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Examining the Impact of Digital Microcredit Programs on Borrower Poverty: Evidence from the M-Shwari Program in Kenya

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Abstract
Since the late 1990s microfinance policies have gained significant momentum in Sub-Saharan Africa to promote financial inclusion and alleviate poverty. Additionally, the widespread adoption of mobile technology and increased access to the internet over the last decade has meant that FinTech has played a major role in reshaping the financial industry. There is still conflicting research analysing the impact of digital microcredit programs on poverty. This has motivated us to examine this topic further. This study delves into the impact of a digital microcredit program on poverty, focusing on the M-Shwari program implemented in Kenya. Our findings differ from the existing literature as we see the need for differentiating between the short-run (income) and long-run (asset value). We find a net positive and significant effect of digital microcredit on the value of assets.

Keywords: Microcredit, Microfinance, AI, Development Economics, Digitalisation

1. Introduction

Since the late 1990s microfinance policies have gained significant momentum in Sub-Saharan Africa to promote financial inclusion and alleviate poverty. Additionally, the widespread adoption of mobile technology and increased access to the internet over the last decade has meant that FinTech has played a major role in reshaping the financial industry (Maino *et al.*, 2019).

There is still conflicting research analysing the impact of digital microcredit programs on poverty. This has motivated us to examine this topic further.

This study delves into the impact of a digital microcredit program on poverty, focusing on the M-Shwari program implemented in Kenya. Our findings differ from the existing literature as we see the need for differentiating between the short-run (income) and long-run (asset-value). We find a net positive and significant effect of digital microcredit on the value of assets.

1.1. M-Shwari Description

M-Shwari was launched in Kenya in November 2012 as the first mobile phone-based microcredit program (Cook McKay, 2015). Using the M-Shwari app, users gained access to an online bank account that facilitated deposits, withdrawals, savings and loans. The average loan amount was approximately USD 4.8.

2. Methodology

To capture the before and after effects of the M-Shwari program in Kenya, we adopted a Difference in Differences (DiD) approach. We assign people to the treatment group if they have taken a loan through M-Shwari because they are the direct beneficiaries of the program.

We fed data from the Mobile Money Dataverse[1] into our model on Stata. Since the M-Shwari was implemented in November 2012, we used the May-Aug 2010 data (Dataset 1) for our controls and the June-Sept 2014 data (Dataset 2) for our treatment analysis. We grouped the data and assigned values to the different qualitative entries and labelled the variable 'treatment'.

We needed a variable to proxy as a measure of poverty in our model. Therefore, in our first regression, we take the dependent variable:

$$Income = Savings + Expenditure$$

Acknowledging that both savings and expenditure are annual, we include this metric as higher expenditure correlates with better access to necessities like food, shelter and education. Savings, on the other hand, act as a buffer against economic shocks or emergencies, common in Kenya due to adverse weather conditions or poor crop seasons (Wineman *et al.,* 2017).

In our model, this dependent variable captures the increase in income between 2010 and 2014. To comprehensively gauge the enduring impact of the program on poverty, we introduce a new dependent variable:

$$Total\ Value\ of\ Assets$$

This variable aims to capture the lasting reduction in poverty attributable to the program. Owning assets like land, livestock or property can be crucial in economies like Kenya (Foeken and Owuor, 2008). Additionally, as seen in Fig. 2, a significant number of the loans were used for business expenditures such as microenterprises and the purchase of durable goods.

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2.1. Control Variables

Gender of the household head (head_gender) is a significant factor behind income and wealth disparities. The "head_gender" is a dummy variable that takes value = 0 if the head of the household is female and 1 if male. Research shows that men are paid over 30% more than women for the same job despite similar qualifications. This could feed into differences in income (World Bank, 2018).

We conjecture that the disparity in asset ownership can be explained by the persistence of patrilineality in Kenya as well as the prevalence of cultural norms that prevented women from owning land (Harari, 2019).

Another important factor to account for was household size (household_size). During the period of the experiment, Kenya's agricultural sector grew rapidly, accounting for almost 70% of all employment in 2010 (Poulton and Kanyinga, 2014). The industry was dominated by smallholdings of less than 3 hectares. This can explain why larger households present lower levels of poverty in Kenya - members of the household can be viewed as labour aid in subsistence farming (Kamuzora, 2001).

Other relevant controls in our regression include education (head_edu=1 if level of education is above 9th grade), age of the household head (head_age) and the value of remittances (remittances_received).

For both regressions, the interaction variable is $treatment * time = treattime$. Also, we use the log specification for income, asset value and remittances received to improve the fit of the data.

