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Locus of Control on Financial Behavior and Financial Risk Attitude

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This paper investigates the impact of locus of control on financial behavior and financial risk attitude. Financial behaviors are captured by savings, payment behavior, and investment, while financial risk attitude is measured by the level of willingness to take financial risks. Using the longitudinal data of Household Income and Labor Dynamics in Australia (HILDA), where locus of control is measured across many waves, we compute the between to within ratios to examine the variations in the locus of control over time. The values of between to within ratios suggest that locus of control is a rarely changing variable, and therefore the fixed-effects vector decomposition model is preferable for our empirical analysis. Our findings reveal that locus of control significantly affects financial behavior and financial risk attitude. Particularly, individuals with an internal locus of control are likely to save more, invest more, be more willing to take financial risks, and have less overdue payments. Moreover, we find that more internal locus of control leads to (1) higher savings and more on-time debt payments for females, (2) lower willingness to take financial risks for older individuals, and (3) higher willingness to take financial risks for higher educated individuals. Our findings are confirmed when we control attrition bias and re-estimate the model using the Partial Random Effects Mundalk (REMT) Transformation.

Key Words: Locus of control; Financial behavior; Financial risk attitude; Savings investment; Payment behavior; Fixed-effects vector decomposition.
JEL Classification Numbers: D90, D91, D14, D10.

1. INTRODUCTION

Due to the development of financial markets, diversification of investor profiles, and increased complexity of financial products, it is important to investigate financial behavior and financial risk attitude (Ozer & Mutlu,

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2019). Financial behavior captures an individual's saving, financial planning, expenditure, and investment behaviors (Ozer & Mutlu, 2019), and financial risk attitude refers to an individual's willingness to take risks while making a financial decision (Saurabh & Nandan, 2018). A key part of the developments in studying financial behavior has been a growing acceptance that financial decision-making is not a purely cognitive process but is also a non-cognitive process. As such, increasing literature has documented the profound impact of non-cognitive skills on financial behavior and financial risk attitude in various contexts (e.g., Abreu & Mendes, 2012; Antonides et al., 2011; Brooks & Williams, 2021; Brown & Taylor, 2014; Mihály et al., 2018; Ozer & Mutlu, 2019). Among these, locus of control (LOC), which refers to individuals' perceptions or belies regarding the causal relationship between their behaviors and life outcomes (Rotter, 1966), has increasingly gained attention across many fields of applied economics.

Theoretically, there are reasons to expect that individuals' LOC are significantly related to their financial behavior and financial risk attitude. The mechanism through which LOC affects financial behavior and financial risk attitude is through individuals' attitude towards money. Since internally controlled individuals tend to bear responsibility for themselves and believe that outcomes in their lives are consequences of their own efforts and actions, they are more likely to budget their money carefully and be disciplined in spending (Lim et al., 2003; Radianto et al., 2021); therefore, internal LOC individuals are expected to save more (Perry & Morris, 2005). Furthermore, while externally controlled individuals believe that money is a source of power and social judgment, those with internal LOC perceive power as something that comes from within themselves; therefore, internally controlled individuals may take steps such as increasing their knowledge about financial matters (Lim et al., 2003), which in turn could affect their financial behavior (Lusardi & Mitchell, 2007; Robb & Woodyard, 2011).

Empirically, studies in the business management field have found that LOC is associated with investment decisions (see Fitra et al., 2018; Putri & Simanjuntak, 2020), short-term and long-term financial planning (see Zainul Arifin et al., 2019), and financial behavior including financial plan management, savings behavior, debts and bill payment, and future investments (see Perry & Morris, 2005; Radianto et al., 2021). While meaningfully contributing to our understanding of the relation of LOC to financial behavior, these previous studies use cross-sectional data with very small samples of individuals working in a specific field (e.g., employees of a particular firm or college students). Also, these studies analyze the relation of LOC to financial behavior at a single time point without concern about the variations in LOC over time. In the economic field, we find a very scant investigation about these associations. Cobb-Clark et al. (2016), drawing on the Income and Labor Dynamics in Australia (HILDA) survey, observed that households with an internal reference person (a main respondent who has more internal LOC) save more of their permanent incomes. Kesavayuth et al. (2018), also drawing on the HILDA survey, revealed that internally controlled individuals are more willing to take financial risks. Salamanca et al. (2020), using an annual panel survey of Dutch households from 1994 to 2015, showed that an increase in internal LOC relates to the rise in the probability of owning equity and the share of household wealth invested in equity. Although these previous economic studies employ longitudinal data with big samples across different fields, thus mitigating some of the limitations relating to the small sample and cross-sectional studies, they utilize ordinary least square (OLS) (see Cobb-Clark et al., 2016; Salamanca et al., 2020) or random effects (RE) model (see Kesavayuth et al., 2018) estimators to estimate the econometric model. Since OLS cannot account for the confounding effects of individual-specific heterogeneity, their estimates might be biased. On the other hand, the parameter estimates of RE model are not consistent if the assumption that there is no correlation between explanatory variables and individual effects is violated. However, this assumption is likely to be violated due to unobserved individual characteristics such as family background, discount rates, etc., which may simultaneously affect LOC as well as financial behavior and financial risk attitude.

