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Understanding the Decision-Making Dynamics of Retail Investors in The Fintech Era – A SEM Approach

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Abstract: Financial technology (Fintech) innovations have substantially transformed the landscape for retail investors by democratizing access to financial markets and providing sophisticated tools that were once exclusive to professional investors. The evolution of the financial technologies such as robo-advisory, algorithmic trading, and AI-driven market analysis has brought the activities of retail investors to the forefront, altering the dynamics traditionally dominated by institutional investors. The growing prominence of retail investors, a cohort marked by distinct investment patterns influenced by their financial goals, access to information, and cognitive biases has been underscored by recent market irregularities and an uptick in individual trading activities. This paper aims to investigate the intricacies of retail investor behaviors in Singapore, specifically examining the determinants that underpin their frequent investment activities in the stock market during the Fintech era. Through a comprehensive survey of 1,076 Singaporean retail investors, we evaluate the relative weight of decision-making factors for individual investors and the potential existence of variable groups that constitute identifiable constructs leveraged during the investment process. Our investigation is two-pronged: we first seek to quantify the significance of varying decisional factors in stock purchases among individual investors. Subsequently, we aim to identify clusters of these factors that consistently inform investment strategies. The goal is to delineate the characteristics of retail investors who engage more actively in the stock market, thus contributing to the academic dialogue on household finance and informing policy development.

1. Introduction

In the dynamic landscape of global finance, the role of retail investors has gained increasing significance, both in terms of capital influx and influence on market behavior. While institutional investors have historically dominated discussions concerning market dynamics, recent market anomalies and a surge in retail trading activities have prompted researchers and policymakers to take a closer look at this segment of the market. Retail investors, often driven by a mix of financial aspirations, information consumption, and behavioral biases (Mullainathan and Thaler, 2000), can exhibit investment patterns distinct from their institutional counterparts. As these patterns can have ripple effects across stock markets, understanding the characteristics that drive frequent investment by retail investors becomes paramount.

The advent of financial technology, or Fintech, has ushered in a new era for retail investors, leveling the playing field and catalyzing a shift in market dynamics. Where the financial markets were once a walled garden, accessible only to those with the right knowledge and capital, innovations such as robo-advisory, algorithmic trading, and AI-driven market analysis tools have shattered these barriers. This democratization of finance has not only empowered individuals with sophisticated investment tools but has also spotlighted the significant role retail investors play in shaping market trends. As these technological advances proliferate, they redefine the traditional market structures and operational modes, previously the stronghold of institutional investors, thus sparking a pivotal transformation in the global financial ecosystem.

Numerous studies have suggested that retail equity investors typically lack information and consistently make systematic mistakes in their equity investment choices. However, more contemporary research points to the contrary (Boehmer *et al.*, 2021). These individuals, armed with an array of digital tools and platforms, have become a force that not only participates in but also influences market dynamics. Understanding the motivations driving retail investors in their decision-making processes is critical to discerning the undercurrents of market trends and movements due to technological innovations.

This paper seeks to investigate this underexplored territory by conducting a comprehensive survey of retail investors, especially in the era of Fintech innovations. In this study, we explore two key questions. Firstly, how significant are the different decision factors for individual investors when they make trading stocks decision. Secondly, what are homogeneous groups of variables that form identifiable constructs that investors rely upon when making equity investment decision.

The primary objective of our research is to delve into the intricate characteristics and key motivators influencing individuals who engage more actively in stock market investments, particularly in the context of the transformative impact fintech innovations have had on information accessibility and trading modalities. By achieving a deeper understanding of these factors, we aim to identify and understand the behavioral patterns that drive frequent trading among individual investors, which can signal shifts in market dynamics. Furthermore, this research aims to add the body of knowledge in behavioral finance, particularly in the context of modern fintech, thereby supporting academic inquiry and the development of new theoretical frameworks.

2. Literature Review and Hypothesis Development

With recent rapid technology developments in the financial industry, the emergence of intelligent fintech-based software has simplified the procedures of securities account opening and trading, making it easier and faster for investors to open accounts, trade, and engage in other investment activities. Such developing financial technologies may also help to eliminate the gap between retail and institutional investors (Chen *et al.*, 2023). Fintech's emergence has the potential to positively influence the economy by simplifying transactional and investment processes (Junianto *et al.*, 2020). With just a smartphone, individuals can trade and invest through a simple process of downloading an app and a single click to become a customer ready to transact.

Fintech also has the capability to influence financial literacy by making financial information readily accessible and to offer a range of straightforward options to the public. It enables a basic understanding of investment without the need for scrutinizing intricate details, thereby enhancing financial literacy among users. Financial literacy encompasses an understanding of personal finance, which is critical for conducting financial decision-making, including evaluating prospects and strategizing for short and long-term financial goals. Enhanced financial literacy can bolster an individual's confidence in making and growing their investment decisions (Awais *et al.*, 2016). Nonetheless, it is not the exclusive determinant of investment decisions. The process of deciding where to invest involves a complex interplay of numerous factors. A pivotal element to consider is an investor's risk tolerance, which may range from minimal to maximal. The level of risk an investor is willing to undertake significantly shapes their investment decision strategies. Classical asset pricing models typically operate under the assumption that investors behave rationally. However, abundant evidence indicates that investor behavior is not uniform and can vary significantly based on their risk tolerance or other distinct traits (Chen *et al.*, 2023).

In the subsequent sections of the literature review, we discuss how retail investors deviate from the predictions of standard economic models due to biases in perceived risk, which influence the frequency of stock trading (H1). We also examine relevant factors that precede decision-making on the trading activities of retail investors. The research outline is included in Figure 1 below.

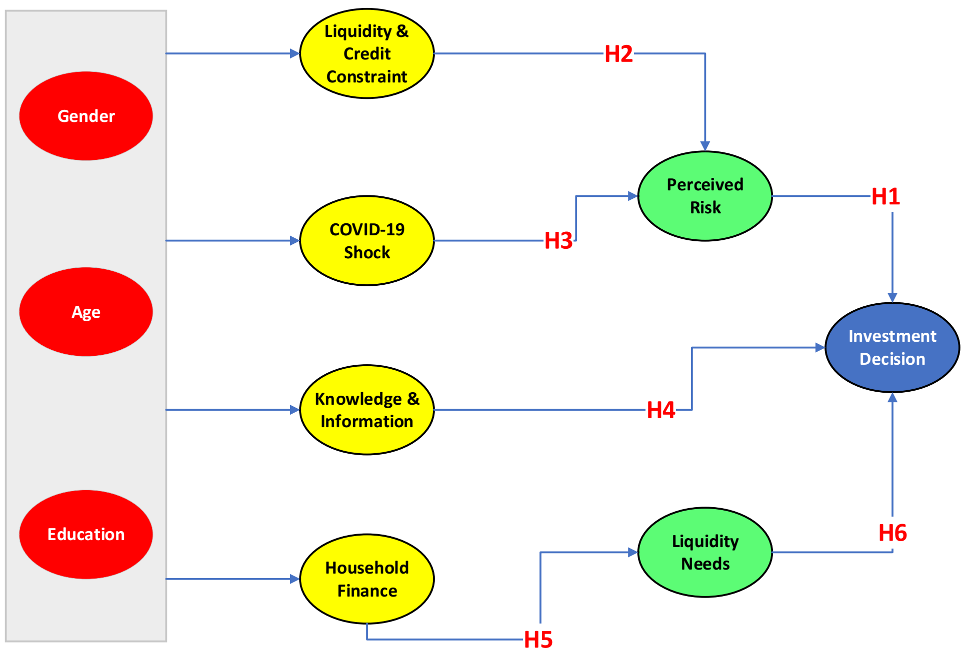


Figure 1: Hypotheses in SEM model

2.1. Perceived Risk (H1)

Shleifer (2000) identifies risk perception as an important and essential factor for understanding investment decision making. In fact, investors, especially noise traders are more likely to be influenced by perceived risk than by objective risk (Diacon and Ennew, 2001). Kahneman (2003) explains this phenomenon with psychology research, where human beings (including investors) often act on intuition rather than rigorous reasonings, by what we observe at a given moment rather than computing expected returns and risks. Specifically, Duxbury and Summers (2004) show that individual investors are consistently loss averse but not variance averse. Various studies have looked at how perception of risk might have influenced investment decisions and the studies found that the higher an investor's perceived risk, the more likely the person will prefer low risk assets and avoid risky assets (Hariharan *et al.*, 2000; Aren and Zengin, 2016; Keller and Siegrist, 2006).

With reference to the literature, we have therefore developed the first hypothesis:

Hypothesis 1: The perception of risk will have a significant impact on an individual investor's investment decision in stocks market

In our study, we employ four survey questions to assess an investor's perceived risk from diverse perspectives, acknowledging the potential biases inherent in self-assessed risk judgments as highlighted by Wang *et al.* (2011). Risk perception is a cognitive assessment, thus is susceptible to many biases (Loewenstein *et al.*, 2001; Slovic, 2016) such as overconfidence, and some other variables such as demographics and personality (Gärling *et al.*, 2009). Among all the demographic variables, gender has received the most attention as psychological research has demonstrated that men tend to be overconfident than women and thus are more likely to take risk when it comes to financial investments (Powell and Ansic, 1997). Barber and Odean (2001) provided empirical stock investments data to show that men trade more excessively compared to women and that such trading behavior has a negative impact on net returns.

Another important demographic variable is age, where age has been shown to have a negative effect on the willingness to take risks (Yao *et al.*, 2011). Other similar studies with the same conclusion that younger investors tend to take more risks than the elders include but not limited to Agnew *et al.* (2003), Bellante and Gren (2004) and Dohmen *et al.* (2011). The level of education has also been associated with investment decision making. Highly educated investors tend to be more subject to overconfidence which may lead to riskier investment behavior (Bhandari and Deaves, 2006; Graham *et al.*, 2009). However, Calvet *et al.* (2009) have shown otherwise that investors with higher education levels are more likely to make rational decisions about rebalancing their portfolios. In this study, we include gender, age and education level as three moderating factors as they will have impact on an investor's risk perception of which the effect will then flow over to the investment decision making process.

2.2. Liquidity and Credit Constraints (H2)

Literature has long documented the role of liquidity and credit constraints on the likelihood of holding risky assets, both empirically (Guiso *et al.*, 1996; Bertaut, 1998; Cardak and Wilkins, 2009) and theoretically (Campbell, 2006). Constrained investors are less likely to hold risky assets, reducing the risky asset ratio of their portfolios. The underlying reason for such a phenomenon can be the inability to take risk or being too risk averse due to the constraints faced.

Following Cardak and Wilkins (2009), our study also measure liquidity and credit constraints from 2 dimensions based on the questions in our survey to test the hypothesis about the impact of constraints on an investor's investment behavior. The question will be used to proxy an investor's liquidity constraints as one who is able to follow a budget, make savings, payoff credit cards or loans is less likely to face liquidity issue. And also, to measure an investor's credit constraints directly.

Hypothesis 2: The existence of liquidity or credit constraints will have a significant impact on an individual investor's perceived risk in stocks market

2.3. COVID-19 Shock (H3)

Previous literature has studied the effects of various negative shocks on one's decision making through risk preference. Callen *et al.* (2014) investigated the relationship between traumatic exposure and economic risk preference and found that violence and fearful recollection do lead to individuals making risk-averse choices. Cameron and Shah (2015) and Cassar *et al.* (2017) made similar conclusions on the changes of people's risk perception. Bernile *et al.* (2017) documented more specific relationships for a particular group of people, the chief executive officers (CEOs). It was found that only those CEOs who have experienced the extreme negative consequences of previous disasters have become risk averse while those who did not witness the extreme downside of disasters have actually become more aggressive.

As discussed previously, an individual's risk preference and or perception will undoubtfully influence his or her investment decision. Malmendier and Nagel (2011) mentioned a significant and persistent effect of prior experience of macroeconomic shocks on stock-market participation, controlling for age, year effects, and household characteristics. Malmendier *et al.* (2020) introduced an experience-based learning model, which is indeed a form of generalized Bayesian learning (Malmendier, 2021), to understand how macro-financial shocks affect investors behavior and market dynamics. COVID-19 is unarguably the unprecedented shock to the world since World War II, causing loss of lives, high unemployment rates, plummeted asset prices and economic downturn. Huber *et al.* (2021) found that there is an impact of the stock market crash on professionals' risk perception, but no such impact was found among students who are considered as the non-professional control group. We are interested in testing whether there is also a similar impact of the COVID-19 shock on laypeople thus developed the sixth hypothesis based on self-reported data.

