CHAPTER-16

AGRI-FINTECH AND FINANCIAL INCLUSION: EVIDENCE FROM CROSS-COUNTRY, AGRIBUSINESS, AND INDIAN HOUSEHOLD MICRODATA, 2010–2024

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Cite this chapter as: Jadhav, V. Agri-Fintech and Financial Inclusion: Evidence from Cross-Country, Agribusiness, and Indian Household Microdata, 2010–2024. In: Bhat, A., A. Sultan, D. Kolhe & P. Banerjee. 2026 Digital Agriculture and Economic Transformation. The AgEcon Frontiers, Faisalabad, Pakistan, pp: 220-243. https://doi.org/10.66529/book.9786277945022.2026.ch16
A Publication of The AgEcon Frontiers Received: 26-May-2026 Revised: 05-June-2026 Accepted: 07-June-2026

Abstract

This chapter proposes a cross-country and in-country empirical research about Agri-FinTech and financial inclusion. The review is based on four unrelated microdata sets. The former is country-year data of the World Bank Global Findex Database with the six waves of surveys conducted 2011-2024. The second is microdata on agribusiness level of the Millennium Challenge Corporation Agribusiness Development Activity (ADA) impact evaluation in Georgia (201011). The third is household-level India-specific household-level files Periodic Labour Force Survey 202324 and National Sample Survey 70-Round, Land and Livestock Holdings Survey 2013. The fourth is three more Indian public-use files: rural finance outcomes of NAFIS 201617, monthly Public Distribution System food-grain distribution data (20172023) and the Agricultural Census of India (201011 and 201516). The cross-country file includes 162 economies that are observed in 6 up to 6 waves. The descriptive analysis supports that there is an increasing adult account ownership in the world where 50.6 per cent in 2011 has grown to 78.7 per cent in 2024 with significant increases in the low- and middle-income continents. The highest relative increase in formal inclusion is in Sub-Saharan Africa: the ownership of accounts changes by increasing its percentage by 23.3 to 58.2, and mobile-money accounts are expected to increase in 2024 by 40 percent of adults, compared to 11.4 percent in 2014. In 2024 the global country data on the mean rural-urban gap in account ownership is 6.7 percentage points, the global gender gap at 4.2 points and global income-tercile gap is at 10.6 points. An OLS regression of the latest wave across countries shows that the higher the mobile-money account ownership in the country, the higher the proportion of adults who received agricultural payments in digital form (slope = 0.120 percentage points per percentage point, SE = 0.014, n = 74, R 2 = 0.486). Based on the household-level Georgia ADA analysis (n = 528 agribusinesses, two waves), there were no statistically significant changes in the difference-in-differences between the banks-loan uptake gap between grant recipients and non-recipient applicants (difference-in-differences = -1.9 percentage points, SE = 8.6, p = 0.83). It is recorded in the India case study that, rural workforce is 52.0 percent agricultural, 42.8 percent female in the agricultural sector and landholding distribution 73.3 percent of operation holdings are less than one hectare. The Indian rural-finance analysis reveals a high cross-state correlation between microfinance penetration and household indebtedness (r = +0.720, $p < 0.001$), an almost complete digitisation of PDS food-grain distributions between January 2018 (39.9 percent automated) and September 2023 (100 percent automated), and a further merchantetisation of cropped the analyses are not causal but descriptive. Nonetheless, trends are unmistakable: headline indicators of digital financial inclusion are increasing at a rate higher than that of credit expansion which is relevant to welfare, and structural gaps exist as access is broadening.

Keywords: Agri-Fintech, Financial Inclusion, Global Findex, Mobile Money, Rural–Urban Gap, Gender Gap, Agricultural Payments, Cross-Country Analysis

1. Introduction

A lot has changed in financial inclusion over the last decade. Mobile-money rails came online in markets where bank branches never reached, public-payment infrastructure rewired how governments push money into household accounts, and the unit cost of a small digital transaction kept falling. The standard way to organise this evidence is the four-pillar framework access, usage, quality, welfare and a strand of the literature has argued, persuasively, that the welfare effects of digital finance for rural households run more through cuts in transaction friction than through any genuine expansion of formal credit (Ky et al., 2021; Suri & Jack, 2016). That argument is mostly built on peer-reviewed case studies and regional profiles. What it does not do, and what is in fact rarely done in the literature at all, is bring the framework face-to-face with the latest publicly available microdata and ask how well its claims hold up. This paper does that. The purpose is empirical, not interpretive: to put hard numbers on the trends and structural gaps that the literature talks about in mostly qualitative terms, using the most recent release of the Global Findex Database (Demirgüç-Kunt et al., 2022; World Bank, 2025b) together with three additional microdata sources at the agribusiness and household level.