To address these limitations, our key contribution is to estimate the impact of LOC on financial behavior and financial risk attitude by employing a fixed effects (FE) model, which allows the correlation between explanatory variables and individual effects. However, a major concern in our empirical model is that if LOC is fixed or rarely changes over time (its within-variance is small relative to its between-variance), the FE model will make it hard for LOC to appear statistically significant because the FE model only uses the within-variance for estimation and disregards the between-variance (Beck, 2001; Plümper & Troeger, 2007). To examine the stability of LOC over time, we conduct Wilcoxon signed-rank test and the test suggested by Cobb-Clark et al. (2013), and compute the between-to-within (b/w) ratio. The results confirm that LOC is a rarely changing variable; therefore, we employ the fixed-effects vector decomposition (FEVD) suggested by Plümper & Troeger (2007) to obtain efficient estimates of LOC. The FEVD model is based on the standard FE model, so it can deal with unobserved heterogeneity. In addition, it recognizes that some of the fixed individual heterogeneities are observable. As such, the FEVD technique allows us to obtain the correct standard errors for the coefficients of the rarely changing variables. Therefore, as a part of its key contribution, our paper provides reliable longitudinal evidence on the relationship between LOC and financial behavior and financial risk attitude.

Besides the main contribution, our paper has some interesting features. First, we try to address the endogeneity issue resulting from the measurement error in LOC by using factor analysis to form an interpretable aggregate of LOC, while most previous studies calculate a single index for LOC by adding the scores of all items (see Buddelmeyer & Powdthavee, 2016; Caliendo et al., 2015; Cobb-Clark & Schurer, 2013; Kesavayuth et al., 2018). Second, we control other non-cognitive skills, including the Big Five and self-esteem, in our model to isolate the impact of LOC on financial behavior and financial risk attitude. Finally, it is also noteworthy that we use lagged LOC to mitigate the issue of reverse causality.

Our main finding reveals that LOC significantly affects financial behavior and financial risk attitude. Particularly, individuals with an internal LOC are likely to have more savings, less overdue payments, more investment, and a higher willingness to take financial risks. Moreover, we find that more internal LOC leads to (1) higher savings and more on-time debt payments for females, (2) lower willingness to take financial risks for older individuals, and (3) higher willingness to take financial risks for higher educated individuals. Our findings are confirmed when we use an alternative estimator, 'Partial Random Effects Mundalk (REMT) Transformation,' and control attrition bias.

The paper is structured in the following manner. Section 2 describes the data and variable measurement, section 3 discusses the empirical model and strategy, section 4 presents the results, section 5 reports the robustness check, and section 6 concludes.

2. DATA AND VARIABLE MEASUREMENT

2.1. Data and Estimation Sample

We draw data from the longitudinal Household Income and Labor Dynamics in Australia (HILDA) survey. HILDA, which the Australian Government funds, collects nationally representative, longitudinal information through both face-to-face interviews and self-completion questionnaires. The sample selected for the HILDA survey is intended to represent all Australian private dwelling residents sampled by a multi-staged approach. The survey started in 2001, repeated yearly, and recently released wave 19 data (corresponding to the year 2019). More information on the sampling method and other technical aspects of the HILDA survey can be found in Watson and Wooden (2012).

This dataset is ideal for our analysis as it captures information on people's personality psychology, including LOC, the Big Five, and self-esteem. It also provides measures of financial risk attitude and financial behavior, including savings, payment behavior, and investment. Furthermore, it contains socio-economic factors including education, employment status, wages, marital status, household size, number of dependent children, household income, physical and mental health, and demographic factors including age and gender. Thus, using HILDA enables us to better understand the effect of LOC on an individual's financial behavior and financial risk attitude.

We draw waves 10, 14, and 18 (corresponding to the years 2010, 2014, and 2018, respectively) for our dependent variables and the nearest lagged waves available for explanatory and control variables (i.e., waves 9, 13, and 17, corresponding to the years 2009, 2013, and 2017, for all control variables; waves 7, 11, and 15, corresponding to the years 2007, 2011, and 2015, for LOC). Moreover, we focus on respondents in the age range of 21 to 60 years old. After excluding individuals with missing answers to the questions used in our analysis, the final sample corresponded to an unbalanced panel of 4,634 observations (2,446 males and 2,188 females). Particularly, there are 1,193 observations in the first wave, 1,643 observations in the second wave, and 1,798 observations in the third wave.

2.2. Variable Measurement

2.2.1. Measures of Financial Behavior and Financial Risk Attitude

Financial Behavior

We measure three dimensions of financial behavior: savings, payment behavior, and investment. These dimensions are expected to cover the major personal financial management practices and are widely used by other studies to measure financial behavior (e.g., Hilgert et al., 2003; Tang & Baker, 2016).

For savings, we use the item 'Which of the following statements comes closest to describing your (and your family's) savings habits?', for which the answers include (1) 'Don't save: usually spend more than income', (2) 'Don't save: usually spend about as much as income', (3) 'Save whatever is leftover at the end of the month — no regular plan', (4) 'Spend regular income, save other income', (5) 'Save regularly by putting money aside each month'. A higher score denotes more savings.

We use the item 'Do you have any unpaid personal bills now overdue?' for payment behavior (overdue paymentss). The answer is measured by a dummy variable equal to one if respondents have unpaid personal bills and zero if the respondents do not have unpaid personal bills.

For investment, we use the item 'Do you or others in this household currently own any investment of this kind — shares, managed funds, and property trusts?', for which the answer is measured by a dummy variable that is equal to one for 'Yes,' and zero for 'No'. Since the investment behavior captured by this item includes that of other household members, we use the item ‘Who makes the decisions about the following issues in your household?’ to filter the data to include only those individuals with a significant decision-making role in the household. Particularly, the answers for this item include (1) ‘Always me’, (2) ‘Usually me’, (3) ‘Shared equally between my partner and myself’, (4) ‘Usually my partner’, (5) ‘Always my partner’, (6) ‘Always or usually other person(s) in the house’, (7) ‘Shared equally among all household members’, (8) ‘Always or usually someone not living in the house’. We only retain the respondents who answer (1) ‘Always me’, (2) ‘Usually me’.