Hypothesis 3: The COVID-19 shock has a significant impact an individual investor's perceived risk in stocks market

2.4. Knowledge and Information (H4)

Prior studies have used financial literacy and financial knowledge interchangeably (Huston, 2010). The OECD has defined financial literacy as a combination of awareness, knowledge, skill, attitude and behavior necessary to make sound financial decisions and ultimately achieve individual financial wellbeing. However, the inconvenient truth is that financial literacy is more of one's subjective financial knowledge measured by the understanding of financial concepts, principles, and products (Lusardi and Mitchell, 2007). Nevertheless, be it subjective or objective financial knowledge, prior studies have found evidence that financial knowledge is an important factor influencing on investment behavior (Hadar *et al.*, 2013; Zhao and Zhang, 2021). Van Rooij *et al.* (2011) found that low-literacy households are less likely to participate in the stock market using Netherlands' household data. In the context of mainland China financial market, positive relationships between the level of financial literacy and the likelihood of holding risky assets (Liao *et al.*, 2017) and mutual fund (Chu *et al.*, 2017) were found. Kim *et al.* (2019) also indicated that millennials in the United States are more likely to have made investments if they have higher levels of financial knowledge. A similar finding for derivatives specifically was reported by Hsiao and Tsai (2018). Bianchi (2018) provided evidence that more literate households are more capable in keeping a good portfolio dynamic thus gained higher returns. Krische (2019) found that individuals who are more financially literate are more likely and willing to make informed investment decisions via financial reporting information. Literature has also documented the difference of financial literacy level caused by the difference in gender, age and education level (Lusardi and Mitchell, 2007; Kaiser *et al.*, 2022) thus they are used as moderating factors as well.

The finance literature has documented empirical evidence for a significant heterogeneity across individuals in investment behaviors. Barnea *et al.*, (2010) and Cronqvist and Siegel, (2014) both found that a genetic factor can explain part of the variance in individual investors' behavior. Their results not only indicated the importance of nature as a determinant but have also shown the significant effect of environmental influences and individual experiences. However, the impact of family environment faded off as an individual aged and gained outside experiences such as work experience in the finance sector that can help to mitigate investment biases. Hassan Al-Tamimi and Anood Bin Kalli

(2009) have found a higher financial literacy level in those who work in the field of finance/banking or investment. With this, we measure the information channel with the working experience in the financial industry. Besides the day-to-day working information, retail investors could obtain information from various channels.

Consumers' information-search behavior has a long history in the literature of marketing. Guo (2001) extensively reviewed the empirical findings on this subject. To make a rational and wise decision, it is essential to conduct information search, as information search is deeply rooted in the cost-benefit analysis framework. Loibl and Hira (2009) extended the literature on consumer information search to particularly investor investment information. Extensive information search was found to be related to a high degree of involvement with investment decision making. The search of information is measured by the time, phone or visit, and number of sources.

Hypothesis 4A: The level of financial knowledge will have a significant impact on an individual investor's investment decision in stocks market

Hypothesis 4B: The access of relevant information will have a significant impact on an individual investor's investment decision in stocks market

2.5. Household Finance (H5)

In the intricate tapestry of financial decision-making, household dynamics play a pivotal role. These dynamics are not limited to earnings and expenditures but extend to the familial responsibilities and commitments an individual shoulders. Campbell (2006) studied household finance using 2001 Survey of Consumer Finances dataset in US. His evidence on participation, diversification and mortgage refinancing results lead to a conclusion that many households invest in an effective manner while a few made severe mistakes, driven by lower wealth level and less education. Guiso and Sodini (2013) documented the rise of household finance literature after Campbell (2006) and developed a framework in household risk preferences and beliefs and discussed the determinants of risk attitudes. Another study in 2016 reviewed and extended the literature on international household finance with 13 developed countries to document the domination of nonfinancial asset (vehicles, real estate, and private business) compared to financial assets, such as: retirement and insurance, deposits, stocks, mutual funds, bonds, and other assets (Badarinza *et al.*, 2016). Their results demonstrate conclusively that some households are significantly worse-off compared to the rest, and that could lead to severe weakness of those household lifetime welfare. Beshears *et al.* in 2018 wrote a book chapter for the Handbook of Behavioral Economics, summarizing key factors regarding to household financial behavior, and addressing interventions from firms, governments, and other parties. They highlight issues such as under-diversification, underperformance as retail investors due to various behavioral biases, poor mutual fund choices, less insurance coverage, and high lottery participation. The authors proposed interventions such as more education and information, through product design and better advice and disclosure. Along the behavioral finance literature, Stango and Zinman (2009) documented the household tendency to underestimate an interest rate and future value given other loan/investment terms, and consequently, the more-biased household borrow more and save less. Gomes *et al.* in 2021 documented the complex, independent, heterogenous decision-making process of household financial decisions. They modeled the lifecycle of asset allocation process (include insurance, trading, retirement saving and financial choices) based on portfolio optimization theory and incorporate survey research on liabilities (mortgage, refinancing, and default) as well as social environment (peer effects, cultural, financial literacy, cognition, and education intervention).

As Campbell (2006) and many scholars suggest, data quality is one of the main constrain in better understanding household finance situations. In this survey, we capture the status of household and imply a living cost based on the following measurements. An investor's marital status can introduce varying degrees of financial interdependence, impacting both immediate and long-term financial needs. Children, undeniably, come with their own set of financial demands, ranging from education and healthcare to daily sustenance. Elderly cohabitants, too, can necessitate specialized care and medical expenses, which may not be predictable. Meanwhile, the presence of dependent adults poses its own unique set of financial challenges, emphasizing the importance of financial resilience and adaptability. Coupled with the overarching context of a household's average monthly income, these factors cumulatively shape an investor's liquidity requirements and investment horizons. Drawing from these parameters, we posit the following hypotheses:

Hypothesis 5: The household-based financial responsibility will have a significant impact on an individual investor's liquidity needs.

2.6. Liquidity Needs (H6)

Liquidity needs in investor decision-making refer to the financial requirements or demands an investor has for readily available funds or assets that can be easily converted into cash to meet their short-term financial obligations or objectives. These needs are typically driven by various factors, including an investor's individual financial goals, risk tolerance, and time horizon (Abraham & Ikenberry, 1994). Investor profiling uncovers the preferences of investors for undertaking investment decisions, arising from all sources of factors. Risk bearing capacity has a high positive correlation with liquidity needs, followed by family responsibilities (Agarwal, 2017). In this paper, we measure the liquidity needs using questions including whether there are sufficient cash flows, resources, planned retiring age and insurance coverages. Existing studies have shown the liquidity needs would impact investment goals (Agarwal, 2017), together with demographic factors to be responsible for different investor profiles and preferences which in turn finally affect their investment decisions.

Hypothesis 6: The liquidity needs will have a significant impact on an individual's investment decision in stocks market.

3. Data and Research Methodology

In our study, we employed a comprehensive quantitative methodology to collect data from a substantial cohort of investors within the Singaporean market. A structured online survey was meticulously designed to capture a wide array of variables, ranging from demographic information to detailed investment behaviors. We successfully administered this survey to a representative sample of 1,076 retail investors based in Singapore. The sampling strategy was crafted to reflect the diverse nature of the investing population, ensuring inclusivity across various age groups, income levels, and investment experiences. The data collection process was rigorously monitored to maintain high standards of reliability and validity. The resulting dataset provides a rich foundation for our analysis, capturing a snapshot of the investment landscape from the perspective of individual investors operating in a dynamic financial hub. The survey responses yield a scale reliability coefficient of 0.71, indicating a moderate level of internal consistency. Such a figure is deemed acceptable within the scope of social science research data (Hajjar, 2018).

This research utilizes the Structural Equation Modeling (SEM) to test the unidimensionality of the constructs and to analyze the antecedents of retail investors' stock investment activities. The SEM is used here because of its several privileges over other approaches in social science. Firstly, SEM has the ability to measure latent variables or test multiple and simultaneous variables relationship (Dasgupta & Singh, 2019). Variables that are directly measured are considered as observed variables, while latent variables are inferred constructs that are not directly measured but are assumed to underlie the observed variables. Additionally, this method is suitable for both exploratory and confirmatory research (Gefen *et al.*, 2011), as it evaluates the entire variable system in the conceptual model simultaneously. SEM can elucidate direct, indirect, and total effects (Wootton, 1994), allowing researchers to test the causal relationships between variables in a more complex system. Finally, SEM results are often presented through path diagrams, which visually depict the relationships between observed and latent variables.

We construct a SEM with latent exogenous and endogenous variables following Jöreskog and Sörbom (1996). The model consists of six measurement sub-models and eight structural sub-models.

Measurement models: describes the relationships between latent and observed variables.

(i) trading = frequencyTrading+ζ_1

(ii) employ = Fulltime + γ_1 Parttime/GIG+γ_2 Unemployed+γ_3 freChngJob+γ_5 FinInd+ζ_2

(iii) house = Married+γ_4 numKid+γ_5 numSenior+γ_6 monthlyIncome+ζ_3

(iv) needs = SufficientCF+γ_7 SufficientResource++γ_8 RetireAge++γ_9 NoInsurance++γ_{10} FullInsurance+ζ_4

(v) channel = FinInd+γ_{11} fromFriends+γ_{12} fromNewspaper+γ_{13} fromForum+γ_{14} fromSocial+ζ_5

(vi) risk = FinInd+γ_{15} RiskTolerance+γ_{16} RiskTakerAsFriend+γ_{17} GameChoice+γ_{18} InheritChoice+ζ_6

Structural models: examines the relationships between latent variables.

(i) creditCons=β_1 Gender+β_2 Age+β_3 Degree+ϵ_1

(ii) knowledge=β_4 Gender+β_5 Age+β_6 Degree+ϵ_2

(iii) risk=β_7 creditCons+ϵ_3

(iv) employ=β_8 Gender+β_9 Age+β_{10} Degree+ϵ_4

(v) channel=β_{11} Gender+β_{12} Age+β_{13} Degree+ϵ_5

(vi) house=β_{14} Gender+β_{15} Age+β_{16} Degree+ϵ_6

(vii) needs=β_{17} Gender+β_{18} Age+β_{19} Degree+ϵ_7

(viii) trading=β_{20} risk + β_{21} Knowledge+β_{22} employ+β_{23} house+β_{24} needs+β_{25} channel+β_{26} COVID+ϵ_8.

4. Empirical Results

4.1. Variable Description and Summary Statistics

The variables definition and summary statistics can be found in Table 1. We measure the decision of investors by the frequency of their trading in stocks, bonds, options, futures, FX, as well as cryptocurrency. The frequency of trading by assigning zero to "no trades", one to "1 to 10 trades", eleven to "11 to 25 trades", twenty-six to "26 to 50 trades", fifty-one to "51 to 100 trades", and one hundred and twenty to "more than 100 trades". The assigned numbers are then divided by 10 to normalize the variables for the later input for SEM model. To use the knowledge in each of the assets to explain investors' trading frequency, this information is also being "quantified". When the survey response is "no knowledge", we assign knowledge of stocks (StockKnow) to be zero, "basic knowledge" as one, "good knowledge" as two and "extensive knowledge" as three. We also assign numbers to trading experience, zero to "no experience", one to "1-year experience", two to "2-3 years' experience", four to "4-5 years' experience", six to "6-10 years' experience" and twelve to "more than 10 years' experience" in trading each of the asset class.

