Financial Well-Being Stratification among Urban Households: A Multinomial Logit Analysis of Digital Payments, Saving Behavior, and Credit Access

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ABSTRACT

Rising global economic uncertainty in the aftermath of the COVID-19 pandemic has underscored the importance of household financial well-being (FWB) as a key pillar of economic resilience, particularly in urban settings. This study analyzes how digital payment adoption, saving behavior, and access to credit contribute to the stratification of FWB among urban households in Indonesia. The analysis uses microdata from the 2017 Survey on Financial Inclusion and Access (SOFIA), focusing on a sub-sample of 2,368 urban households aged 19–40 years across four provinces. FWB is constructed as an ordered categorical variable with four levels Low, Medium, High, and Very High based on multiple indicators of financial capability and access. A multinomial logit model is employed, with results interpreted using Average Marginal Effects (AMEs). The findings indicate that regular saving behavior and access to formal credit are the most consistent determinants of upward mobility across FWB categories. Regular saving significantly reduces the likelihood of being in the Low and Medium FWB categories and substantially increases the probability of attaining High FWB. Access to credit strongly increases the likelihood of reaching the Very High FWB category. The results suggest that financial inclusion in urban contexts should be understood as a combination of disciplined financial behavior and deeper engagement with formal financial services.

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1. INTRODUCTION

Global economic uncertainty has intensified markedly in the aftermath of the COVID-19 pandemic, once again underscoring the central role of household financial well-being (FWB) as a key pillar of family resilience. The pandemic triggered both a public health and financial crisis, leading to widespread declines in household income and purchasing power across countries, including Indonesia (Subroto et al., 2025). Conceptually, FWB refers to a state of financial welfare in which households are able to meet daily needs, remain prepared for unexpected financial shocks, feel secure about their future, and retain the autonomy to make economic decisions that enable them to enjoy life (Kurowski, 2021).

Higher levels of FWB are consistently associated with greater resilience during times of crisis, whereas low FWB increases households' exposure to financial vulnerability (Pandin et al., 2021). In Indonesia, fewer than 10% of households possess savings sufficient to cover more than twelve months of living expenses, while the majority can sustain themselves for less than one month. This reflects a high degree of financial fragility amid ongoing economic volatility (Yan & Basri, 2022).

At the same time, rapid digitalization of the financial sector has transformed the ways in which households manage their finances, with significant implications for their level of FWB (Dluhopolskyi et al., 2023). In Indonesia, financial inclusion has expanded substantially alongside the growing adoption of digital financial services, including mobile banking and digital wallets. These innovations have been shown to accelerate financial inclusion and contribute to economic sustainability during the pandemic (Makusara et al., 2025).

The adoption of digital financial services surged during the pandemic, particularly through the increased use of contactless payment systems to facilitate safe transactions under social mobility restrictions (Kotjoprayudi & Kastaman, 2023). However, expanded access to financial services does not automatically lead to reduced disparities in financial well-being. Empirical evidence suggests that access to formal credit and the practice of regular saving remain persistent challenges in Indonesia (Sari & Sulistyaningrum, 2025).

Despite improvements in financial inclusion, household saving behavior remains weak, and the utilization of formal credit is uneven especially among lower and middle-income households (Salam & Hermanto, 2020). This indicates that broader access to financial services has not yet been matched by an equitable distribution of FWB. Vulnerable groups continue to face constraints related to limited financial literacy and restricted access to capital (Setiawan et al., 2023).

From an academic perspective, empirical studies on household FWB in Indonesia remain relatively limited. Existing research often examines financial determinants in isolation such as financial literacy, saving behavior, or the use of financial technology without employing comprehensive analytical approaches, including multinomial logit models, to classify household FWB levels (Setyawan & Listyarti, 2024). An integrated framework is therefore needed to capture the simultaneous effects of payment channels, saving behavior, and access to formal credit on household financial well-being (Rahmanto et al., 2023).

Moreover, household saving behavior has been shown to shift significantly during periods of heightened economic uncertainty. Evidence from Rwanda, for example, indicates an increased propensity to save as a survival strategy during the pandemic (Tafa et al., 2022). Concurrently, strong financial literacy has been identified as a protective factor against financial vulnerability in times of crisis. Against this backdrop, the present study aims to examine how digital payment channels, saving behavior, and access to formal credit influence the likelihood of urban households falling into specific FWB categories, using a multinomial logit approach. The findings are expected to provide a more comprehensive empirical understanding of the stratification of household financial well-being in

Indonesia and to inform the development of more equitable and sustainable financial inclusion policies (Mansour, 2021; Kohardinata et al., 2024).