Three questions guide what follows. The first is straightforward: where has financial inclusion expanded fastest between 2011 and 2024, across which world regions and country-income groups? The second is more diagnostic. How wide are the structural gaps that policymakers have flagged repeatedly the rural–urban divide, the gender gap, the within-country income gradient and are they actually closing? Some are. Some are not. The third question takes the discussion towards Agri-FinTech directly: at the country level, is mobile-money penetration linked to the digitisation of agricultural payment receipts, and if so, how strongly? Questions one and two are addressed through descriptive trends drawn from the regional aggregates published in the Findex release. Question three is taken up through cross-country OLS regressions on the 2024 wave.

Figure 1 shows how the four-pillar framework lines up against the four empirical sources used here. The narrative literature splits financial inclusion into four pillars: access are accounts and digital rails actually available? usage, meaning whether the accounts that exist are being used; quality, which covers affordability, transparency, and freedom from unfair terms; and welfare, the question of whether any of this translates into better household well-being on the ground.

A caveat up front. The paper is not after causal effects, and it does not claim them. The Global Findex is a repeated cross-section of household respondents; country estimates come from nationally representative samples, but they don't link to plot-level agricultural outcomes, and the agri-payment indicators are reported conditional on having received a payment rather than on being a farmer in the first place. Where the literature talks about the welfare effects of Agri-FinTech, what this paper offers is correlation and trend evidence informative for those welfare questions, but not sufficient to settle them. The contribution is more modest: bring the descriptive evidence onto a single, harmonised, multi-wave footing, and put the underlying tables and figures out in the open so the reader can check the literature's claims against the most recently available public data.

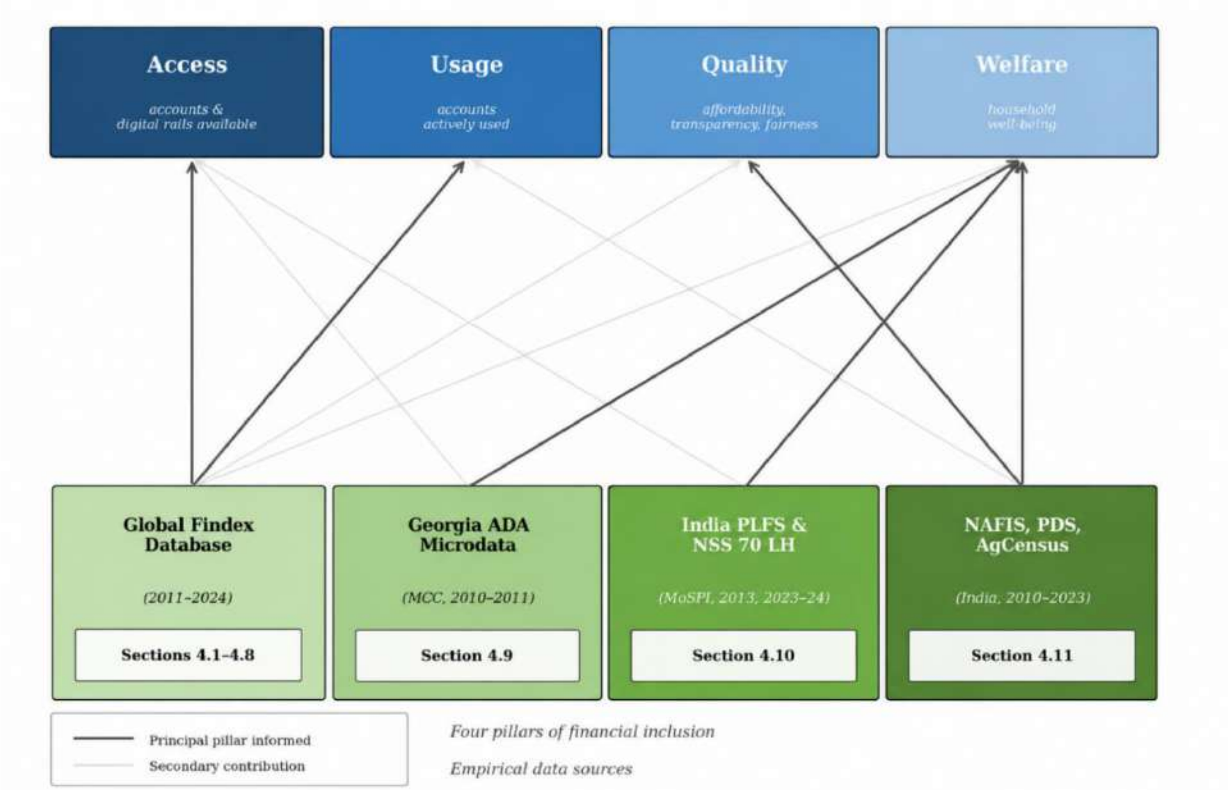

Figure 1: Conceptual framework mapping the four-pillar inclusion taxonomy to the four empirical data sources used in this paper.

