

Financial Inclusion and poverty in Selected Arab Economies: Panel Econometric Evidence 2004-2022

Dr. Benkari Samir

Ferhat Abbas University Setif1, Algeria.

Email: ssamirbbenkari@gmail.com

Pr. Hallam Zouaouia

University of DjilaliLiabes- Sidi Bel Abbes, Algeria.

Email: z.hallam@yahoo.fr

Pr.Bouchikhi Bouhaous

University of Abdel Hamid Ibn Badis-Mostaganem.

Email: bouchikhi.bouhaous@yahoo.fr

Pr. Boudrama Mostefa

Ferhat Abbas University Setif1, Algeria.

Email: b_mostefa19600@gmail.com

Abstract

This study investigates the empirical association between financial inclusion proxies and poverty in Algeria, Egypt, Lebanon, Libya, and Tunisia over the period 2004–2022. The analysis is based on a balanced panel of 95 country-year observations. Financial access is proxied by the total number of automated teller machines, financial usage by outstanding deposits with commercial banks as a percentage of GDP, and poverty by the reported share of the population living below the poverty line. The econometric evidence compares pooled ordinary least squares, random-effects, country fixed-effects, and two-way fixed-effects estimators. To avoid the evidence of heteroskedasticity, strong serial correlation, and borderline cross-sectional dependence, the preferred specification relies on Driscoll–Kraay standard errors. Robustness is further examined using first differences, country-specific linear trends, inverse poverty-spell weighting, a reduced sample containing one observation per distinct poverty spell, alternative functional forms, and an exploratory error-correction model. Although pooled estimates indicate a negative association between ATM expansion and poverty, this relationship disappears and changes sign after controlling for unobserved country heterogeneity and common time effects. In the preferred log–log two-way fixed-effects model, the ATM elasticity is positive but statistically insignificant at 0.102 ($p = 0.152$), whereas the deposit elasticity is negative but insignificant at -0.063 ($p = 0.377$). First-difference estimates provide only marginal evidence of a negative deposit–poverty association, while the error-correction coefficient is negative but statistically insignificant.

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1. Introduction

In a world where economic inequality is widening and millions remain outside the reach of basic financial services, the concept of "financial inclusion" has emerged as a promising solution for addressing poverty and achieving inclusive development. Since its official launch during the "International Year of Microcredit" in 2005, there are more than one term for the phrase financial inclusion; some refer to it as financial encompassing, while others call it financial deepening. Despite the varied terminology, the meaning remains the same, which refers to the development of financial and banking institutions, increasing the effectiveness of monetary policy, and diversifying its tools with the aim of enhancing efforts to attract individuals with limited incomes and connecting them to the financial system. This includes providing financial services to all members of society in both remote and urban areas, through all financial and banking institutions, either directly or indirectly. (Saadouni, 2021), it has transcended its status as a mere banking slogan, evolving into a policy framework through which countries aspire to ensure that all social groups, especially the poorest, have access to affordable, accessible, and effective financial services.

This relationship stems from a firm belief that providing credit, savings, and insurance to marginalized groups can alleviate the financial constraints that hinder their investment in productive activities and human development, thereby contributing to poverty reduction. By four main channels: The first one operates through savings and consumption smoothing. Poor households face volatile earnings and limited liquid assets. Safe accounts and low-cost payment mechanisms can reduce the need to hold cash, protect savings from theft or social claims, and facilitate transfers from family networks. In the presence of health, employment, or price shocks, formal savings and emergency credit can prevent distress sales of productive assets and sharp cuts in food, schooling, or medical expenditure. The long-run mobile-money evidence from Kenya illustrates how financial resilience and changes in saving behaviour can translate into lower poverty (Suri & Jack, 2016). The second channel concerns indivisibilities and credit constraints. The Galor-Zeira and Banerjee-Newman traditions show that unequal access to finance can prevent talented but poor households from investing in education, enterprise, or higher-return occupations. By relaxing those constraints, inclusive finance can improve the allocation of capital and enable households to cross minimum investment thresholds. Rural banking evidence from India is consistent with this mechanism: mandated branch expansion lowered rural poverty and raised non-agricultural output (Burgess & Pande, 2005). A third channel works through transaction costs and market participation. Greater geographic access can reduce travel time, waiting costs, and the risks of cash-based transactions. Reliable payment infrastructure also allows government transfers, wages, and remittances to reach recipients more efficiently. Lower transaction costs can deepen market participation, improve the timing of purchases and sales, and support small-scale entrepreneurship. And finally, The fourth channel is indirect. Financial intermediation can improve the allocation of savings, support investment, raise productivity, and generate employment. (Beck, Demirgüç-Kunt, & Levine, Finance, inequality and the poor, 2007) find that financial development is associated with faster income growth for the poorest quintile through both aggregate growth and distributional changes, (Omar & Inaba, 2020) similarly report that a multidimensional financial inclusion index is associated with lower poverty in a large developing-country panel. These indirect effects, however, depend on whether growth reaches labour-intensive sectors and whether disadvantaged groups can use the financial system productively.

However, this relationship is not linear and is fraught with complexities and fundamental challenges that may prevent financial inclusion from achieving its desired goals in combating poverty. Some studies indicate that simply providing financial services is not enough; it may face structural obstacles such as the "elite monopoly" of the rural credit market, or the lack of financial literacy and knowledge among the poor, which prevents them from effectively benefiting from these services and may trap them in debt

instead of lifting them out of poverty. The effectiveness of financial inclusion in reducing poverty is linked to several factors, including the rate of economic development, the quality of institutions, the efficiency of governance, and the design of appropriate policy frameworks that ensure the inclusiveness, commercial sustainability, and suitability of services to the needs of the target groups.

Therefore, the central problem addressed by this study is the attempt to deconstruct the complex relationship between financial inclusion and poverty, And whether changes in conventional financial inclusion proxies are associated with changes in poverty after persistent country characteristics and common time shocks are removed. The study is organised around four questions:

- Do the pooled correlations between financial access, deposit-based usage, and poverty survive the inclusion of country and year fixed effects?
- Are the results robust to serial correlation, heteroskedasticity, cross-sectional dependence, first differencing, and country-specific trends?
- Do the conclusions change when repeated poverty values receive less weight or when only distinct poverty spells are retained?
- Is there evidence of a stable error-correction mechanism linking poverty and the financial inclusion proxies over the long run?