Financial Risk Attitude

To capture financial risk attitude, we utilize the item ‘Which of the following statements comes closest to describing the amount of financial risk that you are willing to take with your spare cash? That is cash used for savings and investment’, for which the answers include (1) ‘I take substantial financial risks expecting to earn substantial returns’, (2) ‘I take above average financial risks expecting to earn above-average returns’, (3) ‘I take average financial risks expecting to earn average returns’, (4) ‘I am not willing to take any financial risks.’ For ease of interpretation, we reversed the scores so that a higher score indicates higher willingness to take financial risks.

2.2.2. Measures of Locus of Control

Locus of Control

LOC is derived from the responses to seven questions. The questions are (Loc_1) ‘I have little control over the things that happen to me’, (Loc_2) ‘There is really no way I can solve some of the problems I have’, (Loc_3) ‘There is little I can do to change many of the important things in my life’, (Loc_4) ‘I often feel helpless in dealing with the problems of life’, (Loc_5) ‘Some-times I feel that I’m being pushed around in life’, (Loc_6) ‘What happens to me in the future mostly depends on me’, and (Loc_7) ‘I can do just about anything I really set my mind to do.’ Answers are reported on a 7-point scale that ranges from 1 (strongly disagree) to 7 (strongly agree).

From the seven questions above, questions (Loc_1) to (Loc_5) measure external LOC, while questions (Loc_6) and (Loc_7) measure internal LOC. We reverse the score of question (Loc_1) to (Loc_5) so that the higher score implies a more internal LOC.

We employ exploratory factor analysis (EFA) developed by Gorsuch (1983) to check dimensionality and establish dedicated measures. EFA leads to all seven items to be retained for the analysis. These seven items contribute to only one factor corresponding to a single dimension of LOC. After identifying LOC, we apply Bartlett's (1937) approach to calculate the factor scores for LOC. The details of the EFA process to obtain the LOC index is displayed in Appendix 1.

Besides Bartlett's factor score of LOC, we also report the LOC index constructed by taking the average of the seven above-listed items in Table 1.

TABLE 1.

Descriptive Statistics

Variables	Mean	Min	Max	Std. Dev.			b/w Ratio
				Overall	Between	Within	
Dependent Variables							
Savings	3.631	1	5	1.15	1.11	0.45	2.48
Overdue payments	0.035	0	1	0.18	0.18	0.08	2.44
Investment	0.374	0	1	0.48	0.46	0.15	3.13
Financial Risk Attitude	1.744	1	4	0.72	0.70	0.25	2.85
Explanatory Variable							
Locus of Control (Factor Score)	0.001	−4.39	1.41	1.07	1.05	0.36	2.87
Locus of Control (Average)	5.533	1	7	1.07	1.04	0.36	2.86
Control Variables							
Age	40.688	21	60	11.58	11.86	1.98	6.00
Male	0.528	0	1	0.50	0.50	0.00	NA
Education (Years)	13.410	4	18.5	2.36	2.34	0.37	6.32
Employed	0.996	0	1	0.06	0.06	0.03	2.20
Wages (Logarithm)	7.006	3.689	9.400	0.69	0.69	0.20	3.43
Married	0.323	0	1	0.47	0.46	0.11	4.33
Household Size	2.537	1	10	1.41	1.37	0.40	3.42
Number of Children	0.632	0	7	0.98	0.94	0.29	3.20
Household Income (Logarithm)	10.902	4.043	13.789	0.63	0.62	0.22	2.81
Health							
Physical Health	82.175	10.5	100	15.75	15.08	5.73	2.63
Mental Health	76.948	1	100	17.15	16.64	6.39	2.60
Personality Traits							
Self-esteem	4.674	1	5	0.72	0.71	0.27	2.59
The Big Five							
Extraversion	4.360	1.167	7	1.14	1.11	0.27	4.16
Agreeableness	5.373	1.25	7	0.89	0.87	0.27	3.23
Conscientiousness	5.246	1.167	7	0.98	0.96	0.26	3.69
Emotional Stability	5.165	1	7	1.03	1.01	0.31	3.25
Openness	4.352	1	7	1.03	1.01	0.26	3.85

Note: The number of observations for each variable is 4,634.

2.2.3. Control Variables

Besides the commonly controlled socio-economic and demographic variables, including education, employment status, marital status, household size, number of dependent children, age, and gender, there is still a possibility that financial risk attitude reflects factors other than pure risk preferences, such as a person's financial situation (Hanna and Chen, 1997; Chen and Finke, 1996). To alleviate this concern, we also control household income and wages. Previous studies also find that household income and wages determine financial behavior and financial risk attitude (see Hartog et al., 2002; Kesavayuth et al., 2018; Loibl, 2017). Following Kesavayuth et al. (2018), we also control physical and mental health.

We also control for the Big Five personality traits and self-esteem since these traits are shown to determine financial behavior and financial risk attitude (see Brooks & Williams, 2021; Ozer & Mutlu, 2019; Tang & Baker, 2016). Controlling for the Big Five and self-esteem will help us isolate the effect of LOC on financial behavior and financial risk attitude.

The details of the measurement of all control variables are reported in Appendix 2.

Table 1 reports the descriptive statistics for all variables.

It is noteworthy that a variance inflation factor (VIF) analysis allows us to rule out potential multicollinearity regarding the choice of explanatory variables. Furthermore, for ease of interpretation, we standardized self-esteem, health measures (physical and mental health), and the scores of the Big Five (so that the mean is 0 and the standard deviation is 1).

3. EMPIRICAL MODEL AND STRATEGY

Let F_{it} be the set of financial behavior and financial risk attitude variables, i.e., $F_{it} = \{\text{savings, borrowings, investment, financial risk attitude}\}$, where i represents the individual, and t represents time point. Our model takes the following form:

$$F_{it} = \alpha_0 + \alpha_1 LOC_{i,t-1} + X'_{i,t-1}\beta + Z'_i\gamma + u_i + \varepsilon_{it} \qquad (1)$$

where, $LOC_{i,t-1}$ is individual i's level of LOC at time $t-1$. $X_{i,t-1}$ is the vector of time-variant control variables lagged to $t-1$, Z_i is a vector of time-invariant control variables, u_i is the unobserved individual fixed effects, and ε_{it} is the idiosyncratic errors.