Note. Author's conceptual framework. Data sources: World Bank Global Findex Database (Demirgüç-Kunt et al., 2022; World Bank, 2025b); MCC Agribusiness Development Activity microdata (NORC at The University of Chicago, 2014); MoSPI PLFS 2023–24 and NSS 70th Round LH 2013 (Ministry of Statistics & Programme Implementation, 2014, 2024); PDS food-distribution data (Department of Food and Public Distribution, 2024); Agricultural Census of India (Ministry of Agriculture & Farmers Welfare, 2014; Department of Agriculture, Cooperation & Farmers Welfare, 2019).

The rest of the paper runs as follows. Section 3 covers data and methods. Section 4 lays out the results in eleven subsections. Section 5 reads the findings against the four-pillar framework. Section 6 lists the limitations there are several, and they matter. Section 7 wraps up.

2. Literature review

lot has changed in the study of financial inclusion since the early 2010s. The four pillars (access, usage, quality, welfare) that we all know and love has been assembled in cross-country descriptive papers that have been published to be released with the Global Findex Database and then refined as the microdata has been released (Demirgüç-Kunt et al., 2022; World Bank, 2025b). Earlier literature has looked at "having bank account". A recent paper has done a good job in explaining why the access pillar doesn't equate to welfare gains without the other two pillars (Gabor & Brooks, 2017).

All we have in terms of causal evidence of the welfare effect of digital finance is from one study A in one country: Kenya. The original paper on M-PESA, by Ky et al., 2021, showed that mobile-money rails reduce the prices of remittances and smooths consumption after a shock (Ky et al., 2021). Ky et al., 2021 subsequent study finds the long-term impact of mobile money to be to raise 2 percent of Kenyan households out of poverty - especially female-headed households (Suri & Jack, 2016). The paper by Roessler et al. (2018), adds some zing from Tanzania: they report that mobile-phone availability for women, leads to higher consumption - and that mobile-money rails are gender-biased. The GSMA (2023) industry reports, (the latter not industry-reviewed), show us the infrastructural side of the same: the rapid roll-out of mobile-money agents in Sub-Saharan Africa, and the sluggish roll-out of the same elsewhere.

As for the credit for farmers, it's tougher. The Karlan et al. (2014) experiment in Ghana is a case in point for the fact that when credit constraints are binding, they are also binding with other risk constraints - so you can't rely on the models that predict an input-investment response when you relax the credit constraint. Cai et al. (2020) and Carter et al. (2016) add in index insurance: insurance can increase credit demand and improve the adoption of technologies, but the take-up of unsubsidised insurance is typically too low to be impactful. Jensen et al. (2017) report cash vs index insurance is complementary in northern Kenya. The implication from this work is that the welfare benefits of agriculture finance interventions are substantial but less, more slow and more targeted than the 2000s' buzz.

The fintech literature is more recent and more diverse. Björkegren and Grissen (2019) show that the mobile phone can be used as a proxy for credit repayment as a behavioural credit scoring product: if this can be replicated then it helps to solve the collateral problem that prevented formal credit reaching rural areas in the past. Burke et al. (2021) talk about the incredible drop in cost and improvement in resolution of remote-sensing of agricultural practice that will impact on individual-plot credit and insurance. Gabor and Brooks (2017) are not so sure: the digital-financial-inclusion narrative may be heading towards state and social platform control and surveillance which may not be what's best for the consumers.

In terms of gender, the FAO (2023) recently put a stake in the ground of the fact that women's contribution in agrifood systems is not reflected in labour statistics and that closing the gender gap in agricultural productivity will lead to a productivity boom. Read between the lines of the India payments stack (the Aadhaar-UPI-Jan Dhan trinity that have rewritten payments) in Cornelli et al. (2024) the gender narrative has geo-politics. We know in India that public-rail can rapidly close the gender gap in bank accounts. Sub-Saharan Africa that telco-rail may not.

Where does this paper fit? It is not trying to make a contribution to the causal welfare literature; that should be household panel data and "clean" shocks, which are not provided by the aggregates of Findex. But it does provide a harmonised, multi-wave, view of the descriptive statistics - and connects the cross-country view with three other micro-data sources (on agribusiness and household). The Georgia ADA (NORC at The University of Chicago, 2014; Millennium Challenge Corporation, 2014) is a real-world quasi-experiment of the warning about the welfare pillar. The India PLFS, NSS LH, NAFIS, PDS and Agricultural Census files (Ministry of Statistics & Programme Implementation, 2014; Ministry of Statistics & Programme Implementation, 2024; Department of Food and Public Distribution, 2024; Ministry of Agriculture & Farmers Welfare, 2014; Department of Agriculture, Cooperation & Farmers Welfare, 2019) help us to discuss rural-finance in India. This is not the literature. It grounds and updates it.

