A Study of Digital Financial Inclusion in Ukraine and Opportunities for Financial Institutions

by

Bobrov Oleksandr

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Thesis Supervisor: ___________________ Professor Maksym Solodarenko ___________

Approved by ____
Head of the KSE Defense Committee, Professor [Type surname, name]

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NBU National Bank of Ukraine

HHI Herfindahl-Hirschman Index

SEP System of Electronic Payments

ISO International Organization for Standardization

POS Point of Sale

IFC International Finance Corporation

GDP Gross Domestic Product

EU European Union

AME Average Marginal Effect

PP percentage points

CHAPTER 1. INTRODUCTION

Financial inclusion is among the core issues of economic growth and also business innovation. Providing people with the access to bank accounts and mobile payments helps them manage money more efficiently. Financial inclusion promotes economic participation, and it provides new opportunities to businesses and fintech companies (World Bank, 2022). This happens because when people are financially included, they are more likely to save and invest.

This study explores that topic. The main research goal is to understand what factors influence the use of digital financial services in Ukraine and to identify which population groups offer the most potential for future inclusion. To be more specific, the study asks: What are the key influencing factors whether people in Ukraine use digital financial services, and which groups offer the most potential for financial institutions to expand access?

In Ukraine, this issue is very urgent. Although digital financial services expanded in recent years, many people are still left out. According to the Global Findex 2021 dataset used in this work, about 24% of adults in Ukraine did not own a payment card (World Bank, 2022). The number suggest that while some people are already integrated into the digital economy, a large group remains underserved and potentially reachable with the right strategy- something that will be tested as a result of this study. As Ukraine rebuilds, closing this gap will be crucial for long-term recovery, investment, and equality of opportunity.

What makes me assume that there is still a room for market expansion is that mobile phone and internet access were already widespread before the russian invasion of Ukraine in 2022. This means the infrastructure needed to support digital financial services is largely in place (Naumenkova et al., 2019). With these tools available, the next step is understanding why some people use digital finance and others do not. This is where customer segmentation and precise targeting become especially important for banks and fintech firms, who are looking to grow their customer base.

To answer this, the research uses individual-level data from the World Bank's Global Findex 2021 for Ukraine and estimates two weighted logistic models: one for whether a person made any digital payment in the last year, and another for whether a person owns a debit/ATM card. Taken together, these outcomes let us separate "use" from "access." The framework is descriptive rather than causal: the goal is to map which characteristics are most closely linked with inclusion and to quantify the size of those links in percentage-point terms. The core variables are education, income, age, gender, employment, and internet access. Model choices are kept transparent and the analysis uses survey weights so that findings speak to the adult population, not just the sample.

This approach makes the study valuable in two ways. First and foremost, it provides practical insights for financial institutions like Visa, Monobank, or other fintech companies, who can use the findings to adapt their services and better target potential customer base, which is the main focus of my study (Shapoval, 2021; Abbasi & Weigand, 2017). By identifying specific underserved customer segments, the paper can support more effective outreach strategies and customized product design. Additionally though, it offers insights for public policy, by identifying who remains excluded and why.

The main results point away from broad demographics and lean toward structural factors. Patterns in the data suggest that what people know and can comfortably do with digital tools matters more than who they are. Internet access and the ability to use it, together with economic position, appear to shape everyday financial behaviour. This does not tell a full story yet, but already hints that simpler products, clearer pricing, and practical help at the start of the user journey may be more impactful to reach the excluded parts of population, rather than the financial features themselves. Thus, financial institutions main focus to grow the customer should lie within user experience and convenience frame.

It is important to mention that although the data used in this paper reflect a pre-war situation as it is of 2021, many of the core issues- like rural-urban differences and income-based gaps- might still be relevant. In fact, the used dataset and the consequent output of the work can serve as a baseline for business strategies in Ukraine’s recovery phase. This study, therefore, is not only about financial access today but also about helping shape smart decisions in the future.

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

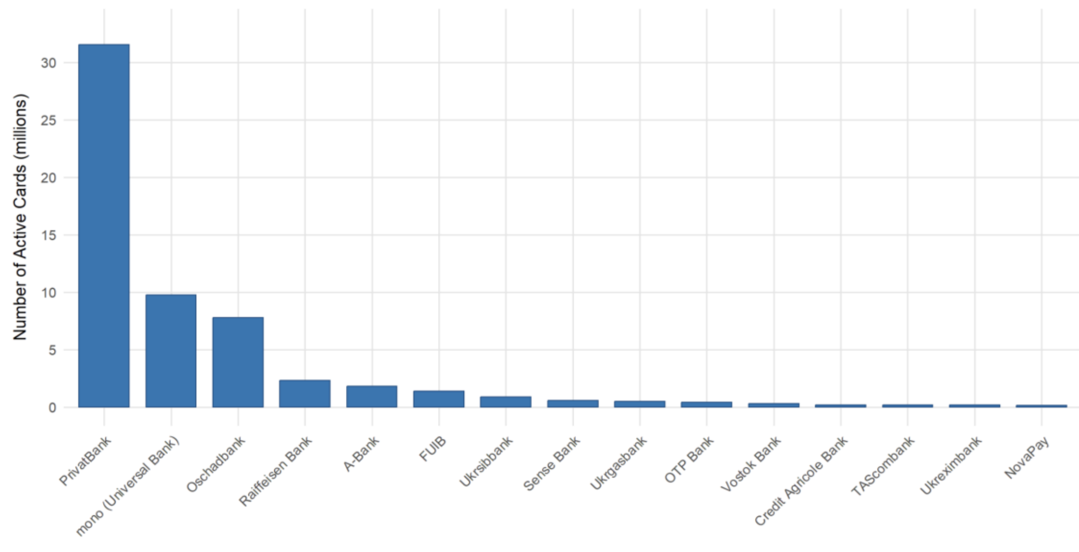
Ukraine's financial services sector has shown resilience when faced challenges such as war, and economic instability as a consequence. In 2023, the National Bank of Ukraine (NBU) reported a net profit of UAH 83.2 billion across the banking sector and UAH 76.6 billion in income tax contributions, collected at a wartime rate of 50% (National Bank of Ukraine, 2024). Despite difficult macroeconomic conditions, retail and corporate lending have continued to grow, while hryvnia-based term deposits increased at a rate of 37.2%, which is the highest of the decade. That is indicating a restoration of public trust in the banking system (National Bank of Ukraine, 2024).