Regression 1:

$$ln\,(income) = \beta_0 + \beta_1\,treatment + \beta_2\,time + \beta_3\,treattime + \beta_4\,household\ size + \beta_5\,head\ age + \beta_6\,head\ gender + \beta_7\,head\ edu + \beta_8\,ln(\,remittances\ received) + \epsilon$$

Regression 2:

$$ln\,(assets) = \beta_0 + \beta_1\,treatment + \beta_2 time + \beta_3\,treattime + \beta_4\,household\ size + \beta_5\,head\ age + \beta_6\,head\ gender + \beta_7\,head\ edu + \beta_8\,ln(\,remittances\ recieved) + \epsilon$$

[1] Sourced from Harvard Dataverse

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	(1) lnincome	(2) lnassets
treatment	0.329	0.636***
	(1.29)	(4.79)
time	0.0557	-0.145
	(0.42)	(-1.93)
treattime	0.223	0.386*
	(0.66)	(2.16)
household_~e	0.0638*	-0.114***
	(2.33)	(-8.17)
head_age	-0.00894	0.00811***
	(-1.91)	(3.39)
head_gender	0.566***	0.769***
	(3.82)	(9.89)
head_edu	0.467**	0.260**
	(3.12)	(3.18)
ln_remitta~d	0.122**	0.158***
	(2.80)	(6.33)
_cons	7.783***	5.994***
	(17.07)	(24.03)
N	700	2954

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 1: Regression Results

3. Empirical Analysis

Our first regression finds no significant effect of the M-Shwari program on household income. This can be explained by looking at the uses of the loans. Approximately 64% of loans were used for business expenditures (livestock, machinery) and the purchase of durable goods, whereas less than 2% of loans were used for everyday purposes (Fig. 2). This explains why income is not sensitive to the treatment.

The results from our second regression show that borrowers from the M-Shwari program experienced a 38.5% increase in the total value of their assets from 2010-2014 when compared to the control group, significant at the 5% level with all our controls being significant at the 1% level.

Again, this can be attributed to a large number of borrowers using loan funds to invest in and sustain microenterprises (Fig. 2). Most microenterprises in Kenya are centred around the production of cash crops such as tea, coffee and sisal (Kikulwe, Fischer, and Qaim, 2014). This often requires specialist capital such as tractors and ploughs for which the loans could have been used.

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The increase in asset accumulation may also be caused by the increase in financial inclusion, particularly concerning women. Evidence shows that 51% of all M-Shwari borrowers were women (Macharia, 2023). Caste and cultural norms have prevented women from owning property in the past, but by allowing women to directly access and manage credit independent of male family members, the M-Shwari program mitigates this challenge.

The positive coefficient of our dummy variable head_gender finds that the total value of the assets in a household is lower when the head is female, following our initial claims that patrilineality hindered the accumulation of assets for women.

However, our regression finds a negative relationship between the dependent variable and household size, with an increase of one member leading to an 11.4% decrease in the total asset value. This could be due to opportunity cost and economic constraints as households have less money to spend on asset accumulation.

The positive coefficients for head education, age and the total value of remittances received are consistent with previous literature.

4. Key Assumptions and Limitations of this Model

Our results are restricted due to the assumptions and limitations we encounter in our model and data. We arrive at our conclusions under the DiD parallel trend assumption.

Moreover, selection bias could arise as the uptake of M-Shwari was not random.

The R-squared values of 10.65% and 8.66% indicate that the variance in our dependent variables is not entirely explained by M-Shwari. The small sample size may have contributed to this. Omitted variables may have exacerbated this issue.

Therefore, it may have been useful to include the values of remittances sent to account for spillover effects between the treatment and control groups. Household incomes and asset levels are both affected by several unobservable factors such as economic climate, geographical mobility and debt levels. This may be why our dependent variables have significant amounts of unexplained variance.

5. Conclusions

Our paper concludes that the digitalization of microcredit lending programs alleviates poverty by examining the effects of MShwari on borrowers in Kenya.

Despite the impact of MShwari on income being statistically insignificant, the total value of assets depicted a positive and statistically significant coefficient. We argue that the short maturity of MShwari loans incentivized borrowers to invest in capital that would produce a sustainable source of future income. However, this contradicts evidence regarding the prevalence of hand-to-mouth consumption preferences in developing countries like Kenya, where available income is spent on immediate consumption (Francois, 2023).

It is difficult to generalise these results due to the uniqueness of Mshwari in Kenya since it had a digital infrastructure, M-Pesa, set in place. Specific government policies may have impacted our dependent variable (Mas and Radcliffe, 2011). For instance, the Matrimonial Property Act of 2013 which strengthened women's rights by allowing them to register their property and could have positively influenced the asset accumulation variable (Mbugua, 2018).

