IMPACT OF GROSS MONTHLY INCOME ON INVESTMENTS IN CRYPTOCURRENCY – 2023

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Abstract

Investments in cryptocurrency have exponentially grown over the past few years and are now one of the most prominent subject matters in the finance world. Understanding the key factors that drive such investments can impact various aspects of macroeconomic policymaking. One key factor that affects these investments is an individual's gross monthly income level. However, this relation has not been explored much, and even less so in the Indian context. Data collection for this paper was conducted using the survey methodology (YouGov Millennial Surveys), and statistical regression techniques were employed for the analysis. We incorporated the control variables of age and employment status in our research. Additionally, we utilised the question on 'describing yourself as an investor' as our mediating variable. Furthermore, we examine the potential moderating influence of a change in investment status over the past 1 year on the dependent variable. Our analysis yielded the following results:(i) Individuals with a higher gross monthly income are more likely to invest in cryptocurrency. (ii) Individuals belonging to lower age slabs are more likely to invest in cryptocurrency (iii) Individuals who work for more hours are more likely to invest in cryptocurrency; (iv) Individuals with a higher gross monthly income are more likely to have higher investment knowledge; (vi) Individuals with more investment knowledge are more likely to invest in cryptocurrency (vii) The positive relation between gross monthly income and investments in cryptocurrency strengthens if there is an increase in investments over the past 1 year.

JEL Classification: G11, G53, D14, E21
Keywords: Cryptocurrency; Investment; Gross Monthly Income; Quota Sampling; Survey; Data; Suppression Effect

1. INTRODUCTION

In the ever-changing environment of finance, the growth of cryptocurrencies has attracted the interest of investors, economists, and researchers alike. Cryptocurrencies, led by the pioneering Bitcoin, have evolved into more than just a financial asset. They now represent a fundamental shift in how we think about and exchange value. As the digital revolution unfolds, concerns regarding the elements that influence an individual's choice to invest in cryptocurrencies emerge. This study takes a deep dive into this matter, attempting to comprehend the nuanced relationship between an individual's gross monthly income and their proclivity to invest in cryptocurrency.

The exploration of this relationship holds profound significance within the contemporary financial landscape. As the cryptocurrency market continues to mature and integrate with traditional finance, understanding the role of income in shaping investment decisions becomes pertinent for multiple stratums of society. Understanding if people from various income brackets are taking part in this digital financial revolution gives information on the potential for cryptocurrencies to bridge economic divides. This understanding can help the government drive the development of targeted regulations that balance innovation and investor protection, thereby resulting in a more resilient financial environment. Taking a bird's eye view, this study may provide insight into wider macroeconomic trends and also the rate of technology adoption. Individuals with differing income levels adopting cryptocurrencies in different ways and speeds could point to broader socioeconomic shifts. Policymakers and industry stakeholders may use this data to predict changes in

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in consumer behaviour, modify infrastructure, and develop regulations that are consistent with changing financial paradigms.

In this paper, we study the impact of gross monthly income on investments in cryptocurrency amongst millennial internet users in India. Information on age and employment status is taken as controls. The change in an individual's investment status over the past year studies the moderating effect of the independent variable, while an individual's investment knowledge is taken as a mediating variable. Section II provides a literature review of the existing studies pertaining to India and other countries as well. Section III includes a detailed note of the methodology used for data collection and analysis. Further, in Section IV, we talk about the findings related to regression analysis, which is followed by Section V, which includes the discussions, interpretations, limitations, and future scope of the study.

2. LITERATURE REVIEW

Research examining the socioeconomic determinants of cryptocurrency ownership and investment has expanded substantially in recent years. Early work suggested that cryptocurrency investors are predominantly younger males with higher digital literacy and risk tolerance (Ante, 2020). However, later studies have offered a more nuanced view of the role of income, wealth, and behavioural characteristics in explaining investment behaviour for this asset class. While income often appears as a significant predictor in cross-sectional data, the relationship between income levels and cryptocurrency ownership varies across countries, data sources, and time periods. For instance, survey evidence from the United States indicated that nearly 44% of crypto owners in 2022 reported household incomes above USD 100,000 (Weber, 2023). This suggests a concentration of participation among higher-income individuals. Contrastingly, data from Brazil shows that cryptocurrency participation is split across income groups and is mediated by financial inclusion and education (Colombo, 2024).

A growing body of literature has moved beyond simple demographic correlations to consider how income interacts with financial literacy, wealth, and risk preferences. Aiello et al. (2024) used transaction-level financial account data to show that crptocurrency investments affect households in heterogeneous ways. Higher-income households tend to treat crypto as a speculative or portfolio-diversification asset, whereas lower-income groups often engage in shorter-term trading driven by liquidity shocks. These results tell us that the link between income and cryptocurrency investment cannot simply be explained by disposable income levels alone. Rather, it is shaped by behavioural and structural factors like investment motives, access to financial products, and trust in formal institutions (Hayashi & Routh, 2024).