We use the lag of LOC relative to our dependent variables because LOC may be driven by or determined jointly with contemporaneous outcomes of financial behavior and financial risk attitude. For example, higher savings and investment may result in individuals' reserving a stronger belief that they can control the outcomes of their lives (more internal *LOC*). In this case, the endogeneity of *LOC* may result in an estimation bias of unclear sign and magnitude. Researchers attempt to eliminate any bias due to reverse causality or simultaneity using lagged measures of LOC (Cobb-Clark & Schurer, 2013).

It is well known that with the presence of unobserved individual heterogeneity, u_i, OLS result in biased estimates. RE and FE estimators are the estimation strategies favored to deal with individual heterogeneity. The parameter estimates of RE models are consistent only if there is no correlation between explanatory variables and individual effects. However, this assumption is likely to be violated because there may be unobserved individual characteristics such as family background and discount rates that may correlate with an individual's *LOC*, financial behavior, and financial risk attitude simultaneously. Therefore, the FE model, which allows the correlation between explanatory variables and individual effects, seems more favorable for our analysis. However, one concern with equation (1) is the stability of *LOC*. In this emerging literature, personality traits are typically seen as being relatively stable or fixed over the relevant time frame (e.g., Borghans et al., 2008; Cebi et al., 2007; Heckman et al., 2006; Heineck et al., 2010). In case *LOC* is fixed over time, we will not be able to estimate the impact of *LOC* using the FE model, and if it is relatively stable over time, the estimates of *LOC* will appear statistically insignificant in the FE model (Beck, 2001; Plümper & Troeger, 2007). Therefore, it is important to examine if LOC is fixed, rarely changing, or time-variant in our sample. To this end, we conducted two tests: Wilcoxon signed-rank test and the test suggested by Cobb-Clark et al. (2013). The results of these tests, as reported in Appendix 3, reveal the following. The result of the Wilcoxon signed-rank test show that, at the aggregate level, we can reject the null hypothesis that *LOC* is stable. The result of the test suggested by Cobb-Clark et al. (2013) shows that although *LOC* varies over the medium and long-run, this variation is very low. Therefore, to confirm if *LOC* is a rarely changing variable, we consider the between-variance (variance across individuals) and within-variance (variance over time) of *LOC*. A variable is an almost time-invariant or rarely changing variable when it has a low within-variance relative to between-variance (a time-invariant variable is a special case where the within-variance is zero). For comparative purposes, Plümper & Troeger (2007) suggest the ratio between a variable's between-variance and within-variance (b/w ratio) as a way of distinguishing whether that variable is a time-invariant/rarely changing or time-variant variable. As a rule of thumb, they recommend a b/w ratio of at least 2.8 as sufficient to classify a variable as rarely changing. The results reported in Table 1 show that *LOC* has a b/w ratio exceeding 2.8. Thus, in our sample, *LOC* is a rarely changing variable.

In this case, according to Beck (2001) and Plümper & Troeger (2007), the FE model will make it hard for *LOC* to appear statistically significant because the FE model uses only within-variance for the estimation and disregards the between-variance. Therefore, Plümper & Troeger (2007) suggest an alternative estimator that is more efficient than the FE model in estimating variables that have low within-variance, namely 'fixed-effects vector decomposition' (FEVD). This model is also used across the relevant literature on personality traits, e.g., Boyce (2010); Powdthavee et al. (2014).

The FEVD model is based on the standard FE model; therefore, it can deal with unobserved individual heterogeneity. In addition, it recognizes that some of the fixed individual heterogeneity is observable. The FEVD technique involves three stages: First, the original model is estimated using FE to obtain the individual fixed effect residuals. Second, the individual fixed effect residuals are regressed on the time-invariant and rarely changing explanatory variables to decompose the individual fixed effect residuals into the observed and unobserved components. Finally, using a pooled-OLS estimator, the dependent variable is regressed on the unobserved component obtained in stage two and all the time-variant, time-invariant, and rarely changing explanatory variables. The final stage allows us to obtain the correct standard errors for the coefficients of the rarely changing variables. Therefore, FEVD is more efficient than FE in estimating the effect of rarely changing variables. Through Monte-Carlo simulations, Plümper & Troeger (2007) find that when the correlation between the rarely changing variable and the unit effect is low, the variable is better included in stage 2 of FEVD than estimated by a standard FE model. However, since the correlation between the unit effect and the rarely changing variable cannot be directly observed because the unit effect is unobservable, Plümper & Troeger (2007) suggests the odd that at a b/w ratio of at least 2.8, the variable is better to be included in stage 2 of FEVD to get more efficient estimates.

