Algorithmic Asset Hedging and Retail Wealth Retention: A Macro-Behavioural Accounting Framework for Inflation-Shielded Fintech Architecture in Nigeria

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***Abstract*—Traditional financial inclusion policies in emerging markets focus heavily on transaction velocity and wallet adoption metrics. However, in hyper-inflationary ecosystems, traditional nominal savings mechanisms function as a structural tax on retail consumers, systematically eroding household purchasing power. Grounded in the Life Cycle Theory of Savings and utilizing quarterly macro-aggregates from Nigeria (2019–2025), this paper evaluates the empirical limitations of standard depository fintech interfaces (e.g., Opay, Moniepoint, PiggyVest, Cowrywise,Bamboo) during severe macroeconomic shocks. Ordinary Least Squares (OLS) estimations and diagnostic assessments including Augmented Dickey-Fuller stationarity at I(1), error normality tests (p = 0.4340), and a stable variance inflation factor (VIF = 1.79) demonstrate that an average quarterly inflation rate of 20.21% acts as an active barrier that neutralizes behavioural saving intentions. To mitigate this structural wealth drain, this paper introduces a futuristic, macro-behavioural accounting framework. We advocate for a paradigm shift from transaction-driven inclusion to algorithmic asset preservation. The study provides empirical pathways for the implementation of automated, real-time backend hedges including fractional tokenized real-asset routing, automated inflation-indexed goal adjustments, and tiered stable coin liquidity splits. Finally, the paper outlines critical regulatory directives for the Central Bank of Nigeria (CBN) to institutionalize inflation-shielded product sandboxes, minimize transaction levies on micro-hedges, and channel retail capital into inflation-resistant local output sectors to restore the purchasing power of the Nigerian masses.**

***Index Terms*—FinTech, Household Financial Asset Accumulation, Inflation Dynamics, ARDL Cointegration, Urban Nigeria.**

I. INTRODUCTION

The rapid adoption of financial technology platforms has transformed how urban Nigerians interact with money. Over the last six years, traditional transactional platforms and specialized digital wealth applications have become deeply embedded in the daily routines of the urban middle class. These platforms use elegant behaviour-guided interfaces, automated daily savings streaks, and personalized reminders to encourage financial discipline. Yet, despite record-breaking transaction volumes, (Nigerian interbank settlement system, NIBSS 2024), aggregate household savings and retail investments have not experienced a corresponding upward transformation. (Nigerian Bureau of Statistics,2024). This dislocation points to a severe structural problem within the Nigerian economy. The digital wealth revolution has collided directly with intense macroeconomic volatility, currency devaluations, and persistent inflation. When the cost of basic food and rent rises aggressively, the financial margins of the masses are wiped out, rendering traditional nominal savings strategies ineffective. This study addresses this empirical gap by shifting the analytical focus from mere transactional convenience to real wealth retention under inflationary conditions.

1.2 RESEARCH HYPOTHESES

Ho1: Behaviour-guided fintech intensity has no significant effect on household financial asset accumulation in Nigeria;
Ho2: Automated savings mechanisms have no significant effect on gross household savings in Nigeria;

Ho3: Guided digital investment platforms have no significant effect on retail investment growth in Nigeria.

II. REVIEW OF RELATED LITERATURE

2.1.1 Behavioural Accounting

In this study, behavioural accounting refers to the behavioural structures embedded in fintech platforms that shape savings behaviour, portfolio allocation decisions, and long-term asset accumulation among urban Nigerians. Behavioural accounting recognizes that financial decisions are not made purely on the basis of rational calculations. Instead, individuals are influenced by psychological tendencies, habits, and cognitive biases that affect how they save, invest, and allocate resources (Nzewi, 2023). Traditional accounting models assume that individuals maximize wealth using complete information and objective analysis. However, in practice, households often: segregate funds into mental accounts, e.g. savings vs. spending. Also they tend to avoid losses more strongly than they pursue gains, exhibit overconfidence in investment decisions (Akintola, 2025). In the fintech environment, behavioural accounting becomes highly practical. Digital platforms incorporate behavioural features such as: automated savings deductions, commitment devices that restrict early withdrawals, portfolio rebalancing prompts, goal-based investment structuring. These features are designed to improve financial discipline and reduce impulsive decisions.