Nevertheless, this research avenue highlights the importance of embracing technological innovations like digital microcredit, offering a pathway toward making informed future policy decisions in the pursuit of socioeconomic development.

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Appendix A.

To make sure our regression residuals are not heteroskedastic, we perform a robustness check. Finding that there is no change in the coefficients from the original regression, and no substantial change in the significance level, we conclude that heteroskedasticity is not a concern to our results. We now trust our model.

Fig. 1: Robustness Checks

```
. reg lnassets treatment time treattime household_size head_age head_gender head_edu ln_remittances_received
```

Source	SS	df	MS
Model	1012.22863	8	126.528579
Residual	8493.93861	2,945	2.88418968
Total	9506.16725	2,953	3.21915586

Number of obs	=	2,954
F(8, 2945)	=	43.87
Prob > F	=	0.0000
R-squared	=	0.1065
Adj R-squared	=	0.1041
Root MSE	=	1.6983

lnassets	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
treatment	.6359754	.1328667	4.79	0.000	.3754543	.8964965
time	-.145109	.0751187	-1.93	0.053	-.2923994	.0021815
treattime	.3855618	.1785221	2.16	0.031	.035521	.7356026
household_size	-.1142758	.0139851	-8.17	0.000	-.1416975	-.0868542
head_age	.0081089	.0023938	3.39	0.001	.0034152	.0128027
head_gender	.7687131	.0777252	9.89	0.000	.6163119	.9211143
head_edu	.2600947	.0817834	3.18	0.001	.0997362	.4204532
ln_remittances_received	.158262	.0250214	6.33	0.000	.1092007	.2073232
_cons	5.994096	.2494776	24.03	0.000	5.504928	6.483264

```
. reg lnassets treatment time treattime household_size head_age head_gender head_edu ln_remittances_received, robust
```

Linear regression

Number of obs	=	2,954
F(8, 2945)	=	47.13
Prob > F	=	0.0000
R-squared	=	0.1065
Root MSE	=	1.6983

lnassets	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
treatment	.6359754	.1570035	4.05	0.000	.3281276	.9438232
time	-.145109	.0755584	-1.92	0.055	-.2932617	.0030437
treattime	.3855618	.1967189	1.96	0.050	-.0001588	.7712824
household_size	-.1142758	.0131457	-8.69	0.000	-.1400514	-.0885002
head_age	.0081089	.0023193	3.50	0.000	.0035612	.0126566
head_gender	.7687131	.0753753	10.20	0.000	.6209194	.9165068
head_edu	.2600947	.0783096	3.32	0.001	.1065475	.4136419
ln_remittances_received	.158262	.0267546	5.92	0.000	.1058023	.2107216
_cons	5.994096	.2451165	24.45	0.000	5.513479	6.474713

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```
. reg lnincome treatment time treattime household_size head_age head_gender head_edu ln_remittances_received, robust

Linear regression                               Number of obs     =        700
                                                F(8, 691)         =       9.67
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0866
                                                Root MSE          =     1.5172

------------------------------------------------------------------------------------------
                        |               Robust
               lnincome | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
------------------------+-----------------------------------------------------------------
              treatment |    .328566   .3659978     0.90   0.370    -.3900351    1.047167
                   time |   .0557433   .1282864     0.43   0.664    -.1961346    .3076211
              treattime |   .2232791   .4198988     0.53   0.595    -.6011514     1.04771
         household_size |   .0637589   .0272599     2.34   0.020     .0102367    .1172811
               head_age |  -.0089409   .0045193    -1.98   0.048    -.0178141   -.0000678
            head_gender |   .5661025   .1414893     4.00   0.000      .288302    .8439031
               head_edu |   .4665598   .1385882     3.37   0.001     .1944553    .7386642
ln_remittances_received |   .1218347   .0445579     2.73   0.006     .0343496    .2093198
                  _cons |   7.782923   .4364695    17.83   0.000     6.925957    8.639888
------------------------------------------------------------------------------------------
```

```
. reg lnincome treatment time treattime household_size head_age head_gender head_edu ln_remittances_received

      Source |       SS           df       MS      Number of obs   =       700
-------------+----------------------------------   F(8, 691)       =      8.19
       Model |   150.73259         8  18.8415738   Prob > F        =    0.0000
    Residual |  1590.64945       691  2.30195289   R-squared       =    0.0866
-------------+----------------------------------   Adj R-squared   =    0.0760
       Total |  1741.38204       699  2.49124755   Root MSE        =    1.5172