Further, recent studies highlight that financial literacy and risk tolerance mediate the relationship between income and cryptocurrency adoption. Hayashi and Routh (2024) find that individuals with higher financial literacy are more likely to view crypto assets as alternative investments rather than gambling instruments, while those with lower literacy levels and higher risk tolerance are more prone to speculative participation. This reinforces the argument that observed income effects may be confounded by omitted behavioural and informational factors (Ante, 2020). Furthermore, Aiello et al. (2024) show that transaction-level analyses often produce weaker or even inverted income gradients compared to survey-based studies, as income interacts with portfolio ersification motives and timing of market entry.

In the Indian context, the academic literature on cryptocurrency investments remains limited compared to the United States or Europe. Indian studies have largely focused on regulatory uncertainty, awareness levels, and technological adoption shaping investment decisions, rather than looking at income. While international evidence establishes income as one of many correlated factors influencing crypto participation, Indian millennials—who experience both rising disposable incomes and greater digital exposure—represent a distinct segment worthy of dedicated analysis. By applying the YouGov–Mint–CPR Millennial Survey to this demographic, the present study contributes India-specific empirical evidence to a literature still dominated by Western data sources. One of the key challenges of using a dataset like YouGov is that it

suffers from self-selection bias, since participation is voluntary and respondents are typically more digitally literate or financially curious than the general population (Steinmetz et al., 2020). This bias inflates ownership estimates and may distort the observed relationship between income and investment. However, research done by Aiello et al. (2024) and Weber (2023) notes that administrative or transaction-level data reduce this form of bias and reveal more accurate participation patterns.

Overall, existing research establishes that income correlates with cryptocurrency investment, but this relationship is complex and context dependent. Higher income may provide the financial flexibility to invest, yet factors such as financial literacy, behavioural biases, and institutional trust significantly moderate this effect (Hayashi & Routh, 2024; Ante, 2020). The current study thus situates the Indian case within this global discourse. It acknowledges that while the question of income and crypto adoption has been explored elsewhere, the Indian experience, with its unique regulatory environment and demographic composition, remains empirically underrepresented. By addressing this gap, this paper aims to add to an emerging body of work on financial behaviour and digital asset adoption in developing economies.

To summarise, given the present financial context, understanding the influence of gross monthly income on cryptocurrency investments is critical. Considering that cryptocurrencies have the potential to democratise access to investing opportunities, as well as the dynamic nature of this asset class, it is critical to understand the variables driving people' choices to invest in cryptocurrencies. This study intends to contribute to a better understanding of the impact of income in affecting investment behaviour in cryptocurrencies by filling a gap in the current literature and exploiting a large dataset. This research aims to give significant insights for people, politicians, and financial practitioners via empirical analysis and the examination of mediating and moderating variables, eventually adding to the larger conversation on cryptocurrency investments.

3. METHODOLOGY

This section will look at the techniques utilised for data collection and analysis. We will discuss the questions selected for the independent and dependent variables, as well as offer an explanation for the confounders used. Following that, we will explore and describe the questions that may be viewed as our mediating and moderating factors. Finally, we will look at the design of the regression model.

3.1. Source of Data

The survey approachis being utilisedto gather data for this investigation. This analysis is based on data from the YouGov-Mint-CPR Millennial Surveys. YouGov is conducting this poll in collaboration with Mint. The Centre of PolicyResearch later joined to help with the conduction of this survey. This is a biannual poll that focuses on the sentiments of the country's digital natives. The information for this study came from the ninth wave of this poll, which was performed in December 2022. This round of surveys gathers data on the financial ambitions and attitudes of Indian internet users.

3.2. Sampling Methodology

This survey employed the quota sampling method as its sampling technique. In order to establish and enforce quotas, different categories such as age, gender, city tier, and region were considered. Utilising 2011 censusdata, the proportion for each quotawas calculated. The total sample size for the ninth phase of this survey was 9698 individuals, of which 49% were females and 51% were males. 78% of the respondents were between the ages of 18 and 39 in order to ensure that there was a larger proportion of millennials in the sample. Additionally, 38% of the respondents belonged to tier 1 cities, 25% to tier 2 cities, and 37% to tier 3 cities. Assigning weights to different categories guaranteed that the sample utilised in the report was representative and accurately reflected the entire demographic of internet users belonging to the Millennial generation in India. The survey was administered by the YouGov India panel utilising laptops or mobile applications. Members were awarded money as compensation for accumulating specific points through survey completion. This provided participants with an incentive, which is a good method to increase the number of responses. However, it may have also increased the proportion l

of survey respondents who were in need of financial assistance, thereby skewing the demographic. Additionally, participants were allowed to complete the survey in multiple sessions, giving them a chance to think their answers through rather than being forced to complete the survey quickly.