A key factor in the stability of Ukrainian financial sector is digitalization. Mobile-first banking and contactless payments have become widespread. It was achieved by both state infrastructure upgrades and the rise of fintech players. Monobank- Ukraine's first mobile-only bank- is a notable example. Since its launch in 2017, it has attracted over 10 million customers, with 9.8 million active cards as of early 2025 (Forbes Ukraine, 2025). Monobank's rapid growth demonstrates the potential of digital-only banking models in a market where mobile phone use is high.

In terms of market structure, Ukraine's payment card market is dominated by a few major players. As of 2024, PrivatBank alone holds 53.7% of the active card market, followed by Monobank (Universal Bank) with 16.6% and Oschadbank with 13.2%. These three institutions together control over 83% of all active cards. This shows that a market of issuing payments cards in Ukraine is highly concentrated and it resembles a monopolistic competition market (Interfax Ukraine, 2025).

A Herfindahl-Hirschman Index (HHI) based on active card market shares confirms this dominance. Calculated using the squared shares of the top 4 card issuers, the HHI reaches approximately 3350- which mathematically confirms my market concentration hypothesis.

Figure 1. Active Payment Cards, by Bank (2025).

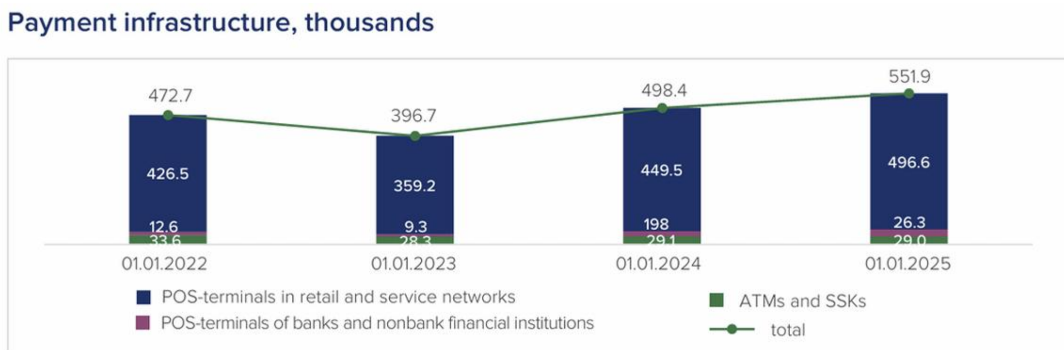


Source: R visualization done by author based on Interfax Ukraine, 2025

On the infrastructure side, Ukraine operates a mix of global and national payment systems (including Visa, Mastercard, American Express, and the national PROSTIR). In 2024, 59 financial institutions participated directly in payment systems. In 2023, the NBU upgraded the System of Electronic Payments (SEP) to ISO 20022 and enabled 24/7 operations- preparing for deeper EU integration. As of January 2025, Ukraine had 132 million issued cards and more than 496.000 POS terminals, 97.5% of which were contactless (see Figure 2).

But inclusion is not yet balanced. According to Global Findex 2021, about 24% of Ukrainian adults did not own a payment card- roughly seven million people without basic digital access. If we were to compare this number in 2024, there are approximately four million Ukrainians that still don't possess an account. The inclusion gap has dropped to 12.4%, but this promising tendency can be mostly explained by the migration from the country, caused by the full-scale invasion. Thus, I attribute this to population decreasing as the main driver, rather than proactive steps towards a more inclusive financial system. (Findex Database, 2021)

Figure 2. Number of POS-terminals in Ukraine, (2022-2025)

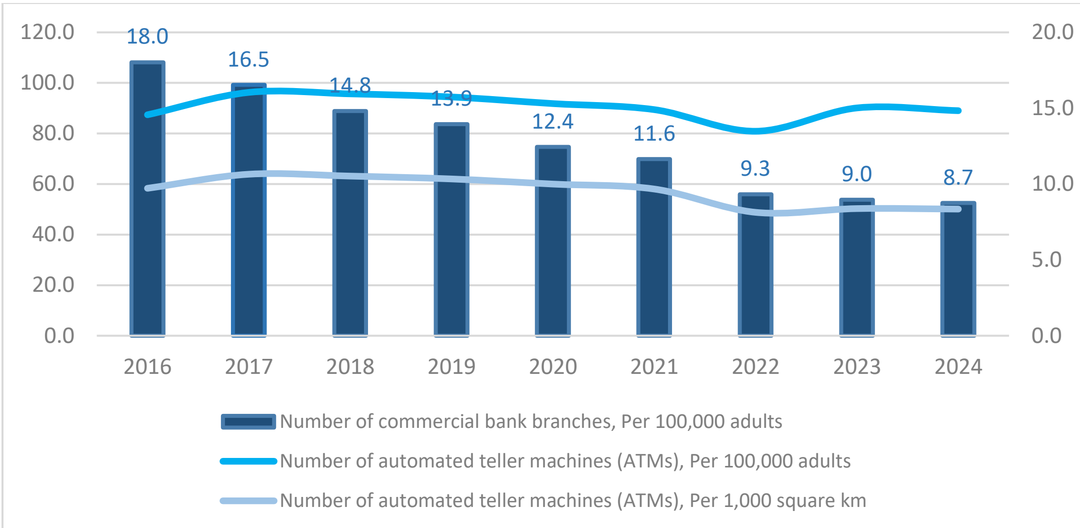


Source: NBU Annual Report, 2024

Both the number of commercial bank branches and ATMs have been in decline in Ukraine since 2016. The number of bank branches per 100,000 adults dropped from 18 in 2016 to 8.7 in 2024, while ATM density, both per population and per area, followed a similar downward trend (Figure 3).

This contraction of the physical network I interpret in two ways: on one hand, it reflects sector consolidation and cost-optimization among banks, accelerated by the 2022 invasion and subsequent migration crisis. On the other hand, it highlights a shift toward digital channels, as Ukrainian consumers increasingly rely on mobile banking, e-wallets, and cashless payment solutions (NBU Report, 2025). Thus, the decline in physical infrastructure does not necessarily mean reduced access to the extent that is seen on the figure, but rather it reflects the ongoing transition focus from physical to digital finance. What additionally backs it off, is that this trend is also notable across neighbouring European countries that are economically comparable with Ukraine, namely Poland, Czech Republic, Latvia, Lithuania, Slovakia and Romania (see Appendix).

