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RACIAL DIFFERENCES IN STUDENT LOAN REPAYMENT: DOES FINANCIAL LITERACY MATTER?

Meng Li, Roosevelt University
Carolyn Wiley, Roosevelt University

ABSTRACT

This study explores how financial literacy affects differences in student loan repayment behavior across three racial groups. The dataset was drawn from the 2021 Survey of Household Economics and Decisionmaking. Logistic regressions revealed that compared with White student borrowers, Black and Hispanic students were more likely to fall behind on their repayments and less likely to pay off their student loan altogether. However, when controlling for both the main and conditional effect of financial literacy, the coefficients for race became statistically insignificant, suggesting that variation in financial literacy and its effectiveness across different racial groups explain a significant part of racial gap in student loan repayment behavior. Separate analysis for each racial group further confirmed that financial literacy affected student loan repayment behavior differently across races. Specifically, improving financial literacy was found to have the greatest impact on promoting desirable 'paid off loan' behavior among White borrowers, and on preventing 'behind payment' behavior among Black borrowers. This study thus suggests that financial literacy education needs to be customized to match the unique needs of the different racial groups to improve student loan repayment behavior.

1-INTRODUCTION

Student loan debt is a common way to finance a college education. As of July 2022, this debt is spread across 48 million student borrowers to finance their college education. As such, student loan debt surpassed the $1.75 trillion mark (Lending-Tree, 2022)[1], and is second in line to mortgage debt. Not only is this debt the highest it has ever been, but it is borne mostly by those who are economically disadvantaged. For example, studies reveal that student debt disproportionately affects Black and Latino students, who are more likely to borrow and take out larger loans than White students (Houle & Addo, 2019; Grinstein-Weiss, Perantie, Taylor, Guo, & Raghavan, 2016; Kim, Chatterjee, Young, & Moon, 2016; Scott-Clayton & Li, 2016; Jackson

[1]"A LOOK AT THE SHOCKING STUDENT LOAN DEBT STATISTICS FOR 2022", (2022). STUDENT LOAN HERO, INC., BY LENDING TREE (*UPDATED: JULY 29, 2022).*

& Reynolds, 2013). Moreover, Black and Latino student borrowers face challenges in managing and repaying their student loans.

The U.S. Department of Education released data in 2017 revealing that 50 percent of Black borrowers who started college in 2003-04 defaulted on their student loans within 12 years (Miller, 2017). Furthermore, Black bachelor's degree graduates, default at five times the rate of White bachelor's degree graduates (21 percent versus 4 percent) and are more likely to default than White dropouts (21 percent versus 18 percent) (Scott-Clayton, 2018). Recent data from the fall of 2019 indicate that Black borrowers who began college in 2011-12 continued to experience high default rates, with one-third (33.4 percent) of Black borrowers who had entered repayment defaulting on their loans within six years, compared with a 13 percent default rate among their White peers (Miller, 2019). Higher student loan default rates were also found in majority-Black and majority-Hispanic areas, with a default rate of 17.7 percent in majority-Black majority areas, compared with 9.0 percent in majority-White areas (Haughwout, Lee, Scally, & Van der Klaauw, 2019). Using the most recent *Survey of Consumer Finances 2019* dataset, Scott III, Mitchell, & Patten (2022) also found that Black students default more often on student loan debts.

The disproportionate difficulty that minority groups face in repaying student loans has been attributed to their greater tendency to accumulate college debt without ultimately obtaining a degree. Research by Shapiro, Dundar, Huie, Wakhungu, Yuan, & Hwang (2017) revealed that Black students have a six-year graduation rate of 38 percent compared to 63.2 percent for White students and 45.8 percent for Hispanic students. Additionally, Hamilton & Darity (2017) found that Black students are one-third (33.3 percent) less likely to finish college compared to their White counterparts, largely due to financial pressures and the predatory practices of for-profit colleges. For-profit colleges have been referred to as "low-value debt bombs" since 80 percent of Black students enrolled in these institutions drop out within six years with an average of US $40,000 of student loan debt, leading to difficulty repaying loans and higher rates of delinquency and defaults (Hamilton & Darity, 2017). However, even after accounting for differences in degree attainment and other student and family background characteristics, the Black-White difference in default rates remains large and statistically significant (Scott-Clayton, 2018).

Previous research on financial literacy has found that Black and Hispanic groups tend to have lower levels of financial literacy compared to their White counterparts (Lusardi & Mitchell, 2023; Al-Bahrani, Weathers, & Patel, 2019; Hill, Johnson, & Shim, 2017; Alvarado, Chapa, & Kim, 2015; and Lusardi, Mitchell, & Curto, 2010. Additionally, these groups may be less likely to experience favorable financial behavioral change from accumulating financial knowledge (Kim & Chatterjee, 2013; Lown & DeVaney, 2010; Lyons, Palmer, Jayaratne, & Scherpf, 2006). Thus, the variations in the financial literacy and its effectiveness across different racial groups may contribute to the racial disparities in student loan repayment behavior. However, prior studies have not investigated the impact of financial literacy on racial disparities in student loan debt repayment. This study is the first attempt to examine whether controlling for both the main and conditional effect of financial literacy can potentially explain the race gap in student loan debt repayment behavior.

The paper is organized as follows: Section 2 contains the literature review. Section 3 presents an overview of data and methodology. Section 4 presents the empirical results. Section 5 presents the conclusions and recommendations for future research in this area.

2-LITERATURE REVIEW ON FINANCIAL LITERACY AND STUDENT LOAN REPAYMENT

Financial literacy is defined as the ability to use knowledge and skills to manage financial resources effectively for a lifetime of financial well-being (U.S. Financial Literacy and Education Commission 2007). Huston (2010) developed a conceptual framework that presents financial literacy as a component of human capital that can enhance one's financial well-being by effectuating desirable financial behaviors. Studies have found that individuals with greater financial literacy tend to make better financial decisions and exhibit more favorable financial behavior (Xiao, Porto & Mason, 2020; Lusardi & Mitchell, 2007c). Recent research has also highlighted the importance of financial literacy in student loan repayment behavior. For instance, Zhang & Fan (2022) found that financial capability and financial education factors were positively associated with desirable financial outcomes such as higher loan satisfaction and lower loan delinquency. Hales (2021) revealed that individual with higher financial literacy were less likely to take out a student loan, while those with lower financial literacy were more prone to student loan delinquency.

The positive association between financial literacy and student loan repayment behavior could be attributed to two key factors. Firstly, better financial knowledge enables students to effectively allocate their financial resources, leading to higher returns on savings (Lusardi, Michaud, & Mitchell, 2017). Consistent with the intuition, financial literacy has been found to have positive roles in higher saving returns (Deuflhard, Georgarakos, & Inderst, 2018), greater stock market participation (Van Rooij, Lusardi, & Alessie, 2011b), lower investment fees (Choi, Laibson, and Madrian, 2010), and better investment diversification (Gaudecker, 2015). In essence, individuals with better financial literacy skills are more likely to achieve higher rates of return on their financial assets, thus facilitating greater savings accumulation. This, in turn, enhances their capacity to repay student loans. Secondly, financial literacy plays a crucial role in minimizing errors in loan payment estimation. Research conducted by Artavanis and Karra (2020) examined the relationship between financial literacy and the discrepancy between actual student loan payments and expected payment amounts. Their findings revealed that individuals with lower levels of financial literacy were more prone to underestimating their future loan payments. This underestimation ultimately hindered their ability to repay their student debt, resulting in a higher likelihood of loan default. Overall, financial literacy is associated with improved resource management and enhanced accuracy in loan payment projections. These factors collectively contribute to students' increased repayment capacity and, consequently, a higher likelihood of successful student loan repayment.

Not only does financial literacy have a positive impact on financial behavior in general, but studies have also demonstrated that the beneficial effect of financial literacy on financial behavior differs among various racial groups. Lyons et al. (2006) found that although financial education programs increased financial knowledge among participants of all races, Black and Hispanic participants were less likely to report positive changes in financial behavior compared to White participants. Similarly, Kim & Chatterjee (2013) found that Black participants were less likely to apply their financial knowledge to their financial decisions compared to White participants. Lown & DeVaney (2010) examined financial behaviors among African American couples in the United States. They found that increased financial knowledge among participants did not necessarily result in positive changes in financial behavior. These studies suggest that the effectiveness of financial literacy's ability to yield better financial decisions is conditional on race, with minority groups exhibiting lower levels of financial behavioral change and application of financial knowledge than their White counterparts.

To account for both the main effect and the conditional effect of financial literacy on student loan repayment, our logistic models for predicting student loan prepayment behavior include financial literacy both as an individual factor and as a part of the interaction term with race. This approach allows our paper to make a two-fold contribution to the literature. First, we aim to determine whether accounting for both the main and conditional effect of financial literacy through race can explain the variation in student loan repayment across different racial groups. Second, we aim to examine how the effectiveness of financial literacy on student loan repayment varies across different racial groups.

3-DATA AND METHODOLOGY

3.1 Sample and Data

The dataset was derived from the *Survey of Household Economics and Decisionmaking* (SHED) conducted by the Federal Reserve Board during October and November 2021. The Survey gathered information from over 11,000 adults pertaining to credit, savings, education, and student loans. Our sample selection involved three criteria. Firstly, we included respondents who attained a certain education level, specifically some college, a college degree, or a master's degree or higher, since student loans are typically available only for those education levels. Secondly, in order to properly evaluate borrowers' repayment behavior, we only included respondents who had actually taken out student loans. Lastly, we restricted our sample to borrowers who self-identified as White non-Hispanic, Black non-Hispanic, or Hispanic. Our final sample consisted of 3,297 respondents, with 2,517 identified as White non-Hispanic, 422 as Black non-Hispanic, and 358 as Hispanic.

Unlike previous studies that have primarily focused on the racial disparity in default rate, this paper examined both the success and struggles of student loan repayment behavior. Specifically, this study used two binary variables, 'paid off loan' and 'behind payment' to measure repayment behavior. Being behind on payment can indicate either delinquency or default status. Delinquency occurs when a payment is not made by the specific due day, while default status is reached when a loan has gone 270 days or more without payment. Financial literacy was measured by the numbers of financial literacy questions answered correctly by the respondents, ranging from 0 to 3. SHED assesses respondents' financial literacy from three questions on interest compounding, inflation, and risk diversification that have been extensively used in the literature (e.g. Lusardi & Mitchell, 2007a, 2007c, & 2008; Lusardi et al. 2010; Van Rooij et al., 2011; Artavanis & Karra, 2020). These three questions pertain to concepts that are relevant to individuals' day-to-day financial choices throughout their lives and capture general ideas rather than context-specific details. Over time, these three questions have demonstrated their effectiveness as a measure of individuals' grasp of fundamental financial principles (Lusardi & Mitchell, 2023). Socioeconomic variables that could influence the repayment behavior, including race, age, gender, marital status, highest educational attainment, parents' education, household income, and employment status, were also extracted from the SHED dataset. Table I presents the description of these variables as shown in the survey.

Table I. Description of Variables as Shown in the 2021 SHED

Variables	Code and Description in the SHED
Financial Literacy: numerical variable The number of financial literacy questions answered correctly by the respondents. 0 = 0 questions answered correctly 1 = 1 question answered correctly 2 = 2 questions answered correctly 3 = 3 questions answered correctly	The three financial literacy questions are as follows: 1. (*FL2*) Do you think that the following statement is true or false: buying a single company's stock usually provides a safer return than a stock mutual fund? 2. (*FL5*) Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow: more than $102, exactly $102, or less than $102? 3. (*FL4*) Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than today, the same as today, or less than today with the money in this account?
Take Student Loan: categorical variable 0 = Never had student loan: Answered No to both question SL1 and SL7 1 = Had taken student loan: Answer Yes to either question SL1 or SL7	(*SL1*): Do you currently have student loan debt or owe any money used to pay for your own education? (*SL7*): Did you borrow or take out any loans to pay for your own education that you have since repaid?
Paid Off Loan: categorical variable 0 = No, not paid off 1 = Yes, have paid off	(*SL7*): Did you borrow or take out any loans to pay for your own education that you have since repaid?
Behind Payment: categorical variable 0 = No, not behind payment 1 = Yes, behind payment	(*SL6*): Are you behind on payments or in collections for one or more of the loans from your own education?
Race: categorical Variable	(*ppethm*): 1 = White non-Hispanic 2 = Black non-Hispanic 3 = Other, non-Hispanic 4 = Hispanic 5 = 2+ Races, non-Hispanic
Age: numerical variable	(*ppage*)

Gender: categorical variable	(*ppgender*): 1=Male 2=Female
Marital Status: categorical variable	(*ppmarit5*): 0 = widowed, divorced, separated, or never married 1 = now married
Education: categorical variable	(*ppeducat*): 1= no high school diploma 2 = high school graduate 3= some college or associate degree 4 = Bachelor's degree 5 = Master's degree or higher
Employment Status: categorical variable	(*ppemploy*):1= working full-time 2= working part-time 3= not working
Parents Education: numerical variable The average score of the highest level of education completed by mother and father.	(*CH2*): What is the highest level of education that your mother completed? (*CH3*): What is the highest level of education that your father completed? -2 = Don't know 1= Less than High School degree 2 = high school diploma 3= some college but no degree 4 = Certificate or technical degree 5 = Associate's degree 6 = Bachelor's degree 7 = Graduate degree
Household Income: numerical variable	(*ppinc7*): Household Income 1= Less than $10,000 2 = $10,000 to $24,999 3= $25,000 to $49,999 4 = $50,000 to $74,999 5 = $75,000 to $99,999 6 = $100,000 to $149,999 7 = $150,000 or more

Note: The codes for variable are enclosed in brackets. The codebook of 2021 *Survey of Household Economics and Decisionmaking* (SHED) can be found in the Federal Reserve website https://www.federalreserve.gov/consumerscommunities/files/SHED_2021codebook.pdf

3.2 Summary Statistics

Table II presents the summary statistics of key numerical variables categorized by race for the sample of 3297 respondents in the study. A close comparison of mean value of household income, financial literacy, and parent education showed that White borrowers had the highest average score on all three measures. Their mean household income score was 5.33, indicating a range from $75,000 to $99,999. Their mean financial literacy score of 2.5 indicated that most White borrowers were able to correctly answer at least two out of three financial literacy questions. Their 'parent education' mean score of white borrowers was 3.8, suggesting the highest average educational attainment for their parents was a certificate or technical degree. Black and Hispanic borrowers scored lower than White borrowers on all three measures. Compared to Blacks, Hispanics scored higher on household income and financial literacy.

However, the parents of Black borrowers have attained higher education levels than those of Hispanics borrowers.

Table II. Summary Statistics for Key Numerical Variables by Race
(For the sample of 3259 respondents used in the study)

Variable	*Mean*	*SD*	*n*	Min	Max	*Mdn*
Age						
White, Non-Hispanic	47.17	15.94	2517	18.00	89.00	46.00
Black, Non-Hispanic	46.41	14.93	422	19.00	84.00	45.00
Hispanic	40.50	13.70	358	20.00	83.00	38.00
Household Income						
White, Non-Hispanic	5.33	1.59	2517	1.00	7.00	6.00
Black, Non-Hispanic	4.61	1.66	422	1.00	7.00	5.00
Hispanic	4.89	1.58	358	1.00	7.00	5.00
Financial Literacy						
White, Non-Hispanic	2.50	0.79	2517	0.00	3.00	3.00
Black, Non-Hispanic	2.04	1.03	422	0.00	3.00	2.00
Hispanic	2.13	0.95	358	0.00	3.00	2.00
Parent Education						
White, Non-Hispanic	3.80	1.91	2517	-2.00	7.00	4.00
Black, Non-Hispanic	2.86	2.02	422	-2.00	7.00	2.50
Hispanic	2.80	2.02	358	-2.00	7.00	2.50

Note: See Table 1 for detailed explanation for measurement of each variable.

Table III presents the percentage breakdown of key categorical variables based on race. Consistent with the documented racial disparity in student loan repayment, the data showed that the Black and Hispanic borrowers were more likely to be behind on the repayment compared to the White borrowers and less likely to have paid off the loan altogether. As illustrated in Figure 1, the percentages of borrowers who had paid off the loan were 63.81%, 37.91%, and 40.78% for Whites, Blacks, and Hispanics respectively. Figure 3 illustrated that the percentages of borrowers who were behind on the loan repayment were 3.1%, 7.82%, and 9.78% for Whites, Blacks, and Hispanics respectively.

Figure 2 shows the variations in financial literacy mean values between borrowers who had paid off the loan and those with an outstanding loan balance, broken down by race. Similarly, Figure 4 illustrates the variations in financial literacy mean values between borrowers who had no delinquency or default and those who were behind on the repayment. In both Figures, White borrowers consistently had the highest financial literacy scores across all loan repayment statuses, followed by Hispanics, and then Black borrowers. Additionally, borrowers who displayed desirable repayment behaviors (paid-off loan and no delinquency or default on student loans) had higher financial literacy mean scores across all three racial groups. It is also evident that Hispanics exhibited the least variation in financial literacy scores between the borrowers with contrasting repayment behaviors, indicating the least effectiveness of financial literacy's ability to yield better student loan repayment behavior in Hispanic group.

Table III. Percentage Statistics for Key Categorical Variables by Race
(For the sample of 3259 respondents used in the study)

	Race		
Variable	White, Non-Hispanic	Black, Non-Hispanic	Hispanic
Race			
White, Non-Hispanic	2517 (100.00%)	0 (0.00%)	0 (0.00%)
Black, Non-Hispanic	0 (0.00%)	422 (100.00%)	0 (0.00%)
Hispanic	0 (0.00%)	0 (0.00%)	358 (100.00%)
Total	2517 (100.00%)	422 (100.00%)	358 (100.00%)
Gender			
Male	1292 (51.33%)	175 (41.47%)	174 (48.60%)
Female	1225 (48.67%)	247 (58.53%)	184 (51.40%)
Total	2517 (100.00%)	422 (100.00%)	358 (100.00%)
Education			
Some college or Associate's degree	619 (24.59%)	152 (36.02%)	129 (36.03%)
Bachelor's degree	1030 (40.92%)	142 (33.65%)	141 (39.39%)
Master's degree or higher	868 (34.49%)	128 (30.33%)	88 (24.58%)
Total	2517 (100.00%)	422 (100.00%)	358 (100.00%)
Employment Status			
Working full-time	1582 (62.85%)	274 (64.93%)	236 (65.92%)
Working part-time	349 (13.87%)	50 (11.85%)	49 (13.69%)
Not working	586 (23.28%)	98 (23.22%)	73 (20.39%)
Total	2517 (100.00%)	422 (100.00%)	358 (100.00%)
Paid off Loan			
No	911 (36.19%)	262 (62.09%)	212 (59.22%)
Yes	1606 (63.81%)	160 (37.91%)	146 (40.78%)
Total	2517 (100.00%)	422 (100.00%)	358 (100.00%)
Behind Payment			
No	2439 (96.90%)	389 (92.18%)	323 (90.22%)
Yes	78 (3.10%)	33 (7.82%)	35 (9.78%)
Total	2517 (100.00%)	422 (100.00%)	358 (100.00%)

Note: Due to rounding error, percentages may not sum to 100%.
See Table 1 for detailed explanation for measurement of each variable.

Figure 1. Percentage of Paid-off Status by Race

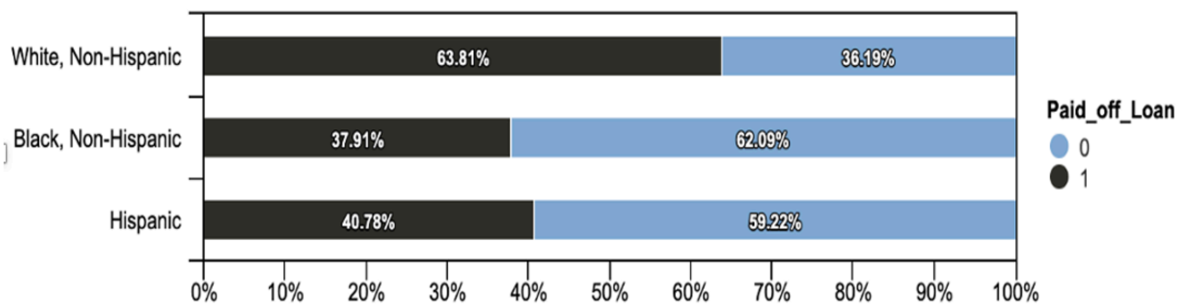
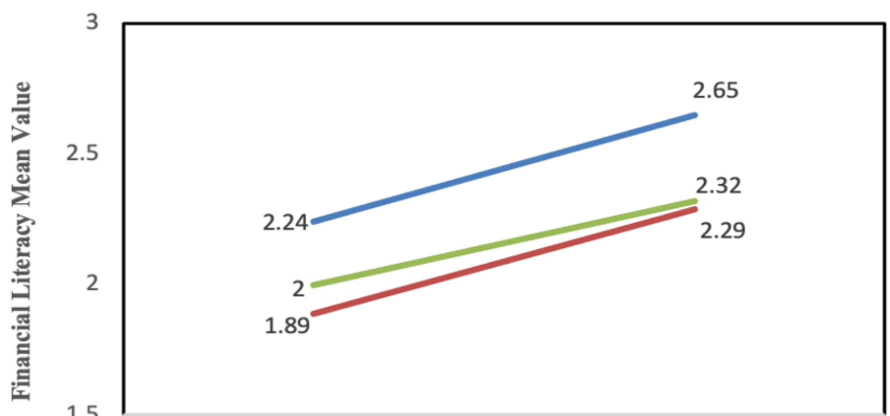


Figure 2. Comparison of Financial Literacy Mean Values by Paid off Status and Race



	With Outstanding Balance	Paid Off Loan
White, Non-Hispanic	2.24	2.65
Black, Non-Hispanic	1.89	2.29
Hispanic	2	2.32

Note: Financial Literacy is measured as the number of financial literacy questions answered correctly by the respondents, ranging from 1 to 3. See Table 1 for detailed description.

Figure 3. Percentage of Behind Payment Status by Race

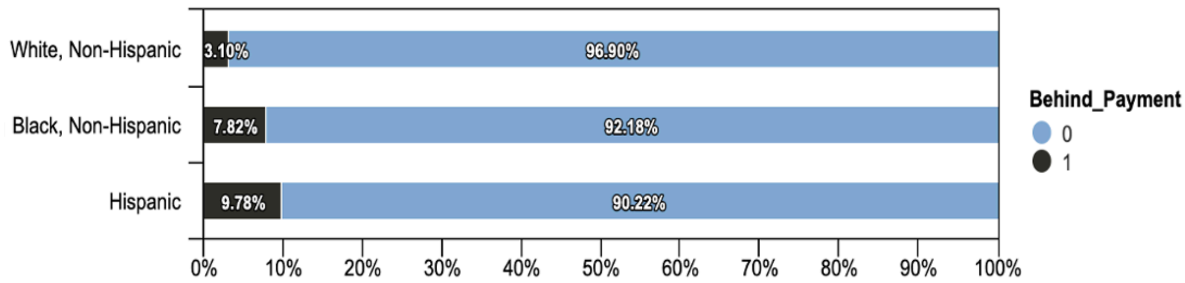
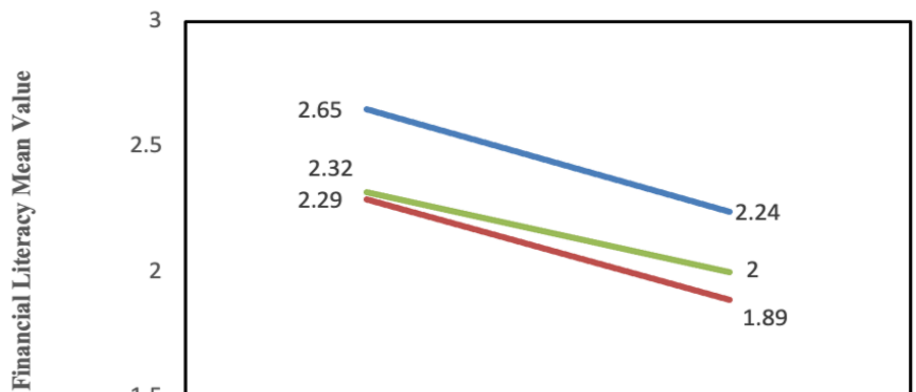


Figure 4. Comparison of Financial Literacy Mean Values by Behind Payment Status and Race



	No Delinquency or Default	Behind Payment
White, Non-Hispanic	2.65	2.24
Black, Non-Hispanic	2.29	1.89
Hispanic	2.32	2

Note: Financial Literacy is measured as the number of financial literacy questions answered correctly by the respondents, ranging from 1 to 3. See Table 1 for detailed description.