2.   METHODS

This study utilizes data from the 2017 Survey on Financial Inclusion and Access (SOFIA), conducted across four provinces in eastern Indonesia: East Java, West Nusa Tenggara (NTB), East Nusa Tenggara (NTT), and South Sulawesi. The survey covers approximately 20,000 adult respondents residing in these provinces and provides comprehensive information on household financial behavior, including the use of digital payment services, saving practices, access to credit, insurance participation, and other dimensions of financial inclusion.

For the purposes of this analysis, a specific sub-sample was extracted from the SOFIA 2017 dataset. The study focuses on young adult households aged 19–40 years living in urban areas. After applying a series of data filtering procedures based on these criteria, the final analytical sample comprises 2,368 individuals. This sub-sample represents a more homogeneous target population namely, young adults in urban settings thereby allowing for a more focused analysis and reducing potential distortions caused by excessive population heterogeneity.

Sampling Design and Data Screening Procedures

The SOFIA 2017 survey was designed using a multi-stage random sampling framework, covering 93 districts, 1,250 enumeration areas, and approximately 20,000 respondents across the four target provinces. From the full survey sample, a stepwise data screening process was conducted as follows.

First, an age-based selection was applied by restricting the sample to respondents aged 19–40 years. This age cohort represents young adults who are typically in their productive and economically active life stage. The age restriction was imposed to maintain analytical focus on a relatively uniform financial life-cycle group and to minimize potential bias arising from intergenerational differences in financial behavior.

Second, a geographic filter was introduced by selecting only respondents residing in urban areas. This urban focus aligns with the study's research context, as urban households are presumed to face different financial infrastructure conditions and enjoy greater access to digital financial services compared to their rural counterparts.

The application of these criteria resulted in a final sample of 2,368 individuals, representing urban households headed by young adults aged 19–40 years. Concentrating on this specific segment enhances population homogeneity and helps avoid aggregation bias that may occur when highly heterogeneous groups are analyzed together without adequate stratification. As a result, this sampling strategy strengthens the internal validity of the study by reducing the influence of confounding factors associated with cross-group differences.

Research Variables

This study employs one dependent variable and several independent variables. Table X summarizes the definitions and measurement of each variable.

Table 1. Variables and Measurement

Variables	Measurement
Financial Well-Being (FWB)	Financial well-being (FWB) serves as the dependent variable in this study. It is a household-level financial well-being index constructed from five core indicators: (1) the ability to manage household financial decisions, (2) saving behavior (i.e., possession of savings), (3) access to loans or credit, (4) ownership of insurance, and (5) allocation of funds for productive purposes. Each respondent is assigned an FWB score ranging from 1 to 5, where 1 represents the lowest level of financial well-being and 5 represents the highest level, based on the combined performance across the five indicators. However, within the urban sub-sample, the FWB category equal to 1 contains only a very limited number of observations. Consequently, this category is excluded from the empirical analysis. As a result, FWB is analyzed as an ordered categorical variable with four levels: Low (level 2), Medium (level 3), High (level 4), and Very High (level 5).
Payment (dummy)	Payment is the primary independent variable and is defined as a binary indicator that takes the value of 1 if the respondent uses electronic or non-cash payment instruments—such as e-wallets, mobile banking applications, or digital cards—for financial transactions, and 0 otherwise. This variable captures the adoption of digital payment channels in household economic activities.
Sent (dummy)	ent is a binary independent variable that equals 1 if the respondent sends money through bank-based transfer mechanisms (e.g., remittances via bank accounts), and 0 otherwise. This variable reflects the use of formal, bank-mediated fund transfer services.
Transfer (dummy)	Transfer is another binary independent variable, coded as 1 if the respondent transfers money through over-the-counter (OTC) services or cash-based money transfer providers (such as post offices, Western Union, or authorized agents), and 0 otherwise. This variable indicates the frequency of cash-based or semi-digital transfer channel usage.

This study employs a multinomial logit regression model to examine the factors influencing the level of household Financial Well-Being (FWB) in urban areas. The multinomial logit approach is appropriate because the dependent variable, Financial Well-Being (FWB), is defined as a discrete, ordered categorical outcome consisting of four levels: Low, Medium, High, and Very High. Given the categorical nature of the outcome variable, the probability that an individual belongs to a particular FWB category is modeled using a multinomial logit framework.