The following demographic information is included in the analysis. Age is assigned as one if the respondent is between 18 and 24 years old, two if between 25 and 34 years old, three if between 35 and 44 years old, four if between 45 and 54 years old, five if between 55 and 64 years old and six if 65 years old and above. Gender is assigned as one if the respondent is female and two if male. Race is assigned as one for Chinese, two for Indian, three for Malay and four for others (alphabetic order). Degree is assigned as one if the survey result is "Below secondary", two for "Secondary", three for "Post-secondary", four for "Diploma", five for "Bachelor", six for "Master" and seven for "Doctorate". The number of children and number of senior dependents are assigned as one if the actual number reported is "0", one if "1-2", two if "3-4" and four if "5 and above".

For the financial industry experience, FinInd is 1 if the person is working in the finance industry and 0 otherwise. For the dummy variable Married, it is defined as 1 if the person is married and 0 if otherwise. We also have quantified the monthly income, whether the person has sufficient cash flow, sufficient future cash flow, and their planned retired age. If the survey question has multiple choices as the answer, we use the average of the range to quantify the responses. The source of information is being quantified as a dummy variable based on each of the channels (from friends, from newspaper, from forum, and from social media). We also measure the retail investors' risk tolerance from conservative (1) to aggressive (3).

Table 1 Summary Statistics

The scale reliability coefficient is 0.71, implies a moderate level of internal consistency.

Variable	*Obs*	*Mean*	*Std. Dev*	*Min*	*Max*	*Definition*
freqStocks	1,076	1.77	3.19	0	12	frequency of trading stocks/10
freqBond	1,076	0.48	1.65	0	12	frequency of trading bonds/10
freqOptions	1,076	0.57	1.80	0	12	frequency of trading options/10
freqFutures	1,076	0.49	1.81	0	12	frequency of trading futures/10
freqFX	1,076	0.46	1.78	0	12	frequency of trading FX instruments/10
freqCrypto	1,076	0.47	1.66	0	12	frequency of trading cryptocurrency/10
StockKnow	1,076	2.38	0.71	1	4	from no knowledge (1) to extensive knowedge (4)
CryptoKnow	1,076	1.64	0.80	1	4	from no knowledge (1) to extensive knowedge (4)
FXKnow	1,076	1.63	0.80	1	4	from no knowledge (1) to extensive knowedge (4)
FutureKnow	1,076	1.58	0.81	1	4	from no knowledge (1) to extensive knowedge (4)
BondKnow	1,076	1.99	0.77	1	4	from no knowledge (1) to extensive knowedge (4)
OptionKnow	1,076	1.66	0.79	1	4	from no knowledge (1) to extensive knowedge (4)
Gender	1,076	1.73	0.45	1	2	Female (1) vs Male (2)
Age	1,076	3.20	1.34	1	6	from 18-24 (1) to 65 and above (6)
Degree	1,076	4.87	1.17	1	7	from Below Secondary (1) to Doctorate (6)
COVID	1,076	3.19	1.09	1	5	Insignificant impact (1) to Severe impact (5)
Fulltime	1,076	0.69	0.46	0	1	Full-time employed dummy variable
ParttimeGIG	1,076	0.12	0.33	0	1	Part-time employed or working on as GIG dummy variable
Unemployed	1,076	0.04	0.21	0	1	Currently unemployed
freChngJob	1,076	5.65	3.81	0.5	10	Frequency of job changes in years
extraIncome	1,076	1.54	3.66	0	22.5	in thousands of dollars
FinInd	1,076	0.15	0.35	0	1	Working in the financial industry dummy
Married	1,076	0.57	0.50	0	1	Married dummy
numKid	1,076	0.88	1.08	0	5.5	Number of children in the household
numSenior	1,076	0.70	0.97	0	5.5	Number of seniors in the household
monthlyIncome	1,076	8.30	5.51	2	15	in thousands of dollars
SufficientCF	1,076	2.26	0.73	1	3	from Not at all (1) to I can fulfil all my current major cashflow needs (3)

cont. table 1

Variable	*Obs*	*Mean*	*Std. Dev*	*Min*	*Max*	*Definition*
SufficientResource	1,076	2.73	1.08	1	4	from Not at all (1) to I can fulfil all my future major cashflow needs (3)
RetireAge	1,076	2.37	1.10	1	4	from Less than 55 years old (1) to After 65 years old (4)
NoInsurance	1,076	0.12	0.33	0	1	No insurance access
FullInsurance	1,076	0.29	0.45	0	1	Full insurance access
fromFriends	1,076	0.04	0.20	0	1	Source of info in investing – friends dummy
fromNewspaper	1,076	0.24	0.43	0	1	Source of info in investing – newspaper dummy
fromForum	1,076	0.23	0.42	0	1	Source of info in investing – investment forum dummy
fromSocialmedia	1,076	0.30	0.46	0	1	Source of info in investing – social media dummy
RiskTolerance	1,076	1.85	0.66	1	3	from Conservative risk tolerance (1) to Aggressive risk tolerance (3)
RiskTakerAsFriend	1,076	2.55	0.72	1	4	from A real risk avoider (1) to A real gambler (4)
GameChoice	1,076	2.07	0.91	1	4	from $1,000 in cash (1) to A 5% chance at winning $100,000 (4)
InheritChoice	1,076	2.18	0.92	1	4	from A savings account (1) to Commodities like gold, silver, and oil (4)

The correlation coefficient matrix is reported in Table 2. In Panel A, we find that trading frequencies and trading knowledge are positively related within one asset class and cross asset classes. In Panel B, we find that age is positively correlated with household income, educational degree, living in larger places, having more kids and senior dependents in the same household. Another interesting point to note is that in Panel E, when a respondent chooses to source investment information from friends, he or she is less likely to do so from other resources, and is more risk averse.

Figure 2: Demographic Information

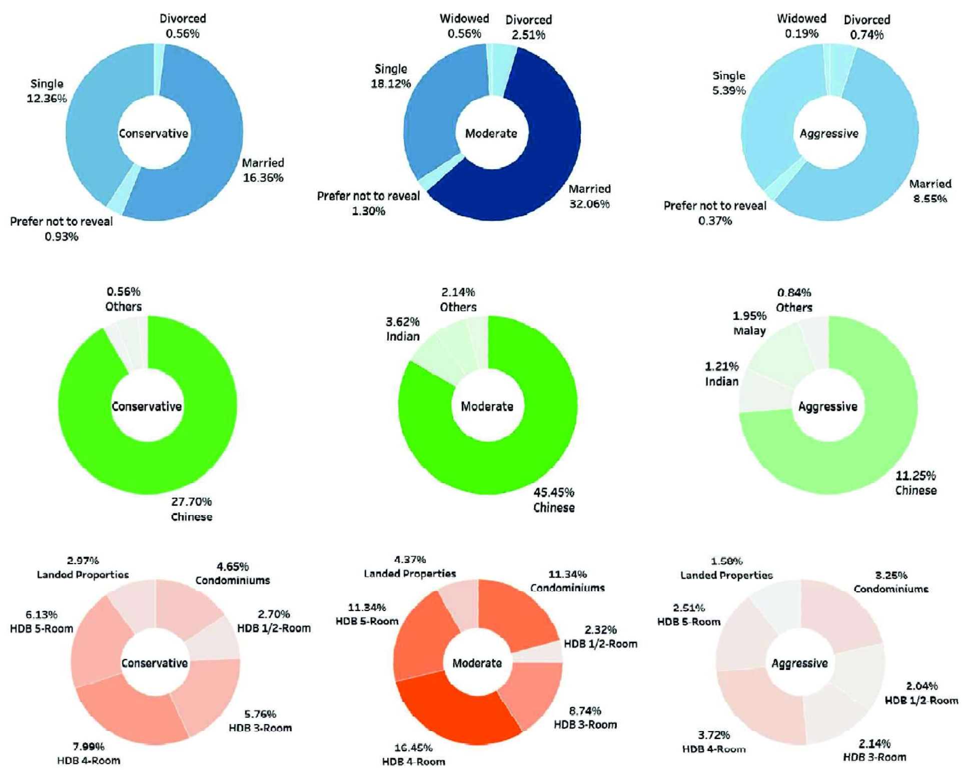


Figure 2.1: Demographic: Marital Status, Residency, Race;

Before the SEM model, we report the demographic information of our dataset along the following perspectives and plot the unit-variate information in Figure 2.

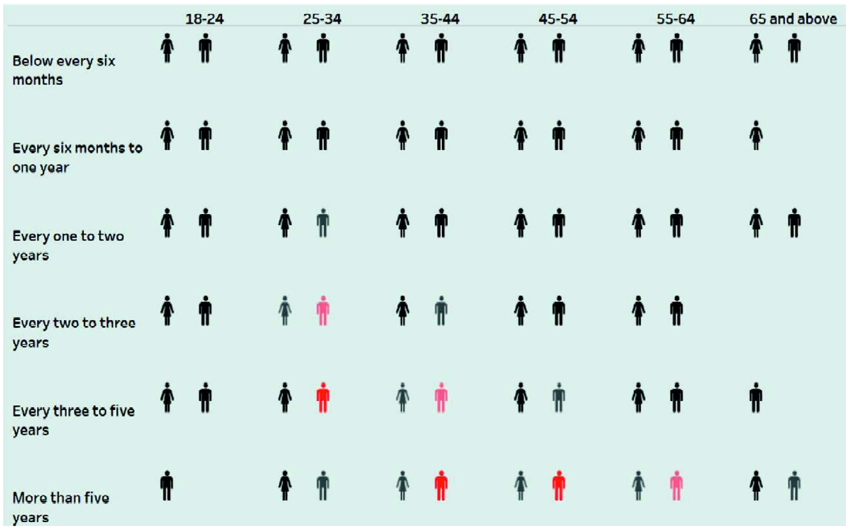


Figure 2.2: Age group versus Frequency to change the job;

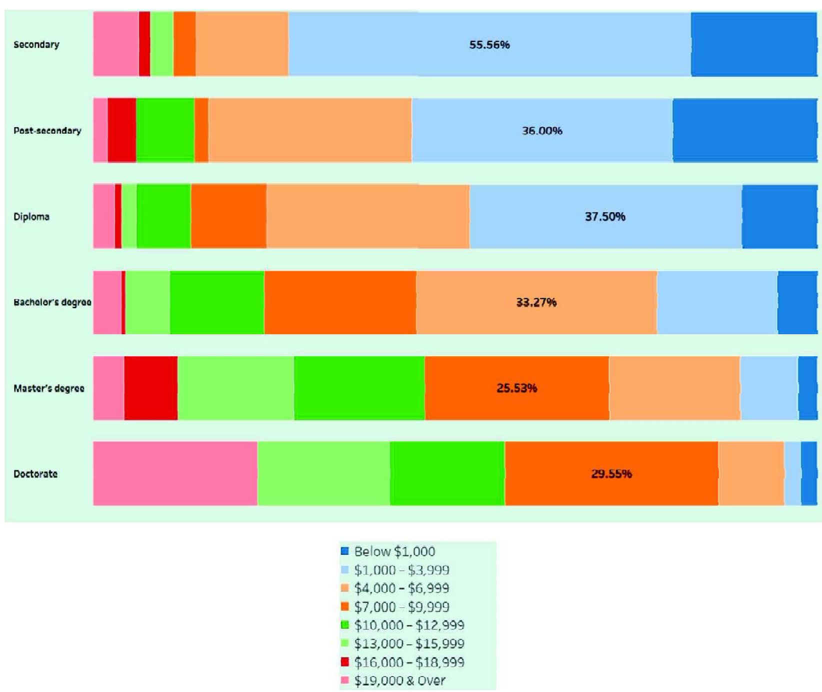
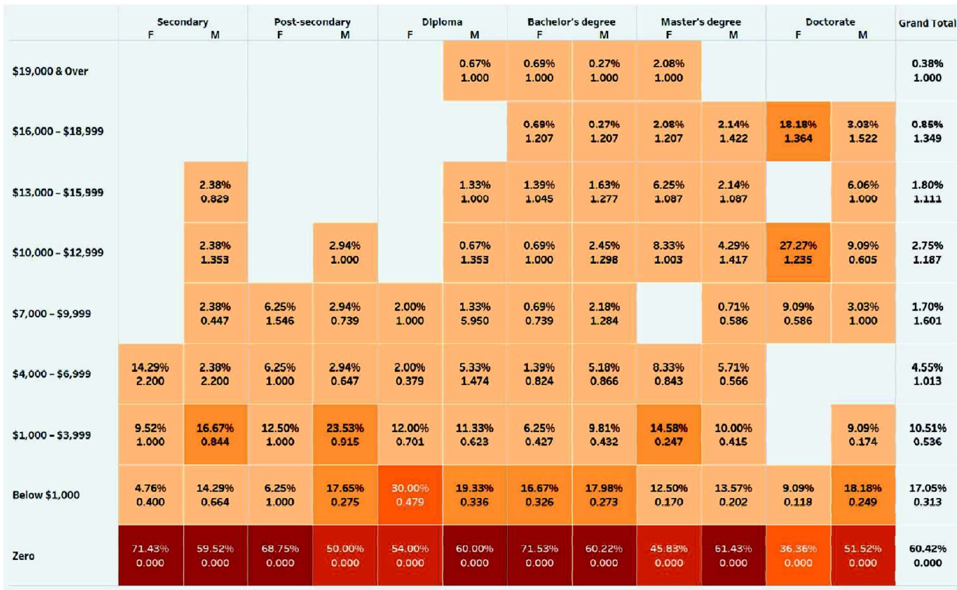


