taking perspective. The skewness statistic of the sample is very close to zero (i.e. 0.09), depicting that the sampling distribution of the risk-tolerance score is not skewed. Likewise, the risk-tolerance score has a negative kurtosis value of -0.04, revealing that the sampling distribution is platykurtic. More importantly, if either of calculating values for both statistical measures is found $< \pm 1$, as the case here, then the distribution of data is considered normal. Hence, we consider that our sampling data are approximately normally distributed, in terms of skewness and kurtosis.

5.2. Frequencies for Categorical Data

The frequencies procedure of analysis can display summary measures for qualitative variables of a sample in the shape of frequency tables, which helps in giving an idea about the distribution of the dataset at a short glance. Frequency distribution of categorical data displays a summarized grouping of information distributed into mutually exclusive categories and the number of times of occurrences in a group. The output of frequency information is reported in Table 2.

The frequency column of Table 2 reports the frequency of each category for independent variables incorporated in the regression model. For instance, out of 382 observations, 76 were female students and 306 were male students. Also, the stated frequencies are transformed to percentages (%age) in the percent column of the table (e.g., 19.9% female and 80.1% male)¹¹. Whereas, the last column of Table 2 demonstrates the cumulative percentage (cp) of observations, which measures the %age of the cumulative frequency within each category.¹² The superiority of this statistic as a method of a frequency distribution is that it provides a better understanding to compare multiple sets of information. As a whole, the results of the frequency procedure display that the composition of the sample is having the highest degree for those privately employed male undergraduate students, who have the smallest level of income

Cumulative percentage (cp) = [Cumulative frequency (CF)/no of observations (n)] * 100.

Total observations (n)=382						
Demographics	Categories	Frequency	Percent (%)	Cumulative percent		
Gender	Female	76	19.9	19.9		
	Male	306	80.1	100.0		
Age	18-24 years	265	69.4	69.4		
-	25-40 years	102	26.7	96.1		
	Above 40 years	15	3.9	100.0		
Qualification	Undergraduate	236	61.8	61.8		
	Postgraduate	146	38.2	100.0		
Job experience	<1 year	254	66.5	66.5		
*	1-2 years	54	14.1	80.6		
	3-4 years	21	5.5	86.1		
	5-6 years	27	7.1	93.2		
	7 years and above	26	6.8	100.0		
Income level	<rs.1 lac<="" td=""><td>301</td><td>78.8</td><td>78.8</td></rs.1>	301	78.8	78.8		
	Rs.1 lac-Rs.2 lac	52	13.6	92.4		
	Above Rs.2 lac-Rs.3 lac	13	3.4	95.8		
	Above Rs.3 lac-Rs.4 lac	5	1.3	97.1		
	More than Rs.4 lac	11	2.9	100.0		
Saving status	<5% of income	242	63.4	63.4		
	5% to 10% of income	76	19.9	83.2		
	11% to 20% of income	35	9.2	92.4		
	21% to 30% of income	16	4.2	96.6		
	Above 30% of income	13	3.4	100.0		
Occupation	Private Employee	134	35.1	35.1		
	Public Employee	62	16.2	51.3		
	Own business/Partnership	52	13.6	64.9		
	Other	134	35.1	100.0		
Location	Karachi	23	6.0	6.0		
	Quetta	219	57.3	63.4		
	Peshawar	55	14.4	77.7		
	Lahore	32	8.4	86.1		
	Islamabad	24	6.3	92.4		
	Chitral	29	7.6	100.0		

Table 2: Frequencies summary of demographic variables

Source: Result extracted from SPSS 24

¹⁰ Where N, Min, Max, S.D, Var. and S.E stands for the number of observations, minimum, maximum, standard deviation, variance and standard error, respectively.

¹¹ The same interpretation can be made for the remaining group of categories.

¹² The statistic of cumulative percentage is computed by using the following formula:

and saving along with the least experience belonging to the region of Quetta.