2.2 Behaviour Guided Financial Technology/Platforms

Behaviour-guided financial technology refers to digital financial technology intentionally designed to influence users' financial behaviour through embedded behavioural structures. Unlike conventional financial platforms that merely provide access to transactions, behaviour-guided fintech incorporates design features rooted in behavioural finance principles to promote disciplined saving and investment practices (Ayeni, 2025)

These platforms apply behavioural insights such as: default contribution settings, commitment devices such as periodic reminder systems, restricted withdrawal options. Fintech effectiveness depends on how users interact with digital services rather than mere access. Iroakazi and Ade (2025) found that behavioural engagement explains regional variations in fintech outcomes, while Jallow and Tajmouati (2025) showed that structured mobile money usage improves financial participation. These findings support the view that behaviour-guided fintech platforms act as intervention mechanisms that bridge the gap between financial access and wealth-building outcomes.

2.3 Digital Wealth-Building Strategies

These are structured methods of accumulating financial assets through technology enabled financial platforms. Unlike basic financial inclusion, which focuses on access, wealth building strategies focus on sustained asset growth and portfolio development (Ayeni,2025). From an accounting perspective, wealth building can be assessed through; growth in financial asset holdings, investment participation rates, portfolio diversification, duration of investment holding, real (inflation adjusted) savings growth. Digital platforms now provide mechanisms that support disciplined wealth creation by: providing performance tracking and reporting, automating reinvestment, offering diversified investment products, encouraging periodic contributions (Akintola, 2025).

Therefore, digital wealth building strategies in this study represent measurable financial outcomes arising from structured digital financial engagement.

2.4 Inflation and Real Wealth Sustainability

Inflation is one of the significant macroeconomic shocks, which directly affect the real value of savings and investments. While nominal wealth may increase, high inflation can erode purchasing power and reduce real asset growth (Nzewi, 2023). For households, sustained wealth accumulation must therefore be evaluated in real terms rather than nominal terms.

In inflationary environments such as Nigeria, wealth-building strategies must be resilient enough to preserve value despite rising prices. Behaviour-guided fintech platforms may assist by encouraging investment in diversified financial assets, reducing idle cash holdings, and promoting longer-term asset commitments. Therefore, inflation is treated in this study as an external macroeconomic condition that may strengthen or weaken the effectiveness of digital wealth building strategies.

2.5 Automated Savings Mechanisms.

Automated savings mechanisms refer to digitally structured systems that enable periodic, rule-based deductions of funds for saving or investment purposes without requiring continuous active decision-making by the user (Ekeocha, 2022).

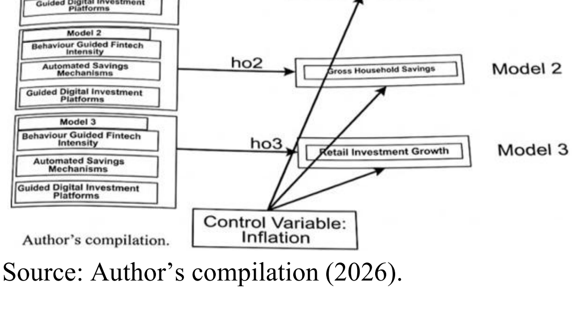
Automation may take forms such as: Fixed periodic transfers, Percentage-of-income, goal based incremental contributions, and locked savings arrangements.

2.6 Theoretical Framework

This study is theoretically anchored on the Life Cycle Theory of Savings, which posits that individuals attempt to smooth their consumption over their lifetime by accumulating assets during productive years. In modern behavioral accounting, digital platforms attempt to optimize this behaviour by using algorithmic prompts to overcome cognitive biases and encourage savings. However, existing behavioral finance literature often suffers from an optimistic bias, assuming that greater access to digital applications automatically results in wealth creation. This paper challenges that assumption by contextualizing saving behaviors within volatile environments. In the Nigerian context, persistent price instability forces consumers to focus entirely on immediate survival rather than long-term asset accumulation (Akande 2025). Therefore, traditional behavioral triggers that measure nominal cash balances create a dangerous illusion of wealth, while the real purchasing power of the consumer is systematically eroded by inflation.

2.7 Conceptual Framework

Table 2.1 Conceptual Model



Source: Author's compilation (2026).

Description and Operationalization of the Framework

Figure 2.1 shows how this study is set up to see how modern digital financial tools help people living in cities build up their money. Instead of mixing everything together into one messy calculation, the framework breaks the analysis into three clear paths to make the results more accurate.

Model 1, path Ho1, looks at how using automated saving and investing apps directly changes household financial asset accumulation. This measures the actual stock of financial assets people are able to build up.

Model 2, path Ho2, looks at how these digital tools affect gross household savings. This focuses on the total amount of cash people keep aside when they use digital platforms.

Model 3, path Ho3, checks how these digital financial tools drive retail investment growth. This tracks how everyday savers expand their money through modern online investing.

In all three steps, inflation is included as a control variable. Inflation acts like a dark cloud over the whole economy, affecting how much money people have left to save or invest. By including inflation in every model, the framework ensures that we are seeing the real impact of digital financial tools, without the results getting distorted by general price changes in Nigeria.