3.3 Methodology

We performed a series of logistic regressions to assess the impact of financial literacy on the student loan repayment behavior across all racial groups. Firstly, for the base model (Eq.1), we regressed the binary repayment variables against various socioeconomic factors. We then include financial literacy scores and their interaction terms with race in the logistic regression along with other socioeconomic covariates (Eq.2). The aim was to determine if the inclusion of the main and conditional effect of financial literacy causes the significance of race factor to disappear. Finally, we ran a logistic regression on financial literacy for each racial group separately to further evaluate the variation in the effectiveness of financial literacy on behaviors such as 'paid off loan' and 'behind payment' for the different racial groups (Eq.3).

We controlled for the following socioeconomic variables that could influence repayment behavior: parents' education, family income, employment status, and the highest level of education attained by the borrowers (Oh 2022; Gross et al., 2019; Scott-Clayton & Li, 2016; Addo, Houle, & Simon, 2016; Jackson & Reynolds, 2013). We chose to use White, non-Hispanic group as a reference group because it represents the largest student population and is often used as a reference group in student loan studies (Scott-Clayton & Li, 2016). The logistic regression equations are provided below:

Equation 1:

$$\text{Logit (Probability of Paid Off Loan or Behind Payment)} = \alpha + \beta 1\times \text{Age} + \beta 2 \times \text{Race} + \beta 3 \times \text{Gender} + \beta 4 \times \text{Marital Status} + \beta 5 \times \text{Education} + \beta 6 \times \text{Employment Status} + \beta 7 \times \text{Parent Education} + \beta 8 \times \text{Household Income} \quad \text{[Eq.1]}$$

Equation 2:

$$\text{Logit (Probability of Paid Off Loan or Behind Payment)} = \alpha + \beta 1\times \text{Age} + \beta 2 \times \text{Race} + \beta 3 \times \text{Gender} + \beta 4 \times \text{Marital Status} + \beta 5 \times \text{Education} + \beta 6 \times \text{Employment Status} + \beta 7 \times \text{Parent Education} + \beta 8 \times \text{Household Income} + \beta 9 \times \text{Financial Literacy} + \beta 10 \times (\text{Black} \times \text{Financial Literacy}) + \beta 11\times (\text{Hispanic} \times \text{Financial Literacy}) \quad \text{[Eq.2]}$$

Equation 3:

$$\text{Logit (Probability of Paid Off Loan or Behind Payment)} = \alpha + \beta 1\times \text{Age} + \beta 2 \times \text{Gender} + \beta 4 \times \text{Marital Status} + \beta 5 \times \text{Education} + \beta 6 \times \text{Employment Status} + \beta 7 \times \text{Parent Education} + \beta 8 \times \text{Household Income} + \beta 9 \times \text{Financial Literacy} \quad \text{[Eq.3]}$$

4-TEST RESULTS

4.1 Logistic Regression Results

Table IV presents a comparison of the logistic regression results for predicting 'paid off loan' status. The base model (Eq.1) was compared with the model that includes financial literacy and its interaction terms (Eq.2). The base model showed that being a minority is negatively related to 'paid off loan' status, confirming the existence of racial disparities in student loan repayment. However, when the main and conditional effect of financial literacy was controlled for in Eq.2, the coefficients for Black and Hispanic student borrowers became statistically insignificant. Moreover, financial literacy's main effect was significant with an odds ratio of 1.39, implying that increasing financial literacy by one level would boost the probability of paying off the loan by 39% for the entire sample.

Table IV. Logistic Regression Results with Age, Race, Gender, Marital Status, Education, Employment Status, Parent Education, Household Income, and Financial Literacy Predicting Paid off Loan for the Entire Sample

	Base Model without Financial Literacy (Eq.1)				With Financial Literacy and Interaction Terms (Eq.2)			
Variable	*B*	*p*		*OR*	*B*	*p*		*OR*
(Intercept)	-4.35	< .001	***	-	-4.95	< .001	***	-
Age	0.08	< .001	***	1.09	0.08	< .001	***	1.08
Black, Non-Hispanic	**-1.12**	**< .001**	***	0.32	-0.61	0.066		0.54
Hispanic	**-0.55**	**< .001**	***	0.58	0.1	0.773		1.11
Female	-0.29	< .001	***	0.75	-0.2	0.031	*	0.82
Now married	0.23	0.017	*	1.26	0.24	0.014	**	1.27
Master's degree or higher	-0.49	< .001	***	0.62	-0.51	< .001	***	0.6
Some college or Associate's degree	-0.29	0.011	*	0.75	-0.24	0.035	*	0.79
Working part-time	0.03	0.834		1.03	0.01	0.938		1.01
Not working	0.13	0.309		1.14	0.12	0.342		1.13
Parent Education	0.06	0.02	*	1.06	0.04	0.088		1.04
Household Income	0.23	< .001	***	1.26	0.21	< .001	***	1.24
Financial Literacy					**0.33**	**< .001**	***	**1.39**
Black, Non-Hispanic × Financial Literacy					-0.2	0.14		0.82
Hispanic × Financial Literacy					-0.27	0.073		0.76
McFadden R2	0.27				0.27			

***significant at 0.001, **significant at 0.01, * significant at 0.05

Logistic Regression Eq.1:

Logit (Probability of Pay Off Loan) = $\alpha + \beta1\times$ Age+ $\beta2 \times$ Race + $\beta3 \times$ Gender+ $\beta4 \times$ Marital Status + $\beta5 \times$ Education + $\beta6 \times$ Employment Status + $\beta7 \times$Parent Education + $\beta8 \times$ Household Income

Logistic Regression Eq.2:

Logit (Probability of Pay Off Loan) = $\alpha + \beta1\times$ Age+ $\beta2 \times$ Race + $\beta3 \times$ Gender+ $\beta4 \times$ Marital Status + $\beta5 \times$ Education + $\beta6 \times$ Employment Status + $\beta7 \times$Parent Education + $\beta8 \times$ Household Income + $\beta9 \times$ Financial Literacy + $\beta10 \times$ (Black $\times$ Financial Literacy) + $\beta11\times$ (Hispanic $\times$ Financial Literacy)

Table V further confirms the significant racial variation in the effectiveness of financial literacy. Financial literacy had a statistically significant impact on the ‘paid off loan’ status among White borrowers (p<0.001) alone, while no significant impact of financial literacy on ‘paid off loan’ status was found for either Black or Hispanic student borrowers. These results suggest that improving financial literacy is most effective in encouraging ‘paid off loan’ behavior among White borrowers.

Table V. Logistic Regression Results with Age, Race, Gender, Marital Status, Education, Employment Status, Parent Education, Household Income, and Financial Literacy Predicting Paid off Loan by Race

Variable	White, Non-Hispanic				Black, Non-Hispanic				Hispanic			
	B	*p*		*OR*	*B*	*p*		*OR*	*B*	*p*		*OR*
(Intercept)	-5.43	< .001	***	-	-4.51	< .001	***	-	-3.53	< .001	***	-
Age	0.09	< .001	***	1.09	0.06	< .001	***	1.06	0.06	< .001	***	1.06
Female	-0.17	0.125		0.85	-0.29	0.205		0.75	-0.31	0.228		0.74
Now married	0.38	0.001	***	1.46	-0.28	0.286		0.76	-0.11	0.686		0.9
Master's degree or higher	-0.59	< .001	***	0.55	-0.56	0.051		0.57	-0.22	0.478		0.8
Some college or Associate's degree	-0.37	0.007	**	0.69	0.05	0.866		1.05	-0.03	0.919		0.97
Working part-time	0.03	0.858		1.03	0.13	0.722		1.14	-0.28	0.461		0.75
Not working	0.08	0.619		1.08	0.22	0.471		1.24	0.15	0.653		1.16
Parent Education	0.07	0.019	*	1.07	-0.03	0.62		0.97	-0.02	0.796		0.98
Household Income	0.22	< .001	***	1.25	0.25	0.004	**	1.28	0.14	0.121		1.15
Financial Literacy	**0.31**	**< .001**	***	**1.36**	0.22	0.079		1.24	0.15	0.278		1.16
McFadden R2	0.29				0.17				0.13			

***significant at 0.001, **significant at 0.01, * significant at 0.05

Logistic Regression Eq.3:

Logit (Probability of Pay Off Loan) = α + $\beta1\times$ Age + $\beta2 \times$ Gender+ $\beta4 \times$ Marital Status + $\beta5 \times$ Education + $\beta6 \times$ Employment Status + $\beta7 \times$Parent Education + $\beta8 \times$ Household Income + $\beta9 \times$ Financial Literacy

Table VI presents a comparison of logistic regression results for predicting ‘behind payment’ status between two models: the base model (Eq.1) and a model that includes financial literacy and its interaction terms (Eq.2). In the base model, being a minority was positively related to ‘behind payment’ status, indicating racial disparities in student loan repayment. However, controlling for the main and conditional effect of financial literacy in Eq.2 resulted in both Black and Hispanic having insignificant coefficients. The main effect of financial literacy was significant with an odds ratio of 0.76, indicating that increasing financial literacy by one level would reduce the likelihood of falling behind on payments by 24% for the entire sample.

Table VI. Logistic Regression Results with Age, Race, Gender, Marital Status, Education, Employment Status, Parent Education, Household Income, and Financial Literacy Predicting Behind Payment for the Entire Sample

	Base Model without Financial Literacy (Eq.1)				With Financial Literacy and Interaction Terms (Eq.2)			
Variable	*B*	*p*		*OR*	*B*	*p*		*OR*
(Intercept)	-1.75	< .001	***	-	-1.4	0.008	**	-
Age	-0.002	0.749		1.00	0.002	0.785		1.00
Black, Non-Hispanic	**0.52**	**0.022**	*	1.69	0.55	0.203		1.74
Hispanic	**0.94**	**< .001**	***	2.57	0.47	0.334		1.60
Female	0.19	0.301		1.21	0.11	0.546		1.12
Now married	-0.32	0.108		0.72	-0.34	0.089		0.71
Master's degree or higher	0.28	0.328		1.32	0.28	0.314		1.33
Some college or Associate's degree	1.06	< .001	***	2.89	1.01	< .001	***	2.74
Working part-time	-0.005	0.982		0.99	0.03	0.911		1.03
Not working	-0.46	0.054		0.63	-0.43	0.072		0.65
Parent Education	-0.01	0.839		0.99	0.007	0.879		1.01
Household Income	-0.4	< .001	***	0.67	-0.38	< .001	***	0.68
Financial Literacy					**-0.28**	**0.026**	*	**0.76**
Black, Non-Hispanic × Financial Literacy					-0.08	0.712		0.92
Hispanic × Financial Literacy					0.24	0.276		1.27
McFadden R2	0.15				0.15			

***significant at 0.001, **significant at 0.01, * significant at 0.05

Logistic Regression Eq.1:
Logit (Probability of Behind Payment) = $\alpha + \beta 1 \times$ Age$+ \beta 2 \times$ Race $+ \beta 3 \times$ Gender$+ \beta 4 \times$ Marital Status $+ \beta 5 \times$ Education $+ \beta 6 \times$ Employment Status $+ \beta 7 \times$Parent Education $+ \beta 8 \times$ Household Income
Logistic Regression Eq.2:
Logit (Probability of Behind Payment) = $\alpha + \beta 1 \times$ Age$+ \beta 2 \times$ Race $+ \beta 3 \times$ Gender$+ \beta 4 \times$ Marital Status $+ \beta 5 \times$ Education $+ \beta 6 \times$ Employment Status $+ \beta 7 \times$Parent Education $+ \beta 8 \times$ Household Income $+ \beta 9 \times$ Financial Literacy $+ \beta 10 \times$ (Black $\times$ Financial Literacy) $+ \beta 11 \times$ (Hispanic $\times$ Financial Literacy)

Table VII displays the comparison of logit results for each racial group separately. The results showed that financial literacy has a negative relationship with 'behind payment' status in Black borrowers, with an odds ratio of 0.59 indicating we can expect a 41% decrease in the likelihood of falling behind on payments for every one level increase in financial literacy. However, no significant impact of financial literacy on 'behind payment' status was found for either White or Hispanic borrowers. These results suggest that improving financial literacy may be most effective in preventing 'behind payment' behavior among Black borrowers.

Table VII. Logistic Regression Results with Age, Race, Gender, Marital Status, Education, Employment Status, Parent Education, Household Income, and Financial Literacy Predicting Behind Payment by Race

	White, Non-Hispanic				Black, Non-Hispanic				Hispanic			
Variable	*B*	*p*		*OR*	*B*	*p*		*OR*	*B*	*p*		*OR*
(Intercept)	-1.2	0.077		-	-2.47	0.024	*	-	-0.33	0.736		-
Age	-0.01	0.244		0.99	0.02	0.119		1.02	0.02	0.322		1.02
Female	0.27	0.30		1.31	0.14	0.728		1.15	-0.45	0.266		0.64
Now married	-0.22	0.427		0.81	-0.49	0.282		0.61	-0.44	0.293		0.64
Master's degree or higher	0.92	0.022	*	2.52	-1.1	0.111		0.33	0.26	0.653		1.29
Some college or Associate's degree	1.63	< .001	***	5.09	0.46	0.342		1.58	0.52	0.226		1.69
Working part-time	-0.006	0.985		0.99	0.17	0.764		1.19	-0.18	0.742		0.83
Not working	-0.79	0.027	*	0.45	0.39	0.39		1.48	-0.53	0.288		0.59
Parent Education	-0.03	0.683		0.97	0.19	0.079		1.21	-0.1	0.325		0.91
Household Income	-0.48	< .001	***	0.62	-0.17	0.249		0.84	-0.39	0.004	**	0.68
Financial Literacy	-0.16	0.242		0.86	**-0.53**	**0.006**	**	**0.59**	-0.13	0.499		0.87
McFadden R2	0.18				0.12				0.09			

***significant at 0.001, **significant at 0.01, * significant at 0.05

Logistic Regression Eq.3:
Logit (Probability of Behind Payment) = α + β1× Age + β2 × Gender+ β4 × Marital Status + β5 × Education + β6 × Employment Status + β7 ×Parent Education + β8 × Household Income + β9 × Financial Literacy

Additionally, among all the socioeconomic factors controlled for, only household income and some college consistently impacted both the ‘paid off loan’ and ‘behind payment’ status of the entire sample. The higher the household income, the more likely borrowers were to pay off their loans and the less likely they were to fall behind on payments. Some college without degree completion was found to be negatively associated with ‘paid off loan’ status and positively associated with ‘behind payment’ status. These findings were consistent with the existing literature that attributes repayment difficulties of minority students to their higher tendency to accumulate college debt without obtaining a degree (Scott-Clayton, 2018; Hamilton & Darity, 2017; Shapiro et al., 2017).

4.2 Wu-Hausman Endogeneity Test

According to Klapper, Lusardi, and Panos (2013), correlations between financial literacy and financial outcomes do not automatically imply causation. To establish a causal link, it is essential to address the potential endogeneity of financial knowledge by conducting an appropriate test. In our study, we conducted a Hausman test (Hausman 1978) to determine if an exogenous source of variation in financial literacy is necessary to assess its causal relationship with loan repayment behavior.

To implement the Hausman test, we need to identify instrumental variables (IVs) that satisfy both the relevance and exogeneity assumptions. After carefully examining the data, we identified "Don't Know" as an instrument as it was correlated with financial literacy (relevance) and appeared to be uncorrelated with the error terms in the loan repayment status estimations (exogeneity). In our dataset, "Don't Know" took a value of 1 if the respondent answered "Don't know" to any of the three financial literacy questions in the SHED survey, and a value of 0 if the respondent did not answer "Don't know" to any of the financial literacy questions.

The Hausman test is conducted by constructing simultaneous equations that include a set of exogenous variables and endogenous variables. In our equations, the exogenous variables consisted of age, race, gender, marital status, education, employment status, parent education, and household income. On the other hand, the endogenous variables were the "Paid off loan" status, the "Behind payment" status, financial literacy, and its interaction terms with race. The Hausman test procedure involved the following steps (Hausman, 1978):

Step 1: Estimate the equation of Financial Literacy with all exogenous variables and the instrument “Don’t Know” as independent variables:

Financial Literacy = $\alpha 1$ + $\alpha 2 \times$ *Don’t Know* + $\alpha 3 \times$ Age+ $\alpha 4 \times$ Race + $\alpha 5 \times$ Gender+ $\alpha 6 \times$ Marital Status +$\alpha 7 \times$ Education + $\alpha 8 \times$ Employment Status + $\alpha 9 \times$Parent Education + $\alpha 10 \times$ Household Income + $\mu 1$

Step 2: Run the linear probability regression with Paid Off Loan or Behind Payment as the dependent variable and the estimated residuals $\widehat{\mu 1}$ from step 1 as an independent variable along with all other variables:

Paid Off Loan or Behind Payment = $\beta 1$ + $\beta 2 \times$ Age+ $\beta 3 \times$ Race + $\beta 4 \times$ Gender+ $\beta 5 \times$ Marital Status +$\beta 6 \times$ Education + $\beta 7 \times$ Employment Status + $\beta 8 \times$Parent Education + $\beta 9 \times$ Household Income+ +$\beta 10 \times$ Financial Literacy + $\beta 11 \times$ (Black $\times$ Financial Literacy) + $\beta 12 \times$ (Hispanic $\times$ Financial Literacy) + $\beta 13$ $\widehat{\mu 1}$+ $\mu 2$

Step 3: Wu-Hausman endogeneity test hypothesis
Null Hypothesis: $\beta 13 = 0$, Financial Literacy is exogenous.
Alternative Hypothesis: $\beta 13 \neq 0$, Financial Literacy is endogenous.

Based on the diagnostic results presented in Table VIII, the Wu-Hausman test did not provide evidence to reject the null hypothesis of exogeneity. This implies that the need for IV estimation to address endogeneity is not warranted., and the original regression results are considered more accurate and reliable than IV estimates.

Table VIII. Diagnosis Test on Endogeneity of Financial literacy in Predicting Paid 0ff Loan and Behind Payment

			Predicting Paid off Loan			Predicting Behind Payment		
	df1	*df2*	Statistics	p-value		Statistics	p-value	
Wu-Hausman	3	3093	2.177	0.0887		0.786	0.5016	
Weak Instrument (Financial Literacy)	3	3096	93.854	<2e-16	***	93.854	<2e-16	***
Weak Instrument (Financial Literacy*Black)	3	3096	116.568	<2e-16	***	116.568	<2e-16	***
Weak Instrument (Financial Literacy*Hispanic)	3	3096	93.743	<2e-16	***	93.743	<2e-16	***
Sargan	0	NA	NA	NA		NA	NA	

***significant at 0.001, **significant at 0.01, * significant at 0.05

Additionally, the null hypothesis of weak instruments was rejected at p<2e-16, providing robust evidence that “Don’t Know” is a strong instrument that meets the relevance assumption. However, due to the limitation of having only one instrument available in the dataset, we were unable to conduct the Sargan test for instrument exogeneity. The Sargan test requires an overidentified equation, where the number of instruments is greater than the number of suspected endogenous regressors. In our case, with only one instrument, the Sargan test cannot be applied.

Nevertheless, we provided theoretical justification for the instrument exogeneity. Firstly, the "Don't Know" responses to the financial literacy questions can be interpreted as genuine uncertainty or a lack of knowledge about specific financial concepts, rather than a deliberate choice or a direct indicator of behavior. This suggests that individuals may not possess sufficient understanding of certain financial aspects without it being directly related to their loan repayment behavior. Secondly, we observed that the "Don't Know" responses appeared to be random and not systematically influenced by factors such as individual preferences, attitudes, or unobserved characteristics that could affect loan repayment behavior. These theoretical reasons enabled us to treat the "Don't Know" responses as exogenous or unrelated to the error term in estimating loan repayment behavior.

The robustness of our instrument selection and the absence of endogeneity provide substantial support for the validity of our original logistic regression estimates, eliminating the need for instrumental variables (IVs). With these findings, we can confidently assert that the observed associations between financial literacy and loan repayment behavior indicate a genuine causal relationship.

5-CONCLUSION

This study sheds light on the significant impact of financial literacy on student loan repayment behavior and how it varies across different racial groups. Overall, the findings indicate that a higher level of financial literacy is associated with a greater likelihood of paying off student loans and a lower likelihood of falling behind on payments for the overall sample. However, the impact of financial literacy on repayment behavior differs significantly among racial groups. This study reveals that financial literacy is most effective in preventing 'behind payment' behavior among Black student borrowers, while it has the most significant impact on promoting favorable 'paid off loan' behavior among White student borrowers.

The observed asymmetry in the impact of financial literacy on loan repayment behavior among different racial groups can potentially be attributed to variations in their levels of financial literacy. As discussed earlier, financial literacy is associated with both higher returns on financial assets and lower forecasting errors in loan repayments. However, the strength of each association may vary depending on borrowers' levels of financial literacy.

Regarding the positive impact of financial literacy on higher returns and savings, Lusardi et al. (2017) highlighted that investment returns and savings tend to increase at a faster rate for individuals with higher levels of education. Therefore, it can be inferred that individuals with higher financial literacy, such as White borrowers in this case, would benefit the most from the positive effects of financial knowledge on investment returns. As their financial literacy improves, their returns and savings accumulation grow at a faster rate, resulting in a higher ability to repay loans in full and on time. This explains why the impact of financial literacy on the 'paid off loan' status was most pronounced among White student borrowers, who generally exhibited the highest level of financial literacy in comparison to the other racial groups in this study.

On the other hand, we posit that the impact of financial literacy on reducing forecasting errors in loan payments is particularly pronounced among borrowers with lower levels of financial literacy. According to Artavanis and Karra (2020), individuals with low financial literacy are more likely to underestimate their future loan payments compared to those with higher financial literacy. Given that Black borrowers generally exhibit lower levels of financial literacy, they are more prone to underestimate the amount they need to repay, which can result in delinquency and default. As a result, the benefit of financial literacy in minimizing forecasting errors is particularly significant among Black student borrowers. This explains the significant negative relationship observed between financial literacy and the 'behind payment' status for this specific group.

In addition to identifying the significant variation in the impact of financial literacy on student loan repayment behavior among racial groups, our study also reveals that controlling for both the main and conditional effect of financial literacy substantially removes the negative impact of belonging to a minority group on student loan repayment behavior. These findings suggest that the variation of financial literacy and its effectiveness across different racial groups can account for a significant part of the racial gap in student loan repayment.