Figure 3. Dynamics of Banking Infrastructure in Ukraine, (2016–2024)



Source: aggregated by author, based on IMF data, 2025

However, policy and industry initiatives are also taking place, attempting to close this gap. In 2024, Ukraine advanced reforms of financial services, credit unions, and insurance to align with EU standards. Also, the NBU and IFC agreed to expand digital financial services and SME access to credit, and a push for cashless payments options in both private and public services.

Internationally, the Global Findex literature provides the standard list of barriers that matter for non-use: cost/affordability, distance/physical access, with trust frequently highlighted in Europe and Central Asia. Cross-country analyses using Findex also show a strong income-usage relation: higher-income environments see more frequent digital payments and account use, which is useful macro context but not causal. This is why a within-Ukraine, person-level analysis is needed to guide business decisions.

In Ukrainian context, two consistent themes appear. First, structural barriers- distrust, unstable income, documentation issues, and regional inequality- slow adoption; infrastructure tends to outpace usage (Naumenkova et al, 2019). Similarly, Shapoval (2021) pointed out that low financial literacy and poor compatibility between different financial systems slows the adoption of digital services. Also, both studies highlight the need to go beyond infrastructure and understand user behavior more deeply. By knowing the motivation or the reasoning of non-using these services will help approach clients in a right way.

My own diagnostics points in the same direction: even with widespread connectivity, internet access did not mechanically translate into higher digital. That suggests that there might be other reasons that prevent from using financial services.

What this means is that the sector is modernizing quickly; infrastructure is in place. But access and use remain not full. The literature provides a clear framework of handling the barriers that exist (cost, distance, documentation) and points to firm-controlled strategies (pricing, distribution, onboarding, literacy/UX). What is missing is a micro-level, Ukraine-specific diagnosis that can:

(i) identify which segments are excluded from digital use,
(ii) rank the reasons for non-use within those segments,
(iii) translate that into delivery choices for banks and fintechs.

This is the gap I seek to fill. Using Global Findex 2021 microdata for Ukraine, I will quantify who is out of digital finance and why, and then connect those findings to firm strategies.

CHAPTER 3. METHODOLOGY

I start from a simple question: who in Ukraine is excluded from financial system, and why? In my case "exclusion" is measured as a lower probability of (i) having made or received at least one digital payment in the last 12 months, and (ii) owning a debit/ATM card. These two outcomes let me separate "use" from "access." I focus on a tight set of socio-economic drivers- sex, age, income quintile, and education- because they are measured consistently in the microdata and align with how financial inclusion gaps are usually tracked. I also include access to internet and employment status variables to further strengthen the results implications. The goal of the empirical work is descriptive rather than causal: I want to quantify the size and direction of the gaps for core groups in the adult population, using the survey weights so the results reflect the population, not just the sample. However, I acknowledge the nature of results being rather correlational then causal, which still can provide defendable results.

The methodological approach for this study followed an iterative process of construction, testing, and refinement to arrive at the model that maximized explanatory power while maintaining statistical efficiency. The general sequence of my steps involved defining the largest viable model, validating the significance of its components using the Wald Test, and reducing complexity as validated by the Akaike Information Criterion (AIC).

For the dataset, the Findex 2021 indicators are built on "survey data covering almost 128.000 people in 123 economies, representing 91 percent of the world's population," and were carried out the same year by Gallup, Inc- an American analytics company.

Ukraine was surveyed during September 27-October 14, 2021 period, using telephone interviews with a dual frame of landline and mobile numbers. The public methodology table lists 1.001 completed interviews for Ukraine, a design effect of 1.88, and a 95% margin of error of 4.3 percentage points for a proportion near 50%. Interviews were conducted in Ukrainian and russian. No territorial exclusions are noted for Ukraine in 2021, however, it is safe to assume the temporarily occupied regions of Ukraine weren't a part of survey. And the sample is described as nationally representative of adults (15+).

For the standardization part, all yes/no items were harmonized to a binary scale where 1 means "Yes" and 0 means "No." When respondents answered "Don't know" or "Refused" they were kept as missing and handled with complete-case analysis whenever a statistic or model used that variable. This keeps the important difference between "No" and "No information," and makes the results more reliable. Below is a more detailed breakdown by each used variable:

- Sex (female_b): Respondents sex. Re-coded to a binary dummy: female_b = 1 for women and 0 for men. "Don't know/Refused" were set to NA. It is entered as a single regressor; the coefficient reads as the difference in probability for women vs. men, holding other covariates fixed.
- Education (educ): Highest completed education. The variable was collapsed to three clear levels and set as an ordered factor: Primary_or_less (reference), Secondary, Tertiary. DN/RF were treated as NA. It is included as two dummies (Secondary, Tertiary) with Primary_or_less as the baseline. Coefficients tell how much higher/lower the predicted probability is relative to Primary or less.
- Age (age_c, age_c2): Respondent age in years. The age variable was calculated as a squared difference between the respondents age and the mean age of the sample.
- age_c = age − mean(age); added a quadratic term age_c2 = age_c^2. The implied "peak age" (where the predicted probability is highest) is reported as:

$$Peak\ age = age_m - \frac{\widehat{\beta}_{age_c}}{2\widehat{\beta}_{{age^2}_c}} \quad [1]$$

Where age_m is the sample mean age, $\hat{\beta}_{age_c}$ and $\hat{\beta}_{age^2{}_c}$ are the estimated coefficients on the centered age and its square. If $\hat{\beta}_{age^2{}_c} < 0$, the curve is concave and this is a maximum, or a peak. If $\hat{\beta}_{age^2{}_c} > 0$, it's a minimum.

- Income quintile (inc_cat): Within-country income position (poorest to richest 20%), strictly mapped to five dummies Q1–Q5 from the original inc_q,; anything outside 1–5 is treated as NA. The observations are entered as dummies with Q1 (poorest) as the reference. Coefficients show the gradient relative to Q1.
- Employment status (emp_in): Respondent's engagement in the workforce (In vs. Out of workforce). Original codes 1 (In) and 2 (Out) are harmonized with "out of workforce" set as the reference baseline (0). The coefficient measures the effect of being In workforce.
- Internet access (internetaccess): Whether the respondent has access to the internet. The coding logic resembles the one done with employment status variable.
- Outcomes y_anydig: made or received any digital payment in the last 12 months (card, phone/internet banking, online bill/merchant), 1/0.

  y_card: owns a debit/ATM card, 1/0. All yes/no items harmonized to 1/0; DN/RF kept as NA.