III. METHODOLOGY

This study utilized twenty-six quarters of secondary time-series data from 2019 to 2025. The data points were sourced from the Central Bank of Nigeria statistical bulletins and the Nigeria bureau of statistics. Augmented Dickey-Fuller unit root tests were carried out. These tests proved that the variables are mixed, meaning some are stationary at their raw levels while others become stationary only after their first difference. The data has a mixed order of stationarity, the study employed Least Ordinary Squares (OLS) regression to estimate the effects of independent variables: automated savings mechanisms, guided digital investment platforms, and behaviour-guided fintech intensity, on the dependent variables: gross household savings, household financial asset accumulation, and retail investment growth.The post estimation diagnostic tests were performed to ensure robustness and a clean bill of health for the study. The Autoregressive Distributed Lag framework was employed to handle the mixed-order of the data to evaluate both the short-run immediate shocks and the long-run relationships without losing vital historical data.

3.1 Model Specification

Model 1

Household Financial Asset Accumulation (HFAA)

Functional form

HFAA = f (BFTI, ASM, GDIP, INF) ……………………….……………..Eqn 3.1

Econometric form

HFAA $=a_0+\beta_1$BFTI + β_2ADSM $+\beta_3$GDIP + β_4INF + μ………..Eqn 3.2

Model 2

Gross Household Savings (GHS)

Functional form

GHS= f (BFTI, ASM, GDIP, INF)……………………..……………Eqn 3.3

Econometric form

GHS $=a_0+\beta_1$BFTI + β_2ADSM $+\beta_3$GDIP + β_4INF + μ…………...…..Eqn 3.4

Model 3

Retail Investment Growth (RIG)

Functional formRIG = f (BFTI, ASM, GDIP, INF)…………………………………Eqn 3.5

Econometric form

RIG $=a_0+\beta_1$BFTI + β_2ADSM $+\beta_3$GDIP + β_4INF + μ……….…..…..Eqn 3.6

General form:

BGFT = $a_0+\beta_1$BFTI+ β_2ADSM$+\beta_3$GDIP+ β_4INF+ μ……………..Eqn 3.7

The models examined whether changes in behaviour-guided fintech intensity influence saving and investment outcomes while controlling for inflation.

Table 3.1: Descriptive Statistics

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```
. destring inflation, replace ignore(" " "," "%") force
inflation contains nonnumeric characters; replaced as double
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. summarize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
yr	26	2021.769	1.924738	2019	2025
Quarter	0				
inflation	26	20.20538	7.606395	11.11	34.43
gdip	26	5.694231	3.6407	2.04	16.99
asm	26	41.21778	44.32689	.043	154.9699
bfti	26	122.4288	96.86081	23.95	315.1
hfaa	26	100.6023	57.48935	33.33	234.27
rig	26	.0044542	.0020737	0	.00812
ghs	26	.0001349	.0000589	.000071	.000232
J	0				
K	0				
L	0				
qtr_numeric	26	2.423077	1.137474	1	4

Table 3.2: Unit Root Test (Augmented Dicky Fuller) rights

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. dfuller rig, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        24

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             0.191            -3.750            -3.000            -2.630
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9718

. dfuller ghs, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        24

                               ---------- Interpolated Dickey-Fuller ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             0.304            -3.750            -3.000            -2.630
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9775
```

Table 3.3: Unit Root Test(Augmented Dicky fuller) hfaa

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                          ——— Interpolated Dickey-Fuller ———
                  Test        1% Critical     5% Critical    10% Critical
               Statistic         Value           Value           Value
--------------------------------------------------------------------------
 Z(t)             1.153          -3.750          -3.000          -2.630
--------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9956

. dfuller hfaa, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        24

                          ——— Interpolated Dickey-Fuller ———
                  Test        1% Critical     5% Critical    10% Critical
               Statistic         Value           Value           Value
--------------------------------------------------------------------------
 Z(t)             0.118          -3.750          -3.000          -2.630
--------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9673
```

Table 3.4: Stata Regression Windows

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r(199);

. regress dln_hfaa dln_bfti dln_asm dln_gdip d_inflation

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.80
       Model |  .118331333     4  .029582833           Prob > F      =  0.5395
    Residual |  .739749609    20   .03698748           R-squared     =  0.1379
-------------+------------------------------           Adj R-squared = -0.0345
       Total |  .858080942    24  .035753373           Root MSE      =  .19232