Figure 2.3: Education background versus Main monthly income;



	Secondary		Post-secondary		Diploma		Bachelor's degree		Master's degree		Doctorate		Grand Total
	F	M	F	M	F	M	F	M	F	M	F	M	
$19,000 & Over						0.67% 1.000	0.69% 1.000	0.27% 1.000	2.08% 1.000				0.38% 1.000
$16,000 – $18,999							0.69% 1.207	0.27% 1.207	2.08% 1.207	2.14% 1.422	18.18% 1.364	3.03% 1.522	0.85% 1.349
$13,000 – $15,999		2.38% 0.829				1.33% 1.000	1.39% 1.045	1.63% 1.277	6.25% 1.087	2.14% 1.087		6.06% 1.000	1.80% 1.111
$10,000 – $12,999		2.38% 1.353		2.94% 1.000		0.67% 1.353	0.69% 1.000	2.45% 1.298	8.33% 1.003	4.29% 1.417	27.27% 1.235	9.09% 0.605	2.75% 1.187
$7,000 – $9,999		2.38% 0.447	6.25% 1.546	2.94% 0.739	2.00% 1.000	1.33% 5.950	0.69% 0.739	2.18% 1.284		0.71% 0.586	9.09% 0.586	3.03% 1.000	1.70% 1.601
$4,000 – $6,999	14.29% 2.200	2.38% 2.200	6.25% 1.000	2.94% 0.647	2.00% 0.379	5.33% 1.474	1.39% 0.824	5.18% 0.866	8.33% 0.843	5.71% 0.566			4.55% 1.013
$1,000 – $3,999	9.52% 1.000	16.67% 0.844	12.50% 1.000	23.53% 0.915	12.00% 0.701	11.33% 0.623	6.25% 0.427	9.81% 0.432	14.58% 0.247	10.00% 0.415		9.09% 0.174	10.51% 0.536
Below $1,000	4.76% 0.400	14.29% 0.664	6.25% 1.000	17.65% 0.275	30.00% 0.479	19.33% 0.336	16.67% 0.326	17.98% 0.273	12.50% 0.170	13.57% 0.202	9.09% 0.118	18.18% 0.249	17.05% 0.313
Zero	71.43% 0.000	59.52% 0.000	68.75% 0.000	50.00% 0.000	54.00% 0.000	60.00% 0.000	71.53% 0.000	60.22% 0.000	45.83% 0.000	61.43% 0.000	36.36% 0.000	51.52% 0.000	60.42% 0.000

Figure 2.4: Education background versus Side-gig monthly income;

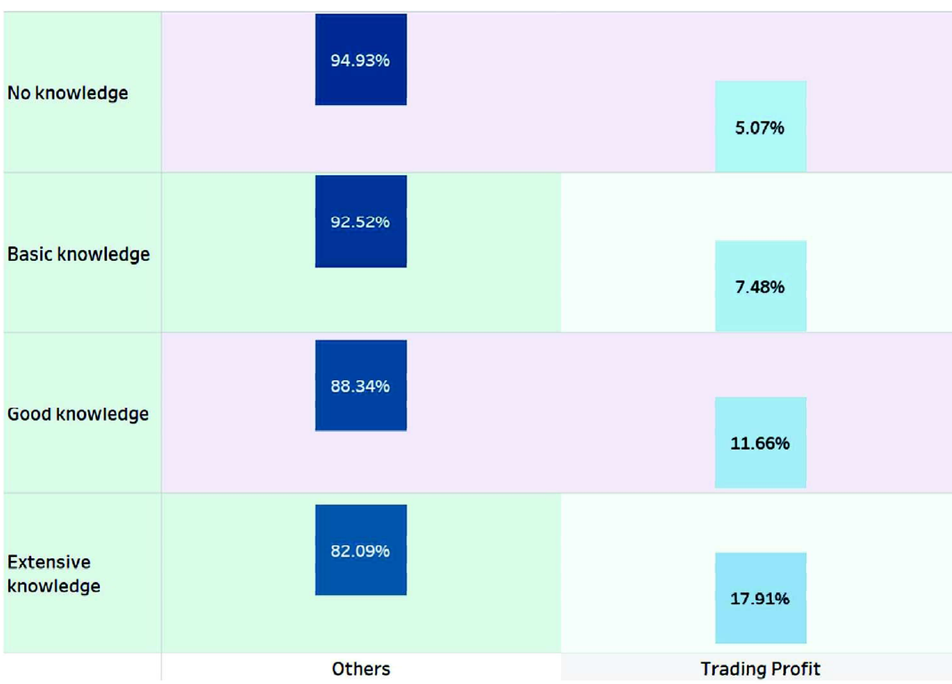


Figure 2.5: Trading knowledge versus Trading profit;

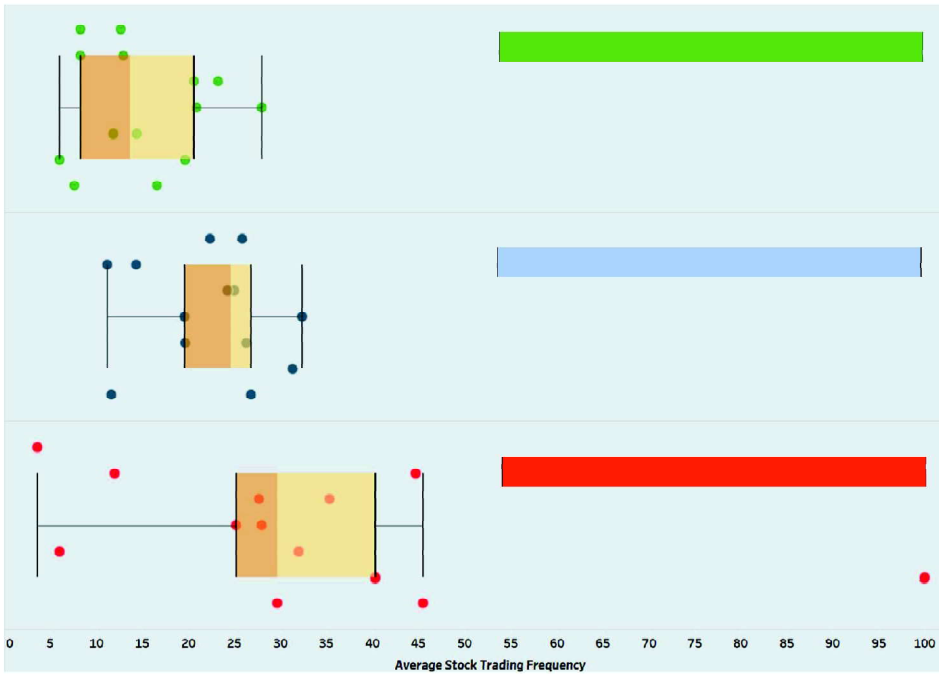


Figure 2.6: Stock trading frequency versus Risk tolerance;

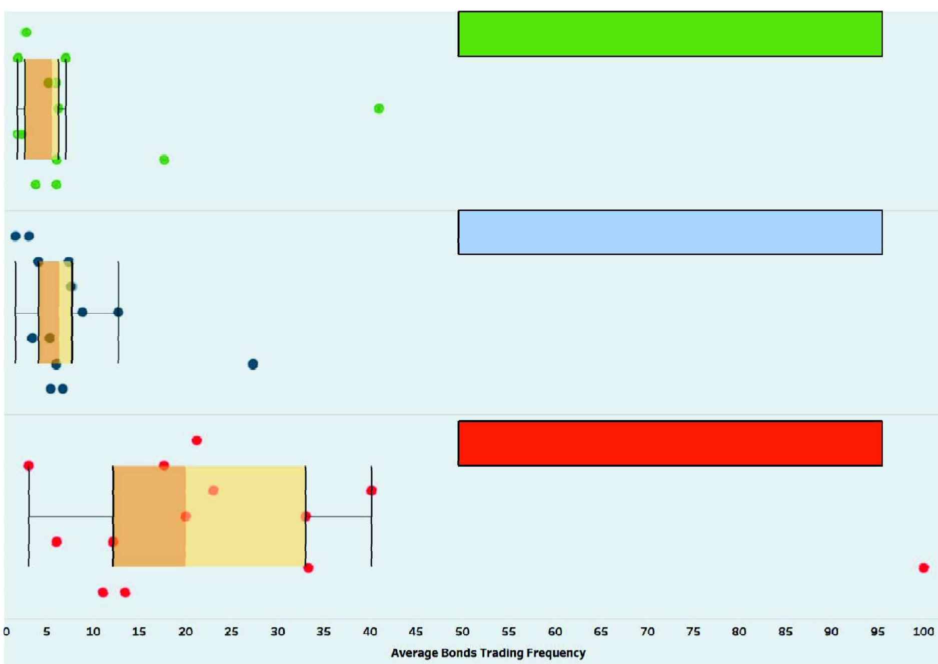


Figure 2.7: Bond trading frequency versus Risk tolerance.

Table 2: Correlation Coefficient Matrix

We report the correlation coefficient matrix of all the variables in the SEM model.

Panel A	*freqStocks*	*freqBond*	*freqOptions*	*freqFutures*	*freqFX*	*freqCrypto*	*StockKnow*	*CryptoKnow*
freqStocks	1.000							
freqBond	0.320	1.000						
freqOptions	0.415	0.531	1.000					
freqFutures	0.317	0.509	0.489	1.000				
freqFX	0.317	0.535	0.471	0.675	1.000			
freqCrypto	0.268	0.614	0.556	0.635	0.648	1.000		
StockKnow	0.370	0.299	0.296	0.259	0.247	0.258	1.000	
CryptoKnow	0.180	0.440	0.384	0.389	0.410	0.541	0.406	1.000
FXKnow	0.199	0.355	0.350	0.431	0.483	0.419	0.433	0.634
FutureKnow	0.256	0.406	0.406	0.522	0.462	0.425	0.452	0.622
BondKnow	0.201	0.384	0.293	0.264	0.268	0.302	0.597	0.506
OptionKnow	0.284	0.374	0.519	0.363	0.362	0.368	0.491	0.581
Gender	0.136	0.026	0.068	0.025	-0.001	0.039	0.171	0.082
Age	0.033	-0.087	-0.064	-0.022	-0.024	-0.101	0.118	-0.221
Degree	0.005	0.003	-0.016	-0.060	-0.023	-0.040	0.227	0.097
COVID	-0.062	-0.030	-0.049	-0.034	-0.052	-0.049	-0.087	0.025
Fulltime	-0.041	-0.008	-0.005	-0.073	-0.036	-0.022	-0.004	0.025
ParttimeGIG	0.065	0.017	0.012	0.064	-0.002	0.019	0.021	-0.029
Unemployed	-0.049	-0.017	-0.042	-0.024	-0.016	-0.018	-0.028	-0.015
freChngJob	0.079	-0.077	-0.099	-0.060	-0.038	-0.096	0.063	-0.150
extraIncome	0.132	0.313	0.288	0.263	0.289	0.323	0.215	0.405
FinInd	0.079	0.015	0.062	0.024	0.015	0.023	0.181	0.055
Married	0.040	0.060	0.029	0.042	0.060	0.038	0.158	0.027
numKid	0.057	0.112	0.067	0.081	0.095	0.109	0.113	0.063
numSenior	0.025	0.105	0.096	0.093	0.090	0.119	0.075	0.103
monthlyIncome	0.090	0.081	0.075	0.048	0.086	0.084	0.187	0.118
SufficientCF	0.119	0.017	0.021	0.051	0.042	0.039	0.281	0.070
SufficientResource	0.107	0.087	0.070	0.077	0.053	0.042	0.325	0.065