This study's findings hold significant implications for policymakers and financial literacy education. Financial literacy education can potentially reduce the racial gap in student loan repayment, but for these programs to be effective, they must be customized to meet the unique needs of different racial groups. To achieve this, Cordero, Gil-Izquierdo, & Pedraja-Chaparro (2022) recommend that financial literacy education be delivered by experts and specialists, rather than by non-specialist teachers. Additionally, before designing the program, a proper assessment of the current level of financial literacy is necessary for customization (Bongini, Iannello, Rinaldi, Zenga, & Antonietti, 2018). It's important to note that the effectiveness of financial literacy education is influenced by a range of complex factors, including cultural values, access to financial resources, and systemic barriers to financial well-being. Therefore, further research should investigate these factors to design financial literacy education programs that can maximize benefits and minimize barriers for each major racial group's unique circumstances and cultural contexts.

Finally, it would be valuable for future research to investigate whether improving financial literacy can also address the gender gap in student loan repayment. Previous studies, such as Saleh, Yu, Leslie, & Seydel (2017), have shown that women may face more challenges in paying off their student debt due to various factors such as industry policies and salary inequities. Despite the availability of extended repayment periods, extended payment options still have negative impact on women compared to men. (Miller, 2017; Saleh et al., 2017). Therefore, it is important to explore whether financial literacy interventions can potentially help mitigate this gender gap in student loan repayment.

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THE EFFECT OF VOLUNTARY DISCLOSURE QUALITY ON TUNISIAN STOCK RETURN VOLATILITY: THE MODERATING ROLE OF OWNERSHIP STRUCTURE

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ABSTRACT

In this article, we investigate the moderating role of ownership structure on the relationship between the quality of voluntary financial disclosure and share price volatility of non-financial companies listed on the Tunis Stock Exchange. The sample of 411 annual reports of non-financial companies listed on the Tunis Stock Exchange is studied and analyzed from 2010 to 2019. GLS method is used. Our findings demonstrate that the impact of voluntary disclosure quality on stock price volatility is statistically significantly negative after incorporating ownership structure as a moderate variable in our empirical model, and further that the positive influence of institutional ownership on stock price volatility is mitigated through its indirect link with voluntary disclosure quality. Our investigation contributes in several ways. We are studying the disclosure quality in a frontier market, in which investor confidence has been seriously impacted following the 2011 revolution. We focus in this respect on the Tunisian stock market, known for its culture of withholding information, as Tunisian companies do a low tendency to voluntarily disclose such information. Additionally, we contribute to the current research literature on voluntary disclosure through examining the moderating role of ownership structure on the relationship between voluntary disclosure and stock return volatility in a frontier market.

Keywords: *Voluntary disclosure quality, stock price volatility, signaling theory, moderating role of ownership structure, frontier market, Tunisian stock market.*

***JEL Classification**– D83, G12, G23, M41, G14, G30*

INTRODUCTION

The lack of transparency between companies and their different stakeholders, such as investors, is perceived as a major problem. This is why voluntary disclosure has emerged as an indispensable tool for helping companies respond to the challenges of sustainable investment. In particularly, voluntary disclosure offers the opportunity to help decrease information asymmetry (Suharsono et al., 2020).

The question of the quality of voluntary disclosure of information is crucial, as inappropriate or partial information would be worse than no information at all. It is this question of the quality of voluntary disclosure that we have focused on in this research, with reference to financial theories such as agency theory and signaling theory.

Agency theory states that minimizing conflicts of interest between managers and shareholders requires the implementation of control and supervision mechanisms. Ownership structure is one of the mechanisms that can minimize abusive behavior on the part of managers and, consequently, increase the quality of voluntary disclosure of financial information. The impact of ownership structure on the quality of voluntary disclosure is one of the most controversial and widely explored areas of research in finance and accounting.

Signaling theory has also emphasized the importance of voluntary disclosure of financial information for different decision-makers. Triyono and Hartano (2000) show that investors' reaction to disclosed information significantly affects upward or downward stock trading activity, as well as the price formation process and stock price volatility.

On this note, a number of prior research articles (Hussainey & Walker, 2009; Coluccia et al., 2017; Azrak et al., 2021; Chen et al., 2022) investigated the relationship between the quality of voluntary disclosure and stock price volatility. In particular, disclosure quality might be instrumental in enhancing stock market decision-making and in raising future earnings forecasts. The reason for this might well be that volatility is an important measure of the information asymmetry that company executives are trying to minimize by disclosing more information.

Hence, new debates took place in Tunisia after the revolution to strengthen information transparency and disclosure quality. This study aims to examine the moderating role of ownership structure on the relationship between voluntary financial disclosure quality and share price volatility of non-financial companies listed on the Tunis Stock Exchange.

We make many valuable contributions to our study. We focus on the quality of disclosure in a frontier market, in which investors' confidence was severely affected by the 2011 revolution. In particular, we concentrate on the Tunisian stock market, known for its culture of withholding information, as companies in Tunisia do not voluntarily disclose such information. Moreover, we contribute to the literature on voluntary disclosure by exploring the moderating role of ownership structure on the relationship between the quality of voluntary financial disclosure and share price volatility of non-financial firms listed on the Tunis Stock Exchange.

The following is the structure of the paper. In Section 2, the literature review and hypothesis development are presented. Section 3 outlines the research methodology. In Section 4, the research results are reported. Finally, section 5 provides the concluding remarks.

2- LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Voluntary disclosure in the Tunisian market

Tunisia's emerging capital market was created in 1969.In this developing country, the economic environment has undergone considerable evolution in the past few years. While financial disclosure is an important field of regulation, one that helps company managers to assess management efficiency, to improve their corporate image and to estimate the profitability of their own investments, but a large number of Tunisian companies are still not disclosing enough information in their annual reports. The Ahmadi and Bouri (2019) findings show that the auditors' membership of an international audit network, the "Big 4", enhances the information disclosed voluntarily in the Tunisian market.

Voluntary disclosure quality and share price volatility

Several previous studies have shown a negative relationship between the quality of financial disclosure and stock price volatility. There are several reasons for this negative relationship. High-quality voluntary disclosure reduces information asymmetry in the market, thereby lowering stock price volatility. In addition, if companies regularly disclose information to the market, the impact of new information on their performance may diminish, leading to less price variation. Voluntary disclosure of good quality leads to transparency in the market, and consequently the valuation of firms will be more consensual for investors, which could lead to a reduction in volatility. The idea that disclosure quality and transparency can reduce share price volatility may encourage companies to disclose more information.

The microstructure theory of financial markets shows that massive disclosure of market information can reduce information asymmetry and lead to price variations that depend on changes in investor demand for shares (Diamond and Verrecchia (1991)). Voluntary disclosure can also reduce the heterogeneity of investors' beliefs about the true value of a company, and consequently reduce share price volatility.

Azrak et al. (2021) find that the provision of additional market information would only slightly increase share price volatility and would therefore not have an economically significant impact on share price volatility in the Gulf Cooperation Council (GCC) countries. Kanakriyah (2016) noted a significant impact of voluntary disclosure on accounting practices in Jordan. Chen et al (2022) have found that the negative relationship between corporate social responsibility (CSR) disclosure and stock return volatility is more accentuated for companies with more information asymmetry, polluting industries and high CSR scores.

Ownership structure and the quality of voluntary disclosure

The relationship between ownership structure and the quality of voluntary disclosure has received a great deal of attention in recent years and is undoubtedly one of the most widely explored areas of research in accounting and finance. Some previous studies in this field have demonstrated the significance of this relationship, while others have not produced conclusive results.

Samaha et al (2012) investigate the impact of a comprehensive set of corporate governance attributes on the degree of voluntary disclosure in Egypt, finding that the degree of voluntary disclosure is lower for companies with a duality position and higher ownership concentration and increases with the proportion of independent directors on the board and company size.

Donnelly and Mulcahy (2008) show that voluntary disclosure increases with the number of non-executive directors on the board, and that companies with a non-executive chairman make more voluntary disclosures than other companies. Furthermore, their results show the absence of a significant relationship between the degree of voluntary disclosure and ownership structure.

The moderating role of ownership structure

Healy, Hutton and Palepu (1999) find that an increase in the quality of voluntary disclosure due to higher institutional ownership has a significant effect on stock price volatility. Nofsinger and Sias (1999)find that greater institutional ownership is associated with higher stock price volatility. It would therefore be relevant to study the relationship between price volatility and ownership structure, in order to fully understand the transition from the impact of ownership structure on the quality of voluntary disclosure to the impact of the quality of voluntary disclosure on price volatility.

Similarly, Bushee and Noe (2000) find that institutions with a large amount of ownership have several reasons to require higher quality of disclosure as a way to offset monitoring costs. At a first stage, as disclosure increases, the impact on the bank's stock price volatility is negative due to lower information asymmetry. They conclude that the smoother behavior of stock prices decreases the cost of capital.

Conflicts of interest are more likely to destroy its independence, and the information obtained by the market may have hidden deviation(Firth et al. (2015)). Analysts may selectively disclose information for personal interests and lack constraints on honest behavior, resulting in inadequate or even biased market information. This will increase information asymmetry, and the company's stock price volatility will be higher.

3- RESEARCH METHODOLOGY

This section explains the sample and data, the regression model and, lastly, the variables measured.

3.1 Sample and data

Our study is empirically based on a sample of all Tunisian non-financial firms quoted on the Tunisian stock market observed over the period 2010-2019. For those listed after 02/01/2010, the data period is from the date of listing to 31/12/2019. The preliminary selected sample comprises all Tunis Stock Exchange listed companies as at December 31, 2019 (81 firms). Financial companies and those for which certain data were not available were eliminated. In the final analysis, we kept a sample of 411 observations (48 firms). The collected data that our empirical study investigates were taken from the annual reports and financial statements of the selected companies, the annual reports of the Tunisian stock exchange, the listing history and the share guide, with an annual frequency during the period 2010-2019.

3.2. Regression model

First of all, to test the impact of the quality of voluntary disclosure on the volatility of the share price of companies listed on the Tunisian stock market, we estimate, in panel data, the following model:

$$VOLAT_{it}=\lambda_0+ \lambda_1 DIV_{it}+ \lambda_2 CSIZE_{it}+ \lambda_3 Qtob_{it}+ \lambda_4 LEVG_{it} + \varepsilon_{it} \quad (1)$$

Secondly, to examine the moderating role played by the ownership structure on this relationship, we use panel data to estimate the following model:

$$VOLAT_{it}=\lambda_0+ \lambda_1 DIV_{it}+ \lambda_2 DIV_{it} * INST_{it} + \lambda_3 DIV_{it} * MANG_{it}+\lambda_4 DIV_{it} * FRG_{it}+ \lambda_5 CSIZE_{it}+ \lambda_6 Qtob_{it}+ \lambda_7 LEVG_{it} + \varepsilon_{it} \quad (2)$$

Where:

$VOLAT_{it}$is volatility of stock price (i) in t (year t).
DIV_{it} is a score measuring voluntary disclosure quality of firm (i) in t.

FRG, MANG and INST represent the percentages of foreign, managerial, and institutional ownership, respectively.
$CSIZE_{it}$ is size of firm (i) in t.
$Qtob_{it}$ is Q-tobin indicator of firm (i) in t.
$LEVG_{it}$ is the debt ratio of firm (i) in t.
ε_{it} is the error term of the model.

3.3 Variable Measurement

This paragraph introduces the dependent variable, the independent and moderating variables and the control variables.

3.3.1 Dependent variable: Stock price volatility

Our measure of stock price volatility (VOLAT) is the annualized standard deviation of returns, calculated using daily stock returns. We first calculated the standard deviation of daily returns as follows:

$$\sigma(x) = \sqrt{v(x)} = \sqrt{\frac{\sum_{t=0}^{n}(X_t - \tilde{x})^2}{n}} \quad (3)$$

$$\tilde{x} = \frac{\sum_{t=0}^{n} x_t}{n} \quad (4)$$

Where V is stock price variance. X_t is stock price variation at time t, and n is the total number of observations.

The calculated standard deviation is then multiplied by the square root of the number of trading days (252) to obtain an annualized standard deviation.

3.3.2. Independent and moderating variables:

Our independent variable is the score measuring voluntary disclosure quality .This score is calculated following the same approach adopted by Katmon et al. (2019)and Boshnak (2021).Then, we calculate a score for each firm in our sample using the item method.

To this end, we first establish a preliminary list of 136 items as initial indicators of disclosure. Then, we select the relevant items from this list to determine the final disclosure index based on accounting standards. Finally, we eliminated 17 mandatory disclosure items from the initial list and therefore the final list consisted of 119 items.

Assignment of scores to each of these 119 items and the calculation of the final voluntary disclosure score for each company in our sample is done according to the following procedure: On the one hand, we assign 1 if the company discloses an item of the list, otherwise 0. On the other hand, and for the forecast items, we assign 2 for the punctual estimations; we attribute 1 for the estimations by interval, and finally 0 for the non-disclosure of the forecast information. Then, the raw score is equal to the total of the scores of the company for all the items. Then, the final score is calculated by the sum of the total relative score of the firm subdivided by the maximum score of the whole sample and then multiplied by 1/5, as follows:

$$\text{DIV} = \frac{\text{RSCOR}_i}{\text{MAXSCOR}} * 20\% \quad (5)$$

Where:

DIV_i is the voluntary disclosure index of firm (i), $RSCOR_i$is the individual score of company (i) and MAXSCOR is the maximum score of the whole sample.

Our moderating variables are foreign ownership, managerial ownership, and institutional ownership. Table 1 details the measurements of these variables for each of the companies in our sample.

Table 1
MODERATING VARIABLES MEASUREMENTS

VARIABLES	MEASUREMENTS
Foreign ownership (FGR)	Total number of shares owned by foreign investors divided by number of shares outstanding.
Managerial ownership (MANG)	Total number of shares owned by the chief executive officer and members of the executive board divided by number of shares outstanding.
Institutional ownership (INST)	Total number of shares owned by banks, insurance companies, other financial organizations and public institutions divided by number of shares outstanding (Lee et al, 2018).

3.3.3 Control variables:

We have three control variables: firm size, Q Tobin,and leverage. Where the firm size (CSIZE) is measured by the natural logarithm of total assets. The Q-Tobin (Qtob) is the market capitalization divided by total assets. Finally, Leverage(LEVG) is measured by the total financial debt divided by total equity and liabilities.

4- RESEARCH RESULTS

In this section, we provide descriptive statistics and regression results.

4.1 Descriptive statistics

Table 2 below presents the descriptive statistics (Mean, Median, Minimum, Maximum, Standard deviation, Kurtosis, Skewness) of the different annual series of the studied variables during the 2010-2019period. We found that volatility of prices of the firms quoted on the Tunisian stock market is between the two extreme values of 137.5% (Maximum) and 4.3% (Minimum), or a fluctuation of around an averaged value of 29.684%.We also found that voluntary disclosure quality of Tunisian companies listed on the Tunis Stock Exchange fluctuates between 0.2 and 0.084, this variability is centered on the average of 0.141. The examination of Table 2 also shows that the average of the foreign ownership in the companies of our sample is 3.817% with a maximum of 59.110% and a minimum of 0%. As shown in Table 2, on average, managerial ownership in our sample firms is 59.777% with a maximum of 99.990% and a minimum of 0%. Table 2 shows also that the percentage of institutional ownership in non-financial firms listed on the Tunisian stock market varies between two extreme values namely

91.670% (Maximum) and 0% (Minimum), that is to say variability around an average value of 45.787%.

Table 2
DESCRIPTIVE STATISTICS

	Mean	Median	Minimum	Maximum	Standard Deviation	Kurtosis	Skewness
VOLAT	29,684%	27.7%	4,3%	137,5%	0.137	20.998	3.321
CSIZE	18,226	18.171	15,359	22,840	1,057	3.422	0.278
LEVG	57,419%	50.20%	0,08%	434,04%	0.538	23.669	3.9
Qtob	1,284	0.867	0,011	18,031	1,421	51.794	5.149
DIV	0,141	0.143	0,084	0,2	0,021	3.976	0.193
FGR	3,817%	0	0,000%	59,110%	0.12189	16.272	3.766
INST	45.787%	44.84%	0,000%	91.670%	0.28577	1.644	-0.208
MANG	59,777%	65.3%	0,000%	99,990%	0.22124	3.972	-1.140

4.2 Regression results

In the following section, we first provide regression results for the impact of voluntary disclosure quality on stock price volatility, and then regression results that test the moderating role of ownership structure on this relationship.

4.2.1 Impact of voluntary disclosure quality on stock price volatility

We experimentally investigate the impact of the quality of voluntary financial disclosure on stock price volatility by estimation of the coefficients of Model 1 in panel data. Table 3 below summarizes the estimated results of a fixed-effects specification.

Table 3
IMPACT OF VOLUNTARY DISCLOSURE QUALITY ON STOCK PRICE VOLATILITY

		Coefficients	P-value
DIV		-1.22059	0.035**
LEVG		-0.0739416	0.002***
Qtob		0.0007887	0.891
CSIZE		-0.0813449	0.001***
Constant		1.992618	0.000 ***
R-square	**Within**	0.0621	
	Between	0.0040	
** : Significant at the 5% level		***Significant at the 1% level	

The findings of the model(1) indicate that the coefficient of the DIV variable is negatively correlated (-1.22059) and is statistically significant at the usual 5% threshold (p-value=0.035), which means that the quality of voluntary financial information has a significant negative impact on the price volatility of non-financial companies listed on the Tunisian stock market. There may be multiple explanations for this impact. In fact, voluntary quality disclosure reduces information asymmetry in the market and, hence, share price volatility. If companies regularly disclose information to the market, the impact of new information on their performance may diminish, leading to less price variation. In this way, the quality of voluntary information disclosure creates transparency in the market and, consequently, the company's valuation will be more consensual for investors, which in turn may reduce share price volatility.

4.2.2. The moderating role of ownership structure

To deepen our empirical analysis of the impact of the quality of voluntary financial disclosure on the price volatility of securities listed on the Tunisian stock market, we added ownership structure as a moderator variable of this relationship.

TABLE 4

THE IMPACT OF VOLUNTARY DISCLOSURE QUALITY ON TUNISIAN STOCK RETURN VOLATILITY: THE MODERATING ROLE OF OWNERSHIP STRUCTURE

		Coefficients	P-value
DIV		-0.3595049	0.343
DIV*INST		0.4414764	0.033**
DIV*MANG		0.2662939	0.309
DIV*FGR		-0.171698	0.790
LEVG		0.0222684	0.153
Qtob		-0.004166	0.437
CSIZE		-0.0209338	0.015**
Constant		0 .670829	0.000 ***
R square	**Within**	0.0000	
	Between	0.3115	
** : Significant at the 5% level		***Significant at the 1% level	

The examination of table 4 shows that the impact of the quality of voluntary financial disclosure on price volatility remains significantly negative even after the addition of the moderating variables measuring ownership structure in model (2). Our results also show a positive relationship between the moderating effect of institutional ownership and price volatility, implying that increasing institutional ownership in firms listed on the Tunisian stock market could increase price volatility, as shown by Sias (1996), Dennis and Strickland (2002), Xu and Malkiel (2003). However, this effect of institutional ownership on volatility seems to be attenuated by its indirect link with the quality of voluntary disclosure of financial information.

The results also show that there is no significance of the moderating effect of managerial and foreign ownership on the relationship between voluntary disclosure and volatility.

CONCLUSION

This paper investigates the relationship between the quality of voluntary disclosure and share price volatility in Tunisia, considering the moderating role of ownership structure. The results support our conjecture that there is a negative correlation between the quality of voluntary disclosure and share price volatility based on a sample of 411 annual reports of non-financial companies listed on the Tunisian stock exchange observed over the period 2010-2019. The significance of this negative impact is mainly due to the increase in the level and quality of voluntary disclosure, which reduces information asymmetry in the market and the anticipated risks to which companies are exposed, leading to a stabilization of stock prices and a reduction in volatility.

We also find that the impact of voluntary disclosure quality on stock price volatility is significantly negative after incorporating ownership structure into our empirical model as a moderated variable, and that the positive effect of institutional property on stock price volatility is moderated by its indirect relationship with voluntary disclosure quality.

This article contributes to the existing literature on voluntary disclosure by exploring the three-way link between voluntary disclosure, ownership structure and price volatility in the Tunisian stock market. The practical implications of our study are relevant to managers, investors and researchers. In this regard, these findings may guide managers in their decision making. In additional, investors are interested in firms with a higher percentage of institutional shareholding, as this type of shareholding enhances the quality of voluntary disclosure and therefore lowers share price volatility.

This study's limitation is that we used as our sample only non-financial companies listed on the Tunisian stock market, which may restrict the generalizability of the findings. As a consequence, this paper may provide future researchers with new lines of investigation. For illustration, potential future research may explore the effect of corporate social responsibility disclosure in particular on volatility and could highlight the significance of the role of institutional investors.

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PREMARKET PRICING UNCERTAINTY AND THE UNDERPRICING OF INITIAL PUBLIC OFFERINGS

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ABSTRACT

All participants in an IPO must evaluate the stock without existing equilibrium price information as a reference point for its fair value. This problem of missing prior price information creates uncertainty in IPO pricing. We show that this uncertainty exists in the premarket valuation process and that IPO underpricing as a premium to investors for bearing this uncertainty increases with valuation volatility. We form IPO portfolios and find a strong, positive relationship between the portfolio mean and the portfolio standard deviation of IPO initial returns. We also find that the portfolio standard deviation alone explains approximately 90% of the variation in the portfolio mean.

JEL classification: G14, G24

Keywords: Initial public offerings, underpricing, premium for pricing uncertainty

1. INTRODUCTION

Despite the extensive literature on initial public offering (IPO) pricing, our understanding of the IPO underpricing phenomenon remains inconclusive. The finding of Lowry et al. (2010) highlights this point. They document that IPO initial returns display extremely high volatility and that volatility varies considerably over time:

> *"While underpricing averages 22% between 1965 and 2005, a relatively small portion of offerings have underpricing that is close to this average: only about 5 percent of the initial returns are between 20% and 25%. Moreover, nearly one-third of the initial returns are negative. The standard deviation of these initial returns over the 1965-2005 period is 55 percent."* (p.1)

Existing IPO pricing theories focus on *intentional* underpricing mechanisms. However, the large and time-varying dispersion of IPO initial returns is difficult to explain as reasonable cross-IPO variations in expected or deliberate underpricing. No clear economic reasons seem to exist for underwriters to deliberately and frequently allow extremely large underpricing and, in particular, overpricing.[2]

A tentative conclusion here is that much of the variation in the initial returns is unanticipated, meaning that considerable pricing errors exist in the pre-issue market. Previous studies do not formally examine the role of pricing errors. For instance, many asymmetric information models explore IPO underpricing in various asymmetric information settings, in which an informed party exists who knows *ex ante* the stock's true value. Since the underwriter is either informed or becomes informed after collecting information, all of those models obtain the offer price as a determinate outcome. Therefore, although the aftermarket price volatility affects the initial return, there is no uncertainty in the offer price. Beatty and Ritter (1986) present a case that further explains this point. In their extended adverse selection model from Rock (1986), the level of information asymmetry depends on *ex ante* uncertainty, and the offer price is a function of the new issue's expected value and the level of uncertainty. In their solution, while *ex ante* uncertainty increases underpricing due to increased asymmetric information costs, it does not make the offer price less accurate. In other words, if the same IPO was priced multiple times in a repeated experiment, the model consistently predicts the same offer price each time, leaving the initial return to change only with the aftermarket price and, thus, display a volatility consistent with the stock's fundamental risk.

Many factors can contribute to the uncertainty and, thus, the difficulty inherent in the pricing problem that limits underwriters' ability to evaluate IPOs accurately. One apparent fact is that no one observes the market value of a new issue until it starts trading in the public market. This fact highlights a universal lack-of-information problem: all participants in an IPO, including the banks and all investors, must evaluate the new stock without prior fair-value information as a reference point for the equilibrium price.[3] Because of this problem, no participant is truly informed, and the usefulness and availability of the premarket information is inevitably constrained by inherent uncertainty. Therefore, we ask about the direct effect of the missing information of prior equilibrium prices *per se* on IPO pricing, leaving aside its possible roles in causing asymmetric information problems. In particular, empirically, how much of the initial return volatility can be explained by this effect?