The corresponding hypotheses follow the conventional inclusion–poverty argument:

- H_1 : A rise in the ATM-based access proxy is associated with a reduction in the poverty rate ($\beta_1 < 0$).
- H_2 : A rise in the deposit-based usage proxy is associated with a reduction in the poverty rate ($\beta_2 < 0$).
- H_3 : Any poverty-reducing relationship remains present after country heterogeneity, common shocks, and dynamic adjustment are taken into account

.2. Previous studies:

Based on the above, this paper seeks to explore the dimensions of this complex relationship, through an analysis of theoretical literature and applied experiences, to determine the real potential of financial inclusion in alleviating poverty, and the conditions and contexts that determine its success or failure in achieving this noble humanitarian goal.

- Deborah Schubert, (2019): The Impact of Financial Inclusion on Poverty in Low- and Middle-Income Countries, this study has empirically confirmed a significant long-term negative relationship between financial inclusion and poverty in low- and middle-income countries, with a stronger relative impact on the extremely poor at \$1.90/day than on those at \$5.50/day. The effect, however, is diminishing, being more pronounced in lower-income nations, which implicitly supports the existence of critical thresholds. While the fixed-effects results are robust, the study acknowledges the limitation of potential reversal causality. Crucially, the findings demonstrate that financial inclusion works best in synergy with investments in education and internet access.
 - Mohammed Tiku , (2025): The Impact of Financial Inclusion on Poverty Reduction in Ethiopia, by using an ARDL model on Ethiopian time-series data (1994–2023), the study confirms a significant long-run negative relationship between financial inclusion and poverty. Primary education completion and insurance services are the strongest poverty-reduction drivers, with one-unit increases reducing poverty by 1.52 and 4.58 units, respectively. Private credit shows a statistically significant but negligible practical effect, while mobile subscriptions have no
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significant long-run impact. Short-run dynamics are weak, but lagged education improvements significantly reduce current poverty with a time lag. Granger causality tests confirm that education, insurance, and private creditors predict future poverty changes. The ECM term is positive and significant, suggesting slow or problematic adjustment towards equilibrium. The study recommends prioritizing education quality, expanding affordable insurance, and integrating mobile technology with other interventions for sustainable poverty reduction.

- Kimty Seng, (2021):The Poverty-Reducing Effects of Financial Inclusion: Evidence from Cambodia, Using an endogenous switching model on 2015 FinScope data, the study finds that financial inclusion significantly reduces poverty in Cambodia, but only when users possess basic financial literacy. Financial users without literacy gain modest income increases (\$7/month), while literate users gain more (\$8/month), with female-headed literate households gaining the most (\$11/month). Financial inclusion also reduces household budget deficits by 26–27%, with literate women achieving the largest reduction (20%). The study confirms that financial literacy reinforces poverty-reducing effects and mitigates budget deficit risks. Gender matters: female users consistently outperform male users in both income gains and deficit reduction. The author recommends prioritizing financial education and targeted gender-inclusive policies for sustainable poverty reduction.
- Chinonyerem Matilda Omenihu, (2024): Financial Inclusion and Poverty Alleviation: A Critical Analysis in Nigeria, Using both macro (IMF 2004–2021) and micro (Global Findex 2021) data with PCA and probit regression, the study holistically examines financial inclusion's three dimensions (access, usage, quality) on poverty in Nigeria. Financial access shows a strong negative relationship with poverty, confirming that improved access reduces poverty rates. Financial usage significantly reduces poverty (marginal effect: -0.051, $p < 0.05$), rejecting the null hypothesis of no effect. However, financial quality shows a negative but insignificant effect on poverty alleviation. The overall financial inclusion index negatively relates to poverty but is also statistically insignificant. Education (secondary/tertiary) significantly reduces poverty likelihood, while females and rural residents are more likely to be poor. The study concludes that usage is the most impactful dimension, recommending tailored financial products and enhanced financial literacy programmes.
- Saha Sumanta Kubar,(2016): Exploring the role of financial inclusion in poverty reduction: An empirical study, This study applies two-stage fixed-effect methods and conditional analysis to examine these issues during the period 2004-2018 . The results reveal that financial inclusion is more effective in poverty reduction in countries where women and the poor have higher access to formal finance. Though financial inclusion significantly affects poverty in countries with high inequalities, high income, and gender inequality diminish its impact. The study also investigates how institutional quality and educational attainment affect financial inclusion's impact on poverty and finds that these factors improve the effect of financial inclusion. The study prescribes that policymakers aim to make financial services accessible to disadvantaged groups. It also recommends that developing countries try to reduce inequalities, improve institutional quality,

and encourage school enrollment along with financial inclusion initiatives to reduce poverty substantially.

3. Methodology and Econometric Tools

To address the study and achieve its specified objectives, we relied on the standard analysis model in panel data models, as it is the most appropriate for analyzing this type of data. Therefore, this section will address the concept of panel data, its importance, and the steps to follow in its estimation

3.1. Concept of Panel Data :

The term "panel data" refers to longitudinal or cross-sectional time-series data that combines observations of a set of individuals over multiple time periods. That is, it combines the characteristics of both cross-sectional data and time-series data at the same time. If the time period is the same for all individuals, the panel data model is called "balanced." However, if the time period differs from one individual to another, the model is called "unbalanced." (Abonazel, 2016). There is some argument among scholars regarding the extent to which panel data should be used in analysis. Some maintain that, in addition to learning about individual change, panel data can help to assess levels and trends over time, in much the same way that cross-sectional data analysis does (though note that cross-sectional analysis does not provide information about change at the individual level). However, others argue that panel data should be used purely for analyzing change, as there can be an issue of "panel attrition" (i.e. individuals dropping out of the observation/survey) when it is used to look at long-term trends. On balance, however, the academic community is of the opinion that it would be a waste of financial resources to focus only on analyzing change, as panel data can be a rich source of information on levels and trends, and that cross-sectional surveys often do not capture certain variables of interest. (Andreß, 2017). The modern approach proposes the basic formula for data regression as developed by (Green, 1991) and from this comes the panel data models in three main forms, which are : Pooled Regression Model (PRM), Fixed Effects Model (FEM), Random Effects Model (REM). (Fangfang & Kefeng, 2015)

3.2. Sample construction and data

Data includes 95 observations for five countries from 2004 through 2022, produces a balanced panel with $N = 5$, $T = 19$, and $NT = 95$.