Participation in the survey was exclusively in the English language, and respondents were expected to possess a functional level of English proficiency. Non-native English speakers may have been adversely affected by this and might have been unable to participate actively in these surveys. As the findings of this research are derived from survey samples, they are susceptible to sampling-related statistical errors. At a confidence level of 95%, the margin of error for the YouGov survey is 1-2 percent, which can be considered a nominal error. This high calibre of data sampling and collection enables the derivation of pertinent conclusions

3.3. Concepts and Propositions

Proposition: Income levelsare significantly associated with the instruments that an individual invests in (particularly cryptocurrencies).
Independent Concept: EconomicWell-being (income)
Dependent Concept: Instruments invested in (specifically cryptocurrency)

3.4. Independent and Dependent Variables, & Hypothesis

As mentioned before, we aim to study the relationship between an individual's gross monthly income levels and their tendency to invest in cryptocurrencies. The ninth wave of the survey captures individuals' gross monthly income levels and their investment patterns. For this, the questions chosen for the independent and dependent variables are listed below:

- Q15_10: Which all instruments have you invested/deposited in? (Dependent Variable)
- SC1: Could you tell us your approximate gross monthly salary?(Independent Variable)

Q15 was a binary question, with responses taking the value of either 0 or 1. We are particularly focusing on the 10th part of question 15, which was specifically about investments in cryptocurrency. A response of 0 implied that the individual has not invested in
(x) More than 4,00,000 INR. Additionally, an option of 'Prefer not to say' was given in this question in case an individual wishes not to reveal his gross monthly income.
Both these questions were framed in a neutral manner so as to avoid any leading tones.
By using these questions for our independent and dependent variables, we crafted the following hypothesis: Individuals with higher gross monthly income are more likely to invest in cryptocurrencies.

3.5. Confounders

We used 'age' and 'employment status' as confounders for this research in order to understand the coefficients of the independent variable and get closer to a causal analysis. The following are the questions picked for these two:

- age_cb: age slabs of the individuals (confounder 1)
- Employment_status_in: the individual's current employment status (confounder 2)

Age_cb divided the individuals who filled the survey according to the following age slabs: (i) 18-29 (ii) 30-39 and (iii) 40+. Age acts as a good confounder because it is connected to both the independent and the dependent variables. A person who is older is more likely to have a higher gross monthly income level. Additionally, an older person is less likely to invest in cryptocurrencies due to them being less tech -savvy and hence mistrusting such an investment or just having old investing habits. Therefore, we expect there to be a negative relation between this confounder and our dependent variable.

Employment_status_in took the following qualitative responses: (i) Not working (ii) Unemployed (iii) Working part-time (Less than 8 hours a week) (iv) Working part-time (8-29 hours a week) (v) Working full time (30 or more hours per week) (vi) Full-time student, (vii) Retired and (viii) Other. This also acts as a good confounder, seeing that it impacts both gross monthly income levels and whether or not an individual has invested in cryptocurrencies. A person who has higher working hours is more likely to have a higher gross monthly income level. Additionally, individuals with higher working hours are more likely to invest in cryptocurrencies due to their inability to actively manage traditional investments

(whereas cryptocurrencies are constantly available) or just their behavioural patterns (high risk tolerance and ambitious financial goals). Therefore, we expect there to be a positive relation between this confounder and our dependent variable. We predict that individuals who work for more hours are more likely to invest in cryptocurrencies. For the purpose of our study, we have discarded the responses of 'Full-time student', 'Retired' and 'Other' since we are primarily focusing on individuals who either have jobs or are looking for them.

3.6. Mediating Variable

We have used "Q14: How would you describe yourself as an investor?" as our mediating variable. The responses to this question took the following responses: (i) I do not invest in either financial or physical assets (ii) I do not invest in physical assets but invest in financial assets (iii) I do not invest in financial assets but invest in physical assets(iv) I invest in physical assets (real estate, gold) as well as financial assets (stocks/bonds/mutual funds).

We have used the responses to this question as a measure of an individual's investment knowledge. Investment knowledge serves as a strong mediating variable. This is because individuals with higher income might be more likely to invest in educating themselves about various investment opportunities, including cryptocurrencies. Hence, they will have more knowledge about how to handle their finances. At the same time, investment knowledge can serve as a pathway to the instruments which individuals invest in. Investment knowledge may positively influence the decision to invest in cryptocurrency. Those with a better understanding of the cryptocurrency market, blockchain technology, and associated risks may feel more confident and willing to engage in cryptocurrency investments. Therefore, we expect there to be a positive relation between our independent variable and this mediating variable and also between this mediating variable and our dependent variable.

3.7. Moderating Variable

We have used "Q16: Has there been any change in your investments in the last 1 year?" as our moderating variable. The responses to this question took the following responses: (i) Yes - have started investing less (ii) No change (iii) Yes - have started investing more.