With that being said, the chosen econometric model was a quasi-binomial logistic regression. I estimate it twice for (i) any digital payment model and (ii) card ownership model.

The general form of the model is the following:

$$ln\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right) = \beta_0 + \beta_1 Female_i + \beta_2 Age_i + \beta_3 Age^2_{Ci} + \beta_4 Education_{\mathrm{i}} + \quad [1]$$

$$+ \beta_5 Income_{\mathrm{i}} + \beta_6 Employment_i + \beta_7 Internetaccess_i + \varepsilon; \quad [2]$$

Where:

- Outcome Y_i: dependent variable (log-odds of the outcome): 1 if person i done any digital payment or owns a debit card; 0 if otherwise,
- β_0: baseline log-odds model (male, mean age, Q1 income quantile, Primary-or-less, not in the workforce, no internet access),
- $\beta_1 Female_i$: female-male gap (1=female and 0=male),
- $\beta_2 Age_i + \beta_3 Age_{Ci}^2$: a curved age effect,
- $Income_{\mathrm{i}}$ income effects for Q2-Q5, relative to Q1,
- $Education_{\mathrm{i}}$: education effects for Secondary and Tertiary levels, relative to Primary-or-less,
- $Employment_i$: employment effect of being in the workforce, compared to being out of it,
- $Internetaccess_i$: an effect of having an access to the internet, compared to the opposite.

The further enhancement was made after running the first model, specifically collapsing income variable into two more general categories: higher income group (Q4–Q5) and lower income group Q1-Q3, as the initial result of each income quantile were inconsistent and might be seen as confusing, both estimation-wise and on AMEs scale. A quick models' comparison with the help of AIC test showed a slight superiority of the model that squeezed the income variable- 805.1 versus 800.1 (see Appendix).

Moving on to the preferred model logic: as the dependent variables are 0/1, raw logit coefficients are on the log-odds scale and not very intuitive. I therefore report Average Marginal Effects (AMEs) in percentage points. An AME tells how the predicted probability changes, on average, when one regressor moves (using the survey weights). For sex, it is the change from male to female. For age, the model includes both age and age^2, so I use a +1 SD shift in centered age (and update age^2) and also report the turning point (peak age) from the quadratic to summarise the life-cycle pattern. For categories, higher income group (Q4–Q5) is compared to lower income group Q1-Q3, and Secondary/Tertiary are compared to Primary or less. The AME table is the main summary of magnitudes, while a simple predicted-probability plot helps connect the model to the descriptive graphs.

Moving forward to robustness tests performed in order to be sure that the model results can be trusted. The below table presents results of multicollinearity test, which gives a safe output. Common decision rules consider values below ~2 as indicating weak collinearity. In my specification, all adjusted GVIFs lie between 1.01 and 1.31, with the largest values observed for the centered age and its quadratic term (age_c = 1.314, age_c2 = 1.253) (Table 1a-1b).

So, the diagnostics indicate low multicollinearity across regressors and any inflation of standard errors is negligible and does not threaten modeling. No other corrective action is required and so the final model is well-posed for interpretation and hypothesis testing.

Table 1a. Multicollinearity test on Model 1, performed by author in R

Term	GVIF	Df	GVIF^(1/(2*Df))
female_b	1.147	1	**1.071**
age_c	1.726	1	**1.314**
age_c2	1.569	1	**1.253**
educ	1.054	2	**1.013**
inc_35	1.093	1	**1.046**
emp_in	1.417	1	**1.191**
internetaccess01	1.335	1	**1.155**

Test is performed on anydig model

Table 1b. Multicollinearity test on Model 2, performed by author in R

Term	GVIF	Df	GVIF^(1/(2*Df))
female_b	1.130	1	**1.063**
age_c	1.559	1	**1.248**
age_c2	1.522	1	**1.234**
educ	1.062	2	**1.015**
inc_35	1.089	1	**1.043**
emp_in	1.395	1	**1.181**
internetaccess01	1.274	1	**1.129**

Test is performed on card ownership model

It is also important for me to acknowledge the limitations before proceeding:

(i) Correlational Nature: The Global Findex dataset employs a cross-sectional design. Consequently, the statistical model establishes associations and predictive power, but cannot infer causality (i.e., higher education does not cause higher inclusion, but is strongly associated with it). Results are presented using correlational language only.

(ii) Pre-War Context: The data reflects the socio-economic landscape of Ukraine in 2021. The subsequent demographic and socio-economic changes following 2022 means the findings establish a critical baseline of pre-conflict structural capabilities but may not accurately reflect the market dynamics of the present day.

CHAPTER 4. DATA

The main dataset in this thesis is the Global Findex 2021 microdata for Ukraine. Global Findex is the World Bank's flagship survey on how adults use financial services. Since 2011 it has been conducted in regular waves (2011, 2014, 2017, 2021), which makes it possible to compare the same indicators over time. The 2021 round interviewed about 128.000 adults in 123 economies and added a focus on digital payments during the COVID-19 period (including card use, mobile and internet payments, and paying merchants and utilities digitally). The survey is designed to be nationally representative of each economy's adult population and all published figures are weight-adjusted at the adult population level.

For Ukraine, the raw micro file contains 1,001 respondents and 113 variables. My analysis centers on two inclusion outcomes- (i) whether a person made any digital payment in the last 12 months and (ii) whether they own a debit/ATM card- and a small set of core demographics. Following the Findex documentation, I treat 2021 responses as a snapshot of behaviors and apply the provided person weights in all descriptive statistics and models so that estimates represent the adult population rather than just the sample.

The used variables are the following:

i. y_anydig: Whether a person made/received any digital payment in the last 12 months (binary 0/1).
ii. y_card: Whether the person owns a debit card (binary 0/1).
iii. wgt: Weight assigned to each observation.
iv. female_b: Sex of the respondent, where 1 = female, 0 = male.
v. inc_cat: Income quantile, from poorest 20% of respondents (Q1) to the richest 20% of the sample (Q5).
vi. educ: Education, whether a responded has a primary or less, secondary or tertiary education.

vii. age_c, age_c2: Age centered at the sample mean and its square allow a non-linear age profile.
viii. emp_in: Whether a respondent is a part of the workforce or not.
ix. internetaccess: Whether a respondent has an access to internet.