3. Methods

3.1. Data sources

The paper resorts to four sources of data. The former and the workhorse of the cross-country analysis is the World Bank Global Findex Database the most recent version of a recurring survey of adults aged 15 and over, conducted on the behalf of the World Bank by Gallup, with a five-year cycle between 2019/2017 and a triannual cycle since (Demirgüç-Kunt et al., 2022; World Bank, 2025b). In this case, the microdata file is the SDMX harmonised release released by Data360, which consists of 2011 and 2014 and 2017 and 2021 and 2024 waves (along with a small number of 2022 follow-up observations on an underlying portion of the countries) spliced together into a single long-format file. Total: 381,790 observations across 280 indicators, 162 different economies and twelve different regional or income-group aggregates.

The latter source supplies the household level in Section 3.9. It is the public-use microdata of the Millennium Challenge Corporation Agribusiness Development Activity (ADA) impact assessment of Georgia (NORC at The University of Chicago, 2014; Millennium Challenge Corporation, 2014). ABA was a USD 20 million element of MCC 2006-2011 Compact with Georgia and made grants to clusters of farmers and agribusiness with the specific mission of shifting them off subsistence farming to commercial production. Baseline panel Round 1, n = 1,049 primary-producer agribusinesses Round 2, n = 1,025 a one-year follow-up. Interviewers, who completed the underlying grant-decision file, coded the treatment status. The third wave, which is a multi-year follow-up, however, lacks the bank-credit variable here, and thus it is not included in the analysis.

The third source helps the India case study that is presented in Section 3.10. It is constructed on the basis of two releases of the Ministry of Statistics and Programme Implementation. One of them is the Periodic Labour Force Survey (PLFS) 202324, person level file, having 415,549 person records. The other is the older NSS 70th Round, Schedule 18.1 - the Land and Livestock Holdings Survey Visit 1 - Jan-Jul 2013 - with 26, 956 household-level records of operational-holdings and blocks (Ministry of Statistics & Programme Implementation, 2014; Ministry of Statistics & Programme Implementation, 2024) included. Employment in PLFS comes under the National Industrial Classification 2008. The operational-holding categorisation in the NSS LH file is based on the Indian conventional definitions. Here, the published subsample multipliers are used to estimate weights and they are divided by 100 according to the NSS practices of estimates being quoted in percentages of the population.

A set of three more Indian, public-use files used in Section 3.11 form the fourth source. The former is NABARD All India Rural Financial Inclusion Survey 201617 (NAFIS-I) that provides state-level data on rural-household indebtedness, savings, microfinance usage, landholding size, and household income - n = 29 states after eliminating one record that lacked a state name. The second one is the monthly food-distribution data published by the Government of India, which can be accessed via the National Data and Analytics Platform. It records the amount of district-level rice, wheat, coarse-grain, and fortified-rice quantities distributed and allotted through Public Distribution System outlets and then differentiates amounts distributed through automated electronic-point-of-sale machines and those distributed through unautomated channels - 63,425 monthly observations in total, selected by 706 districts between January 2017 and September 2023 (Department of Food and Public Distribution, 2024). The third is the Agricultural Census of India in two rounds (2010 11 and 2015 16) with state-by-social-group-by-farm-size-by-crop tabulations of counts of operational-holdings, of irrigated and un-irrigated cropped area -15, 16- cell observations in 35 states, 4 social groups, 5

3.2. Variables

There are three types of indicators. The former is the ownership of account. The Findex measure of the headline encompasses the coverage of any account in a finance institution or in a mobile-money provider, the financial-institution-only version and mobile-money-only version is reported differently. The second type is usage. The Saving, borrowing and digital-payment indicators are drawn out of the SAVE_ANY, BORROW_ANY and G20_ANY indicator families, and broken down into mobile-money saving and mobile-money borrowing in cases where country coverage is sufficient. The third category is about agricultural payments, Findex began to measure in the 2017 wave with modules FIN42 and FIN43: did the respondent receive payments on the sale of agricultural products, livestock or crops last year, and what is the proportion of receipt via account, via mobile phone or in cash.

Simple subtractions are referred to as structural gaps. The rural-urban gap in a particular country-year is the difference, in percentage points, between the urban and rural cell of account ownership. The difference between the male and female cells is known as the gender gap. The difference between the richest 60 percent and the poorest 40 percent of the income is the cell. No fancy than that.