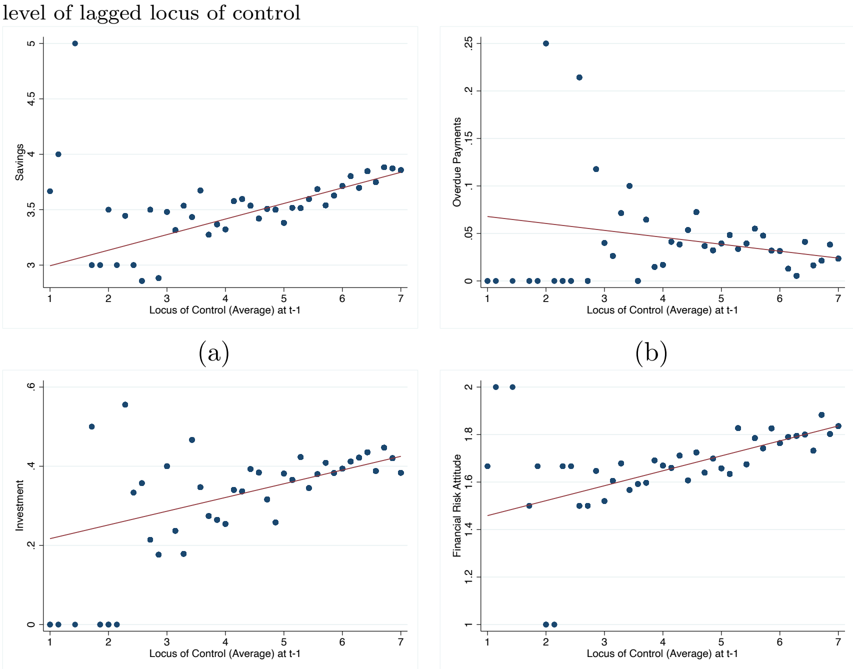
Based on the b/w ratio of all the independent variables — listed in Table 1, we include *LOC* and control variables with a b/w ratio exceeding 2.8 in stage 2 of the FEVD estimation.

4. RESULTS

4.1. Main Results

To shed some light on the nature of the link between *LOC* and financial behavior and financial risk attitude, we plot savings, overdue payments, investment, and financial risk attitude on *LOC*. Figures 1a, 1c, and 1d indicate overall increasing patterns for savings, investment, and financial risk attitude, while Figure 1b shows an overall decreasing pattern for overdue payments. This implies that individuals with more internal *LOC* are likely to save more, invest more, and be more willing to take risks but not have overdue payments. This is our first tentative evidence of the positive relationship between *LOC* and savings, investment, and financial risk attitude and the negative relationship between *LOC* and overdue payments.

FIG. 1. Savings, overdue payments, investment, and financial risk attitude at each level of lagged locus of control



(a) (b) (c) (d)

The estimated impacts of *LOC* on savings, overdue payments, investment, and financial risk attitude are reported in Table 2.

Looking at columns 1 and 3, the estimates suggest that *LOC* positively enters the savings and investment regression equations. The corresponding estimated coefficients are statistically significant at $p-$ value < 0.01. This implies that individuals with more internal LOC report higher savings than their external LOC counterparts, which is consistent with previous studies (see Bucciol & Trucchi, 2020; Cobb-Clark et al., 2016; Perry & Morris, 2005). Relating to the magnitude of the effect, an increase of a standard deviation in the internal sense of control is associated with an approximately 11.3% increase in the frequency of savings. Also, internally controlled individuals report a higher propensity to invest in shares, managed funds, and property trusts. This finding aligns with Salamanca et al. (2020), that find that an increase in internal LOC relates to an increase in the probability of owning equity. Concerning the effect size, a standard deviation increase in the internal sense of control is associated with an approximately 2.68% increase in investment propensity.

The estimates reported in column 2 suggest that LOC negatively predicts overdue payments at $p-$ value < 0.05. Although the impact size is small, the significance of the coefficient estimate implies that individuals with more internal LOC have a lower propensity to have unpaid personal bills. This finding is in line with Perry and Morris (2005) and Park (1981).

As reported in column 4, LOC is positively related to financial risk attitude, which is statistically significant with $p-$value < 0.1. This implies that individuals with more internal LOC tend to be more willing to take financial risks. Our results are supported by Kesavayuth et al. (2018), who find that LOC is positively associated with the financial risk attitude of female and older individuals.

4.2. Heterogeneity

Gender, age, and education are shown to significantly determine LOC (Kesavayuth et al., 2020; Semykina & Linz, 2007; Staats, 1995). In addition, previous researches also show that financial behavior and financial risk attitude also significantly vary by gender, age, and education (Bonsang & Dohmen, 2015; see Kesavayuth et al., 2018; Lep et al., 2021; Walczak & Pienkowska-Kamieniecka, 2018).

Therefore, we examine whether gender, age, and education matter in the relationship between LOC and financial behavior and financial risk attitude. To that end, in our model, we include the interaction terms between LOC and gender, LOC and age, and LOC and education. As such, we rewrite equation (1) as follows:

$$F_{it} = \alpha_0 + \alpha_1 LOC_{i,t-1} + \alpha_2 H_{i,t-1} + \alpha_3 (LOC_{i,t-1} \times H_{i,t-1}) + X'_{i,t-1}\beta + Z'_i\gamma + u_i + \varepsilon_{it} \quad (2)$$

TABLE 2.

