Assessing the effect of Financial Inclusion on Poverty Reduction: A PSM Analysis in Morocco

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Abstract: This study evaluates the impact of financial inclusion on poverty reduction in Morocco using an additive approach. The results show that financial inclusion has a negative effect on poverty, suggesting its potential as a key strategy for poverty reduction. The study also highlights that financial inclusion can have differentiated effects on the most vulnerable segments and disadvantaged populations, requiring particular attention in policy formulation. The results align with previous studies by Saha and Qin (2023) and Omar and Inaba (2020), which found a significant negative association between financial inclusion and poverty in developing countries. The effectiveness of financial inclusion is influenced by equal access to financial services.

The study emphasizes the importance of improving equality of access to financial services to maximize the effectiveness of financial inclusion. The study also highlights the need for policies to foster financial inclusion and targeted measures to build the capacity of poor households to make efficient use of financial services. Finally, the study emphasizes the importance of monitoring the effects of financial inclusion on poverty in Morocco and adapting the national strategy accordingly to meet poverty reduction targets. Morocco is committed to promoting digital financial services and dematerializing social aid transfers for populations affected by climate shocks.

Keywords: Financial inclusion, poverty, impact evaluation, PSM (propensity score matching).

JEL classification: G21; I32; O16; C21.

1. INTRODUCTION

The national strategy for financial inclusion in Morocco is set against a backdrop of economic and social development in the country, aimed at reducing inequalities and improving the well-being of the population. Despite sustained economic growth over recent decades, many people, particularly those living in rural areas and disadvantaged neighborhoods, face challenges in accessing basic financial services. The national financial inclusion strategy focuses on concrete measures to improve access by reducing costs and barriers to financial inclusion and strengthening financial sector regulation and supervision. By aligning this strategy with the United Nations Sustainable Development Goals, in particular the objectives of eradicating poverty and promoting inclusive and sustainable economic growth, Morocco aims to foster sustainable and inclusive economic and social development.

According to the Stratégie Nationale d'Inclusion Financière (SNIF) 2019–2024, Morocco has set itself several objectives to promote financial inclusion in the country. Firstly, it aims to increase the bancarization rate to 80% by 2023, up from 58% in 2017. This increase will be achieved by strengthening the presence of banks in rural areas and disadvantaged neighborhoods, facilitating the opening of bank accounts, and developing financial products tailored to the needs of vulnerable populations. Secondly, the strategy aims to reduce costs and barriers to access to financial services by implementing an interoperable electronic payment system. In addition, it is committed to promoting financial education to improve understanding of financial products and financial risks, thus fostering better use of financial services. Thirdly, SNIF aims to improve the quality and diversity of financial services on offer, particularly for small and medium-sized enterprises. To achieve this objective, the strategy will support financial innovation and strengthen regulation and supervision of the financial sector, thereby guaranteeing its stability and security. In short, Morocco's national financial inclusion strategy is based on these three pillars: improving access to financial services for all Moroccan citizens and strengthening the Moroccan financial system as a whole.

One of the major objectives of this strategy is to reduce poverty in Morocco. According to the World Bank, the COVID-19 pandemic has led to a significant increase in extreme poverty, with around 150 million more people likely to be living in this situation. Faced with this reality, it is essential to identify the policy tools likely to combat poverty. Financial inclusion is recognized as one of these effective levers. Several studies, such as that by Demirguc-Kunt et al. (2017), have demonstrated that access to payment, savings, credit, and insurance services contributes to poverty reduction. Cross-sectional studies by Park and Mercado (2018) also found a negative correlation between financial inclusion and

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poverty. However, more recent research, such as that by Aslan et al. (2017), raises the issue of unequal access to financial services and its potential impact on the effectiveness of financial inclusion as a policy tool. In particular, disadvantaged groups such as women, ethnic minorities, people with disabilities, and immigrants may face particular challenges.

Projections by the Intergovernmental Panel on Climate Change (IPCC) indicate that by 2030, an additional 130 million people could fall into extreme poverty, accentuating global inequalities. This alarming forecast underlines the crucial importance of combating poverty and promoting financial inclusion in developing countries, and Morocco is no exception. Despite sustained economic growth in recent years, the poverty rate in Morocco remains high. According to data from the Haut-Commissariat au Plan (HCP) in 2020, almost 4 million people live below the poverty line, with a particularly high incidence in rural areas, where the rate reaches 17.5%. This socio-economic situation exposes part of the Moroccan population to financial vulnerability and exclusion, making it essential to develop targeted strategies to promote more equitable and effective financial inclusion. These economic and social disparities between urban and rural areas, as well as between different regions of the country, underline the need to assess the impact of financial inclusion on poverty reduction in the country in order to put in place effective policies and measures to improve the socio-economic situation of vulnerable populations.