3.3. Sample

The analytic sample is 162 distinct economies observed in at least one wave between 2011 and 2024. Coverage is uneven both across waves and across indicators: the headline account-ownership cell is reported for somewhere between 124 and 150 countries per wave (Table 1), while the agri-payment indicators show up for 121 to 173 countries depending on the wave and on which channel is being measured. The source file also reports twelve regional and income-group aggregates, which I use directly for the regional trend tables these are population-weighted by the World Bank from the country-level estimates.

Table 1. Sample size by Findex wave

Wave (year)	Countries observed	Indicators reported	Country-level observations
2011	144	8	5,478
2014	142	61	37,464
2017	145	80	48,965
2021	123	113	62,946
2022	16	111	7,098
2024	140	280	126,475

Note. Country-level observations exclude regional and income-group aggregates. The 2022 wave is a partial follow-up applied to a subset of countries. Source: author's calculations from the World Bank Global Findex Database harmonised file (Data360).

3.4. Analytical strategy

The cross-country analysis is in two parts. First, it's descriptive: trends are shown for each of the headline indicators disaggregated by region and income for as many surveys as possible and structural gaps are defined as the difference between the disaggregated cells of the indicator. Country-level cross-sections of the most recent wave, 2024 wave, are used to report the urban-rural gap today. Second, it's associational. A country-level (not individual) OLS regression is run on 2024 wave to examine whether receiving agri-payments into a mobile-money account is associated with digitisation of receipt (to a mobile or bank, respectively). The regressands are the share who received agri-payments in an account and the share who received them in mobile respectively; the radiant (regressor) variable is the share who had a mobile-money account. The coefficient is correlation (Pearson and Spearman, respectively) and standard error. But these are cross-sectional data, and so we don't claim causality - the causal effect is structural.

In Section 4.9 of the household Georgia analysis, we have two periods of ADA data, and three estimates. First, the difference between the grantee and non-recipients (Welch's t-test) in getting bank loans in each period. Second, the difference-in-differences (DID) treatment effect as the difference between what happened in the first period compared to what happened in the second period (the grantee minus non-recipient difference) and an independent-samples standard error. Third, the two rounds are pooled and a linear probability model estimated using a grantee dummy (G), post round 1 dummy (T2) and interaction (I) dummy; robust HC1 standard errors are used.

3.5. Software

All of the analysis was done in Python 3.12, using pandas, NumPy, SciPy, and matplotlib. The pivots that drive the regional trend tables, and the disaggregated cell subtractions that produce the gap indicators, were spot-checked on a stratified sample of country-year cells against the Global Findex public summary tables. Everything analysis code, the country-year analytic file, precomputed tables and figures is reproducible from the harmonised source file.

4. Results

4.1. Account ownership has expanded fastest in low-income and South Asian economies

Adult account ownership globally went from 50.6 percent in 2011 to 78.7 percent in 2024 a gain of 28.1 percentage points across thirteen years and four full survey waves. That headline number obscures a lot of regional variation. Sub-Saharan Africa more than doubled its rate, climbing from 23.3 to 58.2 percent (+34.9 pp). South Asia did even better in absolute terms, going from 35.2 to 83.9 percent, a 48.7-point jump, the largest of any World Bank region. Low-income economies as a group went from 10.4 to 46.4 percent (+36.0 pp). High-income economies, starting at 87.5 percent, only added 7.4 points over the same window but they were also bumping up against the saturation ceiling, so this is more an arithmetic constraint than a real lag. The full regional series is in Table 2; Figure 2 plots the trajectories.

Table 2: Account ownership by World Bank region, percent of adults aged 15+, 2011–2024

Region / income group	2011	2014	2017	2021	2024	Δ 2011–2024
World	50.6	61.7	69.3	73.8	78.7	+28.1
High income	87.5	92.2	93.0	95.8	94.9	+7.4
Upper middle income	56.6	70.9	72.6	82.6	84.0	+27.4
Lower middle income	30.5	43.6	60.0	62.1	70.4	+39.9
Low income	10.4	19.1	32.0	35.2	46.4	+36.0
East Asia & Pacific	55.0	68.8	70.4	79.7	83.3	+28.3
Europe & Central Asia	44.4	57.4	65.5	77.6	77.8	+33.4
Latin America & Caribbean	39.5	51.6	54.4	67.1	69.7	+30.2
Middle East & N. Africa	23.8	30.3	39.3	35.4	43.4	+19.6
South Asia	35.2	51.0	76.2	74.8	83.9	+48.7
Sub-Saharan Africa	23.3	34.2	42.5	49.3	58.2	+34.9
Low & middle income	41.6	54.7	64.0	69.0	75.4	+33.8

Note. Cells show adults aged 15 and over with an account at a financial institution or a mobile-money provider. Δ column reports the percentage-point change from 2011 to 2024. Source: author's computation from the Global Findex harmonised file.