Formally, the probability that individual *i* is classified into FWB category *m* is specified as:

$$P(Y_i = m) = \frac{\exp(\mathbf{x}_i^\top \boldsymbol{\beta}_m)}{\sum_{k=1}^{M} \exp\left(\mathbf{x}_i^\top \boldsymbol{\beta}_k\right)}, m = 1, 2, \ldots, M.$$

where Y_i denotes the observed FWB category for individual i, x_i represents a vector of independent variables (covariates), β_m is the vector of regression coefficients associated with category m, and M denotes the total number of outcome categories. In this study, $M = 4$, corresponding to the four FWB categories ranging from Low to Very High.

Parameter estimation is conducted using the **Maximum Likelihood Estimation (MLE)** method, which identifies the set of parameters β_m that maximizes the likelihood of observing the distribution of FWB categories present in the data. The log-likelihood function for the multinomial logit model is expressed as:

$$\ln \mathcal{L}(\boldsymbol{\beta}) = \sum_{i=1}^{N} \sum_{m=1}^{M} \mathbb{I}(y_i = m) \ln [P(Y_i = m)],$$

where $\mathbb{I}(y_i = m)$ is an indicator function that equals 1 if the observed FWB category for individual i is m, and 0 otherwise. The term $P(Y_i = m)$ represents the predicted probability of individual i belonging to category m as defined by the multinomial logit specification.

The estimation procedure relies on iterative numerical optimization algorithms to obtain parameter estimates $\hat{\beta}_m$ that maximize the log-likelihood function. These estimated coefficients are subsequently used to compute marginal effects, which facilitate interpretation of how changes in explanatory variables influence the probability of households being classified into each FWB category.

In this analysis, all independent variables both the main explanatory variables and the control variables—are incorporated simultaneously into the multinomial logit model. The estimation results are presented in the form of Average Marginal Effects (AMEs) for the key variables of interest, namely *Payment*, *Sent*, and *Transfer*. The interpretation of the findings focuses on the direction, magnitude, and statistical significance of each variable's effect on the probability of households being classified into specific levels of Financial Well-Being (FWB), as indicated by the estimated AMEs.

By adopting this approach, the analysis enables a nuanced assessment of how variations in digital payment adoption, money transfer behavior, and related financial practices are associated with shifts in the likelihood of households occupying different FWB categories. More broadly, this framework facilitates the identification of key determinants such as the use of digital payment channels, saving behavior, and access to formal credit that are systematically linked to disparities in financial well-being among urban households. The use of AMEs further enhances interpretability by translating estimated coefficients into changes in probability, thereby offering policy-relevant insights into the mechanisms through which financial inclusion and financial behavior influence household financial well-being.

3. FINDINGS AND DISCUSSION

The distribution of Financial Well-Being (FWB) categories among urban households in the analytical sample reveals that the majority are concentrated in the High FWB category, accounting for 1,535 observations or 64.93% of the sample. This finding suggests that most urban households in the study exhibit relatively strong financial capacity, including the ability to manage financial obligations and maintain a certain degree of financial security.

The Medium FWB category represents the second-largest group, comprising 627 households (26.53%). These households demonstrate moderate financial resilience but may still face limitations

related to savings adequacy or access to formal financial instruments. In contrast, households classified as having Low FWB make up a relatively small proportion of the sample, with 77 observations (3.26%), indicating that severe financial vulnerability is less common among urban households within this age cohort.

Table 2. Distribution of Financial Well-Being (FWB) Categories among Urban Households

Kategori FWB	Frekuensi	Persen (%)
Rendah	77	3.26
Sedang	627	26.53
Tinggi	1535	64.93
Sangat Tinggi	125	5.29

Finally, the Very High FWB category accounts for 125 households (5.29%) of the sample. Although this group represents a smaller proportion relative to the High FWB category, it reflects a subset of urban households with particularly strong financial positions characterized by higher levels of savings, broader access to formal financial services, and greater capacity to allocate resources for productive purposes.

Overall, the distribution exhibits a right-skewed pattern, with a substantial concentration of households in the High FWB category. This distribution highlights the heterogeneity in financial well-being among urban households and provides an empirical basis for examining how digital financial behaviors and access to financial services are associated with transitions across different FWB levels.