Figure 1 graphically shows the intuition of the research question. Panel A shows the price dynamics of a stock in a secondary market, where an investor observing the current market value at any point in time only faces the price volatility from the stock's fundamental risk. In contrast, investors in an IPO at, say, time t_0, have no prior equilibrium price information other than the offer price. If they knew the equilibrium price (as in Panel B), they would know the expected value V_0 and only face fundamental risk, as in the secondary market case. However, because

[2] Using a sample of IPOs from 1980 to 1997, Purnanandam and Swaminathan (2004) even find that the median IPO at the offer price was significantly overvalued relative to valuations based on industry peer price multiples.

[3] In real-world IPO markets, investors and underwriters obtain useful valuation information from comparable firms.

they do not observe the equilibrium price in a real IPO (as in Panel C), they face two sources of uncertainty: (i) the unknown expected value; and (ii) the aftermarket price fluctuations around the unknown expected value. In the absence of the equilibrium price V_0, the market aggregate belief V_M^b is nothing but the random realization of a volatile premarket valuation. An offer price that must rely on market beliefs is inevitably uncertain. For example, price multiples from industry peers are commonly used in IPO valuations, which can determine V_M^b at a value approximating V_0 in a certain range, as shown by the shadowed area in the figure. This offer price uncertainty, which arises from the first source, is reflected in volatile premarket valuations. We refer to this as IPO pricing uncertainty. Various factors, including those unrelated to issuer fundamentals, such as stock market trends and investor sentiment, can significantly influence premarket beliefs and, thus, the uncertainty.

The notion of underpricing as a premium for pricing uncertainty highlights IPO initial return as a random variable driven by premarket pricing errors instead of by aftermarket price volatility. The latter is from the issuer's fundamental risk and, on an overnight basis, very small. In contrast, the former can vary considerably and, thus, be very large depending on the difficulty and complexity of the pricing task facing the underwriter. The distinction between these two sources of uncertainty is conceptually new and empirically appealing. By treating the offer price as a random variable, we address an important dimension of IPO underpricing—its volatility. The volatility associated with underpricing predominantly comes from IPO pricing uncertainty instead of secondary market return volatility (see, e.g., Loughran and McDonala, 2013). Because this dimension can be sufficiently flexible to generate high and time-varying initial return volatilities, the interpretation of underpricing as a premium for pricing uncertainty squares with the finding of Lowry et al. (2010).

In this paper, we empirically test the effect of IPO pricing uncertainty on the initial return using a sample of U.S. IPOs. One of our key tests faces a challenge: Without prior price information, which is the very reason for pricing uncertainty, we cannot calculate the mean and variance of an IPO's initial return as we can for a seasoned stock using its historical return data. For this reason, we form IPO portfolios and conduct the test by examining the relationship between the mean and standard deviation of the portfolio IPOs' initial returns. In this approach, we sort IPOs by a valuation uncertainty ranking (with cross-sections) or by listing date (in time series) and form portfolios such that the IPOs in each portfolio have relatively similar pricing uncertainty, and their variations in uncontrolled factors are substantially averaged out. We then use the portfolio mean of the initial returns as a proxy for the expected initial return and the standard deviation as a proxy for pricing uncertainty. We form alternative portfolios. For each formation, we run regressions of the portfolio mean on the portfolio standard deviation. As expected, we identify an unusually strong, positive relationship between the portfolio mean and the standard deviation of IPO initial returns. In various specifications, the standard deviation presents the dominant explanatory variable, which alone explains as high as 94% of the variation in the portfolio mean.

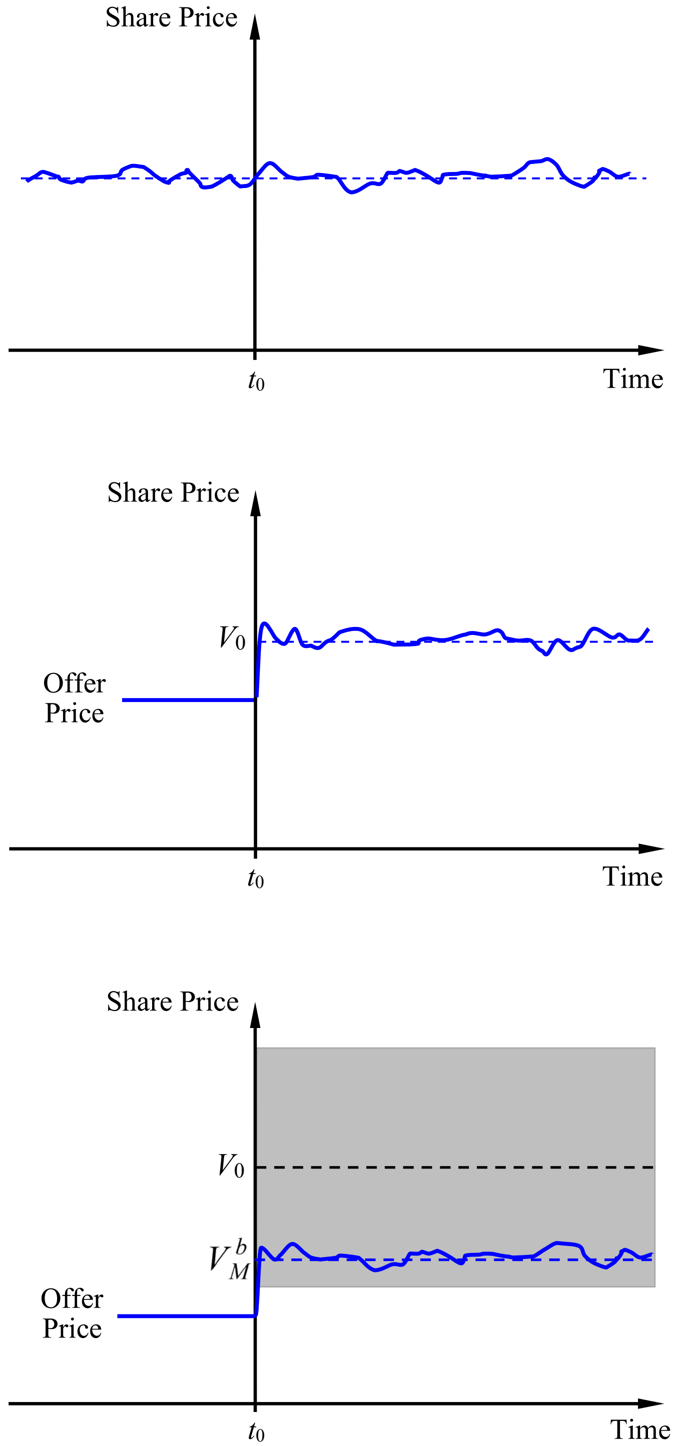
This paper proceeds as follows. Section 2 provides a brief literature review with a focus on short-term IPO performance. Section 3 develops the hypotheses. Section 4 presents our empirical tests. Section 5 concludes the paper.

FIGURE 1. Illustration of Price Dynamics: IPO vs. Seasoned Stock

A. Price dynamics of a seasoned stock

B. Price dynamics of an IPO surrounding the offering date t_0: the *informed* perspective

C. Price dynamics of an IPO surrounding the offering date t_0: the *uninformed* perspective



2. LITERATURE REVIEW

Two groups of papers study IPO underpricing. The first group assumes asymmetric information among issuers, underwriters and investors. Rock (1986) presents a model assuming that some investors are informed and have better information than other investors. If the new shares are priced at the expected value, then the informed investors crowd out the uninformed ones. Therefore, the shares must be underpriced to attract the participation of uninformed investors. Benveniste and Spindt (1989) model the IPO book-building process that induces informed investors to truthfully reveal their private information on the new issue. Underpricing is hence a natural outcome as compensation to investors for disclosing the true value. Sherman and Titman (2002) model book-building IPOs as an information acquisition process in the presence of the moral hazard problem facing investors. They conclude that information is costly, and the underwriter underprices the new issue according to the value of information. Darrien (2005) shows how noise traders' sentiment affects the offer price and the returns in aftermarket trading, where the initial return reflects the private information collected in the book-building process and the sentiment of noise traders. More recently, Chen, Goyal, Veeraraghavan, and Zolotoy (2020) find that high media coverage before an IPO reduces the degree of underpricing.

The second group of papers examines IPO pricing factors other than information asymmetry. Hughes and Thakor (1992) argue that issuers/underwriters underprice stocks to reduce their potential legal liability. Cliff and Denis (2004) find that initial IPO returns are positively related to analyst coverage by lead underwriters. Hence, underpricing is used at least partially as compensation for post-IPO analyst coverage. Our paper fits in with this group of research. We highlight the observation that before the public listing, the issuer's stock had not been traded in the market, so there is no information on its current value (i.e., the equilibrium market price). In the presence of this missing information problem, investors in the IPO require a premium as compensation for this premarket uncertainty in IPO pricing. Specifically, we examine how much initial return volatility can explain underpricing. The notion of underpricing as a premium for pricing uncertainty is consistent with the finding of Lowry et al. (2010) that IPO initial returns display extremely high volatility. Recent studies also address issues related to premarket uncertainty. Chang, Chiang, Qian and Ritter (2017) examine a unique emerging market that requires premarket trading and find that premarket trading prices help set more accurate offer prices and, thus, less price discounts.

Existing IPO pricing theories have focused on intentional underpricing mechanisms that do not consider pricing errors but model the offer price as a determinate outcome. In this study, we focus on the effect of pricing uncertainty due to the lack of prior market equilibrium prices. Intuitively, since this missing information problem reduces the premarket demand, underpricing occurs as an efficient outcome when the premarket demand imposes a binding constraint on the sale of the new issue.

3. HYPOTHESES DEVELOPMENT

To derive our hypotheses, consider the underwriter and the investors in an IPO, where the underwriter represents the risk-neutral issuer, and the investors are risk averse and have heterogeneous preferences. All participants in the IPO are equally uninformed in the sense that no prior equilibrium price information exists so the new issue's expected value is unknown to all participants. To determine the offer price, the underwriter needs to collect information on investors' beliefs through the book-building process and uses the information to derive the premarket demand curve. The timeline for the underwriter's decision is as follows. At time $t_0 = 0$, the underwriter determines the offer price P_0 and allocates shares based on the distribution of the shares demanded at the offer price; at time $t_0 + \Delta t = \Delta t$, the first-day closing price (as the proxy for the immediate aftermarket price), $P_{\Delta t}$, and the initial return, $R = P_{\Delta t} - P_0$, are realized.

The investors face not only fundamental risk from the secondary market but also premarket uncertainty due to missing market equilibrium price information. Their decisions to purchase in the primary market depend on their belief in the new stock's value, which is essentially their best estimate of the true value from their personal preference and any public information available on the new issue. The level of difficulty facing the investors in the valuation determines the degree of the pricing error. Various factors can contribute to the pricing error, including investor heterogeneity and market sentiment.

The underwriter determines the market demand based on information on all investors' intended bids collected during the book-building process. In the absence of the current market price, the underwriter's decision is subject to the market-wide uncertainty in investors' premarket beliefs. This uncertainty presents a source of pricing error in the underwriter's decision. Investors facing uncertainty only purchase the new issue if the offer price is sufficiently lower than their believed value. This discount—the difference between their believed value and the offer price—represents the compensation to the investor for bearing the offer price uncertainty. Therefore, our first hypothesis is the following:

> ***Hypothesis 1.*** *In the presence of pricing uncertainty, underpricing occurs when uncertainty is sufficiently high.*

The economic rationale of this hypothesis is that since the uncertainty from pricing errors reduces the market demand (relative to the case when the stock's current market price was publicly observed), underpricing occurs when the reduced demand imposes a binding constraint on the sale of the new issue.

When the premarket beliefs are inherently uncertain and the underwriter's decision must rely on them, the offer price is inevitably uncertain and bound to vary with market belief fluctuations. One implicit assumption here is that the new issue uncertainty due to imprecise pricing is undiversifiable. Hypothetically, when investors regularly participate in the IPO market and purchase as many shares as needed and at all times, they substantially diversify away this uncertainty by holding a portfolio of all-time IPOs. However, common sense suggests the opposite: IPO pricing uncertainty is difficult for either retail investors or institutions to diversify away. Indeed, because of enormous uncertainty in the timing and availability of future IPOs and the long horizon needed to acquire a diversified portfolio, achieving diversification by relying on new stocks is extremely difficult. A further question is whether investors can diversify away the uncertainty by using stocks from the secondary market. Given the large difference in IPO initial returns and seasoned stock returns (e.g., on an overnight basis, 20% on IPOs vs. 0.05% on seasoned stocks), reducing the initial return uncertainty by holding a portfolio of diversified seasoned stocks is also difficult.

Market beliefs can deviate from the true value for various reasons unassociated with the stock's fundamental risk (e.g., market sentiment). In previous studies, the offer price is modeled as a determinate outcome, where the only source of the uncertainty in the initial return is aftermarket price fluctuations from the stock's fundamental risk. While this conventional component of uncertainty is relatively negligibly small, the pricing uncertainty component as a random draw from the premarket belief distribution becomes dominant. The finding of Lowry et al. (2010) suggests very high volatility of IPO initial returns associated with imprecise pricing. As an illustration, consider a hypothetical IPO with an expected initial return of 20% and a pricing error standard deviation of 25%. A normal distribution of the initial return results in a probability of 0.2 for the realized return to be below -1% and the same probability for the return to be above 41%, leaving a probability of merely 0.16 for the return being within the range of 15–25%. Our second hypothesis is as follows.

> ***Hypothesis 2.*** *The expected value of an IPO's initial return is positively associated with the initial return volatility.*

When the initial return volatility can be measured, it can be used as a proxy for undiversifiable pricing uncertainty. Hence, this hypothesis predicts a positive association between the uncertainty in IPO pricing and the level of underpricing as a premium for taking on the uncertainty.

Lowry et al. (2010) report a positive correlation between the average initial return of IPOs each month and the dispersion of the initial returns each month and conclude that the finding contrasts markedly with the negative correlation between the volatility and mean of secondary market returns. Hypothesis 2 provides a premium for the pricing uncertainty explanation of their observation: When the IPOs each month exhibit similar pricing volatilities, the average initial return is associated with the dispersion of the initial returns dictated by the underlying pricing uncertainty.

4. EMPIRICAL ANALYSIS

In this section, we first examine the link between IPO underpricing and premarket pricing uncertainty (Hypothesis 1) and then conduct a test for the relationship between the expected level and the volatility of IPO initial returns (Hypothesis 2).

4.1. Data and Sample

We collect data on IPOs for 1991–2015 from the Securities Data Company's (SDC) New Issues Database. Following previous studies, we eliminate ADRs, closed-end funds, REITs, spin-offs, and unit issues by choosing only common stocks with an IPO flag equal to one. For each IPO, we collect information on the offer date, preliminary filing price range, offer price, proceeds, SIC code, and VC backing. We also obtain information from SDC on pre-IPO accounting variables for the 12-month period immediately before the filing date, which include revenues, net income, shareholder equity, and long-term debt. Our main empirical results are based on the period from 1991 to 2008, and we use the remaining period from 2009 to 2015 as the robustness check.

To obtain pricing volatility measures, we calculate the volatilities of three price multiples from industry peers: the price-to-earnings ratio, the price-to-EBIT (earnings before interest and taxes) ratio, and the price-to-sales ratio. Investors and investment banks commonly use these multiples to estimate the fair value for IPOs. Purnanandam and Swaminathan (2004) value IPOs using industry peers' price multiplies (such as the price-to-EBITDA, price-to-sales, and price-to-earnings ratios) to determine whether an IPO is underpriced or overpriced. Roosenboom (2012) confirms that the price-multiple approach is one of the main methods underwriters use to determine the fair value for IPOs. Intuitively, for a given IPO, the usefulness of its industry peers' price multiples directly depends on how close or comparable they are. The more divergent the multiples are, the greater is the disagreement among investors and investment banks and hence the higher is the uncertainty and the greater is the difficulty of the IPO valuation. Therefore, although true uncertainty is not observable and cannot be directly measured, the standard deviation of industry peers' price multiples presents a reasonable proxy for uncertainty.

The presumption for this approach is that the price multiples of industry peers do not depend on an IPO's offer price or initial return. Given the IPO pricing process and the scale of the whole market or industry in contrast to that of a new issue, this presumption seems to hold intuitively and is consistent with the common perception that a new issue's price depends on the aggregate market condition but not vice versa. However, the exceptional situation in which an important company's IPO in turn affects the market sentiment—and, consequently, the industry peers' price multiples become endogenous to the IPO—cannot be ruled out. We argue that this possibility does not pose a serious problem to our volatility measures. One apparent reason is that such cases are uncommon. Moreover, any potential effect of such exceptional IPOs can be further mitigated by controlling market sentiment variables. More importantly, our measures are multiple standard deviations, which are not directly or strongly affected by market sentiment, as are stock prices.

Notably, a GARCH model is widely used to describe the variance in the stock return error term when it is serially auto-correlated, which helps capture secondary market uncertainty. By treating the sequence of IPOs as a time-series process, Lowry et al. (2010) use the GARCH model proposed by Nelson (1991) to estimate the time variation in possibly serially correlated IPOs.

A challenge to our test for Hypothesis 2 is the lack of time series data; for each IPO, there is only one observation of the realized initial return, so there is no such measure of return volatility or variance as that we can obtain for a seasoned stock. For this reason, we form IPO portfolios and then examine the relationship between the expected initial return and the initial return variance on a portfolio basis. When the portfolios are adequately constructed such that the IPOs in each portfolio share common features and, thus, have comparable pricing uncertainty, we can use the portfolio mean and variance in the initial returns as a proxy for $E(P_{\Delta t} - P_0)$ and $Var(P_{\Delta t} - P_0)$, respectively, and test their relationship using the portfolio data. Specifically, we form IPO portfolios in two alternative ways: sorting on pricing volatility and listing date. To measure pricing volatility, for each IPO, we identify its industry peers and use the standard deviation of the peers' price multiples (e.g., the price-to-earnings ratio) as a proxy for its pricing volatility. We expect the within-industry dispersion of a price multiple to reflect the difficulty and uncertainty of IPO valuations in that industry. To the extent that the within-industry dispersion is vulnerable to uncontrolled industry heterogeneity, we alternatively form monthly (as in Lowry et al., 2010) and quarterly portfolios. Such listing-date-based time series portfolios have the advantage of capturing over-time variations in pricing uncertainty that are driven by aggregate market conditions instead of by issuer-specific factors.

Our use of the standard deviation of the portfolio IPO initial returns is similar to that by Boeh and Dunbar (2014). To identify the determinates of IPO waves, the authors examine several variables, including ex ante uncertainty, which they measure using the standard deviation of IPO initial returns during a pre-IPO period. The authors argue that this measure captures the market-wide difficulty of banks in valuing new issues ex ante.[4]

In a GARCH model, Lowry et al. (2010) estimate simultaneous equations for the mean and volatility of IPO initial returns. While their data show a positive relationship between the two (Figure 2 and Table II), they do not formally test this relationship but instead focus on the determination of volatility. We conduct a formal test for this relationship, in which we treat volatility as the key determinant of the mean of IPO initial returns, following the predictions of Hypothesis 2.

Our approach of using the industry standard deviation of pricing multiplies is natural, noting that larger standard deviations of pricing multiplies increase the complexity of the pricing problem. As stated in Lowry et al. (2010), this complexity limits the underwriter's ability to accurately price IPOs. Kim and Ritter (1999) argue that since most firms pursuing IPOs in the

[4] To estimate the relationship between the premarket due diligence and book-building processes, Crain, Parrino and Srinivasan (2021) examine how these two processes change with uncertainty. The authors use growth opportunity measures as proxies for uncertainty.

U.S. are young, the discount cash flow approach is not suitable because of the difficulty in forecasting future cash flows. They show that the use of comparable firm multiples is widely recommended. In particular, Roosenboom (2012) uses a unique dataset of 228 reports from French underwriters that allows him to access the pre-IPO valuation process used in practice by investment banks. He finds that the price multiplication approach is one of the main methods that underwriters use to determine the fair value of IPO firms.

More specifically, for each IPO, we identify its industry peers by choosing all seasoned stocks in the same industry under the Fama–French 48 industry classification that had traded at least three years prior to the IPO. We then compute the standard deviation of each price multiple of the seasoned stocks for the pre-IPO year and use it as a proxy for the IPO's pricing volatility. The implication here is that if the industry has more diverse price multiples at the time of the IPO, then it is more difficult for investors and underwriters to evaluate the new issue using the industry valuation information. This proxy has one distinct advantage: because it is purely from industry peers, it has no direct association with the IPO firm's own information structure, such as information asymmetry.

As usual, we use the IPO initial return to measure the degree of underpricing, which is calculated as the difference between the closing price on the first trading day and the final offer price divided by the offer price. The price update is the difference between the final offer price and the midpoint of the preliminary offer prices divided by the mid-preliminary price, and this update is used to capture the underpricing effect of information revelation by institutional investors (Benveniste and Spindt, 1989). To describe underwriter reputation, we follow Carter and Manaster (1990) and Carter et al. (1998) to identify the lead underwriter from SDC and assign a rank on a 10-point scale based on the Loughran and Ritter (2002) classification. For IPOs with more than one lead manager, the average rank of all leading underwriters is used.

To ensure that very small issuers do not disproportionately affect our results, we exclude from the sample IPOs with an offer price below $5 per share (see, e.g., Lowry et al., 2004; Bradley and Jordan, 2002). After removing observations with missing data, our final sample consists of 5,832 IPOs. Table 1 presents the descriptive statistics of the selected variables. The numbers indicate similar IPO characteristics as those in previous studies. On average, IPOs are sold at $13 per share, raise capital of $105 million, and earn an initial return of 19%. Approximately 36% of all issuing firms receive funding from venture capitalists.

The three proxy variables of pricing volatility show reasonable variations across IPOs. Their median values are 35.2%, 7.9%, and 1.6% for the standard deviation of the price-to-earning, price-to-EBIT, and price-to-sales ratios, respectively, which are compared with these volatility measures' corresponding standard deviations of 111.7%, 14.1%, and 1.9%, respectively. In Table 2, the Pearson correlation coefficients show strong correlations between the proxy variables. All three proxy variables are positively correlated with the first-day return, and the correlation coefficients are significant at the 1% level. On the other hand, these pricing volatility proxies are only weakly related or unrelated to issuer size and book-to-market ratio. This observation suggests that the difficulties related to new issue pricing are not closely associated with the issuer's size or growth potential.

Table 1. Summary Statistics

The sample is from the SDC database, which consists of common stock IPOs conducted during 1991-2008. The offer price is the finalized offer price. The price update is the percentage change from the midpoint of initial filing range to the final offer price. The initial return is the percentage change from the final offer price to the first trading day closing price. Proceeds are the total proceeds of the IPO. Market capitalization is the number of shares outstanding times the first trading day closing price. Underwriter ranking dummy is the 10-point scale for leading underwriter ranks assigned by Carter and Manaster (1990) and Carter, Dark and Singh (1998), modified by Loughran and Ritter (2004). VC dummy equals one if the IPO is backed by venture capitalists and equals zero otherwise. Book-to-market ratio is the first book value of equity available from Compustat divided by the first trading day closing price. We obtain three alternative proxy variables for IPO pricing volatility as follows: for each IPO, we identify its industry peers by choosing all seasoned stocks that are in the same industry as the IPO under the Fama-French 48 industry classification and have traded more than three years prior to the IPO; from the industry peers' financial data one year before the IPO date we calculate their price-to-earnings, price-to-EBIT, and price-to-sales ratios, respectively, and then obtain the industry standard deviation of each price multiple as a proxy for the IPO's pricing volatility.