In this study, we aim to assess the impact of financial inclusion on poverty in Morocco. This question is motivated by the importance of financial inclusion for poverty reduction and economic development in the country. To achieve this objective, we chose the propensity score matching (PSM) method, introduced by Rosenbaum and Rubin in 1983.

The PSM method is an effective tool for comparing the effect of financial inclusion on the number of poor households while taking into account differences between groups in terms of socio-economic status and financial inclusion. This methodology enables us to create a fair comparison between households that have access to financial services and those that don't, eliminating potential biases linked to these differences. In this way, we can obtain a more accurate estimate of the impact of financial inclusion on poverty reduction in Morocco.

The remainder of this article is structured as follows: in the second section, we will briefly present the debates surrounding the effects of financial inclusion on poverty reduction, as well as some empirical work similar to our study. The third section will outline our matching methodology used to assess the impact of financial inclusion on poverty, as well as the data used to validate our study. Results and discussions will be presented in the fourth section. Finally, we will conclude this study by presenting the results obtained in the last section.

2. LITERATURE REVIEW

The theoretical framework of our study is based on an in-depth analysis of the theoretical and empirical foundations of financial inclusion and its impact on poverty reduction. Several researchers have attempted to measure financial inclusion using various metrics, such as the number of ATMs, bank branches, depositors, and borrowers, as well as the ratio of insurance premiums to GDP (Kim et al., 2018). However, these indicators present limitations in the overall understanding of financial inclusion. To overcome this, some researchers have proposed composite indices of financial inclusion, combining different dimensions of the latter (Amidžić et al., 2014; Cámara and Tuesta, 2014; Sarma, 2012).

Cross-national research has also shown that financial inclusion primarily reduces poverty by acting on inequality in low- and lower-middle-income countries (Gutiérrez-Romero and Ahamed, 2021). However, other studies, such as that conducted by Koomson and Danquah (2021) in Ghana, have examined the impact of financial inclusion on specific dimensions of poverty, such as fuel poverty, showing encouraging results. Álvarez-Gamboa et al. (2021) carried out an in-depth study to assess the impact of financial inclusion on multidimensional poverty in the provinces of Ecuador over the period 2015–2018. Their results demonstrated a positive and significant effect of financial inclusion on poverty reduction in this region. Churchill and Marisetty (2019) conducted a nationally representative survey in India and found that financial inclusion plays a crucial role in reducing poverty among Indian households.

Awaworyi Churchill et al. (2020) examined the impact of financial inclusion on poverty in Nigeria. They used 2016 Financial Inclusion Insights data for Nigeria to present new evidence on the effects of financial inclusion on household poverty. They measured financial inclusion multidimensionally to reflect access to banks, access to credit, and access to insurance. Their study showed that an increase in multidimensional financial inclusion is associated with a decrease in poverty. Moreover, among the components of financial inclusion, access to a current, savings, or term account is more important than access to credit and insurance in reducing poverty. This study underlines the importance of financial inclusion in the fight against poverty and suggests that financial inclusion can play a crucial role in improving the economic well-being of individuals, particularly in developing countries.

Omar and Inaba (2020) assessed the impact of financial inclusion on reducing poverty and income inequality in 116 developing countries over the period 2004–2016. They used a broad set of financial sector outreach indicators to construct a new financial inclusion index. Their study revealed that per capita income, Internet user ratio, age dependency ratio, inflation, and income inequality significantly influence the level of financial inclusion in developing countries. Furthermore, they provided robust evidence that financial inclusion significantly reduces poverty rates and income inequality in developing countries.

N'dri and Kakinaka (2020) examined the impact of financial inclusion and mobile money on individual well-being in Burkina Faso. They found that over 60% of Burkinabe adults are excluded from financial services by banks and other non-bank financial institutions, so mobile money is expected to fill this gap. They assessed the effects of financial inclusion and mobile money use on an individual's non-monetary well-being in Burkina Faso by applying matching methods. Their results confirm the significant role of financial inclusion in poverty alleviation. More importantly, their analysis shows that as soon as individuals access financial services via mobile money, these favorable effects on poverty alleviation become more substantial.

Kim and Kwak (2021) Similarly, El Ouazzani et al. (2024) conducted a study on the impact of microcredit on household expenditure in Morocco, taking into account the risk of poverty dynamics. They used the propensity score matching (PSM) method as an impact assessment technique. Their results reveal that microcredit beneficiaries tend to reduce their consumption expenditures. This suggests that access to microcredit may lead to changes in household spending patterns, perhaps as a poverty risk management strategy.