A change in investment status in the past 1 year moderates the link between gross monthly income and whether or not an individual invests in cryptocurrencies. An increase or decrease in investments over time can have an impact on the cryptocurrency investments of an individual. This moderating effect captures the nuanced interplay between income, changes in investments, and cryptocurrencies that an individual has invested in.

3.8. Methodology for Analysis

Due to the qualitative nature of the questions pertaining to the independent, dependent, and confounding variables, they have all been coded in order to conduct a regression analysis. By performing a linear regression analysis, the correlation between the variables is determined. The structural model is described in the following manner:

Final model expression (equation form):

$Y = X + C1 + C2 + MoV + MoV^*X$

Tests for the Mediating Variable (equation form):

$MeV = X \quad \& \quad Y = MeV$

Where: Y = Whether or not an individual has invested in cryptocurrency

X = Gross monthly income level of an individual

C1 = Age of an individual

C2 = Employment Status of an individual

MeV = Investment knowledge that an individual possesses

MoV = Change in investment status over the past year

MoV^*X = The interaction term between change in investment status and gross monthly income

4. FINDINGS

4.1. Descriptive Statistics

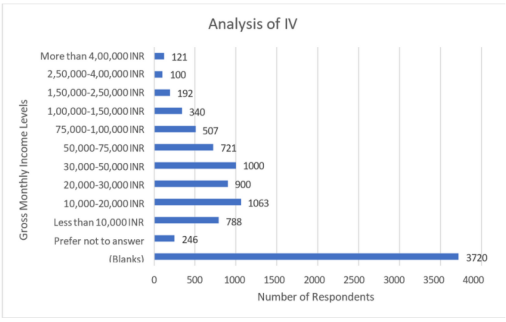
We discovered, based on the results of the survey, that 1221 participants (approximately 12.59%) invested in cryptocurrency. There were 2648 lacking values (approximately 27.30%) in total for this question. Upon examining the independent variable, it was evident that a majority of the respondents had income levels between 10,000-50,000 INR. There were 3720 lacking values in this query (approximately 38.36%). Looking at the confounders,

we find that the majority of the samples belonged to the age slab of 18-29. This makes sense considering that this survey was specifically designed to target millennials. We also observe that a majority of the sample (approximately 41.42%) work full time (30+ hours).

By analysing the data on our mediating variable, we see that the largest proportion (approximately 34.82%) of respondents possess large amounts of financial knowledge (defined here as greater awareness of basic investment products, understanding of risk–return trade-offs, and familiarity with investments in non-traditional asset classes), having made investments in financial and physical assets both. This seems surprising because most of these respondents are millennials. Last, observing the responses to the question that we took as our moderating variable, we notice that there are roughly the same number of respondents for both of our levels. Therefore, we roughly have a similarly large enough sample size to test our hypothesis across all the levels.

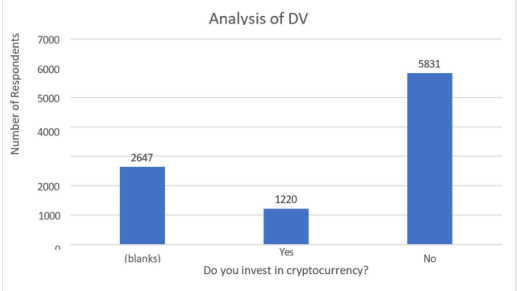
The descriptive statistics (fig 4.1.1 and fig 4.1.2) presented herein offer a comprehensive summary of the responses with respect to the moderating variable, mediating variable, controls, IV, and DV.

Figure 4.1.1: *Distribution of Respondents by Gross Monthly Income Levels*



Source: Author's Survey

Figure 4.1.2: *Distribution of Respondents based on cryptocurrency investment*



Source: Author's Survey

4.2. Regression Analysis

a. Testing the effect of the independent Variable (IV) on the dependent variable (DV)

- Early Test (Y = X) (see Appendix Figure A1)
- Test with Controls(Y = X + C1 + C2) (see Appendix Figure A2)
- Final Model(Y = X + C1 + C2 + MoV + MoV*X) (see Appendix Figure A3)

b. Testing for mediation

- MeV = X (see Appendix Figure A4)
- Y = Mev (see Appendix Figure A5)

4.3. Effect of Gross Monthly Income on Investments in Cryptocurrency

To test the hypothesis, we regressed the responses to the question of whether or not an individual invests in cryptocurrency on the responses to the question of gross monthly income levels. The estimate of the independent variable (gross monthly income) has a positive sign and, as per the p-value (<2e-16), is statistically significantly related to the dependent variable. The beta coefficient value is 0.026379 which signifies that an increase in the gross monthly income levels of an individual will lead to a slight increase in his investments in cryptocurrency.