	Observation	Mean	Median	Standard deviation	Minimum	Maximum
Panel A. IPO variables						
Offer price ($)	5,832	13.257	12.500	5.979	5	97
Price update (%)	5,832	0.588	0	22.808	-98.419	400
Initial return (%)	5,832	18.752	6.920	44.894	-100	636.364
Proceeds ($million)	5,832	104.502	39.200	293.499	0.200	8680
Market capitalization ($million)	5,832	898.855	97.576	7484.30	0	213142
Book-to-market ratio	5,832	0.411	0.288	3.081	-2.374	173.006
Top-tier underwriter dummy	5,832	0.564	1	0.496	0	1
VC dummy	5,832	0.355	0	0.478	0	1
NASDAQ dummy	5,832	0.661	1	0.474	0	1
Panel B. Proxy variables for pricing volatility						
Standard deviation of industry peer price/earnings ratio (%)	5,832	53.941	35.192	111.653	1.213	238.942
Standard deviation of industry peer price/EBIT ratio (%)	5,832	12.446	7.899	14.099	0.079	371.270
Standard deviation of industry peer price/sales ratio (%)	5,832	2.237	1.568	1.932	0.026	22.099

Table 2. Correlation Coefficients for Selected Variables (1991–2008)

This table reports the correlation coefficients between the selected variables. The initial return is the percentage change from the final offer price to the first trading day's closing price. The price update is the percentage change from the midpoint of the initial filing range to the final offer price. Proceeds are the total proceeds of the IPO. Market capitalization is the number of shares outstanding times the first trading day's closing price. The book-to-market ratio is the first book value of equity available from *Compustat* divided by the first trading day's closing price. The standard deviations of industry peer price multiples as proxies for IPO pricing volatility are calculated as in Table 1. *p*-values are reported in parentheses.

	Initial return	Std dev of industry peer price/earnings ratio	Std dev of industry peer price/EBIT ratio	Std dev of industry peer price/sales ratio	Price update	Proceeds	Market cap	Book-to-market ratio
Initial return	1	0.037 (0.012)	0.231 (<0.001)	0.271 (<0.001)	0.473 (<0.001)	0.005 (0.770)	0.022 (0.146)	-0.034 (0.044)
Std dev of industry peer price/earnings ratio		1	0.218 (<0.001)	0.081 (<0.001)	0.013 (0.359)	-0.018 (0.251)	-0.008 (0.572)	-0.009 (0.588)
Std dev of industry peer price/EBIT ratio			1	0.597 (<0.001)	0.082 (<0.001)	-0.074 (<0.001)	-0.015 (0.310)	-0.023 (0.178)
Std dev of industry peer price/sales ratio				1	0.137 (<0.001)	0.167 (<0.001)	-0.008 (0.595)	-0.018 (0.286)
Price update					1	0.130 (<0.001)	0.035 (0.019)	-0.018 (0.284)
Proceeds						1	0.366 (<0.001)	0.037 (0.034)
Market capitalization							1	-0.010 (0.555)
Book-to-market ratio								1

4.2. IPO Initial Return and Pricing Volatility

Table 3 presents our test for the link between underpricing and pricing volatility (Hypothesis 1). In this test, we run a regression of the IPO initial return on each of the pricing volatility proxies, alternatively controlling for conventional issuer and market characteristics variables.

To also control for secondary market factors, we obtain the Fama–French three factors, the momentum factor and the Pastor-Stambaugh value-weighted traded liquidity factor from WRDS. Because each IPO is supposed to be associated with different factor loadings, we cannot directly include the factors in the cross-sectional regression. For this reason, we define the control variables for these factors as follows. For each IPO, we determine a matching stock by choosing a seasoned firm that has traded for at least three years and is in the same industry, in the same size decile, and has the closest book-to-market ratio as the issuer. We then run a time series regression using the monthly return data to obtain the matching stock's factor loadings on the IPO day and use the product of the factor and its factor loading as the control for the factor risk premium.

Following Green and Huang (2012), we also control for the expected skewness of the IPOs, which is a measure of intra-industry skewness estimated from industry peers' recent stock returns. The authors argue that when individual investors trading in the secondary market exhibit a higher preference for skewness than do institutions participating in the primary market, the skewness preference difference between these two types of investors contributes to the IPO initial returns. Aissia (2014) finds that IPOs with high initial returns have higher idiosyncratic skewness, turnover rate and momentum.

In Table 3, the coefficient on the proxy of pricing volatility is positive and statistically significant in all nine regressions. Consistent with Hypothesis 1, these regressions confirm that the first-day IPO return increases with the difficulty related to premarket valuation. This effect is also economically significant. For instance, the ninth regression indicates that for an increase in the volatility proxy (the price/EBIT ratio) of one standard deviation, the initial return increases by three percentage points. It is worth noting that when volatility also affects the cost of information asymmetry (Beatty and Ritter, 1986),[5] this effect could be partially due to the adverse selection problem. Therefore, it is important to control for issuer characteristic variables, including the price update, so that any uncaptured influence of asymmetric information is minimized.

The parameter estimates for the control variables are consistent with those in previous studies. As in Hanley (1993), Loughran and Ritter (2004), and Liungqvist and Wilhelm (2002), the coefficient on the price update is significantly positive, which captures the asymmetric information effect on underpricing (presumably resulting from a partial price adjustment that works to compensate informed investors for revealing favorable private information). The coefficient on the top-tier underwriter dummy is significantly positive in all regressions, supporting the agency cost argument for the role of underwriters in IPO pricing (e.g., Loughran and Ritter, 2004).[6] Our estimates also indicate a positive effect of venture capital backing on the initial return. Although this effect is inconsistent with the certification effect of venture capital (Barry et al., 1990; Megginson and Weiss, 1991; Schultz, 1993), it is in line with more recent

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[5] Beatty and Ritter (1986) model the role of ex ante uncertainty under the adverse selection framework of Rock (1986). They show that when the uncertainty increases the benefit to informed investors, it increases the cost to the issuer that allows the uninformed to break even, thus increasing underpricing.

[6] However, the underpricing–underwriter ranking relation can be complex because an offsetting underwriter–reputation or certification effect can also exist. Indeed, recent studies find mixed results for this relation, which is negative in the 1980s and turns positive in the 1990s (see Lee and Wahal, 2004; Loughran and Ritter, 2003).

studies that find more severe underpricing among venture capital-backed firms during the 1990s (Hamao et al., 2000; Brav and Gompers, 1997; Bradley and Jordan, 2002).[7]

The inclusion of the five secondary market factors and the expected skewness of industry peers does not materially change the major coefficients, although the adjusted R-squared slightly increases with them. As in Green and Huang (2012), the expected skewness is shown to be a significant factor affecting the initial return. When including the expected skewness, three of the secondary market factors (market risk, HML and momentum) show a significantly positive effect on the first-day return.

[7] It is argued that in addition to providing funds, venture capital adds value to the firm by monitoring and governing management, thus a certification effect for venture capital reduces underpricing (Megginson and Weiss, 1991).

Table 3. Regressions of IPO Initial Return on Pricing Volatility

This table reports the regression results for IPO initial return on pricing volatility. The proxy variable for each IPO's pricing volatility is obtained from its industry peers' price multiples (as explained in Table 1). The control variables include the price update, logarithm of IPO proceeds, and the dummy variables for underwriter rank, VC backing, technology stocks, NASDAQ stocks, and the bubble period. To capture potential effects of secondary market factors, we define relevant control variables as follows: For each IPO, we choose a matching stock by picking the seasoned firm that has been listed for at least three years, and is in the same industry, in the same size decile and with the closest book-to-market ratio as the issuer. We run time-series regression using 12-month moving window to obtain the factor loadings for the matching stock on the IPO day, and then use the product of a factor and the factor loading as the control for that factor. Five control variables are thus obtained for market risk premium, small (size) minus big (SMB), high (book/price) minus low (HML), momentum, and liquidity, respectively. Eskewness is the expected skewness of industry peers defined as in Green and Hwang (2012). The signs ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

	Pricing volatility based on price/earnings ratio			Pricing volatility based on price/EBIT ratio			Pricing volatility based on price/sales ratio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	12.561*** (4.64)	12.673*** (4.65)	4.451 (1.24)	11.141*** (4.02)	11.280*** (4.06)	3.583 (1.00)	12.003*** (4.30)	12.173*** (4.35)	2.449 (0.68)
Proxy for pricing volatility	0.010*** (2.37)	0.010*** (2.44)	0.019*** (3.56)	0.214*** (3.35)	0.212*** (3.34)	0.147*** (3.35)	0.704** (2.13)	0.671** (2.03)	1.639** (2.32)
log(Proceeds)	-2.375*** (-4.53)	-2.450*** (-4.66)	-0.938*** (-3.37)	-2.355*** (-4.50)	-2.429*** (-4.63)	-0.834 (-1.22)	-2.574*** (-4.93)	-2.641*** (-5.03)	-1.115 (-1.63)
Underwriter rank dummy	4.588*** (4.55)	4.490*** (4.46)	4.452*** (3.94)	4.568*** (4.53)	4.470*** (4.41)	4.575*** (3.02)	4.552*** (4.51)	4.456*** (4.43)	4.566*** (3.02)
VC dummy	5.990*** (4.73)	5.923*** (4.70)	7.031*** (4.57)	5.293*** (4.12)	5.236*** (4.10)	6.391*** (4.12)	5.896*** (4.65)	5.839*** (4.63)	6.914*** (4.51)
Tech dummy	8.367*** (5.86)	8.235*** (5.90)	7.868*** (4.95)	7.643*** (5.43)	7.520*** (5.39)	7.447*** (4.62)	8.189*** (5.88)	8.073*** (5.84)	6.887*** (4.29)
NASDAQ dummy	4.329*** (3.61)	4.337*** (3.62)	4.343** (2.54)	4.170*** (3.49)	4.179*** (3.50)	4.604*** (2.69)	4.764*** (3.81)	4.751*** (3.81)	4.796*** (2.81)
Bubble dummy	32.071*** (12.45)	32.390*** (12.35)	29.612*** (11.74)	29.431*** (11.41)	29.754*** (11.30)	30.343*** (12.04)	30.471*** (11.85)	30.875*** (11.74)	28.137*** (11.08)
Price update	0.807*** (10.82)	0.806*** (10.78)	0.798*** (25.94)	0.809*** (10.85)	0.808*** (10.81)	0.796*** (25.88)	0.808*** (10.83)	0.807*** (10.80)	0.787*** (25.63)
Market risk premium		1.610 (1.58)	2.852*** (4.22)		1.589 (1.56)	2.753*** (4.07)		1.525 (1.48)	2.774*** (4.12)
SMB		-1.691 (-1.13)	-0.226 (-0.28)		-1.747 (-1.17)	-0.337 (-0.41)		-1.719 (-1.15)	-0.278 (-0.34)
HML		-2.889* (-1.78)	4.246*** (3.66)		-2.833* (-1.75)	4.070*** (3.51)		-2.942* (-1.80)	4.082*** (3.53)
Momentum		1.374 (1.26)	3.200** (2.08)		1.422 (1.31)	2.983* (1.94)		1.392 (1.28)	2.894* (1.89)
Illiquidity		0.156 (1.12)	0.266 (0.26)		0.146 (1.05)	0.224 (0.22)		0.159 (1.14)	0.271 (0.26)
Eskewness			8.143** (2.60)			7.180** (2.28)			6.798** (2.17)
Observation	5,832	5,832	5,832	5,832	5,832	5,832	5,832	5832	5,832
Adjusted R^2	0.307	0.311	0.314	0.309	0.312	0.312	0.308	0.311	0.317

4.3. Pricing Uncertainty and Expected Initial Return: Evidence from Cross-Sectional Portfolios.

For our test for Hypothesis 2, we form IPO portfolios and run a regression of the portfolio mean (as the proxy for the expected initial return or premium) on the portfolio standard deviation (as the proxy for the pricing uncertainty) of IPO initial returns. We first examine three portfolio formations based on valuation volatility: for each of the three pricing volatility proxies discussed above, we sort all sample IPOs by the proxy and divide them into 50 equal-sized portfolios, each of which on average consists of 98 IPOs. The first three plots (A, B and C) in Figure 2 show the relationship between the portfolio mean and standard deviation of IPO initial returns for the three formations.

In these plots, the standard deviation exhibits considerable variations, implying a large variation in the average pricing uncertainty of the IPO portfolios. Consistent with the prediction of Hypothesis 2, the plots indicate a strong, positive relationship between the portfolio mean and the portfolio standard deviation of the initial returns, stretching out from the origin.

Table 4 reports the result of our test, where the dependent variable is the portfolio mean of the initial returns and the key independent variable is the corresponding portfolio standard deviation. In these regressions, we also control for firm age, which is defined as the difference between the firm's founding year and its IPO year. The founding year information is obtained from Jay Ritter's website. The results from the three portfolio formations are very similar. In regressions (1), (4) and (7), the coefficient on the portfolio standard deviation—the only explanatory variable—is positive and statistically highly significant, which alone explains 89% to 94% of the variation in the portfolio mean of the initial returns. The high explanatory power of the single-variable models suggests that the relationship is economically very strong: for a one percentage-point increase in the portfolio standard deviation, the portfolio mean increases by 0.57 to 0.66 percentage points. After IPO characteristics variables (as those in Table 3, but in the corresponding portfolio means) are included, the model's explanatory power in regressions (2), (5), and (8) increases to 94% to 96%.

The observation that the portfolio standard deviation is the dominant factor that alone explains approximately 90% of the variation in the portfolio mean is striking. While this finding is highly consistent with Hypothesis 2, it is difficult to explain using other underpricing mechanisms.

In regressions (3), (6) and (9), we further include the five secondary market factors (also in their portfolio means). Whereas the models' explanatory power further increases slightly, these controls have no material impact on the estimation, and none of their coefficients is statistically significant. This observation lends support to the notion that the uncertainty in IPO pricing is fundamentally different from conventional secondary market risks. When the expected skewness is also included, the coefficient on the portfolio standard deviation slightly improves. The coefficient of firm age is negative but not significant. We leave a more detailed discussion of the role of the expected skewness to a robustness check (the next section).

FIGURE 2. IPO Portfolio Initial Returns: Mean and Standard Deviation

Our sample includes all common stock IPOs conducted during 1991–2008 in the U.S. We form IPO portfolios on pricing volatility or overtime. Plots A, B and C present three cases of portfolio formation on pricing volatility. For each IPO, we identify all seasoned stocks in its industry, calculate each stock's price multiple (price-to-earnings, price-to-EBIT, or price-to-sales ratio), and use the industry standard deviation of the multiple as the proxy for the IPO's pricing volatility. We then rank all IPOs by the proxy and divide them into 50 equal-sized portfolios. Plots D and E present two cases of time-series IPO portfolios: monthly and quarterly. In all plots, the vertical axis represents the portfolio mean, and the horizontal axis represents the portfolio standard deviation of IPO initial returns.

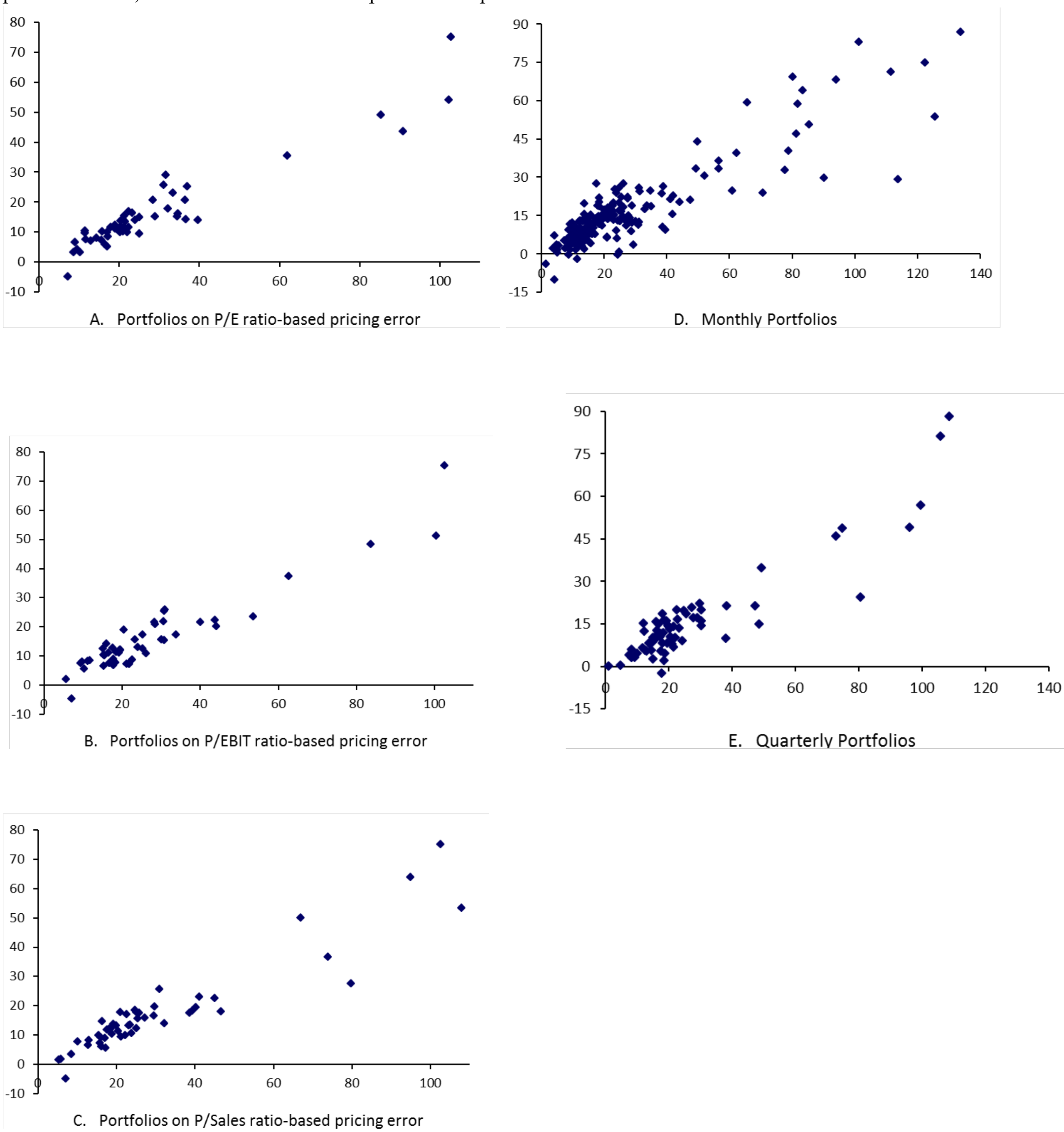

Table 4. Regressions with Cross-Sectional Portfolios of IPOs (Sample Period 1991-2008)

For each IPO, we obtain three alternative proxy variables for the pricing volatility from its industry peers' price multiples (as explained in Table 1). Using each proxy, we rank all IPOs and divide them into 50 equal-sized portfolios. In all regressions, the dependent variable is the portfolio equally weighted average of IPO initial returns (as a measure of the portfolio's expected pricing uncertainty premium), and the key independent variable is the portfolio standard deviation of the initial return (as a measure of the portfolio's pricing uncertainty). The same control variables for IPO characteristics and secondary market factors are as in Table 3 but in portfolio means of each control variable are included. Firm age is defined as the calendar year of the IPO minus the calendar year of the firm's founding. We obtain the founding date of each firm from Professor Jay Ritter's website. The signs ***, **, and * represent significant levels at 1%, 5%, and 10%, respectively.

	IPO portfolios Sorted on Std dev of price/earnings ratio			IPO portfolios Sorted on Std dev of price/EBIT ratio			IPO portfolios Sorted on Std dev price/sales ratio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.312 (-0.28)	5.465 (0.55)	7.207 (0.63)	0.253 (0.24)	17.834 (1.36)	19.766 (1.37)	-2.608*** (-2.63)	-9.311 (-0.63)	-3.523 (-0.24)
Portfolio std dev of IPO initial returns	0.589*** (20.19)	0.381*** (18.73)	0.384*** (17.44)	0.568*** (20.47)	0.500*** (17.44)	0.533*** (16.78)	0.657*** (26.85)	0.619*** (14.87)	0.270*** (8.75)
log(Proceeds)		0.576 (0.78)	0.609 (0.59)		-1.671 (-0.68)	-2.295 (-0.76)		2.111 (0.63)	0.706 (0.21)
Underwriter rank dummy		12.318*** (2.56)	14.137 (0.54)		6.143 (0.76)	5.174 (0.54)		-5.883 (-0.72)	-1.569 (-0.18)
VC dummy		-12.900** (-2.37)	-12.533** (-2.08)		-7.461 (-1.09)	-6.407 (-0.87)		14.811 (1.61)	22.926** (2.31)
Tech dummy		-0.886 (-0.76)	-1.111 (-0.31)		2.558 (0.72)	1.610 (0.40)		0.611 (0.07)	4.174 (0.44)
NASDAQ dummy		14.313** (2.02)	14.528* (1.89)		8.307 (0.72)	7.401 (0.22)		6.187 (0.52)	4.467* (0.35)
Bubble dummy		16.467*** (4.14)	16.347*** (3.69)		13.823** (2.10)	10.993 (1.32)		15.247*** (3.18)	8.364** (2.15)
Price update		0.609*** (5.16)	0.604*** (4.31)		0.638*** (4.11)	0.561*** (6.78)		0.755*** (4.12)	0.895*** (4.93)
Age		-0.246 (-1.64)	-0.202 (-1.14)		-0.114 (-0.82)	-0.135 (-0.91)		-0.142 (-0.65)	-0.171 (-0.75)
Market risk premium			-1.184 (-0.19)			1.861 (0.58)			1.021 (0.05)
SMB			2.113 (0.26)			-6.254 (-0.66)			-5.355 (-0.89)
HML			-4.539 (-0.43)			-14.916 (-0.99)			-8.424 (-1.17)
Momentum			10.827 (1.12)			9.780 (0.83)			8.084 (0.77)
Illiquidity			-5.169 (-0.23)			-0.593 (-0.68)			-1.424 (-1.17)
Observation	50	50	50	50	50	50	50	50	50
Adjusted R^2	0.892	0.961	0.969	0.895	0.962	0.964	0.936	0.950	0.956

4.4. Pricing Uncertainty and Expected Initial Return: Evidence from Time-Series Portfolios

The cross-sectional portfolios are sorted on pricing volatility that depends on the divergence in the valuations of industry peers. With as many as approximately 100 IPOs being included in each portfolio, the sorting is unlikely to be seriously affected by issuer-specific characteristics. This feature of the portfolio data is important because issuer-specific factors, such as asymmetric information and strategic pricing—the main mechanisms examined by previous studies on IPO pricing—are often difficult to quantify or control empirically. On the other hand, however, the cross-sectional portfolios may still be subject to industry heterogeneity to the extent that new issues of different industries inherently have different degrees of valuation uncertainty. For this reason, we further the test by forming time-series portfolios. We sort IPOs by listing date and obtain monthly and quarterly portfolios, alternatively. To ensure a reasonable variability of IPO initial returns within each portfolio, we exclude calendar months that have fewer than 10 IPOs. These time-series formations result in 198 monthly portfolios and 73 quarterly portfolios. The last two plots in Figure 2 (D and E) illustrate the relationship between the initial return means and standard deviations for the time series portfolios, which is also strongly positive and stretches out from the origin.