Djahini-Afawoubo et al. (2023) examined the impact of mobile money on multidimensional poverty reduction. They used Alkire and Foster's (2011) approach to calculate the multidimensional poverty index and adopted an instrumental variable strategy to control for endogeneity bias due to a bidirectional relationship between poverty and mobile money. The results of their research robustly demonstrated that mobile money has a positive and statistically significant effect on reducing multidimensional poverty. This effect of mobile money on poverty reduction appears to be greatest among rural residents, women, and those who are illiterate.

Saha and Qin (2023) studied the impact of financial inclusion on poverty reduction in 156 countries of different income groups over the period 2004–2019. The authors constructed a new composite index of financial inclusion and used static and dynamic panel estimation methods. Their results indicate that financial inclusion has a significant negative association with extreme poverty in developing countries, but not in high-income countries. The effect of financial inclusion on moderate poverty is weaker than that on extreme poverty. Furthermore, the study revealed that improving gender inequality strengthens the effect of financial inclusion on extreme and moderate poverty in developing countries.

Koomson et al. (2023) examined the impact of financial inclusion on multidimensional poverty. They used nationally representative data on living conditions in Ghana, a country with a documented high incidence of multidimensional child poverty. Using different variants of the propensity score matching technique and multidimensional constructs of financial inclusion and poverty, they found that financial inclusion reduces multidimensional poverty. This result is consistent, whatever the threshold used to measure multidimensional poverty and whatever the propensity score matching method used.

In Morocco, Assalih and Ouakil (2020) examined financial inclusion using a panel macroeconomic approach, focusing on African countries. They identified and analyzed the determinants of financial inclusion and explored the barriers that limit access to financial services, particularly bank account ownership, in African countries. To do this, they used the latest available dataset, which was retrieved from the Global Findex and World Bank databases. The extracted dataset included information on underdeveloped African economies. Their econometric results based on the recovered data clearly demonstrated that financial inclusion is strongly correlated with gross domestic product per capita, the number of credits granted to private enterprises, Internet access, and education.

3. MÉTHODOLOGIE

In this study, we aim to assess the impact of financial inclusion on poverty in Morocco, motivated by its importance for poverty reduction and the country's economic development. To do this, we chose the propensity score matching (PSM) method, which is a good way to compare the effect of financial inclusion on the number of poor households while taking into account how different groups are in terms of their socio-economic status and financial inclusion. This method was introduced by Rosenbaum and Rubin (1983).

The sample was made up of two distinct groups: the control group and the intervention group, using the nearest-neighbor matching method. This approach enabled us to identify individuals who were similar in terms of socio-economic characteristics and financial inclusion. Thus, we selected individuals from the intervention group with a financial inclusion score above 2, based on the methods proposed by Rosenbaum and Rubin (1983). Similarly, individuals in the control group with a financial inclusion score below 2 were selected to form the low financial inclusion (untreated) group.

We then used household income to classify individuals as poor or non-poor (with the value 1 for a poor individual and 0 for a non-poor individual). The financial inclusion score was used as a threshold to determine whether each individual was financially included or not. This method enabled us to assess the degree of financial inclusion of each individual in the sample and use it as a treatment variable in the analysis of the impact of financial inclusion on poverty.

Our methodology follows that of Sarma (2012); however, we have made improvements by using six variables instead of the three proposed by Sarma (2012) and by treating each element as a separate dimension instead of using a weighted average of several indicators.

3.1. Data and Description of Variables

This study is based on data from the Findex 2021 global survey, published by the World Bank, due to its relevance in measuring the level of financial inclusion of Moroccan households. This survey is a rich source of information on access to financial services and the socio-economic characteristics of households. The construction of the sample is in line with the field of study, as Findex 2021 data provide specific information on household financial inclusion in Morocco, thus enabling us to meet our research objective concerning the impact of financial inclusion on poverty.

To measure each household's level of financial inclusion, we created a financial inclusion score by aggregating several variables related to access to financial services. The variables included in the financial inclusion score are "Account by purchase," "Purchasing by phone," "Online bill payment," "Borrowing from FI," "Any digital payment," and "Trans G receipt." Each binary variable indicates whether the household has access to this financial service.

The choice of data collection and processing techniques is justified by the nature of the information available in the Findex 2021 survey. The variables selected for our study are based on previous empirical work and the availability of data in the Findex 2021 survey. Using these variables, we can appropriately assess the level of financial inclusion of Moroccan households and its potential impact on poverty. In addition, Findex 2021 data contain information on household socio-economic characteristics, such as level of education, income, and employment, which are used to control for differences between treatment and control groups.