3.3. Econometric specification:

The preferred model is expressed in logarithms. This reduces the influence of the highly skewed ATM stock and permits elasticity interpretation. We refer with i index countries and t index years. The baseline two-way fixed-effects equation is:

$$\ln Pov_{it} = \alpha_i + \lambda_t + \beta_1 \ln ATM_{it} + \beta_2 \ln DEP_{it} + \varepsilon_{it} \dots\dots(1)$$

POV refer to the population below the poverty line. ATM is the total number of automated teller machines which measure the access aspect. Dep is outstanding to the deposits with commercial banks.

The coefficients β_1 and β_2 measure within-country associations after common time shocks are removed. For example, β_1 is the percentage change in the reported poverty rate associated with a 1% change in the ATM stock, holding the deposit proxy and fixed effects constant. Because no added external instrument or exogenous policy shock is available the coefficients are interpreted as conditional associations rather than causal effects.

System GMM is designed for dynamic panels with a sufficiently large cross-sectional dimension. With only five countries, internal instruments would proliferate rapidly relative to the number of groups, Hansen-type tests would have little discriminatory power, and cluster-based inference would be unstable.

The lagged dependent variable could also absorb the stepwise poverty pattern rather than genuine economic persistence. GMM is therefore not treated as the default merely because it appears in one of the source articles.

Fixed effects are preferred because the five economies differ persistently in size, banking structure, conflict exposure, institutional quality, and the measurement level of the poverty variable. A joint test strongly rejects the adequacy of pooled OLS. Year effects are retained even though they are not jointly significant, because the sample contains common events—such as the global financial crisis, regional political shocks, and the pandemic—that may affect all countries to different degrees.

The residual diagnostics reveal heteroskedasticity and strong serial persistence, while the Pesaran CD test is borderline at the 10% level. Driscoll–Kraay standard errors with a bandwidth of two years are therefore used for the preferred inference. This covariance estimator is robust to general heteroskedasticity, serial correlation up to the chosen bandwidth, and contemporaneous cross sectional

dependence under large-T logic. With $T = 19$, the correction is useful but not asymptotically ideal, so the paper also reports multiple sensitivity checks.

3.4. Robustness and data-quality sensitivity

The following specifications are estimated in addition to Equation (1):

Pooled OLS, random effects, country fixed effects, and country fixed effects with country-specific linear trends.

- First differences with year effects, which remove time-invariant country effects and reduce the risk of spurious level relationships.
- Inverse poverty-spell-length weighted TWFE, assigning a total weight of one to each uninterrupted spell of repeated poverty values.
- A 21-observation sample containing the first year of each distinct poverty spell.
- Alternative level and semi-log functional forms to expose scale sensitivity.
- Leave-one-country-out estimates to reveal whether any single country determines the results.
- An exploratory error-correction model with lagged levels and contemporaneous first differences.

$$\Delta \ln Pov_{it} = \phi \ln POV_{i,t-1} + \phi_1 \ln ATM_{i,t-1} + \phi_2 \ln DEP_{i,t-1} + y_1 \Delta \ln ATM_{it} + y_2 \Delta \ln DEP_{it} + a_i + \lambda_t + v_{it}$$

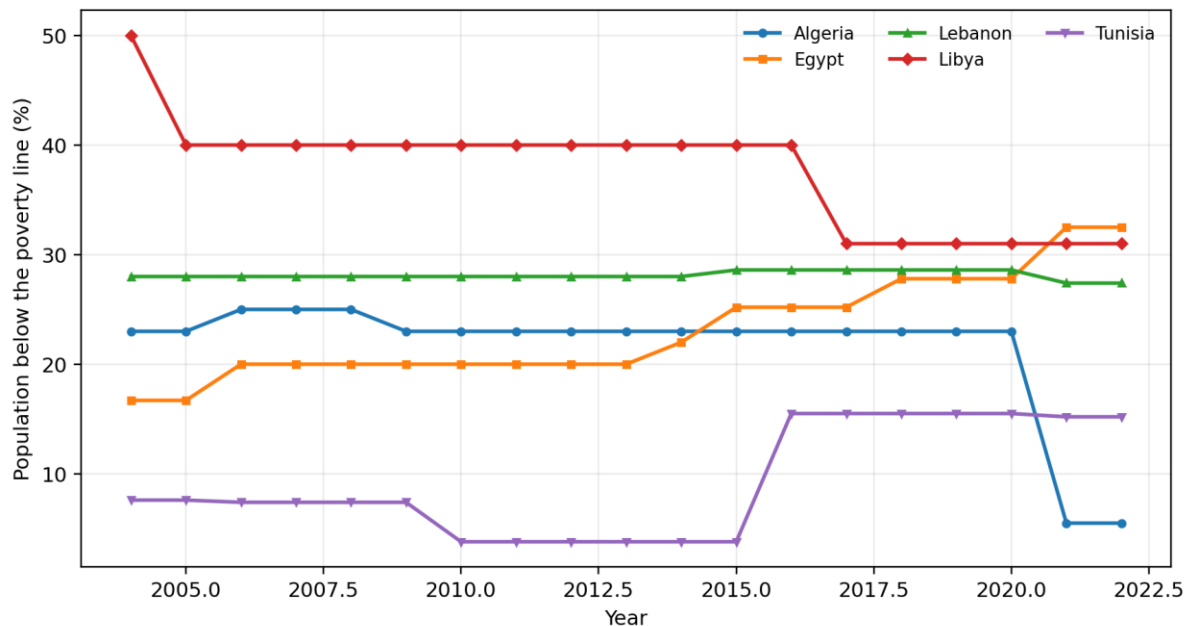
A valid error-correction interpretation requires ϕ to be negative and statistically significant. The implied long-run elasticities are $-\theta_1/\phi$ and $-\theta_2/\phi$. If ϕ is insignificant, the long-run ratios are reported only as descriptive calculations, not as evidence of cointegration.