4.4. Effect of the Confounders

As mentioned above, we added two control variables in the regression model: the age and employment status of an individual. These variables need to be controlled in order to study the impact of the independent variable on the dependent variable.
The first control variable (age) is negatively related to the dependent variable. As per the p-value of 8.46e-05, age is a statistically significant variable. The negative beta coefficient value of -0.028102 matches our prediction that older individuals are less likely to invest in cryptocurrencies. The second control variable (employment status) is positively related to the dependent variable. Moreover, it is statistically significantly related to the dependent variable, as seen by the p-value of 0.0375. The positive beta coefficient value of 0.017342implies that individuals who work more are more likely to

invest in cryptocurrencies.

The estimate of the independent variable continues to be positive and statistically significant (as seen by p-value of <2e-16) even after adding the control variables. The value of its beta coefficient changes from 0.026379 to 0.027081. This signifies that the effect of the independent variable on the dependent variable increases slightly after adding the controls.

This increase can be attributed to the 'Suppression Effect' that is caused by adding the confounder of age into the model. We know that age has a positive correlation with gross monthly income and a negative correlation with investments in cryptocurrency. Therefore, when age wasn't considered in the model, it had suppressed the impact of the IV on the DV. However, now that Age is included in the model, it "suppresses" its own negative correlation with the DV, thereby allowing the true positive relationship between X and Y to emerge more strongly.

4.5. Tests for Mediation: Does investment knowledge mediate the relationship between gross monthly income and investments in cryptocurrency?

The model does not find the moderating variable of change in investment status over the previous year to be independently significant (as seen b p-value of 0.116837). This means that, on its own, the change in an individual's investment status over the past 1 year does not lead to any change in an individual's investments in cryptocurrency. However, the interaction term between our moderating variable and our independent variable is statistically significant (as seen by p-value of 0.000111). This implies that the levels of the moderating variable exert an influence on the relationship between the independent and dependent variables. Put simply, the interaction effect indicates that there is variability in the relationship between the dependent variable and the independent variable as the moderating variable varies across all levels. The beta coefficient, with a value of 0.011160, indicates that an increase in the value of the moderating variable strengthens the relationship between the independent and dependent variables. Therefore, the slope between gross monthly income and cryptocurrency investments will increase or decrease by a factor of 0.011160, contingent on whether investments have increased or decreased over the past year. With the addition of this moderating variable, the other variables in our model change as follows:

1. Gross Monthly Income: The beta coefficient value of our independent variable changes from 0.027081to 0.023243. This decrease in value can be attributed to the fact that some part of the direct effect of the independent variable on the dependent variable is attenuated or moderated by the presence of the moderating variable. This variable continues to remain statistically significant, as seen by the p-value of <2e-16.
2. Age: The beta coefficient value of our first confounder changes from -0.028102to -0.026489. This change indicates that, after considering the moderating variable and its interaction with the independent variable, the effect of age on the dependent variable has been refined/modified. The moderation effect is providing additional insight into how the confounder operates under different conditions. Additionally, this variable continues to remain statistically significant, as seen by the p-value of 0.000205.
3. Employment Status: The beta coefficient value of our second confounder changes from 0.017342 to 0.015480. This decrease in value suggests that, after considering the moderating variable and its interaction with the independent variable, the effect of the second confounder on the dependent variable has decreased. More importantly, this variable is no longer statistically significant at a 5% significance level, as seen by a change in its p-value from 0.0375 to 0.062886. This suggests that, after considering the moderating variable and its interaction with the independent variable, the evidence supporting the significance of employment status weakens. However, the decrease in statistical significance of employment status doesn't necessarily imply that this variable is unimportant. Instead, it may indicate that its impact on the dependent variable is more nuanced and is contingent on the levels of the moderating variable and its interaction with the independent variable.

5. DISCUSSION AND CONCLUSION

5.1. Effect of the Confounders

The analysis reveals evidence that provides further validation for the initial hypothesis. The findings substantiate the present consensus concerning the two variables. The study confirms the hypothesis that a higher gross monthly income level is significantly and positively correlated with investments in cryptocurrency. Given that the sample is representative of millennial internet users as a whole, we can conclude that the findings are applicable to this entire demographic.

With regard to the control variables, the findings indicate that the anticipated negative correlation exists between age and investments in cryptocurrency. Additionally, our hypothesis regarding the second confounder also holds true, and that individuals who work for more hours are in fact more likely to invest in cryptocurrencies.

Considering the mediating variable, we conclude that investment knowledge acts as a crucial mediating factor, given that it is statistically significantly correlated with both the IV and the DV. Additionally, as hypothesised, investment knowledge does increase with higher gross monthly income levels, and an individual possessing more investment knowledge is more likely to invest in cryptocurrency. This can be concluded based on the positive value of the beta coefficients obtained from the tests for mediation.

The moderating variable yields quite intriguing results. It was anticipated that an increase in investments over the past year would lead to more investments in cryptocurrency. Independently, we discovered that the moderating variable is statistically insignificant and had no bearing on the DV. However, it was found that the interaction between the independent and moderating variables was statistically significant and positive in nature. As stated previously, this indicates that with an increase in investments over the past year, the positive relationship between the IV and the DV strengthens.