LOC on financial behavior and financial risk attitude — FEVD

	Savings	Overdue payments	Investment	Risk Attitude
	(1)	(2)	(3)	(4)
Locus of Control	0.113***	−0.00862**	0.0268***	0.0259*
	(0.0258)	(0.00423)	(0.0100)	(0.0149)
Control Variables				
Age	−0.00580***	−0.000679*	0.00559***	−0.00277**
	(0.00218)	(0.000356)	(0.000856)	(0.00126)
Male	−0.148***	−0.00242	0.0260	0.304***
	(0.0486)	(0.00795)	(0.0192)	(0.0281)
Education	0.0253**	−0.00170	0.0202***	0.0436***
	(0.00987)	(0.00162)	(0.00391)	(0.00573)
Employed	1.301**	0.00566	0.0996	−0.0984
	(0.549)	(0.0910)	(0.202)	(0.311)
Wages	0.101**	−0.0243***	0.0258	0.0815***
	(0.0414)	(0.00677)	(0.0163)	(0.0239)
Married	0.0771	−0.0246***	0.0590***	0.138***
	(0.0556)	(0.00911)	(0.0220)	(0.0323)
Household Size	0.0429*	−0.00806**	0.0434***	−0.00687
	(0.0223)	(0.00366)	(0.00884)	(0.0130)
Number of Children	−0.199***	0.0137***	−0.0554***	0.0150
	(0.0313)	(0.00512)	(0.0124)	(0.0181)
Household Income	0.00538	0.0147**	0.0800***	0.0813***
	(0.0441)	(0.00723)	(0.0173)	(0.0255)
Health				
Physical Health	0.00344	−0.0111	0.0133	0.00720
	(0.0523)	(0.00861)	(0.0199)	(0.0299)
Mental Health	0.0368	0.0181*	−0.00667	0.0205
	(0.0600)	(0.00987)	(0.0229)	(0.0344)
Personality Traits				
Self-esteem	−0.0522	0.00260	−0.00557	−0.0149
	(0.0521)	(0.00859)	(0.0198)	(0.0298)
Big Five				
Extraversion	−0.0236	0.00672*	−0.00868	0.0351***
	(0.0226)	(0.00370)	(0.00894)	(0.0131)
Agreeableness	−0.0401*	0.000580	−0.0343***	−0.0507***
	(0.0228)	(0.00374)	(0.00901)	(0.0132)
Conscientiousness	0.115***	−0.0125***	0.00719	−0.0125
	(0.0225)	(0.00369)	(0.00889)	(0.0131)
Emotional Stability	0.00946	−0.00490	0.0184*	0.0346**
	(0.0276)	(0.00453)	(0.0108)	(0.0160)
Openness	0.00539	0.00697*	0.00621	0.0795***
	(0.0231)	(0.00378)	(0.00913)	(0.0134)
N	4,634	4,634	4,634	4,634

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

where $H_{i,t-1}$ represents gender, age, and education, respectively.

First, relating to gender (Table 3) in explaining the relationship between *LOC* and financial behavior and financial risk attitude, we find that more internal *LOC* leads to more savings and lesser over-due payments for females. In this regard, Lim et al. (2003) find that females tend to be more concerned about the budget, evaluation, and retention dimensions of money. Therefore, internally controlled females are likely to have lesser overdue payments than their male counterparts.

TABLE 3.

LOC on Financial Behavior and Risk Attitude by Gender — FEVD

	Savings	Overdue payments	Investment	Risk Attitude
LOC	0.150^{***}	-0.0143^{***}	0.0184	0.0223
	(0.0329)	(0.00539)	(0.0129)	(0.0190)
Male	-0.149^{***}	-0.00238	0.0259	0.304^{***}
	(0.0485)	(0.00795)	(0.0192)	(0.0282)
LOC × Male	-0.0689^{*}	0.0108^{*}	0.0158	0.00694
	(0.0381)	(0.00625)	(0.0150)	(0.0221)
Control Variables	Yes	Yes	Yes	Yes
N	4,634	4,634	4,634	4,634

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Second, on the role of age (Table 4), we find that more internal *LOC* leads to a lesser willingness to take financial risks for older individuals. With age, individuals become more concerned about the shocks in their lives, such as health shocks and retirement (Banks et al., 2020). Therefore, we conjecture that older internally controlled individuals tend to manage their finances to mitigate or insure against these shocks by assuming lower risk-taking behavior.

Third, on the role of education (Table 5), our findings suggest that more internal *LOC* is associated with a higher propensity to take financial risks for higher-educated individuals. This is because, on the one hand, highly educated individuals may have a better understanding of the risk involved in investment decisions (Yao & Hanna, 2005), are better equipped to make financial decisions, and are more accurate in analyzing investment risk and return (Grable & Lytton, 1998). On the other hand, those with internal *LOC* believe that they are in control of their own fate and perceive power as something that comes from within themselves; therefore, internally controlled individuals would take steps such as increasing their knowledge about financial matters (Lim et al., 2003). Overall, higher education

TABLE 4.

LOC on Financial Behavior and Risk Attitude by Age — FEVD

	Savings	Overdue payments	Investment	Risk Attitude
LOC	0.176^{**}	-0.0127	0.0615^{**}	0.0978^{**}
	(0.0725)	(0.0119)	(0.0285)	(0.0420)
Age	-0.00571^{***}	-0.000674^{*}	0.00558^{***}	-0.00275^{**}
	(0.00218)	(0.000357)	(0.000856)	(0.00126)
LOC × Age	-0.00153	0.0000992	-0.000843	-0.00176^{*}
	(0.00167)	(0.000274)	(0.000658)	(0.000969)
Control Variables	Yes	Yes	Yes	Yes
N	4,634	4,634	4,634	4,634

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

and more internal *LOC* could lead to procuring more financial knowledge, which, in turn, could make individuals less risk-averse.

TABLE 5.

LOC on Financial Behavior and Risk Attitude by Education — FEVD

	Savings	Overdue payments	Investment	Risk Attitude
LOC	-0.0498	-0.0281	-0.0139	-0.118^{*}
	(0.108)	(0.0177)	(0.0425)	(0.0625)
Education	0.0253^{**}	-0.00170	0.0202^{***}	0.0436^{***}
	(0.00987)	(0.00162)	(0.00391)	(0.00573)
LOC × Education	0.0123	0.00147	0.00308	0.0109^{**}
	(0.00797)	(0.00131)	(0.00314)	(0.00462)
Control Variables	Yes	Yes	Yes	Yes
N	4,634	4,634	4,634	4,634

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

5. ROBUSTNESS

First, we check if our results are robust by re-estimating our original model using the 'Partial Random Effects Mundalk Transformation (REMT)' proposed by Greene et al. (2011). It is well-known that RE estimation allows reliable estimates for variables with low variation within variation. However, RE estimates are consistent only if the assumption of no correlation between explanatory variables and individual effects is not violated. A common approach to dealing with this core assumption violation is including the individual means of all time-varying variables as explanatory variables, as proposed by Mundlak (1978). Greene et al.