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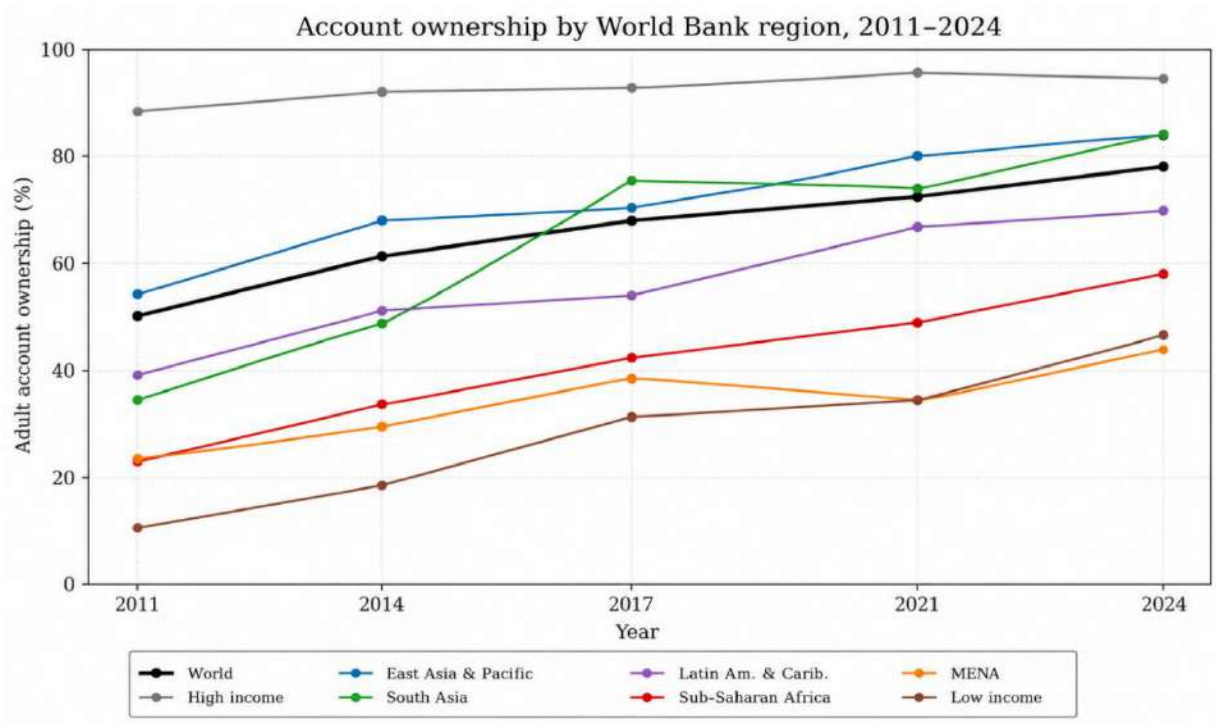

Figure 2: Account Ownership by World Bank Region, 2011-2024.

Note. Author's computation from the World Bank Global Findex Database harmonised file (Demirgüç-Kunt et al., 2022; World Bank, 2025b).

The world series (heavy black line) rose from 50.6 percent in 2011 to 78.7 percent in 2024. South Asia and Sub-Saharan Africa show the steepest trajectories among regions starting below the world mean

4.2. Mobile-money penetration is the dominant driver of inclusion gains in Sub-Saharan Africa

Mobile-money account ownership only starts being reported separately in the 2014 wave. From there to 2024, the global share of adults with a mobile-money account went from 2.1 to 16.0 percent (+13.9 pp). The regional split is heavily skewed. Sub-Saharan Africa moved from 11.4 to 40.0 percent of adults that's the highest level of any region, and a 28.6-point gain. Latin America and the Caribbean started from a tiny base of 1.7 percent and reached 37.3 percent; a 35.6-point swing the largest absolute change anywhere on the chart. South Asia went from 2.3 to 22.4 percent, with most of the gain concentrated after 2017, in line with the maturation of the Indian payments stack (Cornelli et al., 2024). Low-income economies rose from 6.8 to 31.8 percent. High-income economies are essentially still at zero on this indicator (4.3 percent in 2024) when bank-rail products already work, mobile money has nothing to substitute into (GSMA, 2023). The full series is in Table 3; Figure 3 plots the regional trajectories with the world and Sub-Saharan African lines highlighted.