3.2. Analysis Model

Our analytical model uses the nearest-neighbor matching method to assess the impact of financial inclusion on poverty in Morocco. This approach allows us to rigorously compare the causal effect of financial inclusion by controlling for differences between the intervention and control groups in terms of socio-economic characteristics and financial inclusion. The two major steps in our analysis are the construction of the financial inclusion score and the impact estimation ATT (Average Treatment Effect on the Treated).

3.2.1. Building a Financial Inclusion Score

The construction of a financial inclusion score was achieved by aggregating indicators of the financial services to which each household has access. A higher score indicates a higher level of financial inclusion for the household in question. This financial inclusion score method is widely used in the literature to assess access to financial services and its impact on household economic well-being. Specifically, each binary variable indicates whether the household has access to a specific financial service, such as "Account by purchase," "Purchasing by phone," "Online bill payment," "Borrowing from FI," "Any digital payment," or "Trans G receipt." By summing these variables, we created a financial inclusion score for each household, enabling us to measure its level of financial inclusion.

The financial inclusion score $Score_i$ for each household i was calculated by summing the values of several financial inclusion variables X_{ij} where j represents the different variables included in the score. The mathematical formula used is as follows:

$$Score_i = \sum_{j=1}^{n} X_{ij}$$

Where:

- ✓ $Score_i$ is the financial inclusion score for household i.
- ✓ $X_{ij}$is the value of variable j (e.g. "Inf account", "Mobile account", etc.) for household i.
- ✓ n is the total number of financial inclusion variables included in the score calculation.

The additive approach we have used enables a simple aggregation of financial inclusion variables, without assigning specific weights to each variable, unlike weighted approaches which assign specific weights to each variable according to their supposed impact on financial inclusion. Nevertheless, the additive approach offers a first indication of the level of financial inclusion of households.

3.2.2. Estimated Impact ATT

After constructing the financial inclusion score, we estimate the ATT (Average Treatment Effect on the Treated) impact of financial inclusion on poverty. To do this, we use the principle of non-foundation by conditioning the propensity score to eliminate bias due to observable covariates (Heckman and Rubin (1998)). Indeed, matching is a non-parametric technique that avoids potential misspecification of $E(Y_0 \mid X)$. Thus, it allows for arbitrary heterogeneity of causal effects $E(Y_1 - Y_0 \mid X)$.

$$(Y_0, Y_1) \perp w \mid e(X)$$

The proof consists in showing that :

$$\Pr\{(W = 1 \mid Y_0, Y_1, e(X))\} = \Pr\{(W = 1 \mid e(X)) = e(X)\}$$

Involving the independence of (Y_0, Y_1) and W conditional on $e(X)$

$$P\{(W = 1 \mid Y_0, Y_1, e(X))\} = E\{(W \mid Y_0, Y_1, e(X))\}$$

$$= E\{E(W = 1 \mid Y_0, Y_1, e(X), X)\} \mid Y_0, Y_1, e(X)$$

$$= E\{E(W \mid Y_0, Y_1, X)\} \mid Y_0, Y_1, e(X)$$

$$= E\{E(W \mid X)\} \mid Y_0, Y_1, e(X)$$

$$= E\{e(X) \mid Y_0, Y_1, e(X)\} = Y_0, Y_1, e(X)$$

where the last equality stems from the absence of foundation.

The same argument shows that :

$$\Pr\{(W = 1 \mid e(X))\} = E\{(W = 1 \mid e(X))\}$$

$$= E\{E(W = 1 \mid X) \mid e(X)\} = E\{e(X) \mid e(X)\} = e(X)$$

Many procedures for estimating and evaluating causal effects in the absence of foundations involve the propensity score (Rubin 1997).

If the equilibrium hypothesis is satisfied, observations with the same propensity score should have the same distribution of observable (and unobservable) characteristics regardless of treatment (Rosenbaum and Rubin, 1983).

$$W \perp (X) \mid e(x)$$

Any standard probability model can be used to estimate the propensity score:

$$\Pr\{(W_i = 1 \mid X_i)\} = F\{(h(X_i))\}$$

- $h(X_i)$ is a function of the covariates with linear and higher-order terms
- $F(.)$ is a cumulative distribution, e.g. logistics distribution.

$$P\{(W_i = 1 \mid X_1)\} = \frac{exp(h(X_i))}{1 + exp(h(X_i))}$$

The inclusion of higher-order terms in $h(X_i)$ is determined solely by the need to obtain an estimate of the propensity score that satisfies the balancing property. Indeed, the specification of $h(X_i)$ that satisfies the balancing property is generally more parsimonious than the set of interactions required to match cases and controls on the basis of observables. Consequently, the propensity score reduces the problem of the dimensionality of matching treated and control units on the basis of the multidimensional vector X (Abadie and Imbens (2011)). These matching techniques originated in experimental work in the first half of the twentieth century and were advanced and developed in a series of articles by Smith (1997).