4. Empirical Results

4.1 Evolution of the study variables

Figure 1. Reported poverty rates, 2004–2022

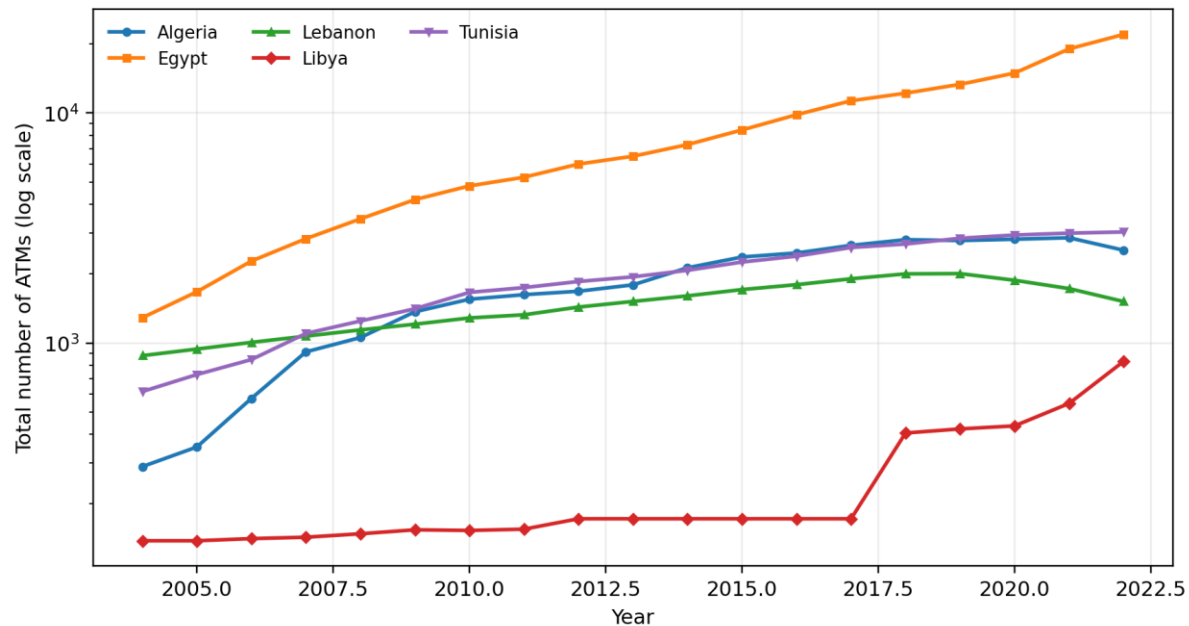
Poverty rates in the supplied panel, 2004–2022



Source: data illustration

Figure 1 shows why the poverty variable requires special treatment. Libya remains at 40% from 2005 to 2016 and then at 31% from 2017 onward. Lebanon takes only three values, and Algeria remains at 23% for twelve consecutive years before dropping to 5.5% in 2021. Tunisia falls to 3.8% for 2010–2015 and then jumps to 15.5% in 2016. These breaks may reflect changes in survey or poverty-line definitions as much as genuine annual welfare changes; the workbook does not permit the two explanations to be separated.

Figure 2. Total ATM stock, 2004–2022
ATM stock in the supplied panel, 2004–2022

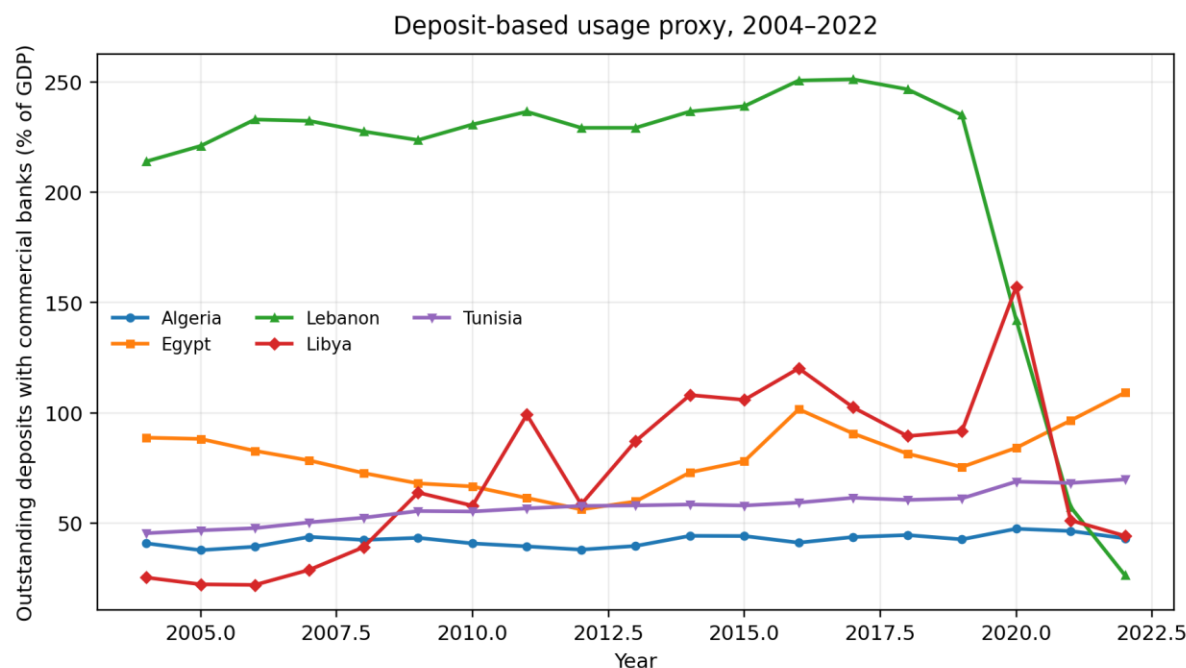


Source: data illustration

ATM stocks generally rise, but the scale differs sharply across countries. Egypt expands from 1,288 machines in 2004 to 21,975 in 2022, whereas Libya increases from 138 to 832. Because these are totals, the cross-country level difference reflects population and economic scale as well as access. Country fixed

effects remove permanent scale differences, but time-varying population and urbanisation remain potential confounders.