Compared with the cross-sectional portfolios, the time-series portfolios have a further advantage: while cross-sectional variations in issuer-specific factors are substantially averaged out in each portfolio, intertemporal variations in pricing uncertainty associated with market-wide uncertainty are highlighted. Hence, unless the IPO dates are frequently clustered by industry, the time-series portfolios are ideal for the test because they are no longer associated with issuer-specific or industry-specific characteristics. To further minimize potential effects due to industry-clustered IPOs, we use a dummy variable to indicate portfolios that exhibit notable industry clustering. Specifically, the dummy variable equals one for a monthly or quarterly portfolio if any industry's IPOs in that portfolio account for 30% or more of all of the IPOs in the portfolio. Applying this threshold percentage to the 12 Fama–French industries, we identify that 33% of the time-series IPOs show industry clustering.

Table 5. Regressions with Time-series Portfolios of IPOs (Sample Period 1991–2008)

We form time-series portfolios by grouping IPO firms over months and quarters alternatively. In all of the regressions, the dependent variable is the portfolio equally weighted average of IPO initial returns (as the measure of the portfolio's expected pricing uncertainty premium), and the key independent variable is the portfolio standard deviation of the initial returns (as the measure of the portfolio's pricing uncertainty). The same control variables for IPO characteristics and secondary market factors as in Table 3 but in portfolio means are included. The industry cluster dummy is defined as follows: for each portfolio, we calculate the number of IPOs for each industry (based on the 12 Fama–French industry classification), and the dummy variable equals one if any of the industries in the portfolio conducted 30% or more of the total IPOs in that portfolio. Firm age is defined as the calendar year of the IPO minus the calendar year of the firm's founding. We obtain the founding date of each firm from Professor Jay Ritter's website. The signs ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

	Portfolio mean of IPO initial return					
	(1)	(2)	(3)	(4)	(5)	(6)
	Monthly portfolios					
Intercept	0.223	-12.398**	-11.132**	-26.763***	-21.580***	-28.744**
	(0.26)	(-2.46)	(-2.29)	(-3.72)	(-3.09)	(-2.06)
Portfolio std dev of IPO initial returns	0.618***	0.482***	0.480***	0.547***	0.336***	0.455***
	(26.96)	(16.23)	(16.96)	(18.86)	(6.15)	(5.24)
log(Proceeds)		1.119	1.261	4.969***	4.847***	2.937*
		(1.28)	(1.49)	(2.89)	(2.92)	(1.92)
Underwriter rank dummy		3.093	2.112	0.438	0.700	0.439
		(1.08)	(0.76)	(0.14)	(0.23)	(0.16)
VC dummy		9.556**	9.695***	9.242**	9.443**	8.831***
		(2.64)	(2.65)	(2.30)	(2.45)	(2.79)
Tech dummy		8.509**	7.919**	9.419**	6.301	5.761*
		(2.16)	(2.10)	(2.37)	(1.63)	(1.83)
NASDAQ dummy		6.293*	5.021	5.545***	5.911***	5.600
		(1.69)	(1.42)	(2.66)	(3.14)	(1.47)
Bubble dummy		3.134	1.534	2.465	-4.747*	10.156***
		(1.11)	(0.55)	(0.91)	(-1.79)	(4.25)
Price update		0.253***	0.354***	0.194***	0.209***	0.529***
		(5.37)	(6.76)	(3.52)	(3.98)	(8.70)
Market risk premium			-0.164***	2.931*	3.174*	1.036
			(-2.81)	(1.73)	(1.95)	(0.76)
SMB			-0.345***	1.558	0.242	1.680
			(-3.42)	(0.64)	(0.10)	(0.86)
HML			0.157*	-0.979	-0.722	-0.186
			(1.85)	(-0.37)	(-0.28)	(-0.90)
Momentum			-0.350	1.300	1.359	1.867
			(-0.86)	(0.85)	(0.93)	(1.32)
Illiquidity			0.013*	0.133	0.157	0.138
			(1.71)	(0.87)	(1.07)	(1.04)
Year				-0.537	-0.587	-0.437
				(-1.15)	(-1.31)	(0.98)
Year × Year				0.002	0.008	0.001
				(0.10)	(0.36)	(0.07)
Industry cluster dummy					-9.791***	-8.051***
					(-4.48)	(-2.79)
Industry cluster dummy × Portfolio std dev of IPO initial returns					0.474***	0.360***
					(4.48)	(3.60)
Age						-0.595
						(-1.59)
Observation	198	198	198	198	198	
Adjusted R^2	0.785	0.838	0.863	0.867	0.880	
	Quarterly portfolios (N=73)					
Intercept	-1.01	-15.85**	-16.39**	-18.06***	-14.38***	
	(-0.90)	(-2.22)	(-2.22)	(-3.61)	(-3.05)	
Portfolio std dev of initial IPO return	0.63***	0.44***	0.44***	0.51***	0.36***	
	(19.61)	(8.93)	(8.81)	(9.73)	(7.09)	

Table 5 presents the regression results from the time-series portfolios, where the upper panel is for monthly portfolios and the lower panel is for quarterly portfolios (the coefficients on the portfolio standard deviation only).[8] The results are qualitatively the same as those from the cross-sectional portfolios in Table 4. Again, the portfolio standard deviation of IPO initial returns represents the dominant factor in all regressions and alone accounts for approximately 80% of the variation in the portfolio mean. To allow for a time trend and industry clustering effect, we include the year variable and its quadratic term in the regression in column 4, and also the industry clustering dummy and its interaction with the portfolio standard deviation in the regression in column 5. While all of the coefficients on the time trend variables are insignificant, those on the industry cluster dummy and the interaction term are statistically highly significant and economically large, indicating a strong industry clustering effect. Clearly, our main result of the coefficient on the portfolio standard deviation of IPO initial returns remains highly significant and is robust to the specification for the various controls. Because the time-varying pattern of the portfolios is unlikely to be driven by issuer- or industry-specific factors, we view these results from the time-series portfolios as stronger evidence than those from the cross-sectional portfolios.

The price update is the independent variable other than the portfolio standard deviation that has a significant impact in all regressions. On the one hand, this variable captures the widely discussed partial price adjustment mechanism (Benveniste and Spindt, 1989; Hanley, 1993) due to information asymmetry. On the other hand, this variable also reflects the imprecision of the filing price and, thus, the difficulty and uncertainty in the IPO valuation; therefore, it may partially capture the impact of pricing uncertainty.

4.5. Further Test and Robustness

Given the very high explanatory power of the IPO portfolio regressions, we need to further check that our results are not driven by some possible effects of extreme data but are robust to the sample period. We also need to check that the portfolio formation processes do not cause any unexpected mechanical relationships. It is easy to rule out data outliers. The plots in Figure 2 show the well-shaped distributions of the portfolio data, where the positive relationship between the portfolio mean and standard deviation of IPO initial returns are strong in all ranges, suggesting that our results are unlikely to be driven by outliers. We also examine the regressions using the portfolio median initial return as the dependent variable, controlling for the portfolio medians of the control variables. The untabulated results remain very strong and robust, and our findings are unchanged.

To check the robustness to the sample period, we redo the regressions in Tables 3 to 5 using IPOs conducted during the extended sample period from 2009 to 2015. Table 6 presents the summarized results for the extended sample tests, where Panels A, B, and C report the regressions with individual IPOs (as in Table 3), cross-sectional IPO portfolios (as in Table 4), and time-series IPO portfolios (as in Table 5), respectively. To save space, we do not report the

[8] To save space, the coefficients on the control variables are not reported in Panel B, which are highly consistent with those in Panel A.

parameter estimates for the various control variables, which are all included in the regressions. The results in this table are highly consistent with those reported in Tables 3−5. The coefficients on the pricing-volatility proxies and the portfolio standard deviations of IPO initial returns are all positive, statistically significant, and economically strong, verifying our findings discussed above. The adjusted R^2 is also very similar in magnitude to those for the corresponding regressions in Tables 3−5, still showing high explanatory powers of the models.

Table 6. Robustness Tests for the Extended Sample Period: 2009–2015

Our sample for the robustness tests in this table includes IPOs from 2009 to 2015. There are a total of 2471 IPOs during this period. All variable definitions are the same as those used in Tables 3, 4 and 5.

Panel A. Regressions using individual IPOs (specifications as in Table 3)			
	(Std dev of price/earnings ratio)	(Std dev of price/EBIT ratio)	(Std dev of price/sales ratio)
Proxy for pricing volatility	0.012**	0.119**	0.978**
	(2.28)	(2.17)	(2.04)
All controls	Yes	Yes	Yes
Observation	2471	2471	2471
Adjusted R^2	0.239	0.254	0.198
Panel B. Regressions using cross-sectional IPO portfolios (specifications as in Table 4)			
	(Sorted on std dev of price/earnings ratio)	(Sorted on std dev of price/EBIT ratio)	(Sorted on std dev of price/sales ratio)
Portfolio std dev of IPO initial returns	0.282***	0.301***	0.412***
	(3.15)	(4.11)	(8.44)
All controls	Yes	Yes	Yes
Observation	50	50	50
Adjusted R^2	0.799	0.851	0.860
Panel C. Regressions using time-series IPO portfolios (specifications as in Table 5)			
	(Monthly portfolios)	(Quarterly Portfolios)	
Portfolio std dev of IPO initial returns	0.412***	0.271***	
	(7.25)	(3.74)	
All controls	Yes	Yes	
Observation	72	24	
Adjusted R^2	0.607	0.426	

To examine whether our portfolio formation strategy creates any unexpected mechanical relationships in the portfolio data, we apply the same strategy to matching seasoned stocks and examine similar regressions using the portfolios of matching seasoned stocks. The logic is that if our results from the IPOs were due to some mechanical relationship caused by the empirical strategy, they should also show up in the regressions for the matching seasoned stocks. To identify matching stocks, for each IPO firm, we choose the seasoned firm that has been listed for at least three years and is in the same industry, in the same size decile, and with the closest book-to-market ratio. We then form seasoned stock portfolios in two dimensions: based on their matched IPOs' pricing volatility proxies and for the same months and quarters. For each of these portfolios, we calculate the mean and standard deviation of the seasoned stock daily returns on the day of the IPO. We then run regressions of the portfolio mean on the portfolio standard deviation of seasoned stock returns, controlling for the secondary market factor variables and the portfolio return skewness.

Table 7 presents the regression results, with Panel A presenting results for the cross-sectional portfolios and Panel B for the time-series portfolios. In all eight regressions, the coefficient on the portfolio standard deviation of matching seasoned stock returns is statistically insignificant, and the sign is mixed. In contrast to the results from the IPO portfolio data, these regressions for the seasoned stock counterparts show no association between the portfolio mean and standard deviation. This observation is echoed by the very low explanatory power of the standard deviation measure of matching seasoned stocks that, together with the constant term, explains less than 3% of the variation in the portfolio mean. This finding is expected. As much of the seasoned stock volatility is diversified away, it has no meaningful predictive power for the mean return. Therefore, we can rule out the possibility that our finding is due to some unknown mechanical relationship caused by the empirical strategy between the portfolio mean and standard deviation.

Table 7. Regressions with Portfolios of Matching Seasoned Stocks

This table presents regressions with portfolios of matching seasoned stocks. To determine each IPO's matching stock, we choose the seasoned firm that has listed for at least three years, and is in the same industry, in the same size decile and with the closest book-to-market ratio as the issuer. We form portfolios of the matching stocks in similar ways as those of the IPOs: on IPO pricing volatility ranking (as in Table 4) and on listing date (as in Table 5). For each portfolio, we compute the equally weighted average and the standard deviation of the matching stocks' return on the IPO day. In all regressions, the dependent variable is the portfolio mean, and the key independent variable the portfolio standard deviation, of the matching stock returns. The same control variables for secondary market factors as in Tables 4 and 5 are included. Pskewness is the skewness of each portfolio. The signs ***, **, and * represent significant levels at 1%, 5%, and 10%, respectively.

	Cross-sectional portfolios formed on the standard deviation of industry peers' price multiples						Time-series portfolios formed on matched IPO date			
	(Price/earnings ratio)		(Price/EBIT ratio)		(Price/sales ratio)		(Monthly portfolios)		(Quarterly portfolios)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	-0.358 (-0.90)	-0.109 (-0.45)	-0.642 (-1.52)	-0.278 (-0.49)	-0.489 (-1.32)	-0.234 (-0.76)	-0.096 (-0.60)	0.023 (0.18)	0.132 (0.64)	0.052 (0.29)
Portfolio std dev of seasoned return	0.116 (0.95)	0.045 (0.70)	0.214 (1.62)	0.510 (0.86)	0.167 (1.48)	0.053 (0.50)	0.052 (0.98)	0.008 (0.19)	-0.017 (-0.27)	-0.001 (-0.02)
Market risk premium		2.170* (2.04)		1.589** (2.01)		2.876*** (3.57)		1.183*** (7.51)		0.778*** (3.22)
SMB		1.708 (1.35)		1.267 (0.98)		2.201** (2.01)		0.829*** (3.02)		1.326*** (2.75)
HML		3.901** (2.51)		1.875* (1.72)		0.543 (0.32)		0.916** (2.39)		1.080 (1.49)
Momentum		1.092* (1.74)		1.001 (1.06)		0.401 (0.67)		0.543 (1.20)		-0.360 (-0.45)
Illiquidity		2.543*** (2.89)		2.789*** (2.65)		2.071** (2.01)		0.167 (0.56)		0.510 (0.95)
Pskewness		2.514*** (2.99)		1.578** (2.57)		2.076*** (2.66)		0.239*** (5.22)		0.171*** (3.74)
Observation	50	50	50	50	50	50	198	198	73	73
Adjusted R^2	0.018	0.355	0.031	0.279	0.023	0.550	0.002	0.366	0.001	0.349

5. CONCLUSION

Given a lack of current or historical stock prices, all participants in an IPO must evaluate the new issue without any equilibrium price information as an anchor point for the fair value. This lack-of-information problem affects not only uninformed individual investors but also the most informed institutional investors and underwriters. As a result, no matter how sophisticated the premarket valuation is, it depends on divergent premarket beliefs and, thus, can significantly deviate from the IPO's fair value. This problem presents a source of uncertainty in IPO pricing that is difficult to diversify. With risk-averse investors who maximize their expected utility, the premarket demand is reduced relative to the case when investors could observe the current market price. Consequently, underpricing occurs as the reduced demand imposes a binding constraint on the sale of the new issue. In this sense, underpricing works as a premium to investors for bearing the uncertainty.

The concept of premarket pricing uncertainty highlights the unpredictability of the offer price. When an IPO's offer price is a random draw from the new issue population subject to pricing error, it can vary greatly depending on investor beliefs and market sentiment. Therefore, the initial return volatility can be considerably higher than the aftermarket price volatility due to the fundamental risk and higher than any expected variation in planned or intentional underpricing. This implication is consistent with the finding in Lowry et al. (2010) that IPO initial returns are unusually volatile, reflecting the phenomenon that a large fraction of overpriced or severely underpriced IPOs are difficult to explain by any intentional underpricing mechanisms.

The notion of underpricing as a premium for premarket pricing uncertainty implies a direct relationship between the expected level and volatility of underpricing. We test this implication by forming IPO portfolios based on the uncertainty ranking or listing date of new issues. We identify an unusually close relationship between the level and dispersion of the initial returns. This relationship is so strong that, for the portfolio data, the dispersion alone explains approximately 90% of the variation in the level.

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RELATIONSHIP BETWEEN DEMOGRAPHIC FACTORS AND BEHAVIORAL BIASES

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ABSTRACT

The purpose of this paper is to examine the influence of demographic factors (Age, Annual Income, Educational Qualification, and Total earning members in the family) on behavioral biases (Availability bias, Confirmation bias, Conservatism bias, and Loss-aversion bias) of policyholders of life insurance. The influence of demographic factors on behavioral biases is based on the structured questionnaire survey designed to collect responses from 407 respondents residing in Bihar, India using a convenient sampling technique.

The results show that behavioral biases are influenced by demographic factors (Age, Annual Income, Educational Qualification, and Total earning members in the family) as there is a significant difference across the categories of various demographic factors with the respective behavioral biases. The study suggests that behavioral biases affect the decisions of the policyholders, so minimizing these biases is needed in their decision-making process and thus to improve their investment strategies. This study is important for life insurance companies and agents to understand the investment behavior of life insurance policyholders. This study contributes to the limited research done in the area of investment decision-making by investors in life insurance. It contributes to the lacking academe on life insurance.

Keywords: *Behavioral Biases, Decision-making, Demographic Factors, Investment, Life Insurance*

INTRODUCTION

Contemporary developments in the field of financial markets throw light on the difference between traditional finance and behavioral finance. Traditional finance assumes that markets, institutions, and even people behave rationally (Baker and Filbeck, 2013), whereas behavioral finance assumes that people make their judgments based on past events, personal preferences, and beliefs. When they face an uncertain situation, they make their decisions based on inconsistency, irrationality, and incompetence (Kahneman and Tversky, 1982; Barros, 2010; Stracca, 2004). Conceptual developments of behavioral finance are made by combining finance and social psychology to solve various puzzles of the market that cannot be solved without any further understanding of psychological dimensions in the decision-making process. Behavioral finance attempts to infer the behavior of investors in a better way by describing the way and situation in which psychological errors impacted the decision-making process (Daniel et al. 1998).

Behavioral biases are the psychological errors that occur from illogical reasoning and errors in the processing of investors' beliefs, ideas, or principles that lead to irrational behavior of the investors. The study contributes to the limited research by investigating the behavioral biases and demographic profile of life insurance policyholders. The majority of prior research undertaken in the area of behavioral finance is completed by considering information from the trading records of investors (Barber and Odean, 2001; Chen et al. 2007). Very limited study has been undertaken using primary data. This study is based on primary data using a structured questionnaire as primary data is a better indicator of investor behavior as compared to secondary data (Lin, 2011).

This study has two main objectives: to determine the presence of behavioral biases among life insurance policyholders and to examine the relation of demographic variables with behavioral biases. Various demographic variables have been used in prior research to depict the investor's profile by using primary as well as secondary data. Among the various demographic variables viz., age, annual Income, and educational qualification of investors play an important role in investors' investment decision-making. The present study also added one more demographic variable named Total earning members in the family to see whether there exist differences across the various categories of the total number of earning members in the family for various behavioral biases.

The study comprises six sections viz., section two describes prior research done related to behavioral biases, research questions, hypothesis development, and the gap found in the previous literature. Section three throws light on the research methodology adopted for the study. Section four shows the results of the study and Section five implies the major findings of the study. And at last section six concludes the study by providing the future scope and limitations of the study.

LITERATURE REVIEW

Meaning of Behavioral Biases

Behavioral finance in opposition to the assumption of perfect knowledge rationality of traditional finance emphasizes that in real life, all decisions are taken with the help of mental shortcuts also known as behavioral biases (Kahneman and Tversky, 1982; Barber and Odean, 2001). Behavioral Finance is the study of the psychological behavior of financial practitioners and their subsequent effect on markets (Sewell, 2005). Available literature in the field of research pointed to two reasons for behavioral biases: biases caused by emotions called emotional biases and biases caused because of inaccurate reasoning called cognitive biases (Pompian, 2006; Sahi et al. 2013). The reason behind the occurrence of emotional biases is illogical reasoning due to various instincts or intuitions and cognitive biases occur because of errors in the processing of information, statistical algorithms, or memory (Pompian, 2006). The above discussion proposes the following research question;

RQ 1: *Do behavioral biases affect the investment decisions of life insurance policyholders?*

Various types of behavioral biases influence the decisions of investors, but we have considered four biases in this study, three biases fall under cognitive biases i.e., Availability bias, Confirmation bias, and Conservatism bias, and one bias falls under emotional biases i.e., Loss-aversion bias (Pompian, 2006; Ritika and Kishor, 2020).

Cognitive Biases

Availability Bias: A bias in which investors take the mental shortcut to estimate the probability of an outcome based on how easily and instantly the outcomes come to mind (Pompian, 2012). This bias influences the probability judgments based on the ease with which a person can think of past events or the ease with which people can imagine the occurrence of an event (Kahneman and Tversky, 1973, 2000). The outcomes that can be easily recalled by people are considered to be more likely than the outcomes that are difficult to recall (Javed et al., 2017). This happens because of the availability bias in which people do not analyze all the opportunities available for investment rather than investing in securities of a company that spends so much money on advertisement (Barber and Odean, 2000; Harris and Raviv, 2005).

Confirmation Bias: It is one of the most frustrating, encountered, and yet understandable biases (Nickerson, 1998). Confirmation bias is a people's inclination to search for information that supports their principles or ideas and ignore information contradicting them (Nickerson, 1998; Myers and Dewall, 2015). It is a type of natural phenomenon that refers to people's likelihood to give attention only to those principles that disprove their beliefs (Ritika and Kishor, 2020). There is a lesser number of studies related to this bias in the literature on behavioral finance (Costa et al., 2017). This bias also leads to the illusion of knowledge (Daniel et al., 1998; Barber and Odean, 2001; Jonas et al., 2001).

Conservatism Bias: It is a bias that clings investors to the past information they had about the investment and gives no notice or little notice to the current information leading them to forecast instead of learning new information (Jain and Kesari, 2019). Conservatism leads investors to behave inflexibly grasping new information about which they already had prior information. The investor generally holds on to the prior positive information and neglects the negative information (Pompian, 2006, 2012). Conservatism bias refers to the susceptibility of people to inadequately update their opinions or forecasts after receiving new information (Barberis et al. 1988). This bias leads to underreaction of the bad forecasts by investors and react according to their prior beliefs (Luo, 2012).

Emotional Bias

Loss-aversion Bias: It arises when investors strongly tend to prefer avoiding losses as opposed to getting profits. It leads investors to hold their losses even if the investment has little or no chance of going back (Pompian, 2012). Loss-aversion bias insists investors take necessary measures to avoid losses and also weigh losses more than they weigh profits (Tversky and Kahneman, 1991; Benartzi and Thaler, 1995). It is a result of the feeling of distress and fear (Kahneman et al., 1991; Barberis and Huang, 2001; Ritika and Kishor, 2020).

Previous literature supports that investors' demographic profile is related to their investment behavior (Baker et al., 2018; Baker and Yi, 2016; Lin, 2011). There are different categories in the same demographic variables and are distinctive from each other. If there is significant differences exist between the demographic attributes and behavioral biases, then it is important to identify among which categories, the differences are significant (Deger and Reis, 2020; Ossareh, Pourjafar, and Kopczewski, 2021; Soni and Desai, 2019). This proposes the following research questions;

> ***RQ 2:*** *Do life insurance policyholders behave differently for behavioral biases based on their demographic attributes?*

Hypothesis Development

Given below are some of the studies that are related to demographic variables and behavioral biases examined in this study with supporting literature:

Age and Behavioral biases: (Deger, and Reis, 2020) in their study examine whether conservatism bias is related to demographic variables including the age of the investors. And they found a significant association. There is a significant influence of age on the loss-aversion bias (Arora and Kumari, 2015; Ossareh, Pourjafar, and Kopczewski, 2021; Sujesh and Dhanya, 2021), whereas (Munyas, 2020; Saivasan and Lokhande, 2022) found no significant difference between age and loss-aversion bias. Ossareh, Pourjafar, and Kopczewski (2021) in their study found significant differences across the categories of age for confirmation bias, and no significant differences were found for availability bias. Sujesh and Dhanya (2021) found no significant difference across the categories of age for confirmation bias. The contradictory result of past studies on the relationship between age and behavioral biases proposes the following hypothesis.

> ***H_o:*** *There is no significant difference(s) across the categories of age in years and behavioral biases.*

Annual Income and Behavioral Biases: Isidore and Christie (2019) in their study examined the relationship between availability, loss-aversion bias, and some other biases with the annual income and found a strong association. Soni and Desai (2019) analyzed the relationship of confirmation bias with the annual income of investors and found no significant difference. Kumar et al. (2018) in their study also examine the association between loss-aversion bias and investors' annual income and found significant differences. The above discussion proposes the following hypothesis.