The standard matching strategy is as follows: associate each treated subject with one or more comparable untreated subjects. i to one or more comparable untreated subjects. Y_i^{obs} a matched result $\hat{Y}_i(0)$ given by the (weighted) results of its neighbors in the comparison group.

$$\hat{Y}_i(0) = \sum_{j\in C(i)} w_{ij} Y_j^{obs}$$

Where

$C(i)$ is the set of neighbors with $w = 0$ of the subject i

w_{ij} is the weight of j untreated, with $\sum_{j\in C(i)} w_{ij} = 1$

The ATT impact is estimated by comparing the average poverty rate between the intervention group (households financially included) and the control group (households not financially included). Let Y_i be the binary variable indicating whether household i is poor $(Y_i = 1)$ or not $(Y_i = 0)$. The binary variable $W_i$takes the value 1 for financially included households and 0 for financially non-included households.

$$ATT = E[Y_i|\ W_i = 1] - E[Y_i|\ W_i = 0]$$

can be estimated as follows:

$$\widehat{ATT} = \frac{1}{N^T} \sum_{i:w_i=1} [Y_i^{obs} - \hat{Y}_i(0)]$$

Where N^T is the number of matched treatments in the sample.

The average of these differences yields the ATT we're interested in. All treated units find a match (Rubin and Thomas, 1996). However, it is clear that some of these matches are quite weak, since for some treated units, the nearest neighbor may have a very different propensity score and, nevertheless, contribute to the estimation of the treatment effect independently of this difference.

Let $e_i(x_i) = p_i$ be the propensity score of the i-unit. Given a treated unit $i$unit, let $I_{m(i)}$ the index of the untreated unit that is the m-th closest to the unit i in terms of a distance measure based on the $||.||$ norm.

$$\sum_{j:w_j\neq w_i} \prod\{||P_j - P_i|| \leq ||P_I - P_i||\}$$

Let $C(i)_M$ be the set of indices of M first matches for the unit i :

$$C(i)_M = [I_1(i), \dots, I_M(i)]$$

$$\hat{Y}_i(0) = \frac{1}{M} \sum_{j\in C(i)_M} Y_j^{obs}$$

According to Imai et al. (2023), the nearest neighbor matching estimator is as follows:

$$\widehat{ATT}^{nearest} = \frac{1}{N^T} \sum_{i:w_i=1} \left[Y_i^{obs} - \sum_{j\in C(i)_M} w_{ij} Y_j^{obs} \right]$$

$$= \frac{1}{N^T} \sum_{i:w_i=1} Y_i^{obs} - \frac{1}{N^T} \sum_{j\in C(i)_M} w_{ij} Y_j^{obs}$$

With, $w_j = \sum_i w_{ij}$

- N^T is the number of observations in the treated group.
- N_i^C is the number of controls matched to the treated observation i.
- w_{ij} is equal to $\frac{1}{N_i^C}$ if j is a control unit of i, and zero otherwise.

4. RESULTS AND DISCUSSIONS

Before embarking on the first step of estimating the impact of financial inclusion on poverty, a descriptive analysis of the data was carried out (see table **1** in the appendices). The results showed that poverty levels varied considerably in the sample studied, with a significant standard deviation for this variable. In addition, the financial inclusion score also showed some variation, with values ranging from 0.46 to 0.70. More specifically, the standard deviation of the poverty variable indicates that poverty levels vary considerably across the sample, underscoring the importance of controlling for this variable when analyzing the impact of financial inclusion on poverty. Our study also examined the impact of control variables, such as gender, age, education, employment and other variables related to financial services. The results showed that age was the most important control variable, exhibiting the greatest dispersion with a standard deviation of 12.29. This may indicate age-related differences in access to and use of financial services.

The next step is to estimate the coefficients of the logistic regression (Table **2** in the appendices), which calculates the probabilities of participation associated with each individual in the sample based on the characteristics of control variables such as gender, age, education, employment and other variables related to financial services.