Figure 3. Outstanding deposits with commercial banks, 2004–2022



Source: data illustration

The deposit proxy is more volatile. Lebanon exceeds 200% of GDP for most of the sample before falling sharply after 2019, while Libya displays large swings and reaches 157.2% in 2020. Egypt declines through the early 2010s and then recovers. Such movements reflect macrofinancial structure, crises, balance-sheet revaluations, and GDP dynamics; they should not be read as direct changes in poor households' use of formal services.

4.2 Descriptive statistics and country profiles

Table 5. Descriptive statistics

Variable	N	Mean	Overall SD	Between SD	Within SD	Min	Max
Poverty rate (%)	95	23.929	10.368	10.360	4.551	3.800	50.000
ATM stock (number)	95	2747.400	3869.616	3144.114	2642.240	138.000	21975.000
Deposits with commercial banks (% GDP)	95	92.057	68.510	66.700	33.114	21.991	251.261
Log poverty rate	95	3.028	0.632	0.588	0.345	1.335	3.912
Log ATM stock	95	7.234	1.233	1.208	0.582	4.927	9.998

Log deposits/GDP	95	4.302	0.638	0.568	0.382	3.091	5.526
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Source: Author's calculations.

The poverty rate averages 23.93%, with a minimum of 3.8% and a maximum of 50%. The between-country standard deviation (10.36 percentage points) is more than twice the within-country standard deviation (4.55 points), indicating that much of the raw poverty variation is cross-sectional. The same pattern appears for the deposit proxy. ATM stock is highly right-skewed in levels, which supports the log transformation.

Table 6. Country profiles

Country	ATM2004	ATM2022	ATM GAGR	Mean Deposits/GDP	Poverty 2004	Poverty 2022	Change (PP)	Unique Poverty Values
Algeria	190	2.532	12.8%	42.2	23.0	5.5	-17.5	3
Egypt	1.288	21,975	17.1%	79.6	16.7	32.5	15.8	6
Lebanon	881	1,515	3.1%	208.6	28.0	27.4	-0.6	3
Libya	138	832	10.5%	72.4	50.0	31.0	-0.6	3
Tunisia	615	3,039	9.3%	57.5	7.6	15.2	7.6	5

Source : Author's calculations

4.3 Overall versus within-country correlation

Table 7. Overall and within-country correlations

Pair	Overall Correlation	Within-country Correlation
Log poverty and log ATM stock	-0.284	0.096
Log poverty and log deposits/GDP	0.233	0.014
Log ATM stock and log deposits/GDP	0.131	0.162

Source: Author's calculation

The distinction is decisive. The overall correlation between log poverty and log ATM stock is -0.284 , which appears to support H1. After each country mean is removed, the correlation becomes $+0.096$. The overall poverty–deposit correlation is $+0.233$, but the within-country correlation is almost zero ($+0.014$). The pooled associations are therefore driven mainly by persistent differences between countries rather than by changes occurring within a country over time.

4.4 Panel unit-root evidence:

Table 8. Fisher-type ADF tests with intercept and trend

Series	Transformation	Fisher Statistic	P-Value	Decision
Log poverty rate	Level	4.871	0.900	Do not reject
Log poverty rate	First difference	64.678	<0.001	Reject unit root
Log ATM stock	Level	11.065	0.352	Do not reject

Log ATM stock	First difference	29.060	0.001	Reject unit root
Log deposits/GDP	Level	11.541	0.317	Do not reject
Log deposits/GDP	First difference	57.683	<0.001	Reject unit root

Source: Eviews 13 outputs

With a deterministic trend, the Fisher tests do not reject a unit root for any variable in levels: the p-values are 0.900 for poverty, 0.352 for ATM stock, and 0.317 for deposits/GDP. The first differences reject at conventional levels. The intercept-only test for ATM stock rejects in levels because Algeria and Tunisia display strong deterministic trends, illustrating the sensitivity of short samples to the deterministic specification. The appropriate conclusion is therefore modest: the series are at most I(1), but the exact integration order is uncertain and the poverty test is mechanically influenced by long repeated spells. First-difference and ECM checks are consequently necessary.

4.5 Model selection and diagnostics

Table 9. Model selection tests

Test	Statistic	Df	p-value	Decision at 5%
Joint significance of country effects	40.831	4, 88	<0.001	Reject
Joint significance of year effects conditional on country FE	0.514	18, 70	0.943	Do not reject
Hausman FE versus RE	1.063	2	0.588	Do not reject

Source: Eviews 13 outputs

Country effects are jointly significant ($F = 40.831$, $p < 0.001$), so pooled OLS is rejected.

Conditional on country effects, year dummies are not jointly significant ($p = 0.943$). The Hausman statistic does not reject random effects ($p = 0.588$), and the RE coefficients are in fact close to the country-FE coefficients. The preferred estimator nonetheless retains fixed effects because the sample is not a random draw of countries and because the institutional and structural differences are plausibly correlated with the financial variables. Year effects are retained as a conservative control for common shocks; results without them are also reported.