5.3. Reliability Statistics

The analysis of Cronbach's alpha (α) is typically used to measure the reliability of the questionnaire. The reliability of 0.6 or higher value is required for a good questionnaire to continue with the research study. However, if a questionnaire has <10 items on a scale, then it is difficult to get a high alpha (α). In such cases, the actual value of must be >0.05.¹³ The output of reliability statistics is shown in Table 3 below.

Table 3 displays that the reliability statistic for the 13-items risk-tolerance scale is 0.63, which is acceptably >0.6 as found in the study conducted by (Nunnally and Bernstein, 1994); hence, indicating a high level of reliability of these constructed scales. Additionally, the outcome of this research is completely in line with the results of (Shah et al., 2018).

5.4. Correlation Analysis

A Pearson's correlation is one statistical method of estimating the relationship between two variables that are scored on a nominal scale level, where Pearson's regression ranges between -1.0 and +1.0.¹⁴ The direction of the relationship between two variables is captured by the sign of the correlation coefficient; a positive

Table 3: Reliability of the questionnaire

Variable	Cronbach's alpha (α)	Number of items	Ν
Risk-tolerance scale	0.634	13	382

Source: Result extracted from SPSS 24

Table 4: Correlation matrix of categorical data

sign shows a positive type of association and a negative sign reveals a negative type of association between two variables. More specifically, if the Pearson's r is found negative, it shows that a pair of variables is negatively associated with each other. On the contrary, if Pearson's r is found positive, the association between two variables is positive. Wherein, the estimated value of the correlation coefficient shows the degree of the connection between two variables. The symmetric correlation matrix for all possible pairs of variables is shown in Table 4.

As a rule of thumb, a value of the correlation is statistically significant if the significance of a correlation is <0.05 or 0.01. For instance, the computed correlation coefficient for age and income is 0.126; whereas, the probability value of this corresponding statistic is 0.013 which is statistically significant at the 5% significance level. Such findings reveal that the relationship between age-income is a direct one, depicting that the level of income moves up as the age of a particular student goes up. More importantly, because the P (0.013) 0.05, reject the null hypothesis of no significant relationship between age and income and confirm that the relationship of the given pair is statistically significant.¹⁶ Except for the experience, the pairwise correlations show a positive association between FRT and all demographics.

5.5. Chi-square Test of Association

The chi-square test of independence is usually used to determine whether or not there is a statistical relationship between two or

H₁: There is a statistically significant association b/w age-income, i.e., $r \ge 0$ or $r \le 0$.

	Total observations (n)=382									
Variable	FRT	GEN	AGE	EGUC	EXPER	INCM	SAV	LOC	OCUP	
FRT	115	0.148**	0.002	0.043	-0.007	0.067	0.071	-0.191**	-0.071	
		(0.004)	(0.975)	(0.401)	(0.894)	(0.192)	(0.167)	(0.000)	(0.168)	
GEN	0.148**	1	0.169**	0.068	0.100	0.017	0.069	-0.082	-0.012	
	(0.004)		(0.001)	(0.184)	(0.051)	(0.734)	(0.177)	(0.111)	(0.810)	
AGE	0.002	0.169**	1	0.318**	0.568**	0.126*	0.220**	0.124*	-0.022	
	(0.975)	(0.001)		(0.000)	(0.000)	(0.013)	(0.000)	(0.015)	(0.670)	
EDUC	0.043	0.068	0.318**	1	0.180**	0.004	0.114*	0.054	-0.189**	
	(0.401)	(0.184)	(0.000)		(0.000)	(0.937)	(0.025)	(0.292)	(0.000)	
EXPER	-0.007	0.100	0.568**	0.180**	1	0.196**	0.262**	0.167**	0.130*	
	(0.894)	(0.051)	(0.000)	(0.000)		(0.000)	(0.000)	(0.001)	(0.011)	
INCM	0.067	0.017	0.126*	0.004	0.196**	1	0.454**	0.044	0.084	
	(0.192)	(0.734)	(0.013)	(0.937)	(0.000)		(0.000)	(0.393)	(0.102)	
SAV	0.071	0.069	0.220**	0.114*	0.262**	0.454**	1	0.116*	0.139**	
	(0.167)	(0.177)	(0.000)	(0.025)	(0.000)	(0.000)		(0.023)	(0.006)	
LOC	-0.191 **	-0.082	0.124*	0.054	0.167**	0.044	0.116*	1	0.090	
	(0.000)	(0.111)	(0.015)	(0.292)	(0.001)	(0.393)	(0.023)		(0.079)	
OCUP	-0.071	-0.012	-0.022	-0.189 * *	0.130*	0.084	0.139**	0.090	1	
	(0.168)	(0.810)	(0.670)	(0.000)	(0.011)	(0.102)	(0.006)	(0.079)		