> ***H_o:*** *There is no significant difference(s) across the categories of the annual income of investors and behavioral biases.*

Educational Qualification: Dhungana et al. (2022) analyzed the association between availability bias and the educational qualification of investors and found significant results whereas (Onsomu et al., 2017) in their study found no significant difference across various educational categories for availability bias. Deger and Reis (2020) in their study examine the relationship between conservatism bias and educational qualification and found no difference.

Munyas (2020) found no significant association between loss-aversion bias and educational qualification. The above discussion proposes the following hypothesis.

> ***H_o:** There is no significant difference(s) across the categories of educational qualification of investors and behavioral biases.*

One more demographic variable (total earning members in the family) was added to this study to examine its association with behavioral biases, as the previous study lacks the investigation of the association between total earning members in the family and behavioral biases. This gap proposes the following hypothesis.

> ***H_o:** There is no significant difference(s) across the categories of total earning members in the family and the behavioral biases.*

Based on the above literature we can find that the investment behavior of life insurance policyholders has still not been explored minutely. We are trying to bridge the gap found in the above literature by examining the relationship between behavioral biases and the demographic profile of life insurance policyholders. Most of the available pieces of literature are related to behaviorally biased investors investing in investment avenues like stocks, mutual funds, pension funds, etc.

Behavioral biases influencing investment decisions in life insurance policyholders (Measures Adopted)

The study adopted a behavioral biases scale from different reputed academic prior research which has been validated by the researchers. The present study deals with the policyholders of life insurance so, the adopted scale is modified in terms of the policies of life insurance to measure the behavioral biases influencing the investment decisions of life insurance policyholders. There are various behavioral biases influencing investors' investment decisions. The study used four behavioral biases viz., Availability bias, Confirmation bias, Conservatism bias, and Loss-aversion bias.

Behavioral Biases	Adopted Scale
Availability Bias Confirmation Bias Conservatism Bias Loss-aversion Bias	Menkhoff et al., 2006; Raut et al., 2018; Ritika and Kishor, 2020; Shusha and Touny, 2016; Shunmugasundaram and Sinha, 2022

RESEARCH DESIGN

Questionnaire design

This study is quantitative and starts with the formulation of a questionnaire that consists of two sections: The demographic profile of respondents and exhibited behavioral biases. The first part of the section consists of general information related to the demographic profile of policyholders like Age, Annual Income, Educational Qualification, etc. The second part comprises questions related to the behavior of policyholders while investing in life insurance using a five-point Likert scale ranging from 1 to 5 where, 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree and 5=Strongly Agree as used in the previous studies for measuring behavioral biases (Pandey and Jessica, 2018). The questionnaire is then judged with the help of respondents who were conveniently selected to assess its clarity and ease of completion. After getting good results in pilot testing, we have moved forward toward the final data collection process.

Sampling and data collection

The target population for the study was life insurance policyholders of Bihar State (India). We have managed the data collection using a convenient sampling technique as it is cost-effective and the availability of data is easy (Van De Vijver & Matsumoto, 2001). There is no direct source from where the data about life insurance policyholders of different companies can be obtained. Therefore, no sampling frame was available for the target population. As the population is unknown, the Cochran formula (Cochran, 1977) is used to determine the sample size given below;

$$n = z^2 / 4e^2$$

$$n = (1.96)^2 / 4(0.05)^2$$

$$= 384.16$$

Where, n = sample size

p = the population proportions

e = acceptable sampling error (e = 0.05)

z = z value at reliability level or significance level.

- Reliability level 95% or significance level 0.05;

z = 1.96

Therefore, the sample size for the study is 384. Finally, a total number of 450 questionnaires were distributed and 407 responses were collected from life insurance policyholders to reduce the redundancy and make it bias-free. The response rate was 90.4 percent.

Variable type and statistical tools used

In this study behavioral biases (Availability bias, Confirmation bias, Conservatism bias, and Loss-aversion bias) are the dependent variables and demographic factors (Age, Annual Income, Educational Qualification, and Total earning members in the family) are the independent variables. In previous studies, various statistical methods such as ANOVA, SEM, and Kruskal-Wallis test were used to measure the association between demographic factors and behavioral biases (Baker et al., 2019; Lin, 2011; Mishra & Metilda, 2015; Saivasan & Lokhande, 2022; Sujesh & Dhanya, 2021). The study used descriptive analysis to get information related to the demographic profile of respondents. ANOVA is used to examine differences among the means of two or more groups (Malhotra and Dash, 2022). The study employs the Kruskal-Wallis test because the test of normality is not passed, with the p-value < 0.05 to assess the difference among the means of two or more groups (Malhotra and Dash, 2022).

ANALYSIS AND INTERPRETATION

Before conducting further statistical tests, two important criteria i.e., reliability and normality test of the data need to be checked. Cronbach's alpha tests are used to determine the internal consistency of the behavioral biases (Availability, Confirmation, Conservatism, and Loss-aversion). The standardized alpha of the behavioral biases Viz., Availability= .883, Confirmation=.866, Conservatism=.866 and Loss-aversion=.797. The mean value or overall reliability of behavioral biases is .900 which falls within the acceptable range of alpha greater than .70 (Sekaran, 2000), thus it assures the reliability of the scale (see Table 1).

Table 1
Reliability Statistics

Behavioral Biases	**Cronbach's Alpha (α)**	**No. of items**	**Variance**
Availability Bias	.883	5	.028
Confirmation Bias	.866	4	.017
Conservatism Bias	.866	5	.009
Loss-aversion Bias	.797	3	.028
Behavioral Biases (Overall)	.900	17	.024

Source: Author Compilation

The normality of the data is checked by the Kolmogorov-Smirnov test as the sample size is less than 1,000 and with p-value <.05. So, the study rejects the test of normality i.e., mean=median=mode. Now, we will proceed with the non-parametric test of One-way ANOVA i.e., the Kruskal-Wallis test (Malhotra and Dash, 2022).

Table 2
Demographic Profile of Respondents

Demographic Factors	Values	Frequency	Percent
Age (in years)	18-25	140	34.4
	26-35	141	34.6
	36-45	65	16.0
	46-55	30	7.4
	Above 55	31	7.6
	Total	**407**	**100.0**
Annual Income (in Rs.)	Below 2.5 lac	170	41.8
	2.5 - 5 lac	121	29.7
	5 - 7.5 lac	58	14.3
	7.5 - 10 lac	38	9.3
	Above 10 lac	20	4.9
	Total	**407**	**100.0**
Educational Qualification	Matriculation	11	2.7
	Intermediate	57	14.0
	Graduate	213	52.3
	Post Graduate	118	29.0
	Doctoral Degree	8	2.0
	Total	**407**	**100.0**
Total earning members in the family	One	149	36.6
	Two	185	45.5
	Three	58	14.3
	More than Three	15	3.7
	Total	**407**	**100.0**

Source: Primary Data

Based on the demographic profile of the sample, most of the sample belongs to the 26-35 years and 18-25 years age group, i.e., 34.6 percent and 34.4 percent in total respectively. Concerning the income of respondents, most of the sample belongs to income group 2.5 lac., and below i.e.,41.8 percent of the sample in total. In terms of educational qualification of respondents, most of the samples are graduates i.e., 52.3 percent in total. It indicates that half of the population of the samples is a Graduate. Concerning the total number of earning members in the family, about 45.5 percent of the sample indicates that there were two earning members in their family.

Behavioral biases among individual investors of life insurance

Determining the behavior of 407 respondents involves taking an average of participants for items of the same construct. Table 2 shows the ranking of behavioral biases among life insurance policyholders. The result of the study shows that the mean of all the biases is greater than 3, which indicates that the respondents are behaviorally biased while investing in life insurance. Conservatism bias ranks 1st whereas availability bias ranks 4th and the result of the study contradicted the previous study done in the past as the mean score of availability bias is lowest among all the other biases (Baker et al., 2019).

Table 3
Ranking of Behavioral Biases

Behavioral Biases	Mean	Rank
Availability Bias	3.2187	4
Confirmation Bias	3.2733	3
Conservatism Bias	3.3995	1
Loss-aversion Bias	3.3833	2

Source: Author Compilation

Demographic Variables and Behavioral Biases

The Kruskal-Wallis test is non-parametric and handy in determining the significance of the mean of differences across categories. The study examines the behavioral bias differences across the various groups of four categorical variables of demographic factors. Kruskal-Wallis 1-way ANOVA (k samples) all pair-wise multiple comparison tests applied to see the results. Only significant results are shown in the study.

Age

The p-value of the Kruskal-Wallis test .960 (>.05) indicates that there is no significant difference(s) across the five categories of age in terms of availability bias. Concerning confirmation bias the p-value of the Kruskal-Wallis test .263 (>.05) indicates that there is no significant difference(s) across the five categories of age.

Fig.1.1
Kruskal-Wallis Test Result for Age

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of AV is the same across categories of Age in Years.	Independent-Samples Kruskal-Wallis Test	.960	Retain the null hypothesis.
2	The distribution of CF is the same across categories of Age in Years.	Independent-Samples Kruskal-Wallis Test	.263	Retain the null hypothesis.
3	The distribution of CS is the same across categories of Age in Years.	Independent-Samples Kruskal-Wallis Test	.049	Reject the null hypothesis.
4	The distribution of LA is the same across categories of Age in Years.	Independent-Samples Kruskal-Wallis Test	.043	Reject the null hypothesis.

The p-value of the Kruskal-Wallis test is .049 (<.05) which indicates a significant difference(s) across the five categories of age for conservatism bias. Further pair-wise comparison results identified that there is a significant difference between the two age groups (46-55 years to 26-35 years) and (18-25 years to 26-35 years) at the 95% confidence level. The detailed view of the pair-wise test shows that the age group of (46-55) yrs. was more conservative than the age group of (26-35) yrs. with h=50.023 and p=.032. The test also revealed that the age group of (18-25) yrs. was less conservative than the age group of (26-35) yrs. with h=-36.620 and p=.008.Concerning loss-aversion bias, the p-value of the Kruskal-Wallis test is .043 (<.05) which indicates a significant difference(s) across the five categories of age. Further pair-wise comparison results identified significant differences across three age groups (36-45 years to 26-35 years), (36-45 years to above 55 years), and (18-25 years to above 55 years) at the 95% confidence level. The detailed view of the pair-wise test shows that the age group of (36-45) yrs. was more by loss aversion bias than (26-35) yrs. and influenced less by loss aversion bias than those (Above 55) yrs. with h=36.260; -62.629 and p=.035;.013 respectively. The test also revealed that the age group of (18-25) was influenced less by loss aversion bias than those (Above 55) yrs. with h=-52.180 and p=.022.

Table 4
Pair-wise Comparison of Age for Conservatism Bias

Sample l - Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
(46-55)-(18-25)	13.404	23.394	. 573	.567
(46-55)-(36-45)	17.754	25.666	.692	.489
(46-55)-(Above 55)	-33.139	29.780	-1.113	.266
(46-55)-(26-35)	50.023	23.379	2.140	.032
(18-25)-(36-45)	-4.350	17.453	-.249	.803
(18-25)-(Above 55)	-19.735	23.081	-.855	.393
(18-25)-(26-35)	-36.620	13.874	-2.640	.008
(36-45)-(Above 55)	-15.385	25.381	-.606	.544
(36-45)-(26-35)	32.270	17.433	1.851	.064
(Above 55)-(26-35)	16.885	23.066	.732	.464

Each row tests the null hypothesis that the Sample1 and Sample 2 distributions are same.
Asymptotic significances are displayed, the significance level is .05.

Table 5
Pair-wise Comparison of Age for Loss-aversion Bias

Sample l – Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
(36-45)-(18-25)	10.449	17.263	. 605	.545
(36-45)-(46-55)	-19.155	25.387	-.755	.451
(36-45)-(26-35)	36.260	17.244	2.103	.035
(36-45)-(Above 55)	-62.629	25.105	-2.495	.013
(18-25)-(46-55)	-8.706	23.140	-.367	.707
(18-25)-(26-35)	-25.811	13.723	-1.881	.060
(18-25)-(Above 55)	-52.180	22.831	-2.285	.022
(46-55)-(26-35)	17.105	23.126	.740	.460
(46-55)-(Above 55)	-43.474	29.457	-1.476	.140
(26-35)-(Above 55)	-26.368	22.816	-1.156	.248

Each row tests the null hypothesis that the Sample1 and Sample 2 distributions are same.
Asymptotic significances are displayed, the significance level is .05.

Annual Income

The p-value of the Kruskal-Wallis test .126 (>.05) indicates that there is no significant difference(s) across the five categories of annual income in terms of conservatism bias. In terms of loss-aversion bias, the p-value of the Kruskal-Wallis test .747 (>.05) indicates that there is no significant difference(s) across the five categories of annual income.

Fig. 1.2
Kruskal-Wallis Test Result for Annual Income

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of AV is the same across categories of Annual Income.	Independent-Samples Kruskal-Wallis Test	.031	Reject the null hypothesis.
2	The distribution of CF is the same across categories of Annual Income.	Independent-Samples Kruskal-Wallis Test	.007	Reject the null hypothesis.
3	The distribution of CS is the same across categories of Annual Income.	Independent-Samples Kruskal-Wallis Test	.126	Retain the null hypothesis.
4	The distribution of LA is the same across categories of Annual Income.	Independent-Samples Kruskal-Wallis Test	.747	Retain the null hypothesis.

The p-value of the Kruskal-Wallis test is .031 (<.05) which indicates a significant difference(s) across the five categories of annual income for availability bias. Further pair-wise comparison results identified that there is a significant difference between the two groups (5-7.5 lac. to above 10 lac.) and (below 2.5 to above 10 lac.) at the 95% confidence level. The detailed view of the pair-wise test shows that the respondents earning an annual income of (above 10 lac.) were influenced more by availability bias than the respondents earning an annual income of (5-7.5 lac. and below 2.5 lac) with h=-81.853; -71.354 and p=.007; .010 respectively. Concerning Confirmation bias, the p-value of the Kruskal-Wallis test is .007 (<.05) which indicates a significant difference(s) across the five categories of annual income. Further, the pair-wise comparison results identified significant differences across three groups (5-7.5 lac. to 2.5 to 5 lac.), (5-7.5 lac. to above 10 lac.), and (below 2.5 lac. to 2.5-5 lac.) at the 95% confidence level. The detailed view of the pair-wise test shows that the respondents earning an annual income of (5-7.5 lac.) were more by confirmation bias than (2.5-5 lac.) and influenced less by confirmation bias than (above 10 lac.) with h=59.796; -66.574 and p=.001; .027 respectively. The test also revealed that the respondents earning an annual income of (below 2.5 lac.) were influenced less by confirmation bias than (2.5-5 lac.) with h=-35.866 and p=.009.

Table 6
Pair-wise Comparison of Annual Income for Availability Bias

Sample l - Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
(5-7.5 lac)-(Below 2.5 lac.)	10.498	17.700	.593	.553
(5-7.5 lac.)-(2.5-5 lac.)	30.613	18.589	1.647	.100
(5-7.5 lac.)-(7.5-10 lac.)	-40.907	24.293	-1.684	.092
(5-7.5 lac.)-(Above 10 lac.)	-81.853	30.183	-2.712	.007
(Below 2.5 lac.)-(2.5-5 lac.)	-20.115	13.844	-1.453	.146
(Below 2.5 lac.)-(7.5-10 lac.)	-30.408	20.886	-1.456	.145
(Below 2.5 lac.)-(Above 10 lac.)	-71.354	27.516	-2.593	.010
(2.5-5 lac.)-(7.5-10 lac.)	-10.294	21.645	-.476	.634
(2.5-5 lac.)-(Above 10 lac.)	-51.240	28.096	-1.824	.068
(7.5-10 lac.)-(Above 10 lac.)	-40.946	32.155	-1.273	.203

Each row tests the null hypothesis that the Sample1 and Sample 2 distributions are same.
Asymptotic significances are displayed, the significance level is .05.

Table 7
Pair-wise Comparison of Annual Income for Confirmation Bias

Sample l – Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
(5-7.5 lac)-(Below 2.5 lac.)	23.930	17.656	1.355	.175
(5-7.5 lac.)-(7.5-10 lac.)	-42.093	24.233	1.737	.082
(5-7.5 lac.)-(2.5-5 lac.)	59.796	18.543	3.225	.001
(5-7.5 lac.)-(Above 10 lac.)	-66.574	30.109	-2.211	.027
(Below 2.5 lac.)-(7.5-10 lac.)	-18.163	20.835	-.872	.383
(Below 2.5 lac.)-(2.5-5 lac.)	-35.866	13.810	-2.597	.009
(Below 2.5 lac.)-(Above 10 lac.)	-42.644	27.448	-1.554	.120
(7.5-10 lac.)-(2.5-5 lac.)	17.704	21.592	.820	.412
(7.5-10 lac.)-(Above 10 lac.)	-24.482	32.076	-.763	.445
(2.5-5 lac.)-(Above 10 lac.)	-6.778	28.027	-.242	.809

Each row tests the null hypothesis that the Sample1 and Sample 2 distributions are same.
Asymptotic significances are displayed, the significance level is .05.

Educational Qualification

The p-value of the Kruskal-Wallis test .334 (>.05) indicates that there is no significant difference(s) across the five categories of educational qualification in terms of confirmation bias. In terms of loss-aversion bias, the p-value of the Kruskal-Wallis test .556 (>.05) indicates that there is no significant difference(s) across the five categories of educational qualification.

Fig. 1.3
Kruskal-Wallis Test Result for Educational Qualification

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of AV is the same across categories of Educational Qualification.	Independent-Samples Kruskal-Wallis Test	.013	Reject the null hypothesis.
2	The distribution of CF is the same across categories of Educational Qualification.	Independent-Samples Kruskal-Wallis Test	.334	Retain the null hypothesis.
3	The distribution of CS is the same across categories of Educational Qualification.	Independent-Samples Kruskal-Wallis Test	.017	Reject the null hypothesis.
4	The distribution of LA is the same across categories of Educational Qualification.	Independent-Samples Kruskal-Wallis Test	.556	Retain the null hypothesis.

The p-value of the Kruskal-Wallis test is .013 (<.05) which indicates significant difference(s) across the five categories of educational qualification for availability bias. Further, pair-wise comparison results identified significant differences across four groups (Doctoral Degree to Post Graduate), (Matriculation to Post Graduate), (Intermediate to Post Graduate), and (graduate to postgraduate) at the 95% confidence level. The detailed view of the pair-wise test shows that respondents who were (Post Graduates) were influenced less by availability bias than those (Doctoral Degrees) and (Matriculation) with h=92.553; 85.314 and p=.030; .020 respectively. The test also revealed that the respondents who were (Post Graduates) were influenced more by availability bias than (Intermediate) and (Graduate) with h=-43.388; -28.617 and p=.021; .032 respectively. For conservatism bias, the p-value of the Kruskal-Wallis test is .017 (<.05) which indicates significant difference(s) across the five categories of educational qualification. Further pair-wise comparison results identified significant differences across three groups (Matriculation to Post Graduate), (Intermediate to Graduation), and (Intermediate to Post Graduate) at the 95% confidence level. The detailed view of the pair-wise test shows that respondents who were (Post Graduates) were more conservative than matriculation and intermediate with h=-73.050; -53.886 and p=.046; .004 respectively. The test also revealed that the respondents who were (Intermediate) were less conservative than those (Graduates) with h=-46.398 and p=.007.

Table 8
Pair-wise Comparison of Educational Qualification for Availability Bias

Sample l – Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
Doctoral Degree-Matriculation	7.239	54.086	.134	.894
Doctoral Degree-Intermediate	49.164	43.946	1.119	.263
Doctoral Degree- Graduate	63.936	41.919	1.525	.127
Doctoral Degree-Post Graduate	92.553	42.525	2.176	.030
Matriculation-Intermediate	-41.926	38.332	-1.094	.274
Matriculation-Graduate	-56.697	35.990	-1.575	.115
Matriculation-Post Graduate	85.314	36.695	2.325	.020
Intermediate-Graduate	-14.772	17.358	-.851	.395
Intermediate-Post Graduate	-43.388	18.775	-2.311	.021
Graduate-Post Graduate	-28.617	13.358	-2.142	.032

Each row tests the null hypothesis that the Sample1 and Sample 2 distributions are same.
Asymptotic significances are displayed, the significance level is .05.

Table 9
Pair-wise Comparison of Educational Qualification for Conservatism Bias

Sample l – Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
Matriculation-Intermediate	-19.164	38.294	-.500	.617
Matriculation-Graduate	-65.562	35.954	-1.824	.068
Matriculation-Post Graduate	-73.050	36.658	-1.993	.046
Matriculation-Doctoral Degree	-76.682	54.031	-1.419	.156
Intermediate-Graduate	-46.398	17.340	-2.676	.007
Intermediate-Post Graduate	-53.886	18.756	-2.873	.004
Intermediate-Doctoral Degree	-57.518	43.902	-1.310	.190
Graduate-Post Graduate	-7.488	13.344	-.561	.575
Graduate-Doctoral Degree	-11.120	41.876	-.266	.791
Post Graduate-Doctoral Degree	-3.631	42.482	-.085	.932

Each row tests the null hypothesis that the Sample1 and Sample 2 distributions are same.
Asymptotic significances are displayed, the significance level is .05.

Total earning members in the family

In terms of availability bias, the p-value of the Kruskal-Wallis test .103 (>.05) indicates no significant difference(s) across four categories to total earning members in the family. The p-value of the Kruskal-Wallis test .053 (> .05) indicates no significant difference(s) across four categories of total earning members in the family in terms of loss-aversion bias.

Fig. 1.4
Kruskal-Wallis Test result for Total earning members in the family

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of AV is the same across categories of Total Earning Members in Family.	Independent-Samples Kruskal-Wallis Test	.103	Retain the null hypothesis.
2	The distribution of CF is the same across categories of Total Earning Members in Family.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
3	The distribution of CS is the same across categories of Total Earning Members in Family.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
4	The distribution of LA is the same across categories of Total Earning Members in Family.	Independent-Samples Kruskal-Wallis Test	.053	Retain the null hypothesis.

The p-value of the Kruskal-Wallis test is .000 (<.05) which indicates significant difference(s) across the four categories of the total earning members in the family for confirmation bias. Further pair-wise comparison results identified significant differences across five groups (One to Two), (One to Three), (One to More than Three), (Two to Three), and (Two to More than Three) at the 95% confidence level. The detailed view of the pair-wise test shows that respondents having (One) earning member in the family were influenced less by confirmation bias than respondents having (Two), (Three) and (More than Three) earning members in the family with h=-36.213; -80.912; -115.515 and p=.005; .000; .000 respectively. The test also revealed that the respondents having (Two) earning members in the family were influenced less by confirmation bias than respondents having (Three) and (More than Three) earning members in the family with h=-44.699; -79.302 and p=.011; .011 respectively. For conservatism bias, the p-value of the Kruskal-Wallis test is .000 (<.05) which indicates significant difference(s) across the four categories of total earning members in the family. Further pair-wise comparison results identified significant differences across four groups (One to Two), (One to Three), (One to More than Three), and (Two to More than Three) at the 95% confidence level. The detailed view of the pair-wise test shows that respondents having (One) earning member in the family were less conservative than respondents having (Two), (Three) and (More than Three) earning members in the family with h=-36.809; -63.946; -98.196 and p=.004; .000; .002 respectively. The test also revealed that the respondents having (Two) earning members in the family were less conservative than respondents having (More than Three) earning members in the family with h=-61.387 and p=.049.