In terms of dataset cleaning, I standardize all yes/no items using a single rule so the variables are consistent across the file. In practice, I recode survey answers to 1 = Yes, 0 = No, and I treat "Don't know/Refused" as missing and not as "No". I also clean the categorical covariates so that income is exactly Q1–Q5, and education is exactly Primary or less / Secondary / Tertiary; any out-of-range values are set to missing instead of being kept as a "Missing" category. Age variable was cleaned for modeling by centering it at the sample mean and creating an age-squared term. This lets the model pick up a U-shaped pattern without collinearity problems.

For the missingness handling, I only record observations, where every variable was presented, so after the filter, the main analysis sample for the digital-payment model is N = 979 out of 1.001 raw records. This approach avoids guessing or filling in values for "Don't know/Refused".

Using the person-weights provided by Findex, roughly 82% of adults in Ukraine report making at least one digital payment in the last 12 months, while about 71% own a debit/ATM card (Table 2). So "digital use" is higher than "card access." That's expected because the Findex "any digital payment" variable is broader: it counts any digital channel (card, phone, internet/mobile banking, utility payments online, etc.). In other words, some adults who don't hold a card still transact digitally (e.g., via bank app transfers or paying bills online). Practically, this tells that digital behaviors have spread beyond card ownership.

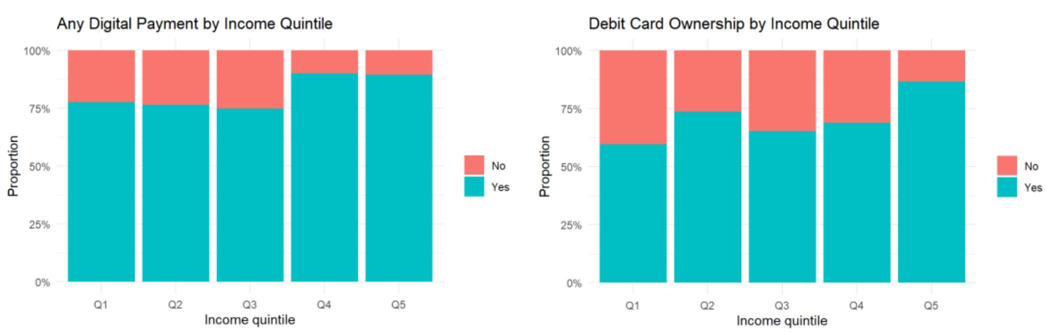
Table 2. Headline weighted shares - shows n (unweighted), % any digital payment done, % card ownership.

n_unw <int>	anydig <chr>	card <chr>
979	81.6%	70.7%

Source: Findex Database, 2021

After the headline shares, it is useful to show who is driving them. To see who drives these levels, I split by income quintile and plot stacked bars (Yes/No) using survey weights. The picture for any digital payment is logical: the share using digital grows as we move from Q1 (poorest) to Q5 (richest). The differences are modest in the middle, but there is a notable increase from Q4. The stacked format makes it easy to see both the "Yes" and "No" portions within each quintile.

Figure 4. Any digital payment/Card ownership by income quintile, stacked bars

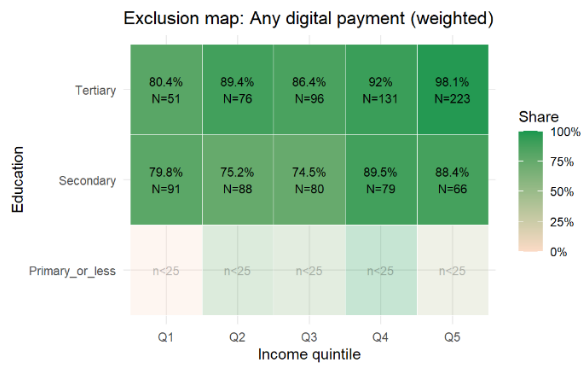


Source: R visualisation done by author, based on Findex Database, 2021

When I repeat the same split for card ownership, the gradient is even steeper. Focusing on Q1, Q3 and Q5- there can be seen a clear upward tendency. This confirms that access to cards remains more uneven than digital use in general.

Income and education often move together, so I show them on a single canvas using an exclusion map. Darker shades of color within rectangles indicate higher inclusion; lighter rectangles indicate lower inclusion. Two patterns stand out visually: within the same income quintile, tertiary education sits above secondary; and the biggest jumps often appear when moving from the middle to the top of the income distribution (Figure 5).

Figure 5. Adoption Matrix: Education and Income within Anydig model, dim N<25



Source: R visualisation done by author based on Findex Database, 2021

CHAPTER 5. RESULTS

This chapter reports the main empirical results, here I refer to two outputs: (i) the regression table with the Estimate, Std. Error and p-values, and (ii) the average marginal effects (AME) table, which translates the model into percentage-point changes in probability. The results will be presented variable by variable.

5.1. Any digital payment model

The regression table reports Estimates on the log-odds scale with p-values (Table 3). A positive estimate means higher odds of making a digital payment; a negative estimate means lower odds, holding other variables fixed. The AME table converts the same model into average marginal effects on the probability scale, shown as AME_pp- percentage-point change (Table 4). AME_pp tells by how many percentage points the predicted probability changes when we move from the reference group to a given category or when we increase age by one standard deviation.