5.2. Causal Argumentation

Logical connection: There is a logical connection between an individual's gross monthly income and their investment in cryptocurrency, as higher earnings are correlated with greater disposable income and financial capability. In general, those with greater gross monthly income have a lower risk aversion as well as greater access to capital for investments, including those speculative assets such as cryptocurrencies.

Precedence of the cause: Normally, gross monthly income denotes the entirety of an individual's earnings prior to the deductibility of any expenses. This consists of one's salary, compensation, bonuses, and any other employment-related income. It generally excludes any investment returns or gains. As a result of this, precedence of the cause is automatically established. It is evident that investments in cryptocurrency cannot lead to a higher gross monthly income, as the gains or returns from such an investment would not be a part of gross monthly income anyway and hence would have no impact on it. Rather, it is the gross monthly income of an individual that impacts whether or not he/she invests in cryptocurrency.

No alternative explanations: Alternative justifications for investments in cryptocurrency could encompass elements such as an individual's age, employment status, investment knowledge or change in investments over the past year. All of these parameters have been adequately incorporated into the statistical model. Therefore, their impacts on the dependent variable will be accounted for, thereby eliminating or minimising the need for any other alternative explanations.

Hence, given that the regression model yields correlation between the two variables, we can establish a fairly causal relationship between gross monthly income and investment in cryptocurrency.

5.3. Limitations and Venues for future research

In the present study, only internet consumers who are members of the millennial generation are considered. This sample is quite specialised. Therefore, the findings of this research cannot be extrapolated to a broader population. This research is restricted to drawing conclusions regarding internet consumers of the millennial generation. Further

investigation is required to confirm the validity of these findings across various other stratums of the population. Furthermore, it is imperative that various segments of society are considered, encompassing diverse demographic and geographical compositions. Conducting research on a heterogeneous sample will assist in refining the implications associated with studies of an individual's investment behaviour.

In this study, although the survey was conducted on a total of 9698 participants, more than half of this data is discarded even from our early test model due to missingness. This suggests that only a small section of our sample had provided their income level as well as their current status regarding investments in cryptocurrency. This number of data points in our sample drops further as we add control variables and our moderating variable. This decrease in value of the sample size could be one explanation as to why the final model recorded a significantly larger R-squared value as compared to the one used for the initial test. Hence, the causal relationship as explained by our regression analysis may not be the case in reality. Future research should consider this aspect and ensure that these surveys are completed by individuals who are able and willing to share such data in order to obtain more precise and reliable findings.

In this study, our dependent variable is whether or not an individual invests in currency. Since this is a binary variable, OLS regression is not very suitable for such a model. This is because OLS regression makes the assumptions that the dependent variable is continuous and normally distributed, conditions which are clearly getting violated in this case. Therefore, by attempting to fit a straight line to binary data, this study has generated a poor model fit. Future research should consider using logistic regression. After all, this technique is specifically designed for binary outcomes, given that it models the relationship between the independent variables and the log-odds of the probability that the dependent variable equals 1. Alternatively, future research could consider asking individuals how much money they invest into cryptocurrency, thereby getting the data as a continuous variable. Finally, future research should incorporate a larger variety of control variables that would facilitate the derivation of better and more accurate conclusions regarding the causal relationship between the IV and DV. It is imperative to address alternative explanations in order to ensure the validity of a causal study and to carry out more robustness checks on our model.

6. ADVANCED FEATURE

In this section of the paper, we will consider using an additional regression model to validate our results: the logistic regression model. This is likely to be a better fit for this particular data set(considering that our DV is a binary variable), thereby providing a better and more accurate understanding of the relationship between our IV and DV. Using the same variables as before, we construct the following model:
Model:

$$\ln\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = \beta_0 + \beta_1 X + \beta_2 C_1 + \beta_3 C_2 + \beta_4 MoV + \beta_5 X * MoV \quad (1)$$

$$\frac{P(Y=1)}{1-P(Y=1)} = e^{\beta_0 + \beta_1 X + \beta_2 C_1 + \beta_3 C_2 + \beta_4 MoV + \beta_5 X * MoV} \quad (2)$$

$$P(Y=1) = \frac{e^{\beta_0 + \beta_1 X + \beta_2 C_1 + \beta_3 C_2 + \beta_4 MoV + \beta_5 X * MoV}}{1 + e^{\beta_0 + \beta_1 X + \beta_2 C_1 + \beta_3 C_2 + \beta_4 MoV + \beta_5 X * MoV}} \quad (3)$$

```
# logistic regression
log_reg<-glm(Investment_Crypto~GrossMonthlyInc
+GrossMonthlyInc*Change_In_Inv+ Change_In_Inv
+Age+Employment_Status+ Investment_Knowledge,
family = binomial)
summary(log_reg)
```

We obtain the results (see Appendix Figure A6)
We can interpret two aspects of these results:

1. The goodness of the fit: The residual deviance in our model is 4553.5, which is lower than the null deviance. This reduction in deviance suggests an improvement in fit over a model with no predictors. Therefore, our model performs better than a null model. Additionally, the AIC value of 4567.5 is a relatively lower value. This suggests that, considering the trade-off with the number of parameters, the model provides a good fit.
2. The coefficients: In this case, we can interpret the beta coefficients of each of the variables as the change in the log-odds of the probability that Y = 1, given that each of the variables changes by one unit, holding all the other variables constant. We observe that the same variables are statistically significant in is model, and their respective beta coefficients have the same sign as compared to the OLS model. This validates our OLS results further.