The results show that the financial inclusion score has no significant effect on poverty reduction, with a coefficient of -0.368 and a p-value of 0.117. This suggests that financial inclusion alone is not sufficient to reduce poverty in Morocco and that other factors need to be taken into account. On the other hand, employment proved to be the most significant control variable, with a coefficient of 0.519 and a p-value of 0.048. The other control variables, such as gender, age, education, and other variables related to financial ser-

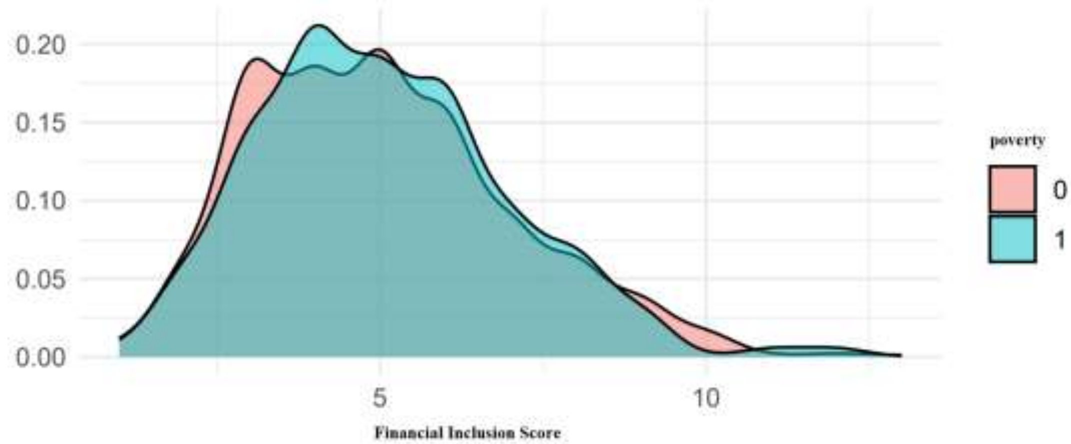

Fig. (1). Propensity score density distribution.

Source: authors' calculations, R software.

vices, show no significant relationship with poverty reduction.

The first matching assumption is conditional independence, which states that, given a treatment score, the potential outcome score is independent of the treatment group to which an individual belongs. In other words, this means that observed and unobserved characteristics that influence the probability of being treated are not correlated with potential outcomes.

To verify conditional independence, we perform difference-of-means tests and chi-square (χ^2) tests for control variables between treatment and control groups. On the one hand, the results of the Student's t-test for two matched samples suggest that the difference in mean poverty rate between the two groups is not statistically significant, with a p-value of 0.18 (see Table **3** in the appendices). This indicates that, although individuals with a high financial inclusion score showed a reduction in their poverty rate compared to those with a low financial inclusion score, this difference is not large enough to be considered statistically significant. On the other hand, the chi-square test (Table **4** in the appendices) indicates a significant relationship between financial inclusion score and treatment, with a P-value of 0.0049.

Concerning the common support region, which is the second necessary condition for the application of the matching method, Fig. (**1**) clearly shows that the distributions of financial inclusion scores for the two poverty groups overlap considerably, confirming that the region of common support is satisfied. This indicates that the two groups have similar financial inclusion scores for a large part of the distribution, enabling a fair comparison between the two groups.

The x-axis represents the variable "financial inclusion score," while the y-axis represents score density, i.e., the proportion of households with specific financial inclusion scores. Depending on the overlap of the density curves, some poor households have high financial inclusion scores, while other non-poor households have lower scores.

After successfully testing the matching hypotheses, it is possible to focus on the impact of treatment on the outcome variable. In this context, the table presents the results of a logistic regression that assesses the impact of financial inclusion on poverty. The results show that the coefficient for the financial inclusion score is -0.29, suggesting a negative association between financial inclusion and poverty. However, this association is not statistically significant, with a p-value of 0.186 above the 0.05 significance level (Table **5** in the appendices).

The results presented in Table **6** and Fig. (**2**) (see appendices) confirm the effect of financial inclusion on poverty. The ATT estimate indicates that financial inclusion has a negative effect on poverty. Indeed, financially included individuals have, on average, a -0.04 reduction in the outcome variable (poverty). This result is statistically significant, reinforcing the idea that financial inclusion is often seen as a key strategy for reducing poverty.

Table **7** (see Appendices) presents the results of the matching quality analysis for various variables linked to financial inclusion and poverty. Analysis of the results shows that financial inclusion has a significant impact on some of the characteristics studied. Individuals who are financially included display distinctive traits such as higher levels of education, a tendency to be younger, and being more often employed. In addition, they are more inclined to use online and digital payments, demonstrating greater adaptation to digital financial services. Furthermore, financially included individuals have a higher propensity to borrow for medical purposes and to receive domestic remittances, demonstrating greater accessibility to financial services to meet specific needs.