Table 3. Any digital payment model output

Term	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.974	0.678	-1.437	0.151
female_b	**-0.130**	0.251	-0.516	**0.606**
age_c	**0.004**	0.008	0.473	**0.636**
age_c2	**-0.001**	0.000	-1.551	**0.121**
educSecondary	**1.491**	0.540	2.758	**0.006**
educTertiary	**2.129**	0.555	3.832	**0.000**
inc_35 (upper)	**0.697**	0.285	2.451	**0.014**
emp_in	**0.525**	0.274	1.916	**0.056**
internetaccess01	**0.853**	0.400	2.134	**0.033**
Pseudo-R: 0.113	Null deviance:	934.9	Residual deviance:	829

Source: done by author in R, based on Findex 2021

The model is overwhelmingly dominated by two structural factors: education and internet access:

i. Education (ref = Primary or less). Secondary education has an estimate of 1.491 ($p \approx 0.006$), which implies much higher odds of using digital payments (odds ratio ≈ 4.9). On the probability scale this means about +27.8 percentage points (AME_pp ≈ +27.8 pp). Tertiary education shows an even larger estimate, 2.13 ($p < 0.001$), roughly 11 times higher odds than primary or less; the AME is about +35 percentage points. Education is therefore the strongest correlate in the model.

ii. The upper-income indicator (inc_35 (upper)) is significant at 5%: estimate 0.697, $p = 0.014$. This indicates an increase in the likelihood of digital payment use for Q4–Q5 compared with the lower three quintiles by +8.7pp, though to a lesser extent than for education.

iii. Internet access is also a clear and positive predictor. The estimate is statistically significant (0.853, $p = 0.033$). Controlling for the other covariates, having internet access is associated with higher predicted probability of using digital payments by +13.5pp.

iv. The indicator for employment status is on the edge of being statistically important (0.525, $p=0.056$). This suggests a believable connection where people who are currently working are more likely to use digital payments. However, the strong support needed for a 5% significance level is just missed. Therefore, I interpret this as a marginal employment advantage, meaning being employed likely helps with digital payment use, but the correlation isn't strong enough to be proven without a doubt in this specific sample.

v. The model showed that gender has no real separate connection to using digital payments. The coefficient is small and not statistically important ($p = 0.606$). This is a key finding because it means that once I considered differences in education, income, employment, and internet access, the likelihood of women and men using digital payments became statistically similar. The data suggests that differences in usage are explained by access and socio- economic position, not gender itself.

vi. The model's data on age (both the linear and squared terms) provided weak evidence of any connection. Neither term was statistically significant (p values were 0.636 and 0.121 respectively). Even though the numbers hinted a pattern of usage rising and then falling with age, mathematically peaking at 47 years, the evidence is simply too weak to trust. This outcome proves that any influence age might have on digital payment use is not independent; instead, it's mostly explained by the highly important factors like education and internet access.

Table 4. Average Marginal Effects, Any digital payment model

Variable	AME (pp)
female_b (1 vs 0)	**-1.689**
age (+1 SD)	**-3.078**
educ:Secondary	**27.824**
educ:Tertiary	**35.002**
inc_upper vs inc_lower	**8.722**
emp_in (In vs Out)	**7.233**
internetaccess (1 vs 0)	**13.533**

Source: done by author in R, based on Findex 2021

Model note. Pseudo-R^2 = 0.113. Results are consistent: education is the dominant correlate of making any digital payment, followed by a smaller but significant positive correlate for upper-income respondents.

5.2. Card ownership model

The output of the 2nd model is presented below in tables and its interpretation afterwards.

Table 5. Card ownership model output

Term	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-1.020	0.635	-1.607	0.108
female_b	**-0.105**	0.211	-0.499	**0.618**
age_c	**-0.012**	0.007	-1.643	**0.101**
age_c2	**0.000**	0.000	-0.461	**0.645**
educSecondary	**1.248**	0.516	2.419	**0.016**
educTertiary	**1.662**	0.522	3.184	**0.001**
inc_35 (upper)	**0.274**	0.224	1.222	**0.222**
emp_in	**0.383**	0.241	1.591	**0.112**
internetaccess01	**0.520**	0.372	1.397	**0.163**
Pseudo-R^2: 0.064	Null deviance:	1107.8	Residual deviance:	1183.9

Source: done by author in R, based on Findex 2021

i. Education (base = Primary_or_less). Education is the only predictor that is statistically significant at 5%. The coefficient for Tertiary is 1.662 (p = 0.001) and for Secondary is 1.248 (p = 0.016). Both are large and positive, meaning adults with secondary and especially tertiary education are much more likely to own a card than those with primary-or-less. Education is the strongest correlate in this model.

ii. Age (centered) and age squared. The linear term is −0.012 (p = 0.101) and the squared term is 0 (p = 0.645). Together these are not significant at 5%. The point estimates suggest a gentle decline in card ownership with age, but the evidence is weak and a clear age pattern cannot be claimed.

iii. Employment (In work vs Out). The coefficient is 0.383 (p = 0.112). It is positive but not statistically significant at 5%. People in work look somewhat more likely to own a card, yet the estimate is imprecise.

iv. Internet access (Yes vs No). The coefficient is 0.520 (p = 0.163). Direction is positive, but it is not significant. This is weaker than in the anydigital payment model.

v. Income (Upper = Q4–Q5 vs Q1–Q3). The coefficient is 0.274 ($p = 0.222$). The association is small and not significant. Unlike the anydigital model, where income had more influence, income does not explain card ownership well once education is in the model.

vi. Female (1 vs 0). The coefficient is −0.105 ($p = 0.618$). This is far from significant, so after controlling for age, income, education, work status and internet access, there is no reliable gender gap in card ownership.

Table 6. Average Marginal Effects, Card ownership model

Variable	AME (pp)
female_b (1 vs 0)	**-2.006**
age (+1 SD)	**-4.832**
educ:Secondary	**28.013**
educ:Tertiary	**35.436**
inc_upper vs inc_lower	**5.195**
emp_in (In vs Out)	**7.593**
internetaccess (1 vs 0)	**10.795**

Source: done by author in R, based on Findex 2021

Model note. Pseudo-R^2 = 0.064, so the model explains only a modest share of variation. The main takeaway is clear: education dominates card ownership; other predictors are directionally sensible but not statistically decisive at the 5% level. Compared with the "any digital payment" model, income and internet access matter less for cards, which aligns with the idea that digital use can happen even without a physical card and is also a consequence of the Findex methodology, where fin2 variable (debit card ownership) excluded mobile money accounts.

5.3 Evidence from both models

Across the two models, education is the strongest predictor of financial inclusion in Ukraine. Adults with secondary and especially tertiary education are far more likely to own a card and to make a digital payment than those with primary schooling only- by around 25-35pp, even after controlling for income, age, and sex. Education is therefore the core structural driver in Ukraine across both measures.

At the same time, the income effect differs across outcomes. Income shows a clear association with digital use, but no robust association with card ownership once other covariates are held constant.