Table 10. Residual diagnostics for the preferred TWFE model

Diagnostic	Statistic	p-value	Interpretation
Breusch-Pagan heteroskedasticity LM	49.876	0.001	Evidence of non-constant residual variance
Breusch-Pagan heteroskedasticity F	3.224	<0.001	Evidence of non-constant residual variance
Jarque-Bera residual normality	42.504	<0.001	Residuals are non-normal (skew=-0.858, kurtosis=5.791)
Ramsey RESET (squared fitted value)	18.738	<0.001	Functional-form/omitted-variable warning
Pesaran CD	-1.831	0.067	Borderline cross-sectional dependence; mean pairwise residual correlation=-0.133

Residual AR(1) coefficient	0.890	<0.001	Strong positive serial persistence; robust covariance is required
Durbin-Watson, preferred TWFE	0.493	-	Far below 2, consistent with positive serial correlation

Source: Eviews 13 outputs

The Breusch–Pagan tests reject constant variance, and the Jarque–Bera statistic rejects residual normality. The RESET test also rejects, signalling omitted variables or functional-form misspecification. Residual serial persistence is severe: the estimated AR(1) coefficient is 0.890 and the Durbin–Watson

statistic is 0.493. The Pesaran CD statistic is -1.831 ($p = 0.067$), which is borderline at 10%. These results justify robust inference but also confirm that the three-variable workbook cannot support a fully specified structural poverty model.

4.6 Baseline panel estimates

Table 11. Baseline estimates: financial inclusion and poverty

Variable/statistic	(1)pooled	(2)RE	(3) Country FE	(4) TWFE	(5) TWFE DK	(6) Country Trends- DK
Log ATM stock	-0.164*** (0.050)	0.044 (0.062)	0.057 (0.064)	0.102 (0.147)	0.102 (0.068)	0.068 (0.163)
Log deposits/GDP	0.272*** (0.096)	0.011 (0.096)	-0.001 (0.097)	-0.063 (0.113)	-0.063 (0.069)	0.049** (0.023)
Country effects	No	Random	Yes	Yes	Yes	YES
Year effects	No	No	No	Yes	Yes	NO
Country trends	No	No	No	NO	NO	YES
Observations	95	95	95	95	95	95
R ²	0.155	0.006	0.704	0.739	0.739	0.806
Adjusted R ²	0.137	-0.016	0.684	0.649	0.649	0.781
Durbin–Watson	0.272	0.527	0.558	0.493	0.493	0.757

Source: Eviews 13 outputs

The pooled model produces two statistically significant coefficients: ATM stock is negative (-0.164 , $p = 0.001$) and deposits/GDP are positive ($+0.272$, $p = 0.005$). Taken literally, the first result would support the access hypothesis while the second would reject the usage hypothesis. This interpretation is not credible because the pooled model ignores the large, persistent differences among the five countries. Its Durbin–Watson statistic of 0.272 also indicates severe residual persistence.

Introducing country effects eliminates both associations. The ATM coefficient becomes $+0.057$ ($p = 0.371$) and the deposit coefficient becomes essentially zero (-0.001 , $p = 0.990$). Random effects yield a similar conclusion. The change from a negative pooled ATM coefficient to a positive within-country coefficient demonstrates that the pooled result is a between-country comparison: countries with larger ATM networks happen to have lower reported poverty on average, but expansions within a country are not followed by a consistent decline in its poverty series.

In the preferred two-way fixed-effects specification, the ATM elasticity is $+0.102$ with a Driscoll–Kraay standard error of 0.068 ($p = 0.152$). The deposit elasticity is -0.063 with a standard error of 0.069

($p = 0.377$). Neither coefficient is statistically different from zero. The point estimates also fail to support a coherent access–use story: access is positive, while usage is negative but imprecise.

Allowing country-specific linear trends does not recover the expected negative ATM effect. The ATM coefficient is +0.068 ($p = 0.683$). The deposit coefficient becomes positive and significant at 5% (+0.049, $p = 0.046$), the opposite of H2. Given the strong trending behaviour and the small sample, this result is better interpreted as further evidence of instability than as proof that deposits increase poverty.

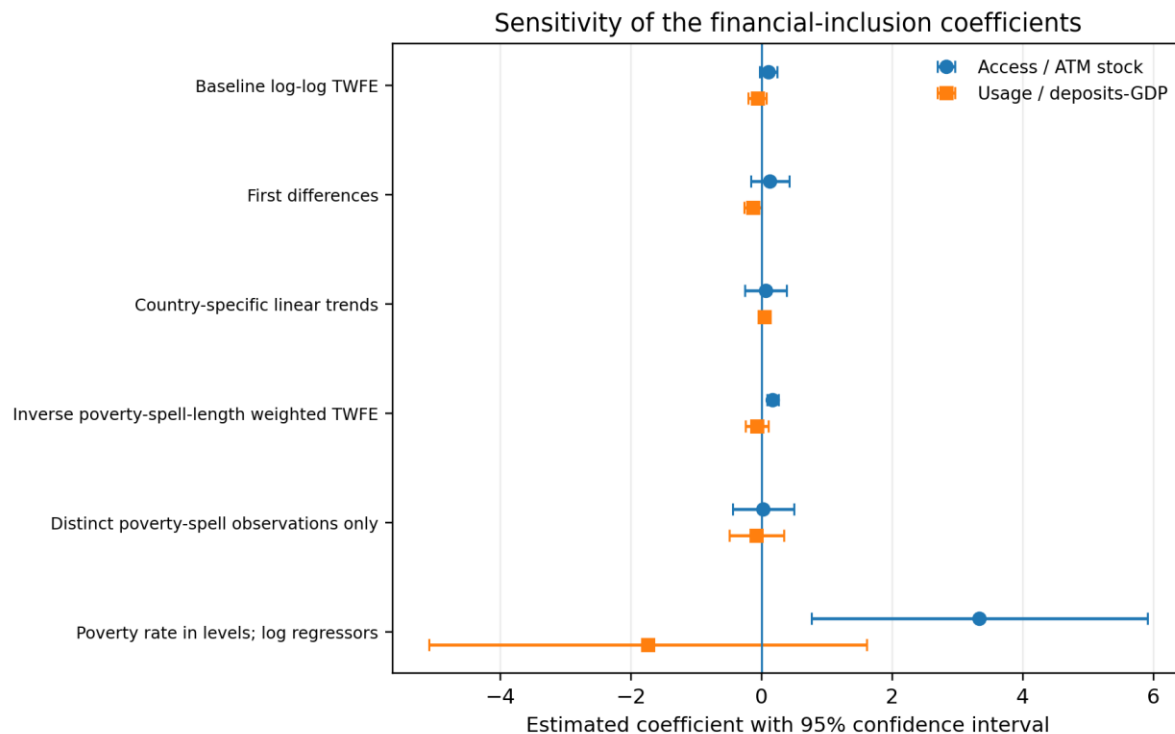
4.7 Robustness, poverty repetition, and functional-form sensitivity/