RetireAge	-0.043	-0.051	-0.049	0.001	0.003	-0.059	-0.016	-0.140
NoInsurance	-0.019	0.015	0.002	0.050	0.047	0.049	-0.224	-0.065
FullInsurance	0.053	0.025	0.037	0.019	0.010	0.027	0.182	0.100
FinInd	0.079	0.015	0.062	0.024	0.015	0.023	0.181	0.055
fromFriends	-0.010	0.039	0.022	0.003	0.004	0.007	-0.111	-0.009
fromNewspaper	-0.038	-0.028	-0.027	-0.007	-0.033	-0.028	0.059	-0.009
fromForum	0.003	-0.025	-0.020	-0.047	-0.014	-0.046	-0.015	-0.040
fromSocialmedia	0.016	0.009	-0.001	-0.023	0.011	0.003	-0.056	0.008
RiskTolerance	0.225	0.213	0.260	0.273	0.252	0.293	0.353	0.328
RiskTakerAsFriend	0.125	-0.013	0.044	0.012	0.022	0.019	0.077	0.083
GameChoice	0.156	0.118	0.150	0.143	0.151	0.169	0.220	0.240
InheritChoice	0.097	0.029	0.091	0.071	0.073	0.044	0.205	0.125

Panel B	*FXKnow*	*FutureKnow*	*BondKnow*	*OptionKnow*	*Gender*	*Age*	*Degree*	*COVID*
FXKnow	1.000							
FutureKnow	0.739	1.000						
BondKnow	0.542	0.553	1.000					
OptionKnow	0.657	0.734	0.584	1.000				
Gender	0.092	0.139	0.111	0.128	1.000			
Age	-0.062	-0.080	-0.001	-0.070	-0.036	1.000		
Degree	0.109	0.071	0.189	0.093	0.014	0.039	1.000	
COVID	0.018	0.006	-0.015	0.012	-0.044	-0.145	-0.036	1.000
Fulltime	-0.026	-0.025	-0.001	0.004	0.051	-0.249	0.140	0.072
ParttimeGIG	0.034	0.071	0.003	0.038	-0.053	0.133	-0.089	-0.011
Unemployed	-0.003	-0.011	-0.016	0.020	-0.009	0.012	0.002	-0.012
freChngJob	-0.111	-0.128	-0.058	-0.137	0.021	0.432	0.006	-0.115
extraIncome	0.360	0.427	0.293	0.376	-0.013	-0.154	0.071	0.101
FinInd	0.137	0.129	0.185	0.123	-0.059	0.000	0.069	0.004
Married	0.068	0.095	0.115	0.071	0.118	0.330	0.180	-0.034
numKid	0.094	0.109	0.102	0.085	0.016	0.275	0.005	-0.076
numSenior	0.084	0.112	0.066	0.093	-0.029	0.013	-0.091	-0.007

monthlyIncome	0.110	0.075	0.179	0.087	0.065	0.016	0.251	-0.115
SufficientCF	0.106	0.084	0.206	0.072	-0.029	0.292	0.235	-0.232
SufficientResource	0.117	0.127	0.268	0.122	-0.010	0.331	0.235	-0.164
RetireAge	-0.053	-0.059	-0.082	-0.076	0.026	0.401	0.001	-0.120
NoInsurance	-0.103	-0.052	-0.161	-0.079	0.011	-0.150	-0.200	0.033
FullInsurance	0.086	0.088	0.122	0.094	-0.010	0.014	0.128	-0.055
FinInd	0.137	0.129	0.185	0.123	-0.059	0.000	0.069	0.004
fromFriends	-0.014	0.011	-0.023	-0.008	-0.066	-0.051	-0.086	0.056
fromNewspaper	0.021	0.028	0.044	-0.001	0.023	0.046	0.066	0.020
fromForum	-0.041	-0.032	-0.015	-0.032	-0.007	0.062	0.055	0.041
fromSocialmedia	-0.014	-0.044	-0.044	0.005	0.008	-0.144	-0.061	0.022
RiskTolerance	0.298	0.309	0.330	0.315	0.130	-0.113	0.091	-0.063
RiskTakerAsFriend	0.046	0.061	0.050	0.067	0.177	-0.156	-0.056	0.029
GameChoice	0.223	0.219	0.166	0.202	0.047	-0.106	0.107	-0.024
InheritChoice	0.111	0.106	0.107	0.124	0.060	0.042	0.087	-0.078

Panel C	*Fulltime*	*ParttimeGIG*	*Un-employed*	*freChngJob*	*extraIncome*	*FinInd*	*Married*	*numKid*
Fulltime	1.000							
ParttimeGIG	-0.548	1.000						
Unemployed	-0.319	-0.080	1.000					
freChngJob	-0.004	0.024	-0.072	1.000				
extraIncome	0.019	0.016	-0.046	-0.147	1.000			
FinInd	0.008	0.081	-0.038	-0.017	-0.070	1.000		
Married	0.079	-0.006	-0.076	0.205	0.060	-0.029	1.000	
numKid	-0.028	0.012	-0.019	0.168	0.111	-0.016	0.477	1.000
numSenior	-0.034	0.016	0.035	-0.010	0.124	-0.024	-0.083	0.151
monthlyIncome	0.230	-0.123	-0.125	0.071	0.126	0.093	0.297	0.155
SufficientCF	-0.066	0.033	-0.027	0.208	-0.051	0.103	0.183	0.068
SufficientResource	-0.048	0.051	-0.037	0.199	0.051	0.097	0.230	0.119
RetireAge	-0.069	0.055	0.034	0.169	-0.107	-0.038	0.182	0.220
NoInsurance	-0.084	0.007	0.055	-0.089	-0.016	-0.092	-0.155	-0.066

FullInsurance	0.054	0.033	-0.059	0.039	0.051	0.060	0.081	0.035
FinInd	0.008	0.081	-0.038	-0.017	-0.070	1.000	-0.029	-0.016
fromFriends	-0.026	-0.017	0.002	-0.090	0.023	-0.017	-0.072	-0.049
fromNewspaper	-0.008	0.055	0.003	-0.001	0.019	-0.014	0.043	-0.001
fromForum	0.012	-0.008	-0.002	0.098	-0.009	0.022	0.007	0.015
fromSocialmedia	0.064	-0.009	-0.045	-0.074	-0.019	0.002	-0.030	0.007
RiskTolerance	-0.002	0.024	0.001	-0.054	0.184	0.078	0.022	0.024
RiskTakerAsFriend	0.001	0.035	-0.041	-0.076	0.026	0.044	-0.074	-0.051
GameChoice	0.034	-0.035	-0.002	-0.048	0.127	0.021	0.036	0.021
InheritChoice	-0.008	0.037	-0.044	0.063	0.073	0.037	0.026	-0.009

Panel D	*numSenior*	*monthlyIncome*	*SufficientCF*	*Sufficient Resource*	*RetireAge*	*NoInsurance*	*Full Insurance*	*FinInd*
numSenior	1.000							
monthlyIncome	-0.050	1.000						
SufficientCF	-0.039	0.264	1.000					
SufficientResource	0.004	0.243	0.729	1.000				
RetireAge	-0.001	0.030	0.128	0.125	1.000			
NoInsurance	0.012	-0.189	-0.291	-0.245	-0.047	1.000		
FullInsurance	-0.029	0.190	0.250	0.221	0.005	-0.242	1.000	
FinInd	-0.024	0.093	0.103	0.097	-0.038	-0.092	0.060	1.000
fromFriends	0.003	-0.132	-0.072	-0.098	-0.034	0.110	-0.026	-0.017
fromNewspaper	-0.021	0.050	0.090	0.071	0.013	-0.083	0.066	-0.014
fromForum	-0.016	0.050	0.035	0.074	0.026	-0.081	0.011	0.022
fromSocialmedia	0.020	-0.014	-0.128	-0.137	-0.049	0.063	-0.072	0.002
RiskTolerance	0.046	0.136	0.148	0.146	-0.072	-0.081	0.124	0.078
RiskTakerAsFriend	-0.003	0.019	-0.001	-0.045	-0.122	0.050	0.039	0.044
GameChoice	0.017	0.135	0.088	0.064	-0.058	-0.048	0.100	0.021
InheritChoice	-0.028	0.092	0.153	0.142	-0.029	-0.110	0.114	0.037

Panel E	*From Friends*	*From Newspaper*	*From Forum*	*From Socialmedia*	*Risk Tolerance*	*Risk Taker As Friend*	*Game Choice*	*Inherit Choice*
fromFriends	1.000							
fromNewspaper	-0.116	1.000						
fromForum	-0.112	-0.312	1.000					
fromSocialmedia	-0.135	-0.375	-0.364	1.000				
RiskTolerance	-0.055	-0.019	-0.029	0.003	1.000			
RiskTakerAsFriend	-0.045	0.012	-0.026	0.000	0.297	1.000		
GameChoice	-0.016	0.002	0.016	-0.040	0.345	0.131	1.000	
InheritChoice	-0.072	0.051	0.035	-0.065	0.272	0.100	0.251	1.000

A generation shift is shown on the result of switching job question (Figure 2.2). Respondents from Gen Z category tend to drive the movement, with more than 30% of them changing jobs within 6 months. Millennials generation' job hoping shows on every 3 to 5 years for female respondents and more than 5 years for male respondents. From the report from LinkedIn in 2015, a person's age is able to influence the decision to change jobs and younger workers are more likely to be looking for new opportunities actively. However, to take note, this survey was conducted during post-COVID era when there is still after impact of greet resignation and subsequent hiring crisis. Across the age groups, changing jobs every 2 to 3 years are dominated by the respondents from the age group of 25-34 years, while respondents in between 34 to 64 have less frequent job change.

Based on the academic background (Figure 2.3), respondents' monthly income clearly distinguishes between bachelor's degree holders and non-holders. The majority of the respondents with bachelor's degree and above earned at least SGD$4,000 per month, while their counterparts show high proportion in the range between SGD$1,000 and SGD$4,000 per month.

With the number of gig workers increasing in Singapore, the analysis regarding this type of employment is also worth being discussed. The data (Figure 2.4) shows that around 40% of the respondents are earning from their side gig jobs and close to 12% of the respondents earned higher from their side gig job compared to their main job's monthly income (side gig income/main monthly income > 1).

Based on the knowledge about stock trading, the respondents are showing positive correlation to their trading profit as a source of income (Figure 2.5). Within the group of "no knowledge in stock trading", only 5.07% respondents select trading profit as one of their top 3 sources of income. while for respondents with "extensive knowledge", close to 18% of them indicated profit from stock trading as one of their sources of income.

Based on the respondents' risk tolerance, the frequency of stock trading shows significant differences for each category. For respondents that are more conservative, the trading frequency median is 14 times in a year. The lowest frequency is 6 times from the female respondents that have education background below secondary. The moderate investors group has a median trading frequency of 25 times in a year. And the highest trading frequency is from male respondents that have doctorate degree in education. The last category is those who are aggressive in terms of risk tolerance. This category has the highest median compared to the other two groups, trading 30 times in a year.

There is a possibility of outliers for this category, which is from the female respondents that have below secondary education level.

Slightly different compared to the stock trading frequency, for bonds transaction, the median frequency between conservative and moderate are almost similar, with 6 and 7 times respectively. For aggressive respondents, the median bonds transactions number is more than double of the other two categories, which is 20 times in a year. Similar to possible outlier in the stock transactions analysis, under this category the female respondents with education level below secondary indicate an average of 100 bonds transaction in a year.