The internet access patterns suggest that it is associated with digital use rather than with product ownership. In the anydig payment model, having internet access is positively associated with reporting at least one digital transaction during the past year. This is intuitive, as connectivity lowers the everyday frictions of paying online, receiving transfers, or using a banking app. In contrast, the card-ownership model shows no reliable association with internet access once other factors are held constant. A card is a banking product, not a connectivity product, and respondents can still report digital activity without owning a physical debit card.

Employment shows a positive direction in both outcomes, but the estimates are imprecise and do not reach conventional significance in the card model. Once education and income are included, employment adds little extra information, because it is closely related to those variables. In practice, employment is a useful targeting flag (for example, salary-linked banking onboarding), but it is not the main driver of inclusion in these specifications.

The same can be said about age and gender predictors- the models do not find a statistically reliable impact on the mentioned variables. This suggests that apparent gaps by age or gender are largely explained by differences in schooling, access, or economic position rather than by age or gender themselves. For business policy and product design, it is therefore more effective to remove practical barriers, such as interface complexity or onboarding steps, than to treat age or gender as the root of the problem.

5.4 Implications

Educational background and digital proficiency play a decisive role in determining who uses digital finance in Ukraine. Adults with only primary schooling are far less likely to use digital payments or own a card. National surveys show that 40.4 % of adults have digital skills below the basic level, and only 38 % have advanced skills. More than half of adults believe they need further digital training. These suggest that a large portion of the population lacks the skills needed to navigate mobile banking and online payments (Ministry of Digital Transformation of Ukraine Study, 2023).

Income and employment status also matter. As the result of this study, it was found that income correlates with an increase in the likelihood of making digital payments. Earlier research indicates that the poorest, people outside the labor force and rural residents experience the highest exclusion, with up to 68–75 % of adults in these groups not participating in formal finance (Naumenkova et al, 2019). Physical infrastructure contributes to this divide. The number of bank branches per 100,000 adults fell sharply: from 18 in 2016 to 8.7 in 2024, leaving rural residents without nearby access. In these regions the exclusion rate reaches 67.7 %. Although the probit models found no significant gender effect once education and income were controlled for, previous Findex data show that women's exclusion rates remain higher than men's, especially among low-income and rural households.

Connectivity and trust form another important dimension. While 93.8 % of adults have home internet access, usage varies by age: 96 % of adults aged 18–29 use the internet daily, compared with 71 % of those aged 60–70 (Findex Report, 2021). Digital payments depend on internet access, so even small connectivity gaps can negatively affect usage. A final barrier is trust: 54 % of unbanked adults in Ukraine cite lack of trust in the financial system. This mistrust usually comes from unclear fees or poor consumer experiences, which makes people reluctant to open or use accounts.

The barriers that keep people from using digital finance are interconnected and differ across groups. Basing on the literature used and the study itself, they can be ranked by their relative importance for non-use of digital finance.

1. Limited digital skills and education. Low digital proficiency is the biggest obstacle. More than two-fifths of adults possess digital skills below the basic level, and educational attainment is the strongest predictor of digital financial use. Without the ability to use smartphones or navigate applications, people simply cannot make digital payments.

Banks and fintechs should therefore invest in practical education programmes. Interactive tutorials built into mobile apps can help first-time users complete their first payment. Partnering with schools, community centres and women's groups can extend this support to rural areas and older adults. Training should be presented in simple language and focus on building confidence, since many people, especially the elderly, say they need more digital training.

2. Lack of money and affordability concerns. Financial capability is a close second. Globally, 62 % of unbanked adults cite not having enough money as a reason to remain outside the system. In Ukraine this share is 58.4 % (Findex Report, 2021). Even when digital accounts exist, fees for maintenance or cash withdrawals can deter low-income users.

Providers can address this barrier by offering basic digital accounts without minimum balances and by reducing or waiving monthly fees. Micro-savings and micro-credit products tailored to irregular incomes would help low-income households manage cash flows. These services can be delivered through mobile wallets so users do not need to travel to a branch. Simplified fee structures and clear communication are essential so that users know what they are paying for.

3. Mistrust in financial institutions. Over half of unbanked Ukrainians say they do not trust banks or payment providers. Earlier research confirms that opaque pricing and poor customer service discourage account use.

Banks and fintechs must demonstrate reliability to win over sceptical customers. Publishing transparent fee schedules and using push notifications to show when charges are applied can help. Strengthening customer support through call centres and local agent networks ensures that users can resolve problems quickly. Fraud prevention measures such as two-factor authentication and clear consumer protection policies also increase confidence. Working with respected community leaders and local businesses may further reassure users.

4. Physical and infrastructure barriers. Distance to bank branches matters, especially in rural areas. Branch closures and poor infrastructure leave many communities underserved, and digital payments require stable internet access.

For banks and fintechs, this means that maintaining a human touchpoint in rural areas is critical. Partnering with post offices, pharmacies or local shops to act as agent points can mitigate the effect of branch networks number decrease and make cash-in or cash-out services easier. At the same time, providers should focus on designing lightweight mobile applications that work in low-internet environments and do not require constant connectivity. These steps are not about assuming poor infrastructure everywhere, but about aligning product design with the real usage patterns of older and rural Ukrainians. Finally, simple tutorials built into apps and responsive phone support can help users build confidence and bridge the skills gap highlighted in the national digital literacy report by Ministry of Digital Transformation.

5. Documentation and formalities. A quarter of unbanked adults globally lack the documents needed to open an account. Displaced people and informal workers often struggle with KYC requirements.

Providers can use digital identity platforms, such as Ukraine's Diia system, for remote verification. Progressive accounts with transaction limits allow customers to start using digital services with minimal paperwork and later upgrade when they can provide more documentation. Clear guidance during the onboarding process, offered in multiple languages, will help people feel comfortable and reduce drop-out.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusion of findings

As a result of my study, it was examined who in Ukraine is most likely to use digital finance and who remains outside it. Using Global Findex 2021 microdata and weighted logistic models, two clear patterns emerged. First, education stands out as the most consistent predictor of inclusion across both outcomes (any digital payment and debit card ownership): adults with secondary and especially tertiary education are much more likely to be included than those with primary schooling only.

At the same time, the two outcomes differ. Internet access and income are more strongly tied to reporting at least one digital transaction than to simply holding a card. In the card model, education remains decisive while income and internet fade in significance; this is consistent with the idea that people can transact digitally through bank apps even without a physical card. Other factors: employment and gender have turned out to be statistically insignificant across both models.