Table 12. Robustness and sensitivity estimates

Specification	ATM/ACCESS Coefficient	Deposits/ Usage Coefficient	N	R ²	Inference
Baseline log-log TWFE	0.102 (0.068)	-0.063 (0.069)	95	0.739	DK(2)
First differences	0.131 (0.149)	-0.130* (0.068)	90	0.205	DK(2)
Country-specific linear trends	0.068 (0.163)	0.049** (0.023)	95	0.806	DK(2)
Inverse poverty- spell-length weighted TWFE	0.171*** (0.043)	-0.072 (0.090)	95	0.664	WLS with DK(2)
Distinct poverty- spell observations only	0.025 (0.238)	-0.079 (0.213)	21	0.620	OLS HC3
Poverty rate in levels; log regressors	3.336** (1.312)	-1.740 (1.712)	95	0.829	DK(2)
Raw levels with standardized regressors	4.747*** (0.375)	-2.016*** (0.536)	95	0.882	DK(2)

Source: Eviews 13 outputs

Figure 5. Coefficient sensitivity across comparable specifications



Source: Eviews 13 outputs

First differencing produces an ATM coefficient of +0.131 ($p = 0.394$) and a deposit coefficient of -0.130 ($p = 0.075$). The latter is the only specification that offers even marginal evidence consistent with H2: a 1% increase in deposits/GDP is associated with approximately a 0.13% decline in poverty growth, but the result is not significant at 5% and is sensitive to the sparse changes in the dependent variable.

The inverse-spell weighted model gives each distinct poverty spell a total weight of one, preventing twelve repeated years from dominating one updated observation. It yields a positive and significant ATM coefficient (+0.171, $p = 0.001$) and an insignificant deposit coefficient. This does not support financial access as a poverty-reducing channel; instead, it underscores the risk that ATM stock is capturing time-varying scale or formal-sector expansion.

The more conservative 21-observation spell sample is especially informative. Once only one observation per poverty spell is retained, the ATM coefficient is +0.025 ($p = 0.915$) and the deposit coefficient is -0.079 ($p = 0.711$). Neither is distinguishable from zero. Because even these 21

observations are not verified survey dates, the null result should not be read as precise; it simply demonstrates that the full annual sample overstates the amount of independent poverty information.

Alternative level specifications generate statistically strong but non-comparable coefficients, including a positive ATM effect. That contrast with the log specification confirms that the results depend heavily on scale and functional form.

4.8 Dynamic error-correction results

Table 13. Exploratory error-correction model

Term	Coefficient	Robust SE	T/Z	p-value	Interpretation
Lagged log poverty (adjustment term)	-0.086	0.129	-0.663	0.516	Short-run or adjustment coefficient
Lagged log ATM stock	0.045	0.088	0.515	0.613	Short-run or adjustment coefficient
Lagged log deposits/GDP	-0.026	0.058	-0.452	0.657	Short-run or adjustment coefficient
Change in log ATM stock	0.166	0.184	0.903	0.379	Short-run or adjustment coefficient
Change in log deposits/GDP	-0.125	0.104	-1.202	0.246	Short-run or adjustment coefficient
Derived long-run ATM elasticity	0.527	1.408	0.374	0.708	Derived as $-\theta_{ATM}/\phi$
Derived long-run deposit elasticity	-0.307	1.115	-0.276	0.783	Derived as $-\theta_{Deposits}/\phi$

Source: Eviews 13 outputs

The adjustment coefficient is negative (-0.086), as required for convergence, but it is far from statistically significant ($p = 0.516$ with robust inference). The model therefore provides no evidence of a stable long-run equilibrium relationship. The derived long-run elasticities— $+0.527$ for ATM stock and -0.307 for deposits—have p-values of 0.708 and 0.783, respectively. They must not be interpreted as cointegrating coefficients. The ECM result rejects H3 and confirms that a panel-ARDL narrative would be unsupported by the supplied data.

4.9 Discussion

The central empirical finding is not that finance has no role in poverty reduction. It is that the two supplied aggregate indicators do not exhibit a robust poverty-reducing relationship in this five-country panel. This distinction is important. The theoretical mechanisms require effective access, appropriate products, affordability, trust, and productive use. A total ATM count and a deposits-to-GDP ratio are several steps removed from those household capabilities.

The results align more closely with the regional findings of Neaime and Gaysset (2018, 2024) than with large global panels. Their MENA and Mediterranean estimates also find no significant effect of financial inclusion on poverty. The present study adds a measurement explanation: when country heterogeneity and the low frequency of genuine poverty updates are recognised, the apparent pooled relationship disappears. Regional macro panels may therefore struggle not only because the underlying

effect is conditional, but also because poverty and inclusion are measured with proxies that do not vary at the same economic frequency.

The first-difference deposit result deserves cautious attention. Its negative sign is consistent with the idea that greater mobilisation and use of deposits improve resilience, but the p-value is only 0.075 and the effect does not survive the other sensitivity checks. It can motivate a better-designed study, not a strong policy conclusion.

The positive ATM coefficients after fixed effects are also instructive. ATM expansion may occur in response to population growth, urbanisation, inflation, or formalisation, all of which can coincide with reported poverty changes. The coefficient may also reflect reverse causality: governments and banks could expand infrastructure where exclusion and poverty are recognised as problems. Without population normalisation and controls, the sign cannot be assigned a structural interpretation.

5. Conclusion and Policy Implications

This paper examined the association between financial inclusion and poverty in Algeria, Egypt, Lebanon, Libya, and Tunisia over 2004–2022 using every observation contained in the supplied Excel file. The empirical procedure followed a disciplined sequence: data audit, descriptive analysis, correlation decomposition, Fisher-type unit-root tests, model selection, residual diagnostics, fixed-effects estimation, robust covariance correction, data-quality weighting, first differences, dynamic error correction, and country-deletion sensitivity.