4.2. SEM Model

The first SEM model is to understand the decision of retail investors' stock trading. The evaluation results are reported in Table 3, and the significant paths are identified by the * in Figure 3.

Table 3: SEM results on Stock Trading

We estimated the following SEM results using eight structural sub-models and six measurement sub-models as described in the research methodology section, and in studying stock trading activities, we use *stockTrading* for *Trading*, and *stockKnow* as *Knowledge*. Estimated coefficient, standard error, test statistics and p-value are reported. standard error, test statistics and p-value are reported.

$$\text{Trading} = \beta_{20}\ \text{risk} + \beta_{21}\ \text{Knowledge} + \beta_{22}\ \text{employ} + \beta_{23}\ \text{house} + \beta_{24}\ \text{needs} + \beta_{25}\ \text{channel} + \beta_{26}\ \text{COVID} + \epsilon_8$$

Panel A: Structural Models

Dependent Variable	*Moderator*	*estimate*	*std. error*	*test statistic*	*p-value*
creditCons	Gender	0.044	0.032	1.377	0.168
creditCons	Age	-0.015	0.011	-1.325	0.185
creditCons	Degree	0.010	0.008	1.348	0.178
StockKnow	Gender	0.277	0.049	5.635	0.000
StockKnow	Age	0.057	0.016	3.627	0.000
StockKnow	Degree	0.131	0.016	8.314	0.000
risk	creditCons	7.754	5.670	1.367	0.171
employ	Gender	-0.001	0.018	-0.058	0.954
employ	Age	-0.103	0.025	-4.131	0.000
employ	Degree	0.026	0.010	2.622	0.009
channel	Gender	0.003	0.008	0.341	0.733
channel	Age	0.011	0.010	1.137	0.256
channel	Degree	0.015	0.012	1.222	0.222
house	Gender	0.015	0.013	1.221	0.222
house	Age	0.031	0.015	2.138	0.032

Dependent Variable	*Moderator*	*estimate*	*std. error*	*test statistic*	*p-value*
house	Degree	0.001	0.003	0.409	0.682
needs	Gender	-0.050	0.072	-0.698	0.485
needs	Age	0.282	0.026	11.049	0.000
needs	Degree	0.245	0.027	8.989	0.000
stockTrading	risk	1.186	0.156	7.600	0.000
stockTrading	StockKnow	1.696	0.126	13.478	0.000
stockTrading	employ	-2.209	1.423	-1.553	0.120
stockTrading	house	0.801	0.429	1.867	0.062
stockTrading	needs	0.460	0.115	4.013	0.000
stockTrading	channel	-24.280	20.333	-1.194	0.232
stockTrading	COVID	-0.150	0.085	-1.766	0.077

Panel B: Measurement Models

Latent Variable	*Measurement Variable*	*estimate*	*std. error*	*test statistic*	*p-value*
stockTrading	freqStocks	1.000	0.000		
employ	Fulltime	1.000	0.000		
employ	ParttimeGIG	-0.370	0.088	-4.222	0.000
employ	Unemployed	-0.017	0.054	-0.318	0.750
employ	freChngJob	-10.064	2.766	-3.639	0.000
employ	extraIncome	4.562	1.635	2.790	0.005
employ	FinInd	0.134	0.132	1.018	0.308
house	Married	1.000	0.000		
house	numKid	7.177	3.214	2.233	0.026
house	numSenior	0.615	0.157	3.913	0.000
house	monthlyIncome	4.250	1.001	4.244	0.000
needs	SufficientCF	1.000	0.000		
needs	SufficientResource	0.965	0.041	23.380	0.000
needs	RetireAge	0.097	0.037	2.615	0.009
needs	NoInsurance	-0.098	0.013	-7.355	0.000
needs	FullInsurance	0.084	0.039	2.157	0.031
channel	FinInd	1.000	0.000		
channel	fromFriends	-0.824	0.703	-1.171	0.242
channel	fromNewspaper	1.555	1.611	0.966	0.334
channel	fromForum	1.515	1.466	1.033	0.301
channel	fromSocialmedia	-1.930	2.001	-0.965	0.335
risk	RiskTolerance	1.000	0.000		
risk	RiskTakerAsFriend	0.487	0.054	8.969	0.000
risk	GameChoice	0.677	0.055	12.381	0.000
risk	InheritChoice	0.516	0.050	10.307	0.000

Panel A reports the results from structure models, and we find that risk perspective is statistically associated with stock trading behavior, suggesting that the more aggressive an individual investor is, the higher the frequency of their trading. We also find that with more knowledge, the person tends to trade more. And in terms of needs (measured by current and future cash flow sufficiency, insurance access and retirement age), we find that the higher the cash flow sufficiency, the more the person tends to trade. We also document a negative impact of COVID-19 on stock trading behaviors of retail investors in Singapore. Panel B reports the results from measurement models for details of the association between each survey question to the corresponding measurement. Risk perspective measurements are all positively correlated, suggesting a consistent representation of the respondence risk preferences. Needs are measured by current and future sufficient cash flows, and insurance access which are highly correlated. The NoInsurance dummy variable is negatively associated with needs.

The second SEM model tests on the decision of retail investors' bond trading and the results are documented in Table 4 with the significant paths identified by the * in Figure 4.

Table 4: SEM results on Bond Trading

We estimated the following SEM results using eight structural sub-models and six measurement sub-models as describe in the research methodology section, and in studying bond trading activities, we use *bondTrading* for *Trading*, and include *stockKnow* as well as *bondKnow*. Estimated coefficient, standard error, test statistics and p-value are reported.

$$\text{Trading} = \beta_{20}\ \text{risk} + \beta_{21}\ \text{stockKnow}+\beta_{22}\ \text{bondKnow}+\beta_{23}\ \text{employ}+\beta_{24}\ \text{house}+\beta_{25}\ \text{needs}+\beta_{26}\ \text{channel}+\beta_{27}\ \text{COVID}+\epsilon_8$$

Panel A: Structural Models

Dependent Variable	*Moderator*	*estimate*	*std. error*	*test statistic*	*p-value*
creditCons	Gender	0.042	0.031	1.349	0.177
creditCons	Age	-0.014	0.011	-1.298	0.194
creditCons	Degree	0.011	0.008	1.334	0.182
StockKnow	Gender	0.271	0.048	5.691	0.000
StockKnow	Age	0.060	0.016	3.832	0.000
StockKnow	Degree	0.128	0.016	8.156	0.000
BondKnow	Gender	0.189	0.052	3.607	0.000
BondKnow	Age	0.001	0.018	0.063	0.949
BondKnow	Degree	0.118	0.018	6.536	0.000
risk	creditCons	8.591	6.401	1.342	0.180
employ	Gender	-0.003	0.008	-0.364	0.716
employ	Age	-0.020	0.006	-3.211	0.001

Dependent Variable	*Moderator*	*estimate*	*std. error*	*test statistic*	*p-value*
employ	Degree	0.007	0.003	2.256	0.024
channel	Gender	-0.049	0.015	-3.270	0.001
channel	Age	-0.010	0.006	-1.658	0.097
channel	Degree	-0.039	0.010	-3.880	0.000
house	Gender	0.038	0.022	1.732	0.083
house	Age	0.059	0.016	3.588	0.000
house	Degree	0.006	0.007	0.850	0.396
needs	Gender	-0.043	0.063	-0.679	0.497
needs	Age	0.253	0.023	10.900	0.000
needs	Degree	0.213	0.024	8.754	0.000
bondTrading	risk	0.584	0.049	11.841	0.000
bondTrading	StockKnow	0.845	0.040	21.220	0.000
bondTrading	BondKnow	0.771	0.046	16.700	0.000
bondTrading	employ	11.936	3.423	3.487	0.000
bondTrading	house	1.428	0.316	4.518	0.000
bondTrading	needs	0.473	0.032	14.801	0.000
bondTrading	channel	10.857	3.077	3.529	0.000
bondTrading	COVID	-0.063	0.038	-1.662	0.096

Panel B: Measurement Models

Latent Variable	*Measurement Variable*	*estimate*	*std. error*	*test statistic*	*p-value*
bondTrading	freqBond	1.000	0.000		
employ	Fulltime	1.000	0.000		
employ	ParttimeGIG	0.018	0.164	0.110	0.913
employ	Unemployed	-0.088	0.123	-0.718	0.473
employ	freChngJob	-8.298	3.263	-2.543	0.011
employ	extraIncome	28.525	8.161	3.495	0.000
employ	FinInd	-0.535	0.289	-1.854	0.064
house	Married	1.000	0.000		
house	numKid	3.609	0.908	3.977	0.000
house	numSenior	0.635	0.192	3.306	0.001
house	monthlyIncome	4.485	1.096	4.093	0.000
needs	SufficientCF	1.000	0.000		
needs	SufficientResource	1.197	0.045	26.731	0.000
needs	RetireAge	0.096	0.040	2.408	0.016
needs	NoInsurance	-0.099	0.014	-7.162	0.000
needs	FullInsurance	0.084	0.040	2.115	0.034
channel	FinInd	1.000	0.000		
channel	fromFriends	0.311	0.107	2.896	0.004
channel	fromNewspaper	-0.555	0.409	-1.356	0.175
channel	fromForum	-0.298	0.248	-1.201	0.230
channel	fromSocialmedia	0.229	0.233	0.984	0.325
risk	RiskTolerance	1.000	0.000		
risk	RiskTakerAsFriend	0.305	0.038	8.068	0.000
risk	GameChoice	0.546	0.040	13.644	0.000
risk	InheritChoice	0.394	0.037	10.635	0.000

We focus on the results in Panel A from structure models. Risk perspective is positively and statistically associated with bond trading behavior, consistent with what we find in stock trading behavior. We also find that with more knowledge of stock, as well as more knowledge of bond, a person tends to trade more. Similarly, we find that needs (measured by current and future cash flow sufficiency, insurance access and retirement age) and information channel measure are both positively increasing with the trading frequency, while COVID-19 is negatively associated with trading frequency of bond. Unlike the previous result, house type and employment condition also show positive and significant association with the bond trading behavior.

The third SEM model is to study the decision of retail investors' derivatives trading. Table 5 contains the statistics, and the significant path are identified by the * in Figure 5.

Table 5 SEM results on Derivatives Trading

We estimated the following SEM results using eight structural sub-models and six measurement sub-models as describe in the research methodology section, and in studying derivatives trading activities, we use *derivativesTrading* for *Trading*, and include *stockKnow* as well as *DerivKnow*. Estimated coefficient, standard error, test statistics and p-value are reported.