Finally, the "financial inclusion score" variable shows a value of 1.0000, suggesting that it is closely related to financial inclusion and can be used as an overall measure to assess the degree of financial inclusion. Concerning the poverty variable, although the mean difference was negative, potentially indicating a relationship between financial inclusion and poverty reduction, this difference did not reach statistical significance. This means that the variations observed in the poverty variable between the financially included and non-included groups could be due to chance rather than a real effect of financial inclusion on poverty.

CONCLUSION

This study has carried out a rigorous assessment of the impact of financial inclusion on poverty reduction in Morocco. By using an additive approach to create a financial inclusion score, we were able to simplify the aggregation of financial inclusion without assigning specific weights to each variable. This methodology enabled an accurate comparison between a treatment group that benefited from financial inclusion and a control group that did not. Our results significantly indicate that financial inclusion has a negative effect on poverty, suggesting its potential role as a key strategy for reducing poverty. Our results also highlight that financial inclusion can have differentiated effects on the most vulnerable segments and disadvantaged populations, requiring particular attention in policy formulation.

Our results are in line with the study by Saha and Qin (2023), who also found a significant negative association between financial inclusion and poverty in developing countries. They also pointed out that the effectiveness of financial inclusion is influenced by equal access to financial services. In addition, the study by Omar and Inaba (2020) also showed that financial inclusion significantly reduces poverty rates and income inequality in developing countries, reinforcing our findings. In summary, our results reinforce the idea that financial inclusion can be used as an effective tool for poverty reduction. However, to maximize the effectiveness of financial inclusion, it is crucial to improve equality of access to financial services. These results could be explained by the differential effects on the most vulnerable segments and disadvantaged populations, as highlighted in the SINF report on Morocco (Banque Al-Maghrib, 2021).

In this context, Morocco is committed to promoting digital financial services and the dematerialization of social aid transfers for populations affected by climate shocks. However, inequalities in access to financial services could be behind the variation in results. In line with the work of Lusardi and Mitchell (2014), it is essential that policies to foster financial inclusion are accompanied by targeted measures to build the capacity of poor households to make efficient use of financial services. This holistic approach could help maximize the benefits of financial inclusion and further reduce poverty in the country. However, it is important to note that financial inclusion remains a priority for Morocco, which has launched an ambitious national strategy for financial inclusion in 2019. This strategy plans to strengthen access to financial services for the poorest and most vulnerable populations, particularly in rural areas. It is therefore important to continue monitoring the effects of financial inclusion on poverty in Morocco and to adapt the national strategy accordingly to meet poverty reduction targets.