Source: Result extracted from SPSS 24. "*" shows the significance at the 5% level of significance [Sig. (2-tailed)]. "**" shows the significance at the 1% level of significance [Sig. (2-tailed)].

¹³ The closer to 1 that value is, the more likely how these items are measuring the same construct.

¹⁴ The zero Pearson's regression indicates no relationship between a bivariate variable at all.

¹⁵ It is understood that every variable will always correlate with itself at r=+1.00 in the diagonal column of the correlation matrix, no matter the variable. It shows a perfect correlation between the two variables. However, such correlations are not very interesting from the perspective of analysis.

^{16.} The mutually exclusive statistical hypotheses for this probability value are stated as:

H₀: There is no significant association b/w age-income, i.e., *r*=0.

more nominal variables. For such intention, the statistical test considers a contingency table to deeply analyze the categorical variables. The contingency table is also called a crosstab, where information is arranged according to the number of categorical variables. This statistical test is considered only to compare nominal variable cases; however, it is not generally acceptable to make comparisons between groups of continuous variables or between nominal and continuous variables. In addition, it cannot provide any statistical inferences about the causal relationship between two categorical variables. The null hypothesis of the chi-square test of independence can be formulated in the following fashion, which is tested against its alternative hypothesis¹⁷.

The cross-tabulation and chi-square test findings are given in Tables 5 and 6, respectively.

The results in Table 5 provide an idea about the observed and expected counts for the two categorical variables namely, risktolerance and age. The expected count is what we would expect to observe if there was no association between variables. For example, if risk-tolerance had no relationship with gender, so risk-tolerance was independent of whether or not someone is male/female. Similarly, we would expect to observe around 6 females who were high risk-loving and around 23 males who were high risk-loving in nature. From the table, we can see that our observed counts are different from those expected counts, and the chi-square test statistic helps to determine if those observed counts are different enough for the association to be significant. The chi-square test will tell us the association between two variables is significant; however, it does not tell us how strong the association between two variables is. Therefore, the Phi and Cramer's V test statistic is suggested to measure the strength of the association for two variables.

The Pearson Chi-square statistic is 12.045 and the degree of freedom for this statistic is 4; whereas, the corresponding probability value is 0.017. Since the probability value is less than the significance level (α =5%), meaning that our result is statistically significant. Hence, we accept the null hypothesis which says that there is a significant association between risk-tolerance and gender. Similarly, the symmetric measures reported in Table 7 also support the underlying fact.