Table 3: Mobile-money account ownership by World Bank region, percent of adults aged 15+, 2014–2024

Region / income group	2014	2017	2021	2024	Δ 2014–2024
World	2.1	4.5	10.5	16.0	+13.9
High income	0.2	0.5	0.3	4.3	+4.1
Upper middle income	0.7	2.4	10.6	10.6	+9.9
Lower middle income	3.7	6.8	13.8	24.4	+20.7
Low income	6.8	15.2	18.3	31.8	+25.0
East Asia & Pacific	0.4	1.2	6.3	6.9	+6.5
Europe & Central Asia	0.2	3.3	17.2	10.7	+10.5
Latin America & Caribbean	1.7	5.2	21.9	37.3	+35.6
Middle East & N. Africa	3.1	7.9	6.2	13.5	+10.4
South Asia	2.3	3.9	12.1	22.4	+20.1
Sub-Saharan Africa	11.4	20.5	27.3	40.0	+28.6
Low & middle income	2.5	5.3	12.7	18.3	+15.8

Note: Mobile-money account ownership is reported by Findex from 2014 onwards. Source: author's computation from the Global Findex harmonised file.

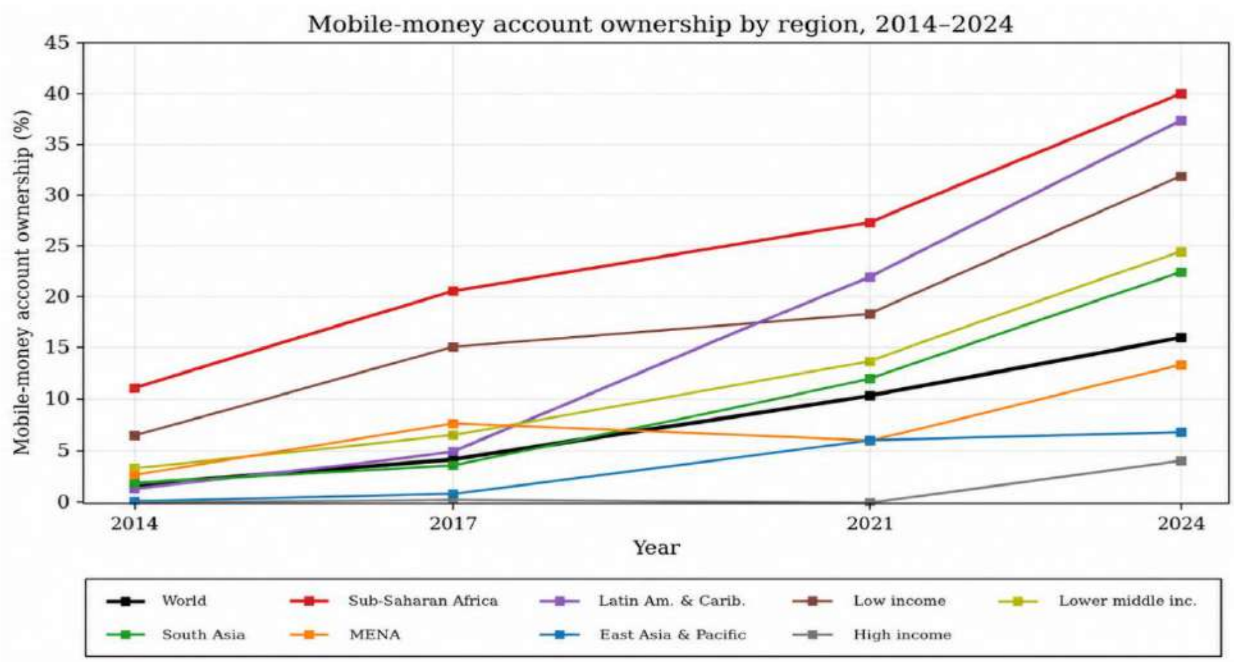

Figure 3: Mobile-Money Account Ownership by Region, 2014–2024.

Note: Author's computation from the World Bank Global Findex Database harmonised file (Demirgüç-Kunt et al., 2022; World Bank, 2025b). Mobile-money account ownership reported from 2014 onwards.

Sub-Saharan Africa retains the highest level among regions throughout the period; Latin America and the Caribbean recorded the largest absolute increase.