3.1. Model Adequacy and Predictive Fit

The multinomial logit model is estimated using the maximum likelihood method, and key model fit statistics are reported in Table 3. The log-likelihood value of the fully specified model is –525.996, representing a substantial improvement over the null model log-likelihood of –2,131.306. This marked increase (i.e., becoming significantly less negative) indicates that the inclusion of explanatory variables greatly enhances the model's ability to explain variation in Financial Well-Being (FWB) categories.

The likelihood ratio (LR) test further confirms the overall significance of the model. The LR chi-square statistic ($\chi^2 = 3{,}210.620$; df = 54) is statistically significant at the $p < 0.001$ level, implying that the set of independent variables jointly contributes to explaining differences across FWB categories. In other words, the null hypothesis that all slope coefficients are equal to zero is decisively rejected.

Table. 3 Model Fit and Predictive Performance

Indicator	
N (observasi)	2364
Log-likelihood (model)	-525.996
Log-likelihood (null)	-2.131.306
LR χ^2	3.210.620
df (derajat bebas)	54
Pseudo R²	0.755
p-value (uji LR)	< 0.001

Additionally, the model yields a Pseudo R² value of 0.755, suggesting that approximately 75.5% of the variation (deviance) in household FWB categories is accounted for by the explanatory variables

included in the model. While Pseudo R² measures are not directly comparable to the R² in linear regression, this relatively high value indicates strong explanatory power and a high degree of predictive adequacy.

Overall, these results demonstrate that the multinomial logit specification exhibits excellent model fit and substantial explanatory capacity, supporting the relevance and appropriateness of the selected variables in explaining variation in financial well-being among urban households.

3.2. Average Marginal Effects

The estimation results are presented in the form of **Average Marginal Effects (AMEs)** for each Financial Well-Being (FWB) category, as reported in Table 3. AMEs quantify the magnitude of change in the predicted probability (expressed in percentage points, pp) of belonging to a given FWB category following a one-unit change in a predictor variable. For binary (dummy) variables, the AME represents the discrete change in probability when the variable shifts from 0 to 1, holding all other variables constant at their observed values and averaging across the sample. For example, an AME of +2 pp for the High FWB category associated with a dummy variable implies that households possessing this characteristic have a 2percentage point higher probability of being classified as High FWB than those without it, ceteris paribus. For continuous variables (e.g., age measured in years), the AME reflects the change in probability associated with a one-year increase in the variable.

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Table 3. Output AMEs for *Payment*, *Sent*, and *Transfer*

Variable	Low	medium	High	Very High
Payment (1 = Yes)	-0.006 (0.004)	0.009 (0.010)	-0.030* (0.016)	0.027** (0.014)
Sent (1 = Transfer bank)	-0.001 (0.002)	0.004 (0.006)	0.000 (0.012)	-0.004 (0.011)
Transfer (1 = OTC)	0.007 (0.005)	-0.009 (0.007)	0.028** (0.013)	-0.026** (0.012)

First, regular saving behavior emerges as the most consistent and influential predictor of household financial well-being. The variable *Regular Saving* (1 = Yes) is significantly associated with a lower probability of being classified into lower FWB categories and a higher probability of occupying upper FWB categories. Specifically, households that save regularly exhibit a reduced likelihood of falling into the Low and Medium FWB categories (by approximately 3.6 pp and 10.5 pp, respectively; both statistically significant at $p < 0.05$), alongside a substantial increase in the probability of being classified as High FWB (approximately +32.9 pp; $p < 0.01$). Interestingly, regular saving is also associated with a lower probability of being in the Very High FWB category (–18.8 pp; $p < 0.01$), a counterintuitive finding that is further explored in the discussion section.

Second, access to or experience with borrowing (*Borrow* = 1) also exerts a strong and statistically significant influence. Households that have previously accessed loans or credit display a markedly lower probability of belonging to the Low, Medium, and High FWB categories (reductions of

approximately 3.7 pp ($p < 0.05$), 3.2 pp ($p < 0.10$), and 13.8 pp ($p < 0.01$), respectively). Conversely, access to credit is associated with a substantial increase in the probability of attaining the Very High FWB category (approximately +20.8 pp; $p < 0.01$). This pattern suggests that access to credit plays a critical role in enabling households to reach the highest levels of financial well-being, whereas the absence of credit access may constrain upward mobility across FWB categories.