Trading = β_{20} risk + β_{21} stockKnow+β_{22} DerivKnow+β_{23} employ+β_{24} house+β_{25} needs+β_{26} channel+β_{27} COVID+ϵ_8

Panel A: Structural Models

Dependent Variables	*Moderators*	*estimate*	*std. error*	*test statistic*	*p-value*
creditCons	Gender	0.038	0.028	1.343	0.179
creditCons	Age	-0.016	0.013	-1.294	0.196
creditCons	Degree	0.013	0.009	1.353	0.176
DerivKnow	Gender	0.161	0.046	3.470	0.001
DerivKnow	Age	-0.036	0.014	-2.514	0.012
DerivKnow	Degree	0.050	0.015	3.233	0.001
StockKnow	Gender	0.232	0.047	4.978	0.000
StockKnow	Age	0.059	0.015	3.948	0.000
StockKnow	Degree	0.122	0.016	7.759	0.000
risk	creditCons	6.993	5.241	1.334	0.182
employ	Gender	0.020	0.010	2.081	0.037
employ	Age	0.012	0.004	2.808	0.005
employ	Degree	-0.004	0.003	-1.439	0.150
channel	Gender	0.047	0.019	2.492	0.013
channel	Age	0.007	0.007	0.945	0.345
channel	Degree	0.078	0.014	5.635	0.000
house	Gender	0.029	0.020	1.421	0.155
house	Age	0.055	0.017	3.311	0.001
house	Degree	0.004	0.006	0.667	0.505

Dependent Variables	*Moderators*	*estimate*	*std. error*	*test statistic*	*p-value*
needs	Gender	-0.057	0.057	-1.000	0.317
needs	Age	0.228	0.023	9.807	0.000
needs	Degree	0.189	0.024	7.977	0.000
derivativesTrading	risk	0.662	0.041	16.050	0.000
derivativesTrading	StockKnow	0.591	0.037	16.128	0.000
derivativesTrading	DerivKnow	1.190	0.050	24.011	0.000
derivativesTrading	employ	-5.532	1.151	-4.808	0.000
derivativesTrading	house	0.860	0.200	4.297	0.000
derivativesTrading	needs	0.344	0.035	9.961	0.000
derivativesTrading	channel	-3.849	0.814	-4.729	0.000
derivativesTrading	COVID	-0.079	0.035	-2.294	0.022

Panel B: Measurement Models

Latent Variable	*Measurement Variables*	*estimate*	*std. error*	*test statistic*	*p-value*
derivativesTrading	freqFutures	1.150	0.034	34.026	0.000
derivativesTrading	freqFX	1.098	0.034	32.154	0.000
employ	Fulltime	1.000	0.000		
employ	ParttimeGIG	-0.229	0.111	-2.066	0.039
employ	Unemployed	0.115	0.134	0.859	0.390
employ	freChngJob	6.062	1.797	3.372	0.001
employ	extraIncome	-30.708	9.713	-3.161	
employ	FinInd	-0.261	0.165	-1.577	0.115
house	Married	1.000	0.000		
house	numKid	3.848	1.085	3.548	0.000
house	numSenior	0.670	0.200	3.348	0.001
house	monthlyIncome	4.731	1.143	4.139	0.000
needs	SufficientCF	1.000	0.000		
needs	SufficientResource	1.375	0.090	15.356	0.000
needs	RetireAge	0.086	0.042	2.056	0.040
needs	NoInsurance	-0.095	0.014	-6.689	0.000
needs	FullInsurance	0.094	0.045	2.065	0.039
channel	FinInd	1.000	0.000		
channel	fromFriends	-0.193	0.061	-3.167	0.002
channel	fromNewspaper	0.349	0.263	1.325	0.185
channel	fromForum	0.291	0.206	1.412	0.158
channel	fromSocialmedia	-0.211	0.174	-1.212	0.226
risk	RiskTolerance	1.000	0.000		
risk	RiskTakerAsFriend	0.160	0.028	5.680	0.000
risk	GameChoice	0.565	0.030	19.064	0.000
risk	InheritChoice	0.389	0.032	12.258	0.000
DerivKnow	OptionKnow	1.000	0.000		
DerivKnow	FutureKnow	1.183	0.045	26.040	0.000
DerivKnow	FXKnow	1.054	0.044	23.824	0.000

Based on the results from structure models in Panel A, we find that risk perspective is also positively and statistically associated with derivatives trading behavior, consistent with what we find in both stock and bond trading behaviors. We also find that with more knowledge on stock, as well as more knowledge on derivatives, an investor tends to trade more frequently. Similarly, we find that needs (measured by current and future cash flow sufficiency, insurance access and retirement age) and house type are both positively increasing with the trading frequency, while COVID-19 is negatively associated with trading frequency of derivatives. Unlike the previous result, employment condition and information channel are in negative and significant association with the derivatives trading behavior. This implies that there are different information channels for the derivative traders and their employment condition (full time vs part time, frequency of job changes, and extra income) also varied from stock traders.

The fourth SEM model is used to investigate the decision of retail investors' cryptocurrency trading. Table 6 contains the model statistics, and the significant paths are identified by the * in Figure 6.

Table 6: SEM results on Cryptocurrency Trading

We estimated the following SEM results using eight structural sub-models and six measurement sub-models as describe in the research methodology section, and in studying cryptocurrency trading activities, we use *cryptoTrading* for *Trading*, and include *stockKnow* as well as *CryptoKnow*. Estimated coefficient, standard error, test statistics and p-value are reported.

$$\text{Trading} = \beta_{20}\ \text{risk} + \beta_{21}\ \text{stockKnow}+\beta_{22}\ \text{CryptoKnow}+\beta_{23}\ \text{employ}+\beta_{24}\ \text{house}+\beta_{25}\ \text{needs}+\beta_{26}\ \text{channel}+\beta_{27}\ \text{COVID}+\epsilon_{8}$$

Panel A: Structural Models

Dependent Variables	*Moderators*	*estimate*	*std. error*	*test statistic*	*p-value*
creditCons	Gender	0.040	0.030	1.329	0.184
creditCons	Age	-0.014	0.011	-1.282	0.200
creditCons	Degree	0.012	0.009	1.327	0.185
StockKnow	Gender	0.260	0.048	5.462	0.000
StockKnow	Age	0.061	0.015	3.921	0.000
StockKnow	Degree	0.129	0.016	8.202	0.000
CryptoKnow	Gender	0.110	0.051	2.142	0.032
CryptoKnow	Age	-0.123	0.019	-6.436	0.000
CryptoKnow	Degree	0.067	0.017	3.931	0.000
risk	creditCons	8.145	6.154	1.324	0.186
employ	Gender	0.016	0.009	1.859	0.063
employ	Age	0.011	0.004	2.656	0.008
employ	Degree	-0.005	0.003	-1.711	0.087

Dependent Variables	*Moderators*	*estimate*	*std. error*	*test statistic*	*p-value*
channel	Gender	0.017	0.015	1.152	0.250
channel	Age	0.003	0.006	0.466	0.641
channel	Degree	0.051	0.013	3.810	0.000
house	Gender	0.035	0.021	1.619	0.105
house	Age	0.058	0.016	3.574	0.000
house	Degree	0.006	0.007	0.858	0.391
needs	Gender	-0.056	0.071	-0.789	0.430
needs	Age	0.281	0.025	11.147	0.000
needs	Degree	0.240	0.027	8.861	0.000
cryptoTrading	risk	0.649	0.049	13.260	0.000
cryptoTrading	CryptoKnow	1.133	0.036	31.846	0.000
cryptoTrading	StockKnow	0.688	0.038	17.955	0.000
cryptoTrading	employ	-12.461	3.709	-3.360	0.001
cryptoTrading	house	1.466	0.324	4.530	0.000
cryptoTrading	needs	0.250	0.039	6.372	0.000
cryptoTrading	channel	-7.739	2.218	-3.489	0.000
cryptoTrading	COVID	-0.098	0.037	-2.637	0.008

Panel B: Measurement Models

Latent Variable	*Measurement Variables*	*estimate*	*std. error*	*test statistic*	*p-value*
cryptoTrading	freqCrypto	1.000	0.000		
employ	Fulltime	1.000	0.000		
employ	ParttimeGIG	-0.230	0.136	-1.696	0.090
employ	Unemployed	0.101	0.132	0.769	0.442
employ	freChngJob	8.307	2.576	3.224	0.001
employ	extraIncome	-29.928	9.280	-3.225	0.001
employ	FinInd	-0.351	0.261	-1.344	0.179
house	Married	1.000	0.000		
house	numKid	3.661	0.920	3.980	0.000
house	numSenior	0.677	0.204	3.322	0.001
house	monthlyIncome	4.661	1.153	4.042	0.000
needs	SufficientCF	1.000	0.000		
needs	SufficientResource	0.991	0.042	23.689	0.000
needs	RetireAge	0.101	0.037	2.706	0.007
needs	NoInsurance	-0.093	0.013	-7.142	0.000
needs	FullInsurance	0.082	0.038	2.137	0.033
channel	FinInd	1.000	0.000		
channel	fromFriends	-0.250	0.093	-2.685	0.007
channel	fromNewspaper	0.429	0.352	1.216	0.224
channel	fromForum	0.451	0.313	1.443	0.149
channel	fromSocialmedia	-0.243	0.240	-1.012	0.312
risk	RiskTolerance	1.000	0.000		
risk	RiskTakerAsFriend	0.303	0.041	7.493	0.000
risk	GameChoice	0.640	0.051	12.509	0.000
risk	InheritChoice	0.447	0.042	10.619	0.000