The preferred two-way fixed-effects estimates do not support the two main hypotheses. The ATM elasticity is positive and insignificant, while the deposit elasticity is negative but insignificant. First differences provide only weak 10% evidence for the deposit proxy. The distinct-spell sample is entirely insignificant, and the error-correction coefficient does not confirm a long-run relationship. Coefficient signs and significance change across functional forms and weighting schemes. The correct conclusion is therefore one of non-robust association rather than a poverty-reducing effect.

For policy, the results caution against equating infrastructure counts or aggregate bank balance sheets with inclusive outcomes. Expanding ATMs may improve convenience, but poverty policy should monitor whether excluded adults actually open and use low-cost accounts, receive digital payments, build precautionary savings, access suitable credit, and obtain consumer protection. Deposit growth should be disaggregated by households, firms, account size, gender, region, and activity status wherever possible.

The findings also support better integration between financial-inclusion strategy and social policy. Government payments can encourage account use, but dormant or pass-through accounts create little durable capability. Financial literacy, affordable digital connectivity, transparent pricing, interoperability,

grievance mechanisms, and institutional quality determine whether access becomes welfare-enhancing use.

Recommendations:

- Shift from infrastructure expansion to usage activation, ensuring that new ATMs and bank branches are accompanied by financial literacy programs and simplified account-opening procedures that reach excluded households.
- Leverage digital payment systems for social transfers, channeling government subsidies, wages, and remittances through formal accounts to create sustained usage rather than dormant accounts.
- Develop micro-savings and micro-insurance products tailored to poor households, as the current deposit/GDP proxy reflects corporate and elite wealth rather than household resilience-building.
- Strengthen institutional quality, consumer protection, and transparent pricing, since weak governance conditions the conversion of financial access into welfare gains, as confirmed by Aracil et al. (2022).
- Adopt a multidimensional approach combining financial inclusion with education, employment, and infrastructure investments, because the RESET test indicates that financial variables alone cannot explain poverty dynamics.
- Prioritize mobile money and digital financial services over traditional ATM expansion, as digital channels have proven more effective at reaching the poor and building financial resilience in contexts like Kenya.
- Establish harmonized, survey-based poverty measurement systems across Arab economies, ensuring that poverty data is collected at the same frequency as financial indicators to enable credible long-run policy evaluation.

References

- Abonazel, M. R. (2016). Generalized random coefficient estimators of panel data models: Asymptotic and small sample properties. *American Journal of Applied Mathematics and Statistics*, 4(2), 46–58. <https://doi.org/10.12691/ajams-4-2-1>
- Aghion, P., Howitt, P., & Mayer-Foulkes, D. (2005). The effect of financial development on convergence: Theory and evidence. *The Quarterly Journal of Economics*, 120(1), 173–222. <https://doi.org/10.1162/0033553053327515>
- Beck, T., Demirgüç-Kunt, A., & Levine, R. (2007). Finance, inequality and the poor. *Journal of Economic Growth*, 12(1), 27–49. <https://doi.org/10.1007/s10887-007-9010-6>
- Burgess, R., & Pande, R. (2005). Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review*, 95(3), 780–795. <https://doi.org/10.1257/0002828054201242>
- Deborah, S. (2019). *The impact of financial inclusion on poverty in low- and middle-income countries* [Master's thesis, HEC Liège—Management School of the University of Liège].
- Greenwood, J., & Jovanovic, B. (1990). Financial development, growth, and the distribution of income. *Journal of Political Economy*, 98(5), 1076–1107. <https://doi.org/10.1086/261720>
-

- Hellal, A., & Hafsi Bouenbaou, Y. (2021). The effect of oil price changes on government spending in Algeria in the short and long term: A standard study using the time-series analysis approach. *Revue Algérienne d'Économie et Gestion*, 15(2), 237–258.
- Hu, F., & An, K. (2015). The empirical research of the relationship between consumption and income for Chinese urban residents. *Open Journal of Applied Sciences*, 5, 251–258.
- Meherhera, M. (2021). Evolution of financial depth in the Algerian banking system and mechanisms for its improvement: An analytical study for the period 2008–2018. *Journal of Economics and Human Development*, 12(2), 163–177.
- Neaime, S., & Gaysset, I. (2018). Financial inclusion and stability in MENA: Evidence from poverty and inequality. *Finance Research Letters*, 24, 230–237. <https://doi.org/10.1016/j.frl.2017.09.007>
- Neaime, S., & Gaysset, I. (2024). Financial inclusion, integration, and stability asymmetries in the Mediterranean region. *The Journal of Economic Asymmetries*, 30, Article e00386. <https://doi.org/10.1016/j.jeca.2024.e00386>
- Omar, M. A., & Inaba, K. (2020). Does financial inclusion reduce poverty and income inequality in developing countries? A panel data analysis. *Journal of Economic Structures*, 9(1), Article 37. <https://doi.org/10.1186/s40008-020-00214-4>
- Pesaran, M. H. (2004). *General diagnostic tests for cross-section dependence in panels* (Cambridge Working Papers in Economics No. 0435). Faculty of Economics, University of Cambridge.
- Saadouni, M. M. (2021). Financial inclusion and its impact on achieving the Sustainable Development Goals. *Journal of Legal and Economic Research*, 197–238.
- Sang, K. (2020). *The poverty-reducing effects of financial inclusion: Evidence from Cambodia*. Economic Research Institute for ASEAN and East Asia.
- Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, 354(6317), 1288–1292. <https://doi.org/10.1126/science.aah5309>
- Tiku, M. S. (2025). *The impact of financial inclusion on poverty reduction in Ethiopia: An ARDL analysis using Ethiopian time-series data, 1994–2023* [Master's thesis, Addis Ababa University]. <https://etd.aau.edu.et/bitstreams/e6383940-b716-4bf8-b9e2-a64bb10c653b/download>