Third, the adoption of electronic payment instruments (*Payment* = 1) appears to shift the distribution of probabilities across FWB categories. The results indicate that the use of non-cash payment channels slightly reduces the probability of being classified as High FWB (approximately –3.0 pp; $p < 0.10$), while simultaneously increasing the likelihood of being in the Very High FWB category (+2.7 pp; $p < 0.05$). This pattern implies that urban households actively using digital payment instruments are more likely to transition from high to very high levels of financial well-being, rather than remaining within the high category.

In contrast, the use of traditional or semi-cash transfer channels such as over-the-counter (OTC) transfers and ATM-based transactions exhibits an opposing pattern. Both OTC transfers and ATM usage are positively associated with the probability of being in the High FWB category (AMEs of approximately +2.8 pp ($p < 0.05$) and +2.2 pp ($p < 0.10$), respectively), while being negatively associated with the probability of reaching the Very High FWB category (–2.6 pp and –2.4 pp, respectively; $p < 0.05$). These findings suggest that reliance on traditional transaction channels is more prevalent among households with relatively high but not the highest levels of financial well-being.

Finally, several variables do not exhibit statistically significant associations with FWB categories. The *Sent* variable (bank-based money transfers) shows no meaningful effect across any FWB category, with AMEs that are small in magnitude and statistically insignificant. Similarly, internet access does not appear to be significantly associated with differences in FWB probabilities within this model. In addition, household age (proxied by the age of the household head) does not show a statistically significant effect. The estimated AMEs are close to zero across all categories, indicating that age-related differences do not directly distinguish levels of financial well-being once other financial characteristics are controlled for.

Discussion

Low Financial Well-Being (FWB) Category

Within the Low FWB category, two financial variables exhibit the most consistent and statistically significant effects in reducing the probability of households remaining at this lowest level of financial well-being: *Borrow* and *Regular Saving*. The estimation results indicate that households with prior experience or access to credit (*Borrow* = 1) are significantly less likely to fall into the Low FWB category, with the probability reduced by approximately 3.7 percentage points (pp) ($p < 0.05$) compared with households without credit access. Similarly, households that save regularly are substantially less likely to be classified as Low FWB; regular saving behavior reduces the probability of belonging to this category by around 3.6 pp ($p < 0.05$).

These findings suggest that greater engagement with formal financial services—either through access to credit or through consistent saving practices is associated with a lower likelihood of experiencing low financial well-being. In other words, active financial behavior and financial inclusion appear to serve a protective role against the risk of remaining in the lowest FWB category.

Medium Financial Well-Being (FWB) Category

For the Medium FWB category, a pattern similar to that observed in the Low FWB category emerges, with regular saving behavior again acting as the dominant factor. Households that save regularly have a significantly lower probability of being classified as Medium FWB, with an estimated

AME of approximately –10.5 pp (p < 0.01). This sizable effect indicates that consistency in saving enables households to move beyond a moderate level of financial well-being toward higher levels.

Access to credit (Borrow = 1) also plays a role in this category, albeit with a smaller magnitude. Households with borrowing experience are less likely to remain in the Medium FWB category, with the probability decreasing by approximately 3.2 pp (p < 0.10). This result suggests that engagement with credit services may help households exit the middle tier of financial well-being, potentially by providing additional liquidity or capital that supports improved financial conditions. Overall, both regular saving and credit access appear to facilitate upward mobility from Medium FWB to higher levels.

High Financial Well-Being (FWB) Category

The High FWB category represents the most prevalent level of financial well-being in the urban sample, encompassing approximately two-thirds of households. The AME results indicate that regular saving is the strongest predictor of being classified within this category. Households that save regularly exhibit a 32.9 pp higher probability of attaining High FWB (p < 0.01) relative to those that do not, underscoring the central role of saving behavior in achieving strong financial well-being.

In addition, the use of traditional transaction channels, such as over-the-counter (OTC) transfers and ATM services, is positively associated with the High FWB category, although the effects are more modest in magnitude. Specifically, households using OTC transfer services have a 2.8 pp higher probability of being classified as High FWB (p < 0.05), while ATM usage increases this probability by approximately 2.2 pp (p < 0.10). These findings suggest that, despite ongoing financial digitalization, traditional and semi-cash financial channels remain common among households with relatively high financial well-being.