Table 10
Pair-wise Comparison of Total Earning Members in the Family for Confirmation Bias

Sample l – Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
One-Two	-36.213	12.781	-2.833	.005
One-Three	-80.912	17.970	-4.503	.000
One-More than Three	-115.515	31.452	-3.673	.000
Two-Three	-44.699	17.473	-2.558	.011
Two-More than Three	-79.302	31.171	-2.544	.011
Three-More than Three	-34.603	33.634	-1.029	.304

Each row tests the null hypothesis that the Sample1 and Sample 2 distributions are same.
Asymptotic significances are displayed, the significance level is .05.

Table 11
Pair-wise Comparison of Total Earning Members in the Family for Conservatism Bias

Sample l – Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
One-Two	-36.809	12.800	-2.876	.004
One-Three	-63.946	17.996	-3.553	.000
One-More than Three	-98.196	31.498	-3.117	.002
Two-Three	-27.137	17.499	-1.551	.121
Two-More than Three	-61.387	31.217	-1.966	.049
Three-More than Three	-34.251	33.683	-1.017	.309

Each row tests the null hypothesis that the Sample1 and Sample 2 distributions are same.
Asymptotic significances are displayed, the significance level is .05.

FINDINGS

The findings of the studies are given below:

Hypotheses	**Result**
1. A. H_o: No significant difference across the categories of Age and Availability Bias	Accepted
B. H_o: No significant difference across the categories of Age and Confirmation Bias	Accepted
C. H_o: Categories of Age = Conservatism Bias	Rejected
D. H_o: Categories of Age = Loss-aversion Bias	Rejected
2. A. H_o: Categories of Annual Income = Availability Bias	Rejected
B. H_o: Categories of Annual Income = Confirmation Bias	Rejected
C. H_o: Categories of Annual Income = Conservatism Bias	Accepted
D. H_o: Categories of Annual Income = Loss-aversion Bias	Accepted
3. A. H_o: Categories of Educational Qualification = Availability Bias	Rejected
B. H_o: Categories of Educational Qualification = Confirmation Bias	Accepted
C. H_o: Categories of Educational Qualification = Conservatism Bias	Rejected
D. H_o: Categories of Educational Qualification = Loss-aversion Bias	Accepted
4. A. H_o: Categories of Total earning members in family = Availability Bias	Accepted
B. H_o: Categories of Total earning members in family = Confirmation Bias	Rejected
C. H_o: Categories of Total earning members in family = Conservatism Bias	Rejected
D. H_o: Categories of Total earning members in family = Loss-aversion Bias	Accepted

1. The result of the study shows that life insurance policyholders have undergone all the biases and among all four biases Conservatism bias ranks first and Availability bias ranks fourth but the mean score is above 3 in contradiction to the previous study done by (Baker et al., 2019).

2. The result of the study indicated a significant difference across the categories of age for conservatism bias and loss-aversion bias. For conservatism bias, the age group of (46-55)

years policyholders were more conservative than (26-35) years and the age group of 26-35) years was more conservative than the policyholders of (18-25) years. The findings revealed that conservatism bias increases with the increase in age of policyholders and it supports the previous study done by (Deger and Reis, 2020). Concerning the loss aversion bias it was found that the age group of (36-45) years policyholders were more loss-averse than that of (26-35) years, and policyholders belong to above 55 years were more loss-averse than the age group (36-46) years and (18-25) years. The findings support the results of previous studies in terms of loss-aversion bias (Arora and Kumari, 2015; Ossareh, Pourjafar, and Kopczewski, 2021; Sujesh and Dhanya, 2021), whereas contradict the previous study done by (Munyas, 2020; Saivasan and Lokhande, 2022). It was also found that the result of the study shows that there are no significant differences across the categories of age for availability bias and confirmation bias, and the findings contradict the previous study done by (Ossareh, Pourjafar, and Kopczewski; 2021) and support the study for confirmation bias (Sujesh and Dhanya; 2021). Concerning the age of policyholders, we have found significant differences across the categories of age for conservatism bias and loss-aversion bias and also found no significant differences for availability bias and confirmation bias. The psychological aspects behind these findings were the conservative mindset of older adults than the younger ones, the tendency of older adults to invest in risk-free or low-risk avenues, and also less willingness of older adults to change their beliefs or update their investment decisions (Yoon and Gutchess, 2012). Older adults put less effort into information search, updating their knowledge with newly available information, and confirming the same with the existing or new information (Ozanne and Kardes, 2000).

3. The result of the study indicated significant differences across the categories of annual income for availability bias and confirmation bias. For availability bias, policyholders who were earning above ₹ 10 lac. rely on immediately available information for making decisions than those who were earning below ₹ 2.5 lac and between ₹ 5-7.5 lac. The result of the study supports the previous study done by (Isidore, and Christie, 2019). Concerning the confirmation bias, the result of the study revealed that policyholders earning above ₹ 10 lac. favor the information that supports their knowledge while making investment decisions over those who were earning between ₹ 5-7.5 lac. The same patterns have been seen in some other categories of income groups. The findings revealed that higher-earning policyholders always look for information that is consistent with their knowledge to confirm their existing beliefs; the result related to confirmation bias supported the previous study that high-income-earner groups are more affected by confirmation bias (Soni and Desai, 2019). The result of the study agrees with a previous study done by (Kumar et al., 2018) and contrasts with the previous study done by (Isidore and Christie, 2019) in the case of loss-aversion bias. Concerning the annual income of policyholders, we have found significant differences across the categories of annual income for availability bias and confirmation bias and also found no significant differences for conservatism bias and loss-aversion bias. The psychological aspects behind these findings were the easy and early access of information by high-earner adults than those who have low income and can also confirm their knowledge and new information from various financial experts, agents, online platforms, etc. The income of policyholders does make a greater impact on the conservatism and loss-aversion biases

because the psychological aspect influencing conservatism bias and loss-aversion bias in decision-making is the age of the adults (Yoon and Gutchess, 2012).

4. The result of the study indicates that the difference across the categories of educational qualification is significant only for availability and conservatism bias. For availability bias, policyholders having educational qualifications of the doctoral degree and matriculation generally make decisions based on immediately available information than postgraduate policyholders. Further, the results also revealed that postgraduate policyholders make their decisions based on immediately available information than policyholders having educational qualifications of intermediate and graduate. The findings of the study support the previous study done by (Dhungana et al., 2022) and contradict the previous study done by (Onsomu et al., 2017). Concerning the conservatism bias, policyholders who have educational qualifications of postgraduate were more conservative than those who have intermediate and matriculation degrees. It was also found that graduate policyholders were more conservative than those who have intermediate educational qualifications. Highly educated policyholders were more conservative than less educated individuals and the result is contradictory with the previous study done by (Deger and Reis, 2020), who found no significant difference. The study also found that the result of the study agrees with the previous study done by (Munyas, 2020) in the case of loss-aversion bias. Concerning the educational qualification of policyholders, we have found significant differences across the categories of educational qualification for availability bias and conservatism bias and also found no significant differences for confirmation bias and loss-aversion bias. The psychological aspects behind these findings were the readily available information and the eagerness to learn new information every day as a highly educated adult. It can cause highly educated adults to be over-optimistic or over-pessimistic while making investment decisions than the less educated adults leading to availability bias and conservatism bias (Gervais et al., 2003). The educational qualification of policyholders does not play a major role in confirmation bias and loss-aversion bias because policyholders have sufficient knowledge provided by the agents, and they do not want to confirm their knowledge. They also found very a limited amount of risk involved in life insurance, thus educational qualification does not influence the loss-aversion bias.

5. One more demographic variable added in the study found significant differences across the categories of total earning members in the family for confirmation bias and conservatism bias and no significant difference across the categories of total earning members in the family was found for availability bias and loss-aversion bias.

CONCLUSION

This study contributes to the limited literature on life insurance academe by assessing the relationship between demographic factors and behavioral biases exhibited by life insurance policyholders while making decisions in life insurance policies. This study was conducted in the context of Indian life insurance policyholders. The study concludes that the association between conservatism bias and loss aversion bias with age is significantly different. Further, we have found a significant difference across the categories of annual income for availability and confirmation bias. The study also revealed that for availability bias and conservatism bias, the differences across the categories of educational qualifications were found to be significant. Finally, we find significant differences across the categories of total earning members in the family for confirmation bias and conservatism bias. Additionally, the study concluded that, with the increase in age and income of policyholders, the level of bias increases. Future research could use these results and compare them across the world.

In life insurance, policyholders knowingly or unknowingly exhibit biased behavior while making investment decisions. Life insurance policyholders show the same behavior as other investors investing in different avenues such as stocks, mutual funds, pension funds, gold, real estate, and cryptocurrencies. Investors do not always make rational decisions; sometimes, their decisions are based on their own beliefs, intuition, mental shortcuts running behind their minds, etc., which makes their decisions biased. Therefore, further research needs to be undertaken to understand investor behavior in detail. This study helps policyholders make them aware of the biases they have gone through while making investment decisions in life insurance and helps them improve their investment strategies by avoiding those biases. This study used a convenient sampling technique, in which data are collected from the respondents as per the convenience of the researcher not at random, so there are chances of implicit bias by the researchers, and the sample may not cover all income levels, social, educational levels, etc. Future research can be conducted using a probability sampling technique that helps generate results with high confidence. The study used the Kruskal-Wallis test; future research can be undertaken using different statistical methodologies such as regression and the Friedman test.

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APPENDIX

Kindly give your responses for the following statements related to Life Insurance Policy from 1 to 5 where (1- SD- Strongly Disagree, 2- D- Disagree, 3- N- Neutral, 2- A- Agree, 1- SA- Strongly Agree)

STATEMENTS	SD	D	N	A	SA
(A) AVAILABILITY					
1. While considering the track record of my investment in policies I give more preference to its recent benefits					
2. Advertisements are main the source of information for my investment decision in life insurance policies					
3. I ignore previous records before making any investment decision in life insurance					
4. I consider the recent information of the policies before investing in it					
5. The information from my relatives, close friends, and peers is a reliable source for my investment decision in life insurance					
(B) Confirmation					
1. I am not selective in collecting information about the policy purchased by me*					
2. I value positive information more than negative information regarding the purchase decision of life insurance					
3. I value positive information more than negative information about the life insurance company, I trust					
4. I ignore the information that does not match my thoughts regarding my future policy purchase decision					
(C) CONSERVATISM					
1. I react when I know new facts/information about life insurance policies					
2. I don't easily change my policy-related decisions once they made					
3. I stick to old policies because the future is uncertain					
4. I prefer to invest in less risky investment policies					
5. I keep updating my knowledge while investing in life insurance policies*					
(D) Loss Aversion					
1. I avoid taking decisions due to fear of incurring losses					
2. Making a loss of Rs. 1,000 is more painful than the happiness of making a profit of Rs. 1,000					
3. I have a fear of inadequate investment advice from agents and family members.					

EFFECT OF TRANSFORMING ACCOUNTING PRINCIPLES TO IMPROVE STUDENTS' PERFORMANCE AND RETENTION

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ABSTRACT

Principles of Accounting I is a required course for all business majors in the College of Business at Bowie State University. The course had a high failure rate, which resulted in many students migrating to other majors in the university. This problem initiated a study to improve teaching and assessment techniques. A new teaching methodology was developed from a course redesign in an effort to reduce the failure rates. The redesign model requires students to complete graded pre-lecture reading assignments to ensure advanced preparation. The new model was implemented in all Fall 2018 sections, increasing students' enrollment in each section from 25 to 30. The changes reduced the need for many adjunct faculty, which is a cost-saving for the College of Business. Course enrollment steadily decreased from 2006 to 2015 but rebounded and increased consistently after fully implementing the redesign model in Fall 2018. Furthermore, DFW rates declined from 53% in Spring 2018 to 44% in Fall 2018, 42% in Spring 2019, 45% in Fall 2019, and 27% in Spring 2020. The course redesign data showed a steady decrease in DFW rates and a steady increase in enrollment over multiple semesters. Full-time faculty are teaching all course sections to ensure consistency and accountability with the course redesign, thus maintaining the positive trend.

INTRODUCTION

Universities have been faced with decreased enrollment and retention rates, challenges with timely graduation, and financial difficulties leading to a heightened appeal to attract, pass, retain, and graduate the enrolled students to increase the institution's viability. The College of Business at Bowie State University was experiencing a consistent decline in enrollment and retention because of the high failure and withdrawal rates and D grades in the introductory accounting courses required of all business majors. This declining trend in enrollment was also a major concern for the accounting program to attract potential accounting majors. Therefore, it was necessary to refocus the introductory accounting courses to align with today's students' learning styles without sacrificing student learning and effective instruction. In addition, the course redesign was consistent with the education literature and similar initiatives of the National Center for Public Policy and Higher Education (NCAT 2014).

The initial introduction of accounting to a student lays the foundation to understand and interpret accounting information in later courses and future careers (Warren & Young, 2012).

Unfortunately, DFW (grades D, F= failure; W= withdrawal) rates in introductory accounting courses are usually high (Froman, 2001 and Kealey et al., 2005). Accounting requires analytical thinking abilities resulting in many students struggling in the course. Students who lack a solid motivation to invest extra time to succeed in accounting are often discouraged, and they stop trying (De Lange et al., 2003 and Sargent, 2009). This experience for some students may mean forgoing a career in accounting, and for others, it may delay earning their degree or even cause them to drop out of college entirely. The Pathways Commission was formed in 2010 to "identify better ways to attract, educate, and continue to develop the human resources that accounting needs in order to fulfill the accounting profession's responsibility to protect the information needs of participants in our economy" (Black, 2012, p. 602). It is a desirable priority in the principles of accounting to emphasize the improvement of students' performance to garner interest in accounting as a career.

The authors of this paper share their experience from redesigning the accounting principles as effective learning strategies and educational pedagogy using the course content, tools, and technological enhancements to improve the declining retention, pass rates, and decrease the withdrawal rates by cultivating interest in the introductory accounting classes.

LITERATURE REVIEW

Generally, many students are challenged and intimidated by math-related subjects because they believe math is complex and challenging to learn (Ashcraft & Krause, 2007; Eccles &Midgley, 1990; Gottfried, Marcoulides, Gottfried, Oliver & Guerin, 2007). This perceived difficulty results in poor grades, which lowers self-confidence in math-related tasks (math self-efficacy) (Pajares & Miller, 1994), creates math anxiety (Hembree, 1990), and results in the students avoiding math tasks (Boekaerts, 1997; Hackett, 1985). Approximately 22 percent of newcomers in college take remedial math courses, and about half of college algebra students fail (Thiel, Peterman, & Brown, 2008). Students who fear failure in math-related courses bring this perceived thinking into the introductory accounting courses.

Students' use of digital media provides convenient platforms for remediation, individualization, and reteaching, which are now available in modern textbooks as supplemental learning aids. Although various supplemental study assistance is available for students that need help outside the classroom, the literature shows that participation is exceptionally low (R. A. Blanc, L. E. DeBuhr & D. C. Martin, 1983), and the few that attend are the more motivated students (Etter et al., 2000). For example, studies of introductory accounting classes show that the average participation rate is 26.79 percent (Etter et al., 2000).

Accounting is complex and taxing with the short-term memory of novices or low achievers who have not systematically linked ideas together or know a large body of facts (Smith, diSessa, & Roschelle, 1993). However, as cited in one study of accounting principles, complicated material could be simplified by walking students through example problems before asking them to complete problems themselves (Ayres, 2006). This approach has been effective in many other accounting studies (Halabi, Tuovinen, & Farley, 2005). The course redesign team in the College of Business at Bowie State University accomplished this objective by creating "In-

Class Activities/Problems" to be worked on in class with the professor before assigning "Homework Problems" done by the students at home.

Transforming Principles of Accounting

The course redesign targeted the entire introductory course rather than one section because various sections were taught by adjunct faculty or new professors resulting in a lack of consistency. Therefore, it was necessary to standardize the materials and the technological tools across sections to curtail effort duplication and minimize faculty dissimilarities to allow each instructor to exploit strengths and shroud weaknesses (Twigg, 2005). A major objective of the course is to motivate business majors to remain engaged in learning accounting issues as they relate to business. As cited by the Accounting Education Change Commission (AECC) that was formed to improve the academic preparation for accountants, "the primary objective of the first course in accounting is for students to learn about accounting as an information development and communication function that supports economic decision-making" affording students an overview or "introduction" to accounting (Accounting Education Change Commission, 1992, pp. 1-2).

Because not all faculty members would have sufficient technological experience, Smith, and Robinson (2003) suggested sharing technology leadership to minimize the development time and costs. The few that are trained will influence others, as has been incorporated by the College of Business at Bowie State University. Textbook publishers provide automated grading systems of assigned work, including low-stakes quizzes through online homework management software, which has become increasingly popular by providing instant feedback and reducing the grading time for instructors(Humphrey & Beard, 2014). The instant feedback is appreciated by students when doing homework because they also receive guided solutions for incorrect answers (Wooten & Dillar-Eggers, 2013). Further, technology offers instructors an opportunity to monitor students' progress and performance, track time on task, and intervene individually (De Lange et al., 2003 and Gaffney et al., 2010). These tools can be easily supplemented using other textbook materials available on the internet, such as videos and guided examples provided by McGraw-Hill Connect Systems.

Low Motivation for Success

As confirmed by empirical research, most of the accounting instructors know from their experience that motivation is more valuable in predicting the students' success in introductory courses than their ability (Kruck & Lending, 2003), and students taking principles of accounting courses can improve their low aptitude by increasing their effort (Wooten, 1996). Therefore, instructors' motivational efforts may be one of the key issues to encourage non-business majors who may have a minimal level of interest, especially for the less confident students. Some of the proposed techniques to motivate introductory accounting students may include novel ways to learn with immediate feedback (De Lange, Suwardy & Mavondo, 2003). However, it has been shown in some studies that students will not complete extra work voluntarily without significant course credit (Elikai & Baker, 1998). In the College of Business at Bowie State University, it was found that when Interactive Videos/LearnSmart were assigned, very few students did the work until some points were assigned. This approach is supported by Gee's (2003) principles for maximizing learning through interactive video settings.

Improving Learning

This section provides information on how the targeted course objectives were addressed as they relate to the critical learning outcomes that are assessed for ACBSP accreditation. Two course redesign objectives were identified for the Principles of Accounting I course in the College of Business. The first outcome was to reduce the DFW rates that necessitated students to repeat the course. The second outcome was to improve the students' understanding of and the application of accounting cycle concepts as the foundation for success in later accounting courses. This section provides information on how the targeted course objectives were addressed.

Course Outcome 1: *Improve understanding and application of the accounting cycle.*

This outcome involves the accounting processes required to prepare financial reports to communicate the business performance results with decision-makers. The accounting processes begin with the initial identification of required business documents such as receipts, the recording process by preparing journal entries and adjusting journal entries resulting in the preparation of financial statements as a means of communication with the decision-makers.

Understanding the accounting cycle is integral to a successful progression to later courses in accounting. Because the accounting cycle is critical to understanding accounting, the concept is tested throughout the semester in all sections to improve knowledge retention and success as students transition into the Principles of Accounting II course.

To better understand the application of the accounting cycle, the course work is designed to follow the steps in the order provided, and each assignment has a designated due date for all students to ensure timely completion:

- Interactive Videos (reading): The students must complete this graded reading assignment before the chapter discussion with the professor.
- Class Discussions: The professor discusses each chapter material after the students have completed the interactive videos assignment.
- In-Class-Activities (problem-solving): The students are required to complete this graded problem-solving assignment in class with the professor's assistance.
- Homework Problems (problem-solving): The students are required to complete this graded problem-solving assignment on their own at home after practicing the In-Class Activities.
- Pop Quizzes: The students must take a pop quiz during class time after completing all the preceding assignments.

Course Outcome 2: *Reduce DFW rates in redesigned courses by 10 percent during the first year of implementation.*

Eleven to twelve sections are offered yearly for the Principles of Accounting I in the College of Business, on average about 330 students. The same professor taught two sections during Fall 2017 and Spring 2018 to measure outcome 1. One of the course sections was taught using the traditional teaching format (control section), while the second section (pilot section) used the Redesigned Model. The Supplemental Model described by the NCAT was used for the pilot section during the two semesters, while the control section continued using the traditional format. Face-to-face class sessions were used in both sections to facilitate topic reviews, discussions, and problem-solving learning activities.

Table 1
FALL 2017 DFW RATES FOR PILOT, CONTROL, AND OTHER SECTIONS USING TRADITIONAL METHODS

Course Section	Total # Enrolled	Total # DFW	DFW Percentage
Pilot (1)	25	4	16%
Control (1)	14	6	43%
All Sections (5)	105	53	50%

As shown in Table 1 above, in Fall 2017, the first semester of the redesign process, the students in the pilot course section performed better than those in the control section. The pilot section DFW rate was 16 percent compared to 43 percent for the control section. When the pilot section is compared to all sections that used the traditional teaching method, the students in the pilot section performed better by more than 30 percentage points in reducing the DFW rates (16 percent compared to 50 percent).

Table 2
SPRING 2018 DFW RATES FOR PILOT, CONTROL, AND ALL SECTIONS USING TRADITIONAL METHODS

Course Section	Total # Enrolled	Total # DFW	DFW Percentage
Pilot (1)	31	9	29%
Control (1)	29	19	66%
All Sections (5)	124	66	53%

As shown in Table 2 above (second semester of redesign study), the DFW rate for the pilot section compared to the control section that used the traditional teaching method decreased by more than 30 percentage points and by more than 20 percentage points compared to all sections. However, such a wide range in the decrease of DFW rates may not be consistent each semester because of differences in the college-level preparedness of the enrolled students. It was expected that at least a 10-percentage point decrease in DFW rates would be experienced in the Principles of Accounting I course when the redesigned model was fully implemented, beginning Fall 2018. Consistent with the goal for the course redesign, enrollment has increased from 105 students in Fall 2017 to 179 students in Fall 2018.

Table 3
DFW RATES FOR ALL SECTIONS UPON FULL-IMPLEMENTATION (FALL 2018-FALL 2020)

Semester Offered	Course Section	Total # Enrolled	Total # DFW	DFW Percentage
FALL 2018	All Sections (6)	179	78	44%
SPRING 2019	All Sections (5)	147	62	42%
FALL 2019	All Sections (6)	163	73	45%
SPRING 2020*	All Sections (5)	149	40	27%
FALL 2020**	All Sections (6)	134	68	51%

*Spring 2020 reflects the transition from f2f to Synchronous learning due to COVID-19 and lack of "Proctoring Software" for exams and quizzes.
** Fall 2020 experienced high withdrawal rates due to COVID-19 and use of proctoring software.

All course sections are now taught by full-time faculty to ensure consistency in applying the adopted course redesign procedures. The faculty anticipated a reduction in the DFW rate of 10 percentage points. The results reflect a decrease in the DFW rate from 53% to about 45%.

The goal is to continue monitoring key metrics within the course and make modifications as necessary to further reduce the DFW rates.

CONCLUSIONS

Because the accounting cycle concept is tested throughout the semester, the students performed better on the final examination than the traditional methods. After the full implementation in Fall 2018, the DFW rates had declined from 53% in Spring 2018 to about 45% in Fall 2019, and 27% in Spring 2020 with the Fall 2020 increasing to 51%. The accounting faculty will continue to apply the lessons learned from the course redesign initiative to ensure students' success in the two accounting principles courses and incorporate some of the concepts learned in the upper-division accounting courses.

In the future, several more years of data will be collected to determine the overall success of the accounting course redesign initiative with a closer examination of the specific student learning outcomes within the ACCT 211 course. The analysis of student performance on the specific accounting cycle steps may provide valuable insight for improving student learning. The faculty anticipates that Spring 2021 through Fall 2022 may present some anomalies within the data sets because of the COVID-19 pandemic and pivot to strictly online learning; however, the initial course redesign to reduce DFW rates shows promising results. A more detailed study results paper will be published in the future.

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