APPENDIX

Figure A1: *Regression Results: Effect of Gross Monthly Income on Cryptocurrency Investment*

```
Call:
lm(formula = Investment_Crypto ~ GrossMonthlyInc)

Residuals:
    Min      1Q  Median      3Q     Max
-0.3526 -0.2207 -0.1680 -0.1152  0.8848

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     0.088826   0.011918   7.453 1.08e-13 ***
GrossMonthlyInc 0.026379   0.002558  10.312  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3933 on 4779 degrees of freedom
  (4917 observations deleted due to missingness)
Multiple R-squared:  0.02177,   Adjusted R-squared:  0.02156
F-statistic: 106.3 on 1 and 4779 DF,  p-value: < 2.2e-16
```

Source: Author's calculations

Figure A2: *Regression Results: Effect of Income, Age, and Employment Status on Cryptocurrency Investment*

```
Call:
lm(formula = Investment_Crypto ~ GrossMonthlyInc + Age + Employment_Status)

Residuals:
    Min      1Q  Median      3Q     Max
-0.3881 -0.2236 -0.1694 -0.1097  0.9465

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        0.058679   0.037976   1.545   0.1224
GrossMonthlyInc    0.027081   0.002672  10.134  < 2e-16 ***
Age               -0.028102   0.007143  -3.934 8.46e-05 ***
Employment_Status  0.017342   0.008333   2.081   0.0375 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3928 on 4768 degrees of freedom
  (4926 observations deleted due to missingness)
Multiple R-squared:  0.02528,   Adjusted R-squared:  0.02467
F-statistic: 41.22 on 3 and 4768 DF,  p-value: < 2.2e-16
```

Source: Author's calculations

Figure A3: *Regression Results: Effect of Gross Monthly Income on Cryptocurrency Knowledge*

```
Call:
lm(formula = Investment_Knowledge ~ GrossMonthlyInc)

Residuals:
    Min      1Q  Median      3Q     Max
-2.6572 -0.8733  0.2574  0.9960  1.5187

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.350689   0.029753   45.40   <2e-16 ***
GrossMonthlyInc 0.130652   0.006655   19.63   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.112 on 5730 degrees of freedom
  (3966 observations deleted due to missingness)
Multiple R-squared:  0.06302,   Adjusted R-squared:  0.06286
F-statistic: 385.4 on 1 and 5730 DF,  p-value: < 2.2e-16
```

Source: Author's calculations

Figure A4: *Regression Results: Effect of Income, Change in Investment, Age, and Employment Status on Cryptocurrency Investment*

```
Call:
lm(formula = Investment_Crypto ~ GrossMonthlyInc + GrossMonthlyInc *
    Change_In_Inv + Change_In_Inv + Age + Employment_Status)

Residuals:
    Min      1Q  Median      3Q     Max
-0.4467 -0.2133 -0.1635 -0.1106  0.9468

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                  0.072622   0.037956   1.913 0.055767 .
GrossMonthlyInc              0.023243   0.002766   8.402  < 2e-16 ***
Change_In_Inv               -0.020831   0.013281  -1.568 0.116837
Age                         -0.026489   0.007129  -3.716 0.000205 ***
Employment_Status            0.015480   0.008321   1.860 0.062886 .
GrossMonthlyInc:Change_In_Inv  0.011160   0.002884   3.869 0.000111 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3917 on 4766 degrees of freedom
  (4926 observations deleted due to missingness)
Multiple R-squared:  0.03123,   Adjusted R-squared:  0.03021
F-statistic: 30.72 on 5 and 4766 DF,  p-value: < 2.2e-16
```

Source: Author's calculations

Figure A5: *Regression Results: Effect of Gross Monthly Income on Cryptocurrency Knowledge*

```
Call:
lm(formula = Investment_Knowledge ~ GrossMonthlyInc)

Residuals:
    Min      1Q  Median      3Q     Max
-2.6572 -0.8733  0.2574  0.9960  1.5187

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    1.350689   0.029753   45.40   <2e-16 ***
GrossMonthlyInc 0.130652   0.006655   19.63   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.112 on 5730 degrees of freedom
  (3966 observations deleted due to missingness)
Multiple R-squared:  0.06302,   Adjusted R-squared:  0.06286
F-statistic: 385.4 on 1 and 5730 DF,  p-value: < 2.2e-16
```