------------------------------------------------------------------------------------------
               lnincome | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
------------------------+-----------------------------------------------------------------
              treatment |    .328566   .2552504     1.29   0.198    -.1725933    .8297253
                   time |   .0557433   .1329662     0.42   0.675    -.2053229    .3168094
              treattime |   .2232791    .338343     0.66   0.510    -.4410245    .8875828
         household_size |   .0637589    .027383     2.33   0.020     .0099951    .1175227
               head_age |  -.0089409   .0046845    -1.91   0.057    -.0181385    .0002566
            head_gender |   .5661025   .1483315     3.82   0.000     .2748681     .857337
               head_edu |   .4665598   .1496643     3.12   0.002     .1727084    .7604112
ln_remittances_received |   .1218347   .0435562     2.80   0.005     .0363164    .2073531
                  _cons |   7.782923   .4558918    17.07   0.000     6.887823    8.678022
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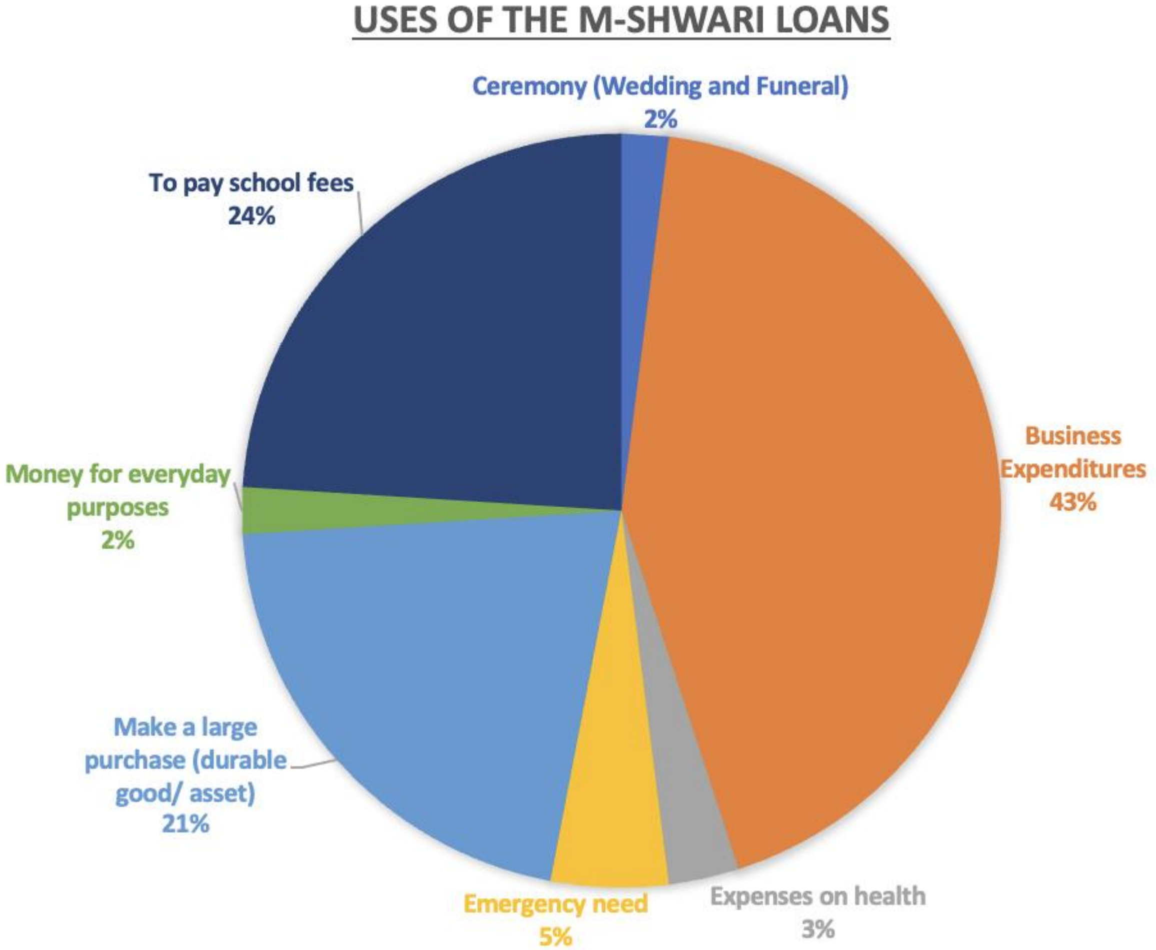

Fig 2: Data collected from Harvard Mobile Money Dataverse (Suri and Jack, 2014)

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