5.6. Multinomial Logistic Regression

As we know that the multinomial logit model is the multiequation model, where the financial risk-tolerance variable with five categories has created four separate equations. In our analysis, the low risk-tolerance is taken as the reference category; and hence, we are comparing all the remaining categories with the reference point. For example, the regression

 Table 5: Risk-tolerance versus gender cross-tabulation (5×2)

Variable	Categories/	Counting	Gen		Total
	Groups		Female	Male	
Risk- tolerance	Low risk	Observed count ¹⁸	2	9	11
		Expected count	2.2	8.8	11.0
	Below- average risk	Observed count	23	46	69
	C	Expected count	13.7	55.3	69.0
	Moderate risk	Observed count	35	148	183
		Expected count	36.4	146.6	183.0
	Above- average risk	Observed count	14	76	90
	C	Expected count	17.9	72.1	90.0
	High risk	Observed count	2	27	29
		Expected count	5.8	23.2	29.0
Total (N)		Observed count	76	306	382
		Expected count	76.0	306.0	382.0

Source: Result extracted from SPSS 24

Table 6: Chi-square tests

Test statistic	Value	Degree of	Asymp. Sig.	
		freedom	(2-sided)	
Pearson Chi-square	12.045*	4	0.017	
Likelihood ratio	11.947	4	0.018	
Linear-by-linear association	8.339	1	0.004	
No of valid cases		382		

Source: Result extracted from SPSS 24. (*) 1 cell $(10.0\%)^{19}$ has expected count <5. The minimum expected count is 2.19

Table 7: Symmetric measures

Test statistic		Value	Approx. sig.		
Nominal by	Phi	0.178	0.017		
nominal	Cramer's V	0.178	0.017		
Number of valid	cases	382			

Source: Result extracted from SPSS 24

coefficient estimate of gender is 0.84, meaning that male students prefer to take a below-average 0.84 times as compared to the lower risk. The effect of this variable is significant in all equations, revealing that there is a significant difference between males and females towards a risky task, i.e., male students are more risk-tolerant than females. Similarly, the postgraduate students prefer to take a below-average risk as compared to the lower risk. On the other side, the estimated parameter of experience is negative, which means that students who are having a year experience prefer 0.24 times less below-average risk than the low risk. All the remaining variables appeared

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 H_0 : Variable 1 is independent of variable 2.

H₁: Variable 1 is not independent of variable 2.

¹⁷ These hypotheses can also be expressed in the following equivalent way:

H₀: Variable 1 is not associated with variable 2.

H₁: Variable 1 is associated with variable 2.

¹⁸ It shows the actual number of information for a particular cell.

¹⁹ If this percentage value > 20%, then the basic assumption of the chi-square test is violated.

Table 8: Results from the multinomial logistic model

Number of observations=382LR Chi-square (28)=49.02 Prob. >Chi-square=0.0083Pseudo R²=0.7494²⁰ Log likelihood=-472 13984

Category	Risk	Coefficient	S.E.	z	$\mathbf{P} > \mathbf{Z} $	95%	C.I
1	(base outcome)						
2	Gender	0.841	0.850	0.99	0.022**	-2.505	0.823
	Education	1.607	0.739	2.18	0.030**	-3.055	-0.160
	Experience	-0.244	0.283	-0.86	0.388	-0.310	0.798
	Income	0.288	0.403	0.72	0.074***	-1.078	0.501
	Occupation	0.149	0.284	0.52	0.010*	-0.705	0.407
	Saving	0.207	0.378	0.63	0.028**	-0.850	0.436
	Location	0.133	0.247	0.54	0.088***	-0.616	0.349
	Constant	5.945	1.874	3.17	0.002*	2.27	0.916
3	Gender	0.120	0.828	0.14	0.055***	-1.742	1.503
	Education	1.179	0.701	1.68	0.093***	-2.552	0.195
	Experience	-0.175	0.269	-0.65	0.515	-0.351	0.701
	Income	0.052	0.362	0.14	0.085***	-0.762	0.657
	Occupation	0.255	0.272	0.94	0.049**	-0.787	0.278
	Saving	0.207	0.306	0.68	0.099***	-0.807	0.393
	Location	0.221	0.235	0.94	0.046**	-0.683	0.240
	Constant	6.168	1.810	3.41	0.001*	2.621	9.713
4	Gender	0.083	0.860	0.10	0.023**	-1.601	1.767
	Education	0.907	0.720	1.26	0.008*	-2.318	0.505
	Experience	-0.118	0.279	-0.42	0.673	-0.430	0.665
	Income	0.120	0.381	0.32	0.043**	-0.867	0.627
	Occupation	0.450	0.280	1.61	0.007*	-0.996	0.969
	Saving	0.167	0.320	0.49	0.023**	-0.782	0.469
	Location	0.323	0.247	1.31	0.020**	-0.807	0.161
	Constant	5.750	1.865	3.10	0.002*	2.109	9.381
5	Gender	0.090	1.097	0.82	0.011**	-1.248	3.050
	Education	1.193	0.799	1.49	0.035**	-2.759	0.372
	Experience	-0.184	0.304	-0.60	0.545	-0.412	0.780
	Income	0.097	0.401	0.24	0.009*	-0.688	0.881
	Occupation	0.713	0.316	2.25	0.024**	-1.333	-0.093
	Saving	0.204	0.342	0.60	0.051***	-0.466	0.874
	Location	0.174	0.269	0.64	0.019**	-0.701	0.354
	Constant	3.334	2.06	1.62	0.106	-0.707	7.375