(2011) adjust Mundlak's approach by including the individual means of only time-varying variables with sufficiently high within-variance. This approach allows for obtaining more reliable coefficients of explanatory variables with low within-variance than FE (Greene et al., 2011). Greene et al. (2011) also suggest that the individual means included will be for variables with relatively low b/w ratios, where the criterion for choosing the unit means is inverse of the FEVD model. Based on the b/w ratios reported in Table 1, we select the control variables with b/w ratios smaller than 2.8 and add their individual means to our original model. The partial REMT estimates reported in Table 6 further support our earlier findings, except for overdue payments.

TABLE 6.

LOC on Financial Behavior and Risk Attitude — REMT

	Savings	Overdue payments	Investment	Risk Attitude
Locus of Control	0.0808^{***}	-0.000147	0.0130^{*}	0.0221^{*}
	(0.018)	(0.00333)	(0.00678)	(0.0114)
Control Variables	Yes	Yes	Yes	Yes
N	4,634	4,634	4,634	4,634

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Second, a potential concern is that the selection bias due to the panel survey can drive our results. This is the case that respondents who have lower *LOC* (more external *LOC*) are less likely to respond to the survey or more likely to drop out of the panel survey than their counterparts (Kesavayuth et al., 2018). To investigate this issue, we include the dropout dummy variable that takes the value of 1 if the respondent drops out of the survey in the following waves and 0 otherwise. Moreover, to see if the impacts of *LOC* on financial behavior and financial risk attitude vary by the fact that the respondent has either stayed or dropped out of the survey in the following waves, we control for the interaction between *LOC* and dropout dummy. As is evident from Table 7, *LOC* continues to impact both financial behavior and financial risk attitude significantly. In addition, we see that only on overdue payments, the impact of *LOC* is significantly different for those who have dropped out. Thus, the total effect of *LOC* on overdue payments can be computed as the sum of the coefficient estimates of *LOC* and *LOC* $\times$ Dropouts, which is -0.0027 and significant.

TABLE 7.

LOC on Financial Behavior and Risk Attitude — Attrition

	Savings	Overdue payments	Investment	Risk Attitude
Locus of Control	0.126^{***}	-0.0170^{***}	0.0328^{**}	0.0431^{**}
	(0.0340)	(0.00557)	(0.0132)	(0.0196)
Dropouts	0.108^{**}	-0.0122	-0.0485^{**}	0.00842
	(0.0528)	(0.00870)	(0.0200)	(0.0301)
LOC × Dropouts	-0.0234	0.0143^{**}	-0.00966	-0.0292
	(0.0367)	(0.00601)	(0.0144)	(0.0212)
Control Variables	Yes	Yes	Yes	Yes
N	4,634	4,634	4,634	4,634

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

6. CONCLUSION

Financial behaviors and attitudes towards financial risk significantly determine an individual's financial well-being (Ozer & Mutlu, 2019). Therefore, it is important to understand the factors that influence an individual's financial behaviors and financial risk attitude. While extensive literature focuses on cognitive skills' role in explaining attitudes and behavior towards financial issues, non-cognitive skills and personality traits have only recently been recognized to predict these attitudes and behaviors. We complement the existing literature by verifying the role of *LOC*, a personality trait that has been increasingly receiving attention in many fields of applied economics, on financial behavior and financial risk attitude.

We draw data from the HILDA survey and employ a fixed-effects vector decomposition model to estimate the impact of *LOC* on financial behavior and financial risk attitude, where financial behavior is captured by savings, payment behavior, and investment; and financial risk attitude is captured by an individual's degree of willingness to take risks. We find that *LOC* significantly affects financial behavior and financial risk attitude. Particularly, individuals with an internal *LOC* are likely to save more, invest more, be more willing to take financial risks, and have less overdue payments. Moreover, we find that more internal *LOC* leads to (1) higher savings and more on-time debt payments for females, (2) lower willingness to take financial risks for older individuals, and (3) higher willingness to take financial risks for higher educated individuals. Our findings are confirmed when we control attrition bias and re-estimate the model using the REMT.

These findings have implications for policymakers, educators, and financial institutions. First, it may be recommended for policymakers and educators to recognize the role of non-cognitive skills, in addition to financial knowledge, in forming financial behaviors and financial risk attitudes. Second, financial institutions should identify that customers and investors with different levels of *LOC* exhibit differences in savings, payment behavior, investment, and attitude towards financial risk; consequently, their demands for financial products are also different. Therefore, in their effort to create tailored financial products and portfolios for their customers and investors, financial institutions need to consider the psychological characteristics of these customers and investors, including *LOC*. Third, it is important to recognize that the attributes linked with more internally controlled individuals include higher savings, less overdue payments, more investment, and a higher willingness to take financial risks. Therefore, in their efforts to enhance the efficiency of community-wide financial behavior, policymakers and educators may focus on promoting financial education programs that aimed at developing individuals' *LOC*.

Finally, we highlight the following limitations in our study. First, although we try to mitigate the endogeneity issue of *LOC* resulting from reverse causality and measurement error by using lagged *LOC* and employing factor analysis to establish a dedicated measure for *LOC*, *LOC* may still be endogenous due to omitted variables. There might be unobservable characteristics that simultaneously affect individuals' *LOC*, financial behavior, and financial risk attitude. Even through an extensive literature review, we could not identify a conventional instrumental variable (IV) to address this source of endogeneity. We recommend for future studies explore and address this issue in more detail. Furthermore, the impact of LOC on overdue payments is inconsistent between FEVD and REMT models; therefore, we cannot convincingly conclude on this relationship.