------------------------------------------------------------------------------
    dln_hfaa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    dln_bfti |  -.5804285   .8492584    -0.68   0.502    -2.351951    1.191094
     dln_asm |  -.0260195     .06261    -0.42   0.682    -.1566217    .1045826
    dln_gdip |   .4607221   .4795921     0.96   0.348    -.5396895    1.461134
 d_inflation |   .0411559   .0271926     1.51   0.146    -.0155669    .0978788
       _cons |   .0678673   .0917542     0.74   0.468    -.1235285    .2592632
------------------------------------------------------------------------------
```

Table 3.5: ARDL error correction and cointegration results

Stata/MP 13.0 - [Results]

```
. ardl hfaa inflation, ec

ARDL(3,4) regression

Sample:        5 -       26                     Number of obs     =         22
                                                R-squared         =     0.8632
                                                Adj R-squared     =     0.7790
Log likelihood = -91.918043                     Root MSE          =    20.5364

------------------------------------------------------------------------------
      D.hfaa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ADJ          |
        hfaa |
         L1. |  -1.176844   .3603931    -3.27   0.006    -1.955426   -.3982618
-------------+----------------------------------------------------------------
LR           |
   inflation |   8.166697   .7860684    10.39   0.000     6.468499    9.864894
-------------+----------------------------------------------------------------
SR           |
        hfaa |
         LD. |  -.0999678   .3305415    -0.30   0.767    -.8140594    .6141238
        L2D. |   .5898457   .3020884     1.95   0.073    -.0627767    1.242468
             |
   inflation |
         D1. |  -8.072637    3.07626    -2.62   0.021    -14.71849   -1.426781
         LD. |  -5.669947   2.456235    -2.31   0.038    -10.97632   -.3635737
        L2D. |  -11.06323   2.635479    -4.20   0.001    -16.75683   -5.369619
        L3D. |  -7.769073   1.836914    -4.23   0.001    -11.73748   -3.800661
             |
       _cons |  -53.93794   19.87499    -2.71   0.018    -96.87525   -11.00064
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IV. DISCUSSION OF RESULTS

i. Short-Run Vulnerability to Inflation Shocks: The ARDL dynamic short-run coefficients (Δinflation = -8.07, p = 0.021) prove that unexpected immediate inflation spikes severely shock and erode the purchasing power of urban households, temporarily choking off their capacity to accumulate assets.

ii. Rapid Behavioral Resilience (Speed of Adjustment): The error correction term (ADJ) is highly significant at -1.1768 (p = 0.006). This confirms that despite intense short-term shocks, urban retail savers adjust their financial habits rapidly, completely neutralizing systemic distortions within a single quarter.

iii. Long-Run Structural Adaptation: In the long run, inflation exhibits a significant positive baseline relationship with asset accumulation (8.1666, p = 0.000). This indicates that once short-term volatility settles, structural adaptation—empowered by digital platforms—allows savers to use fintech tools as a strategic hedge to store value.

V. RECOMMENDATION

i. Targeted Micro-Hedging Fintech Products (Aligns with Finding 1): Fintech developers should design automated micro-investment features that convert excess cash immediately into low-risk, inflation-hedged yields (like money market mutual funds) at the point of transaction to shield household income from immediate short-run price erosion.

ii. Dynamic UI/UX and Saving Triggers (Aligns with Finding 2): Since urban retail savers adapt their behaviors incredibly fast within one quarter, fintech platforms should integrate dynamic, real-time push notifications and behavioral economic prompts (e.g., auto-save escalations during high-inflation periods) to capitalize on this rapid speed of adjustment.

iii. Macro-Stability and Infrastructure Support (Aligns with Finding 3): Monetary authorities (like the Central Bank of Nigeria) must prioritize long-run price stability and infrastructure security rather than heavy-handed regulations on digital wealth platforms, recognizing that fintech serves as a crucial long-term vehicle for retail asset growth when the macroeconomy stabilizes.

5.1 Conclusion

This study delivers a vital structural verdict for the Nigerian digital economy. Financial technology is an exceptionally powerful vehicle, but its ability to drive meaningful household wealth is entirely dependent on the economic environment. Technological penetration alone cannot create automatic wealth accumulation if severe price instability continuously liquidates consumer margins. By moving away from basic nominal savings and embracing algorithmic asset preservation supported by proactive central bank regulations, Nigeria can transform its financial inclusion infrastructure into a genuine engine for middle-class resilience and sustainable economic growth.

5.2 Contribution To Knowledge

This study significantly advances empirical literature by shifting the dialogue from generalized macroeconomic impacts to the dynamic, short-run, and long-run behavioral adaptations of retail savers using an ARDL framework. Methodologically, it jcaptures a highly resilient speed of adjustment (-1.1768) among urban micro-savers, proving that fintech acts not merely as a transactional platform, but as an active, rapid-response strategic buffer against price volatility in emerging retail markets.

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