So, know-how, proxied by education, is central in Ukraine's digital inclusion story. In practical terms, inclusion follows two pathways:

(i) capability → card access,

(ii) and capability + connectivity → digital use.

6.2 Business and Policy Implications

6.2.1 Implications for Financial Institutions

For banks and fintechs, the findings of this study imply that customer base growth will come from designing journeys that meet digital finance specific knowledge capability of users, not just connectivity. Education being the strongest correlate suggests that complex onboarding and feature-heavy apps will keep the gap wide. Banking firms and fintechs should then prioritise simple, low-barrier entry points into core use cases (wage receipt, P2P transfers, bill pay, etc) and pair them with in-app guidance that helps first-time users complete a successful action. Where income is tight and trust is fragile both well-documented barriers in Ukraine- transparent pricing, and clear communication about fees will matter more than new features. These steps directly target the most cited reasons for non-use (i.e insufficient funds, mistrust) and align with the pattern that usage improves when capability and small frictions are addressed together.

Banking branches distribution should remain hybrid. As there is an ongoing trend of physical branch density decline that will likely preserve, and it has been part of the transition toward digital bank branches across multiple European countries, including Ukraine- that does not mean physical touchpoints are already irrelevant. Agents or partner outlets in rural areas can give customers a physical customer support for cash-in/cash-out operations, onboarding support, and any problem resolution, especially for older users. This helps link digital journeys to communities that still face skill and trust constraints.

6.2.2 Policy Implications

Policymakers must act strategically based on these correlational findings. Firstly, I recommend to implement financial literacy programs in universities/schools/other educational institutions as vital part of digital finance system, given the strong link between education and account ownership and payments usage. Second, consumer protection and transparency standards should make fees and dispute resolution simple to understand, as this directly targets the trust problem reported by unbanked Ukrainians.

6.3 Limitations and Directions for Future Study

Three limitations deserve emphasis. First, the design is cross-sectional and descriptive. The models show strong associations, especially for education, but do not imply causality.

Second, the evidence is pre-war: the 2021 Findex snapshot reflects Ukraine before the full-scale invasion. Post-2022 migration, income shocks, and regional damage may have changed both demand and supply, so the estimates should be read as a baseline rather than a current state of things. Third, a small number of predictors was used intentionally to keep the analysis interpretable; this choice may leave out institutional or behavioural factors that also shape usage.

That being said, to ensure this study remains relevant, I would consider several future research steps:

(i) Post-conflict update: The most important next step is for me to find and analyze post-2022 survey data to see how the connections between Education and Internet Access have changed due to the war.

(ii) Cross-country analysis: It is something that has not been done in this iteration of research, however it is also something that will further drive the academic weight of results. So, a comparative analysis should be done comparing Ukraine to a Europe and Central Asia countries. This would make the results more interpretable- whether Ukraine's case is unique among European countries or not, and take the best-practices from other countries experiences.

REFERENCES

Devdiscourse. (2024). IFC and National Bank of Ukraine sign deals to support economic recovery amid war. https://www.devdiscourse.com/article/business/3139154

Forbes Ukraine. (2025). Monobank reports 9.8 million active cards. Retrieved from https://forbes.ua

IFC. (2024). IFC and National Bank of Ukraine strengthen partnership to boost financial sector resilience. https://www.ifc.org/en/pressroom/2024

IT Ukraine Association. (2024). Digital Tiger: Ukraine's IT Industry Report 2024. Retrieved from https://itukraine.org.ua/files/DigitalTiger2024.pdf

Naumenkova, S., Mishchenko, S., & Dorofeiev, D. (2019). Digital financial inclusion in Ukraine: Challenges and prospects. Bulletin of the NBU, 4, 22–35. doi:10.21511/imfi.16(3).2019.18

National Bank of Ukraine. (2023). Annual report 2023: Strategy of recovery. https://bank.gov.ua/en

National Bank of Ukraine. (2023b). SEP upgraded to ISO 20022 standards. https://bank.gov.ua/en/payments/sep

National Bank of Ukraine. (2024). Annual report 2024. https://bank.gov.ua/admin_uploads/article/annual_report_2024_eng.pdf?v=13

Shapoval, O. (2021). Digitalization of Ukraine's financial sector: Barriers and opportunities. Journal of Financial Transformation, 53, 77–88. doi:10.21511/imfi.18(4).2021.18

World Bank. (2022). Global Findex Database 2021.

Harvard Kennedy School. (2023). Ukraine's digital transformation: Innovation and resilience. https://www.hks.harvard.edu/centers/cid/voices/ukraines-digital-transformation-innovation-resilience

Interfax Ukraine. (2025). Ukraine banking sector market share of issuing payment cards.

Ministry of Digital Transformation Study on Financial Literacy in Ukraine. (2023). Дія.Освіта — Дослідження

IMF, Financial Access Survey (2025)

APPENDIX

Table A1. Commercial Bank Branch Density per 1,000 km^2

Country	2021	2022	2023	2024
Poland, Republic of	23.8	22.6	21.8	21.3
Romania	21.8	21.5	21.1	20.8
Czech Republic	23.5	21.9	20.3	19.4
Slovak Republic	21.1	20.7	20.0	19.4
Ukraine	18.0	15.4	16.1	15.5
Lithuania, Republic of	11.1	10.5	10.2	9.6
Latvia, Republic of	6.6	5.2	4.7	4.4

*Some European countries were taken based on geographical proximity and comparable economic development

Table A2. Commercial Bank Branch Density per 100,000 adult population

Country	2021	2022	2023	2024
Poland, Republic of	23.8	22.6	21.8	21.3
Romania	21.8	21.5	21.1	20.8
Czech Republic	23.5	21.9	20.3	19.4
Slovak Republic	21.1	20.7	20.0	19.4
Ukraine	18.0	15.4	16.1	15.5
Lithuania, Republic of	11.1	10.5	10.2	9.6
Latvia, Republic of	6.6	5.2	4.7	4.4

*Some European countries were taken based on geographical proximity and comparable economic development

Table A3. Anydigital models AIC test

Anydig model specifications	Df	AIC
glm_ext	12	805.1
glm_pref	9	800.07

*collapsing of income from five quantiles to two categories- lower (Q1-Q3) and upper (Q4-Q5).