Source: Author's calculations

Figure A6: *Regression Results: Effect of Income, Knowledge, and Demographic Variables on Cryptocurrency Investment*

```
Call:
glm(formula = Investment_Crypto ~ GrossMonthlyInc + GrossMonthlyInc *
    Change_In_Inv + Change_In_Inv + Age + Employment_Status +
    Investment_Knowledge, family = binomial)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.2243  -0.6825  -0.5764  -0.4613   2.3434

Coefficients:
                             Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -2.85366    0.28119 -10.149  < 2e-16 ***
GrossMonthlyInc              0.12675    0.01808   7.008 2.41e-12 ***
Change_In_Inv               -0.10230    0.09235  -1.108  0.26799
Age                         -0.17569    0.04784  -3.672  0.00024 ***
Employment_Status            0.11218    0.05768   1.945  0.05179 .
Investment_Knowledge         0.28426    0.04538   6.263 3.77e-10 ***
GrossMonthlyInc:Change_In_Inv  0.05600    0.01871   2.994  0.00276 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 4735.6  on 4771  degrees of freedom
Residual deviance: 4553.5  on 4765  degrees of freedom
  (4926 observations deleted due to missingness)
AIC: 4567.5

Number of Fisher Scoring iterations: 4
```

Source: Author's calculations

REFERENCES

1. "2018 Cryptocurrency Survey - Foley & Lardner LLP," n.d. https://www.readkong.com/page/2018-cryptocurrency-survey-4545930.

2. Aiello, David, Scott R. Baker, Tetyana Balyuk, Marco Di Maggio, and Michael J. Johnson, 2024. The Effects of Cryptocurrency Wealth on Household Consumption and Investment. Working Paper. Federal Deposit Insurance Corporation. https://www.fdic.gov/system/files/2024-07/johnson-paper.pdf

3. Ante, Lennart, 2020. Individual Cryptocurrency Investors: Evidence from a Population Survey. BRL Working Paper No. 6. Blockchain Research Lab. https://www.blockchainresearchlab.org/wp-content/uploads/2020/05/BRL Working-Paper-No-6-Individual Cryptocurrency-Investors-Evidence-From-A-Population-Survey.pdf

4. Campino, João, et al,2024. "Decoding the Cryptocurrency User: An Analysis of Demographics and Sentiments." https://www.sciencedirect.com/science/article/pii/S2405844024027026

5. Colombo, João A,2024. "Are Crypto and Non-Crypto Investors Alike? Evidence from a Brazilian Digital Platform." https://www.sciencedirect.com/science/article/pii/S0160791X24000162

6. Elu, Juliet, and Miesha Williams, October 21, 2022. "COVID-19 Cryptocurrency Investment: Wealth Disparities and Portfolio Diversification." Journal of Economics, Race, and Policy. https://doi.org/10.1007/s41996-022-00108-6.

7. Fujiki, Hiroshi(May 18, 2021). "Crypto Asset Ownership, Financial Literacy, and Investment Experience." Applied Economics 53, no. 39: 4560–8. https://doi.org/10.1080/00036846.2021.1904125.

8. Hayashi, Fumiko, and Irena Routh, August 2024. Financial Literacy, Risk Tolerance, and Cryptocurrency Ownership. Kansas City Fed Working Paper No. RWP24-03. Federal Reserve Bank of Kansas City. https://www.kansascityfed.org/documents/10038/rwp24-03hayashirouth.pdf

9. Malmendier, Ulrike, Stefan Nagel, and Zhen Yan (April 11, 2020). "The Making of Hawks and Doves." Journal of Monetary Economics 117: 19–42. https://doi.org/10.1016/j.jmoneco.2020.04.002.

10. Steinmetz, Fred, Marc Von Meduna, Lennart Ante, and Ingo Fiedler (August 14, 2021). "Ownership, Uses and Perceptions of Cryptocurrency: Results from a Population Survey." Technological Forecasting and Social Change 173: 121073. https://doi.org/10.1016/j.techfore.2021.121073.

11. Weber, Michael,2023. Do You Even Crypto, Bro? Cryptocurrencies in Household Finance. NBER Working Paper w31284. National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w31284/w31284.pdf

12. Xi, Dingli, Timothy Ian O'Brien, and Elnaz Irannezhad (August 6, 2020). "Investigating the Investment Behaviors in Cryptocurrency." The Journal of Alternative Investments 23, no. 2 : 141–60. https://doi.org/10.3905/jai.2020.1.108.

13. Zhao, Haidong, and Lini Zhang (June 1, 2021). "Financial Literacy or Investment Experience: Which Is More Influential in Cryptocurrency Investment?" International Journal of Bank Marketing 39, no. 7: 1208–26. https://doi.org/10.1108/ijbm-11-2020-0552.