APPENDIX 1

Exploratory Factor Analysis (EFA) for Locus of Control Measure

We employ exploratory factor analysis (EFA) developed by Gorsuch (1983) for the 7 selected items to check dimensionality and establish dedicated measures. Based on the literature on EFA, three conditions for extracting a factor are applied. First, only factors with eigenvalues > 1 are extracted and retained. Second, only items with the highest factor loading that exceeds 0.4 on the expected factor and exceeds the second-highest factor loading by more than 0.1 (to avoid cross-loaded measures) are retained.

Third, following Heckman (2013), we need at least three measures for each factor to achieve identification.

The eigenvalue of 3.25, reported in Table A1.1, suggests that only one factor can be extracted. Factor loadings reported in Table A1.2 shows that all factor loadings are above our predetermined criteria of 0.4. The internal consistency of our measure is further confirmed by the Cronbach's alpha of 0.8463 for this factor.

Table A1.1. Eigen-value

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.250	2.544	0.929	0.929
Factor2	0.706	0.633	0.202	1.131
Factor3	0.074	0.130	0.021	1.152
Factor4	−0.056	0.058	−0.016	1.136
Factor5	−0.114	0.030	−0.032	1.104
Factor6	−0.144	0.075	−0.041	1.063

Table A1.2. Pattern matrix of factor loadings

Variable	Factor 1	Uniqueness
LOC_1	0.647	0.558
LOC_2	0.778	0.358
LOC_3	0.787	0.347
LOC_4	0.791	0.338
LOC_5	0.743	0.411
LOC_6	0.413	0.503
LOC_7	0.508	0.454

APPENDIX 2

Descriptions of Measurement of Control Variables

Table A2.1. Measurement of Control Variables

Variables	Description
Male	Dummy variable representing respondent's gender, = 1 if male and 0 if female
Age	Respondent's age at June 30 of the survey year
Education	Number of years of education
Employed	Dummy variable representing respondent's current employment status, = 1 if employed and 0 if unemployed
Wages	Logarithm of current weekly gross wages and salary of the respondent's main job
Married	Dummy variable representing the respondent's current marital status, = 1 if 'legally married' and 0 = otherwise
Household Size	Number of in-scope persons in household
Number of Children	Number of dependent children
Household Income	Real household financial year disposable total income (= positive disposable income — negative disposable income)(Thousands of Dollars)
Health	
Physical Health	Measured by 21 questions from the 36-item Short Form Survey (SF-36) along 4 physical health dimensions (physical functioning, role-physical, body pain, and general health). Each dimension is provided in a standardized form on a 0-100 scale with higher score representing better physical health. We generate an aggregate score for physical health by computing the average of these 4 dimensions for each observation.
Mental Health	Measured by 14 questions from the 36-item Short Form Survey (SF-36) along 4 mental health dimensions (social functioning, role-emotional, mental health, and vitality). Each dimension is provided in a standardized form on a 0-100 scale with higher score representing better mental health. We generate an aggregate score for mental health by computing the average of these 4 dimensions for each observation.

Table A2.1. continued

Variables	Description
Personality Traits	
Self-esteem	Measured by the question 'In the last four weeks, about how often did you feel worthless?'. Answers range on a 5-point scale from 1 'All of the time' to 5 'None of the time'.
The Big Five	
Extraversion	Measured by the question 'How well do the following words describe you? 1) talkative, 2) bashful, 3) quiet, 4) shy, 5) lively, 6) extroverted'. The answer for each item ranges on a 7-point scale with 1 = 'does not describe me at all', 7 = 'describe me very well'. The score for items 2, 3, and 4 are reversed. An aggregate score for Extraversion is generated by computing the average of these 6 items for each observation.
Agreeableness	Measured by the question 'How well do the following words describe you? 1) sympathetic, 2) kind, 3) cooperative, 4) warm'. The answer for each item ranges on a 7-point scale with 1 = 'does not describe me at all', 7 = 'describe me very well'. An aggregate score for Agreeableness is generated by computing the average of these 4 items for each observation.
Conscientiousness	Measured by the question 'How well do the following words describe you? 1) orderly, 2) systematic, 3) inefficient, 4) sloppy, 5) disorganized, 6) efficient'. The answer for each item ranges on a 7-point scale with 1 = 'does not describe me at all', 7 = 'describe me very well'. The score for items 3, 4, and 5 are reversed. An aggregate score for Conscientiousness is generated by computing the average of these 6 items for each observation.
Emotional Stability	Measured by the question 'How well do the following words describe you? 1) envious, 2) moody, 3) touchy, 4) jealous, 5) temperamental, 6) fretful'. The answer for each item ranges on a 7-point scale with 1 = 'does not describe me at all', 7 = 'describe me very well'. The score for all items are reversed. An aggregate score for Emotional Stability is generated by computing the average of these 6 items for each observation.
Openness	Measured by the question 'How well do the following words describe you? 1) deep, 2) philosophical, 3) creative, 4) intellectual, 5) complex, 6) imaginative'. The answer for each item ranges on a 7-point scale with 1 = 'does not describe me at all', 7 = 'describe me very well'. An aggregate score for Openness is generated by computing the average of these 6 items for each observation.

APPENDIX 3

Locus of Control Stability Test

Table A3.1. Wilcoxon signed-rank test

H0:	$Prob > |z|$
LOC Wave 9 = Wave 13	0.0242
LOC Wave 9 = Wave 17	0.0078
LOC Wave 13 = Wave 17	0.0175

Table A3.2. Distributions of Medium and Long-Run Changes in Locus of Control Test suggested by Cobb-Clark et al. (2013)

Difference in LOC	**Mean**	**Std. Dev.**	**Min**	**Max**
Wave 13 & 9 (medium term)	.7885	6.4502	−19	21
Wave 17 & 13 (medium term)	.5556	6.1042	−20	21
Wave 17 & 9 (Long term)	1.3440	6.4236	−19	20

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