By contrast, adoption of electronic payment instruments (Payment = 1) is negatively associated with the probability of being in the High FWB category (approximately –3.0 pp; p < 0.10). This result implies that households using e-payment systems are less likely to remain in the High FWB category a pattern that aligns with their increased likelihood of reaching the Very High FWB category, as discussed below. Notably, households with borrowing experience (Borrow = 1) also exhibit a substantially lower probability of being classified as High FWB (approximately –13.8 pp; p < 0.01). This pronounced reduction is consistent with the interpretation that borrowing households tend to move beyond the High FWB category toward the highest level of financial well-being rather than remaining at this stage. Taken together, the results for the High FWB category suggest that strong saving behavior and continued use of traditional financial channels increase the likelihood of achieving high financial well-being, whereas deeper engagement with modern financial services and credit access appears to propel households further upward into the Very High FWB category.

Very High Financial Well-Being (FWB) Category

At the Very High FWB level, the influence of key variables contrasts sharply with patterns observed in the lower categories. Borrowing experience (*Borrow* = 1) emerges as the most influential factor, with households that have accessed credit exhibiting a markedly higher probability of attaining the highest level of financial well-being. The marginal effect of borrowing reaches approximately +20.8 pp (*p* < 0.01). the largest effect observed among all variables highlighting the critical role of credit access in enabling urban households to reach the top tier of financial well-being.

The use of electronic payment instruments (*Payment* = 1) is also positively associated with the Very High FWB category, although the magnitude is more moderate. Adoption of digital payment channels increases the probability of being classified as Very High FWB by approximately 2.7 pp (*p* < 0.05). This

finding suggests that digital payment technologies may function as enablers of optimal financial well-being, potentially through enhanced transaction efficiency, improved financial record-keeping, or easier access to complementary digital financial services.

Conversely, reliance on traditional transaction channels, such as OTC transfers and ATM usage, is negatively associated with the likelihood of being in the Very High FWB category. Households that depend on these channels exhibit lower probabilities of reaching the highest FWB level, with AMEs of approximately –2.6 pp and –2.4 pp, respectively ($p < 0.05$). This pattern indicates that households at the top of the financial well-being distribution are less reliant on cash or semi-cash transaction mechanisms and may instead favor more advanced digital or investment-oriented financial tools.

One particularly noteworthy finding concerns the role of regular saving behavior in the Very High FWB category. Contrary to its positive effects at lower and intermediate levels, regular saving is significantly and negatively associated with the probability of being classified as Very High FWB, reducing the likelihood by approximately 18.8 pp ($p < 0.01$). While regular saving is clearly beneficial for progressing from low to high financial well-being, this inverse relationship at the highest level suggests substantial heterogeneity in financial behavior among the most affluent households.

A plausible interpretation is that households with Very High FWB may rely on asset accumulation and liquidity management strategies not fully captured by the survey's definition of "regular saving." These households may prioritize investments in financial instruments, diversified asset portfolios, or alternative saving patterns (e.g., irregular but large allocations) that differ from conventional saving behavior. As a result, the indicator of regular saving does not increase monotonically with financial well-being at the highest level and may even move in the opposite direction. This finding opens an important avenue for discussion regarding divergent financial strategies between households that are *financially secure* and those that are *financially affluent*, where traditional saving practices may be supplanted by more sophisticated financial management approaches among the highest FWB group.

4. CONCLUSION

The findings from the multinomial logit estimation for urban households confirm that differences in Financial Well-Being (FWB) categories are shaped not only by socio-demographic characteristics but, more importantly, by variations in financial behavior and access to formal financial services. Overall, the probability of transitioning from lower to higher FWB categories is highly sensitive to two key factors: (i) household engagement in disciplined financial management practices particularly regular saving behavior, and (ii) access to or experience with formal financial services, especially credit and borrowing. Additionally, the results reveal distinct patterns in the use of traditional financial channels (ATM and over-the-counter transfers) versus digital channels (electronic payments), with meaningful implications for financial well-being mobility across the FWB spectrum.

Substantively, these findings suggest that financial literacy and financial inclusion in urban contexts should not be understood merely as access to financial services. Rather, they should be conceptualized as a combination of *financial capability* the ability to manage day-to-day finances effectively and *financial deepening*, reflected in the intensity and sophistication of financial service usage. The observed behavioral heterogeneity at the highest FWB level most notably the negative association between regular saving and the probability of attaining Very High financial well-being underscores the need for a more granular perspective when analyzing the financial strategies of the most affluent households. These households are likely to rely more heavily on investment activities and diversified asset allocation strategies rather than conventional saving practices captured by standard survey indicators. Consequently, future research and policy interventions should account for differentiated financial behaviors across welfare strata to promote more inclusive and sustainable improvements in household financial well-being.

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