Figure 3: SEM on Stock Trading

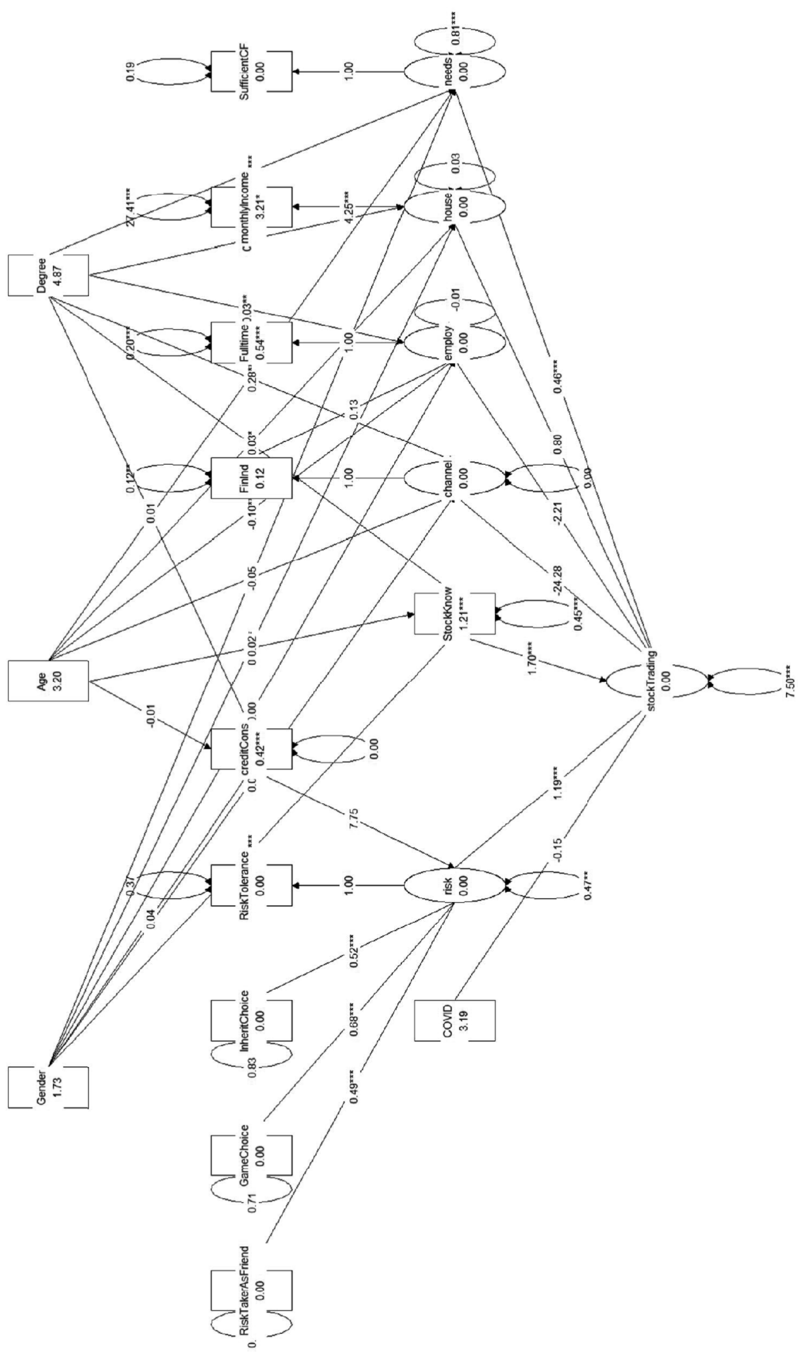


Figure 4: SEM on Bond Trading

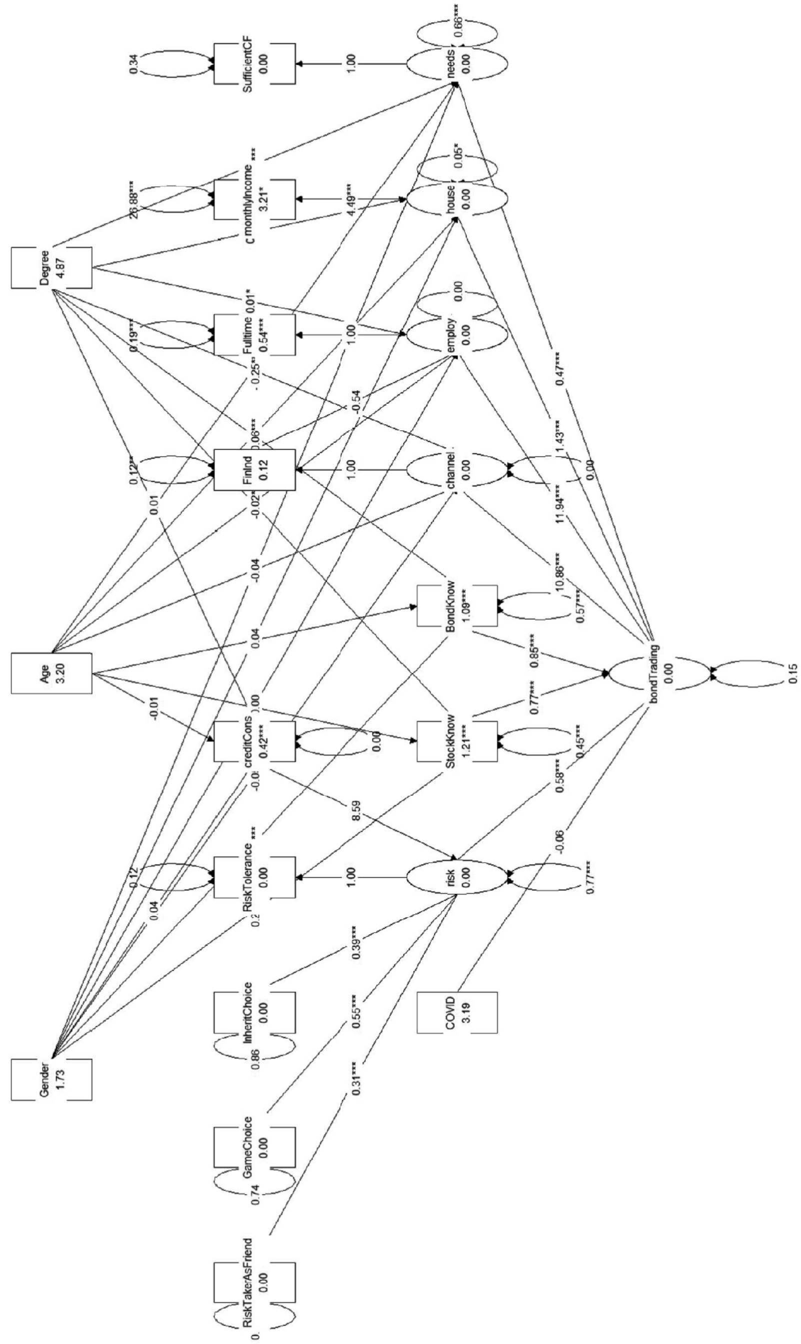


Figure 5: SEM on Derivatives Trading

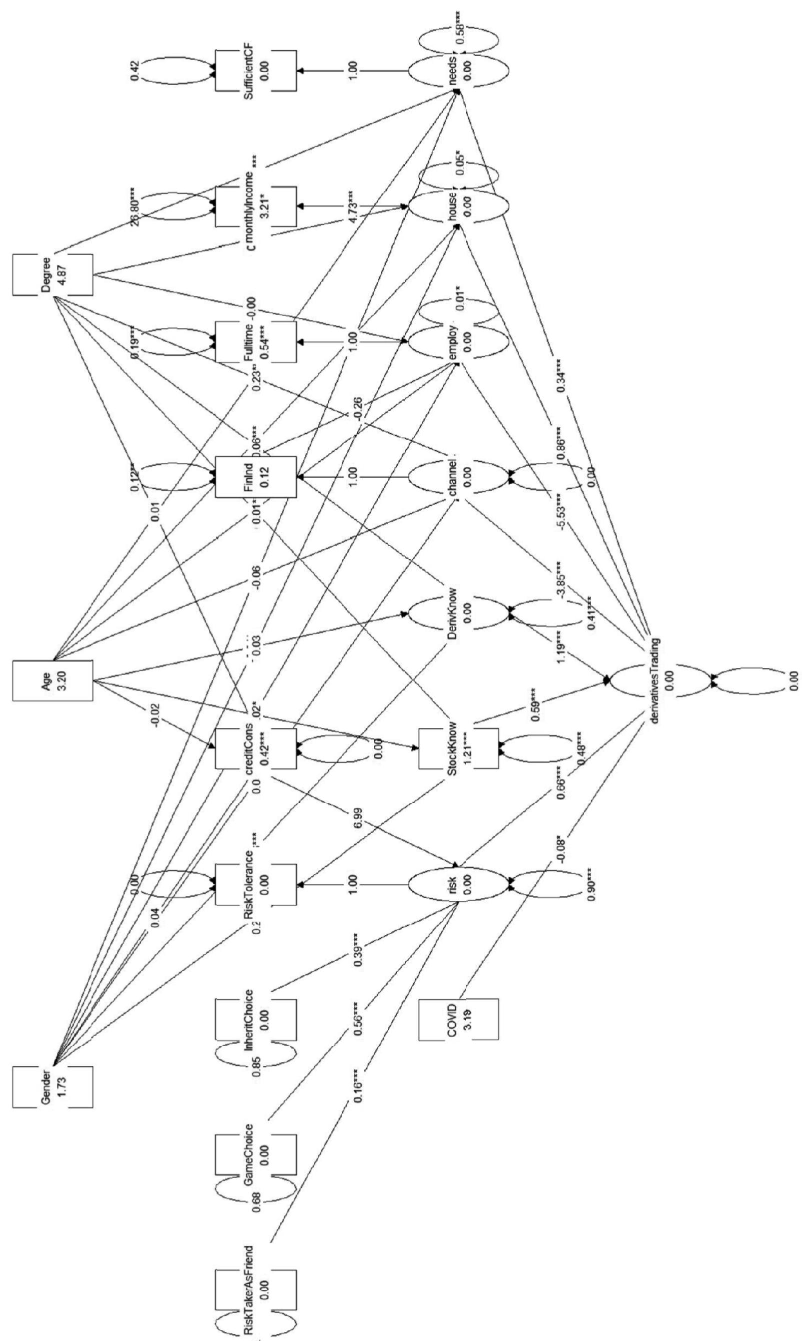
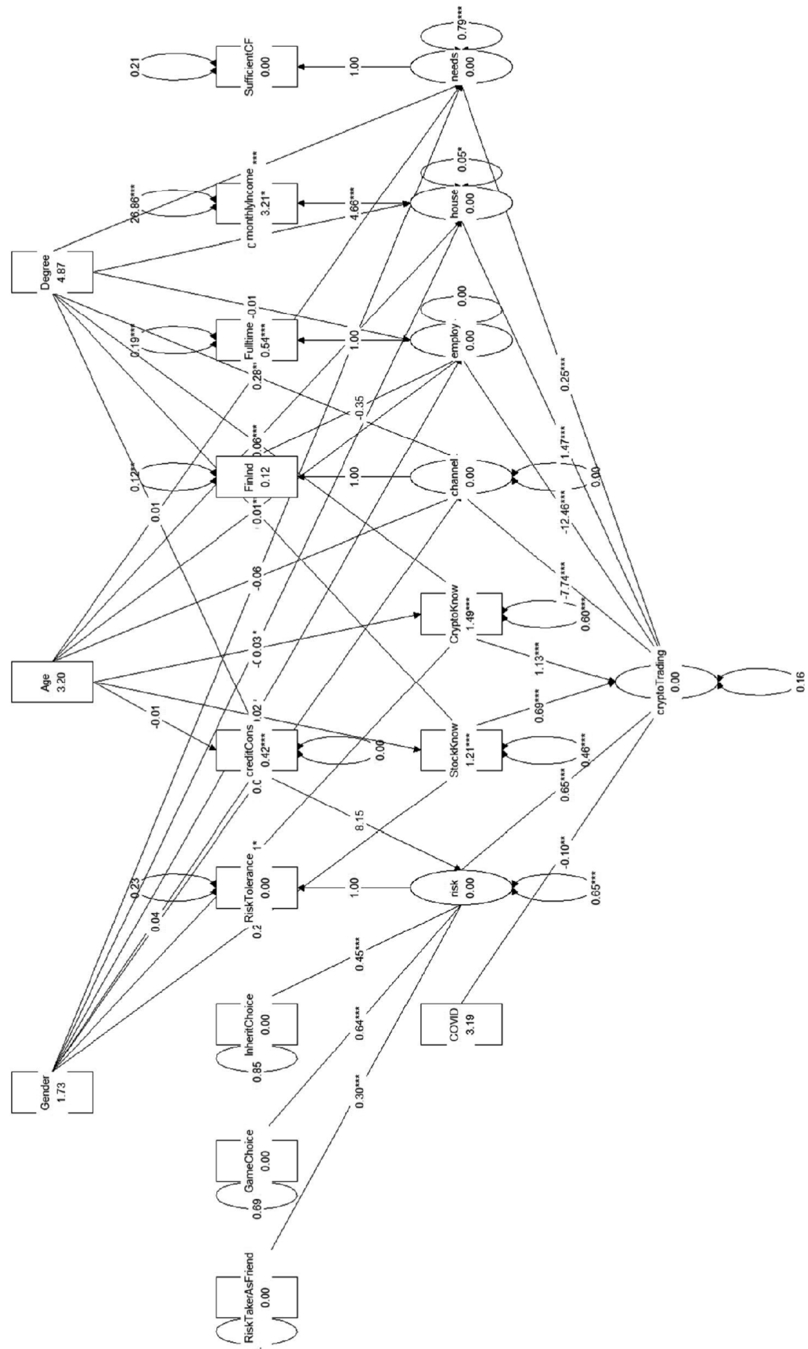


Figure 6: SEM on Cryptocurrency Trading



Panel A reports the results from structure models, and we find that risk perspective is positively and statistically associated with cryptocurrency trading behavior, consistent with what we find in stock trading behavior. We also find that with more knowledge one possesses on stock, as well as cryptocurrency, a person tends to trade more, indicating some level of confidence. Similarly, we find that financial needs (measured by current and future cash flow sufficiency, insurance access and retirement age) and house types are both positively increasing with the trading frequency, while COVID-19 is negatively associated with trading frequency. Unlike the stock trading result, employment condition and information channel are in negative and significant association with the cryptocurrency trading behavior. This also implies that the cryptocurrency traders rely on different information channels and their employment condition also differ. Based on the above analysis, cryptocurrency and derivatives trading decisions results are found to be similar to each other, while bond and stock trading decision paths are more close.

5. Conclusion

Our comprehensive survey of 1,076 Singaporean retail investors furnishes a profound understanding of the intricate drivers underpinning financial resilience in the modern trading landscape. The demographic breakdown presented paves the way to a richer interpretation of the data, elucidating crucial patterns among marital status, residency type, race, job-switching tendencies, and income sources.

A particularly noteworthy trend manifests within generational job-switching habits. Amidst the post-COVID backdrop, characterized by the Great Resignation and its subsequent hiring challenges, Gen Z emerges as the vanguard of fluidity in the job market. Interestingly, income levels are found to be intricately tied with educational qualifications, with a pronounced income distinction between those with and without bachelor's degrees. As the gig economy burgeons, our findings underscore the rising significance of side gigs. A significant portion of respondents not only derives income from such roles, but a subset even out-earns their primary occupation through them. Knowledge in stock trading, unsurprisingly, mirrors trading profits, affirming the instrumental role of informed decision-making in trading outcomes.

Leveraging on the Structural Equation Modeling (SEM), we have discerned various factors influencing retail investors' trading decisions. Risk appetite, knowledge about the financial products, and financial needs consistently emerge as pivotal determinants across various categories of financial assets. Moreover, the pervasive impact of the COVID-19 pandemic on trading behaviors cannot be overlooked. To encapsulate, our findings serve as an illuminating window into the trading behaviors and decisions of Singaporean retail investors. They unravel the intricate tapestry of influences, from demographic determinants to the prevailing socio-economic climate, which collectively shape financial decision-making in today's dynamic market landscape. While this research casts light on several pertinent areas, it also unfurls new horizons and questions warranting future exploration.

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