Source: Results extracted from STATA 16. "*," "***", and "***" show significance at the 1%, 5%, and 10% level of significance, respectively.

with the expected positive sign and each determinant of the model is significant, except the experience, and the analysis of this study is consistent with other empirical studies including, (Grable, 2000; Nobre et al., 2016; Onsomu et al., 2017; Shah et al., 2018). Besides, the Pseudo R² value is 0.7494 (74.94%) which signifies that the estimated model is reasonably fit. The findings are reported in Table 8.

In addition, all the null hypotheses have been tested against the alternative hypotheses for checking the individual significance of each independent dummy variable incorporated in the proposed econometric model. The results of the hypothesis testing show that we accept the null hypothesis as the probability value for each dummy variable is >0.05, meaning that the variables are significant.

6. CONCLUSION AND IMPLICATIONS

The primary objective of this empirical study was to investigate the degree to which FRT attitudes differ between a sample of 382 business graduates studying at different universities in Pakistan. While the empirical results from this research study concur with previous findings reported by Grable and Lytton (1999), this research adds to the body of empirical literature in many ways. First, this research attempt was able to replicate the 13-item GL-RTS (1999) research validity. Using primary data from a completely different sample in a separate country, the empirical findings reported here reveal interesting similarities. Second, the findings of significance test revealed that the proposed econometric model is completely in accordance with the manipulated data and showed the effects of demographic features viz. gender, age, education, experience, income, saving, location, and occupation to financial risk-tolerance. Seven out of 8 demographics were found to be useful factors in differentiating among the levels of financial risk-tolerance. The findings confirm that demographics do play a role in differentiating financial risk-tolerance attitudes.

The empirical results of the current analysis have widespread implications for practical purposes. Based on the results of the multinomial logistic model, it can be noted that the income of a person has a significant positive partial influence on the FRT. This means that the higher the level of income, the higher the tolerance of financial risk to the retail investors would be.

²⁰ It is not of primary importance for the dummy dependent variable models.

Similarly, the results on gender in connection with financial risk-tolerance need more attention. (Belsky et al., 1993) concluded that the demographics show that females have a longer life expectancy, exhibit greater responsibility towards their families, and have lower earning potentials over the life span. This stresses the need for females to be educated to enable them to use risk prudently in ensuring sufficient return to solve their financial problems.

Further research can be conducted to probe whether other determinants, including personality type, sensation seeking, race, herding, family background, overconfidence, culture, expectations, birth order, and financial knowledge have an impact on the FRT. Similarly, this research can be extended to make a comparison between countries. Lastly, though measuring the financial risktolerance score is a complicated process in the decision-making domain, an understanding of financial risk-tolerance would be beneficial to the financial service providers to sustain a rewarding relationship with their clients.

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