APPENDICES

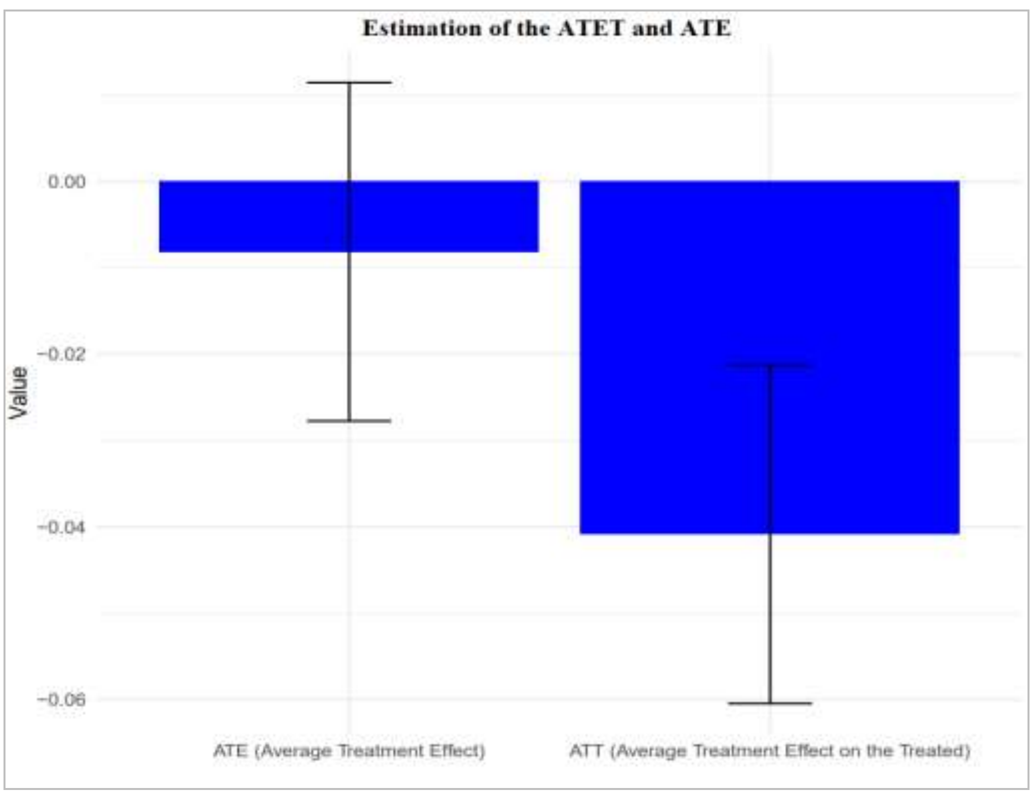

Fig. (2). Estimation of the ATET and ATE.

Source: authors' calculations, R software.

Table 1. Descriptive Statistics.

-	Mean	St. Dev.	Min	Max
Gender	0.58	0.49	0	1
Age	34.20	12.29	15	80
Education	1.60	0.69	1	3
Employment	0.73	0.44	0	1
Account by purchase	0.70	0.46	0	1
Purchasing by phone	0.06	0.24	0	1
Online bill payment	0.11	0.31	0	1
Borrowing for medical purposes	0.27	0.44	0	1
Borrowing from FI	0.06	0.23	0	1
Domestic Money Transfers	0.03	0.16	0	1
Trans G receipt	0.38	0.49	0	1
Pension beneficiary G	0.28	0.45	0	1
Any digital payment	0.70	0.46	0	1
Financial inclusion score	0.16	0.36	0	1
Poverty	0.16	0.36	0	1

Source: authors' calculations, R software.

Table 2. Regression Coefficients of Variables Influencing Financial Inclusion.

Variable	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-1.992063	0.527051	-3.780	0.000157 ***
Financial inclusion score	-0.368167	0.234664	-1.569	0.116669
Gender	-0.160306	0.210463	-0.762	0.446274
Age	0.004269	0.0087078	0.490	0.623969
Education	0.183503	0.141615	1.296	0.195046
Employment	0.519091	0.262403	1.978	0.047904*
Account by purchase	-0.313276	-0.216744	-1.445	0.148349
Purchasing by phone	-0.039026	-0.390724	-0.100	0.920439
Online bill payment	-0.438204	-0.340078	-1.289	0.197559
Borrowing for medical purposes	-0.181514	-0.220811	-0.822	0.411058
Borrowing from FI	0.245508	0.361424	0.679	0.497142
Domestic Money Transfers	0.062365	-0.212489	-0.293	0.769140
Trans G receipt	0.195538	-0.255901	-0.764	0.447799
Pension beneficiary G	-0.483108	-0.644396	-0.750	0.453431
Any digital payment	-0.123578	-0.239898	-0.515	0.606465

Notes: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$
Source: authors' calculations, R software

Table 3. Comparison of means between the treatment group and the control group using Student's t-test.

Données	Treatment Group	Control Group	Difference
Number of Observations	500	500	
Mean	0.1488	0.1897	-0.0419
Standard Deviation	0.3564	0.3920	-
t-value		-1.3261	
Degrees of Freedom		871	
p-value		0.1852	
Confidence Interval		(-0.1014, 0.0196)	

Source: authors' calculations, R software.

Table 4. Poverty Rate in the Treatment Group and Control Group.

-	Poverty Rate	Number of Observations
Treatment Group	0.15	500
Control Group	0.19	500

Source: authors' calculations, R software.

Table 5. Logistic Regression (Financial Inclusion Score).

Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.4523	0.1934	-7.510	5.92e-14 ***
Financial Inclusion Score	-0.2919	0.2207	-1.323	0.186

Notes: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$.
Source: authors' calculations, R software.

Table 6. Estimation of the ATET and ATE.

Estimate	Value
ATET (Average Treatment on the Treated)	-0.040871195***
ATE (Average Treatment Effect)	-0.008146149***

Notes: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$.
Source: authors' calculations, R software.

Table 7. Quality of the Matching.

Variable	Diff.Un
Gender	0.0147
Age	-0.1723***
Education	0.2445**
Employment	0.0786*
Account by purchase	-0.0331
Purchasing by phone	0.0069
Online bill payment	0.0756

Borrowing for medical purposes	0.2427***
Borrowing from FI	0.0471
Domestic Money Transfers	-0.0394
Trans G receipt	-0.0058
Pension beneficiary G	0.1733**
Any digital payment	0.1939**
Financial inclusion score	1.0000***
Poverty	-0.0409

Notes: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Source: authors' calculations, R software.

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