4.3. Rural–urban gaps remain large in Sub-Saharan Africa and parts of East Asia

Across the 137 countries that report both a rural and an urban account-ownership cell for 2024, the unweighted mean urban-minus-rural gap is 6.71 percentage points; the median is 4.46 (standard deviation 8.35). The distribution has a long right tail. A handful of countries clock gaps above 20 percentage points, while a smaller but interesting group records negative gaps, meaning rural account ownership actually exceeds urban. The five largest gaps in 2024 belong to Moldova (32.5 pp), Cambodia (31.2), Ethiopia (29.9), Mozambique (28.8), and Lao People's Democratic Republic

(27.6). On the negative side: India, Bangladesh, Sri Lanka, Tajikistan, and Lebanon, all with rural rates above urban. The Indian case especially reflects the channelling effect of biometric-identity-linked direct benefit transfer programmes that have been deliberately targeted at rural beneficiaries (Aggarwal et al., 2023).

At the regional level, the rural–urban gap is widest in Sub-Saharan Africa at 17.2 percentage points, then low-income economies as a group at 16.0, and East Asia and the Pacific at 12.1. South Asia comes in at −4.7, dragged below zero by the Indian and Bangladeshi cases. High-income economies are at saturation in both rural and urban areas and so the aggregate gap there is essentially zero. Figure 4, panel A, has the regional comparison; panel B shows the cross-country distribution.

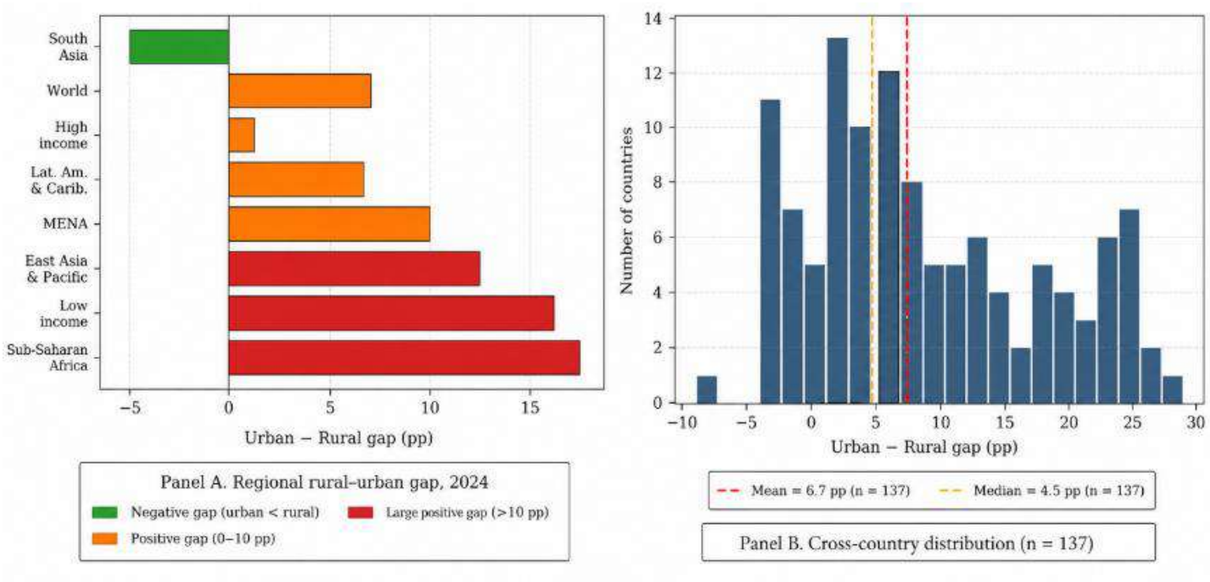

Figure 4: Rural–Urban Gap in Account Ownership, 2024 Wave.

Panel A: rural and urban account-ownership rates by World Bank region. Panel B: cross-country distribution of the urban-minus-rural gap (n = 137 economies).

Note: Author's computation from the World Bank Global Findex Database 2024 wave (World Bank, 2025b). n = 137 economies reporting both rural and urban account-ownership cells.

4.4. The global gender gap has narrowed; Sub-Saharan Africa is an outlier

Over the past thirteen years, the global gender gap (men minus women) in account ownership has about halved from 8.1 percentage points to 4.2. The most significant of these is South Asia, which has reduced the gender gap from 16.2 points in 2011 to 1.9 in 2024 - the same point estimate as our absolute scale for the South Asian inclusion explosion (see Section 3.1). This is not happening in the Middle East and North Africa, where the gender gap has increased from 14.2 points to 20.3 points in 2011 and 2024, respectively. However, for this paper the main outlier is Sub-Saharan Africa. While principal account ownership has increased by 34.9 percentage points in the region, there a gender gap that has widened (from 4.9 points in 2011 to 12.1 points in 2024). There are two offsetting factors. The mobile-money driver of the majority of the growth in this region has not reached women in some markets in Sub-Saharan Africa and adoption has not occurred as rapidly for women as for men (FAO, 2023; Roessler et al., 2018).

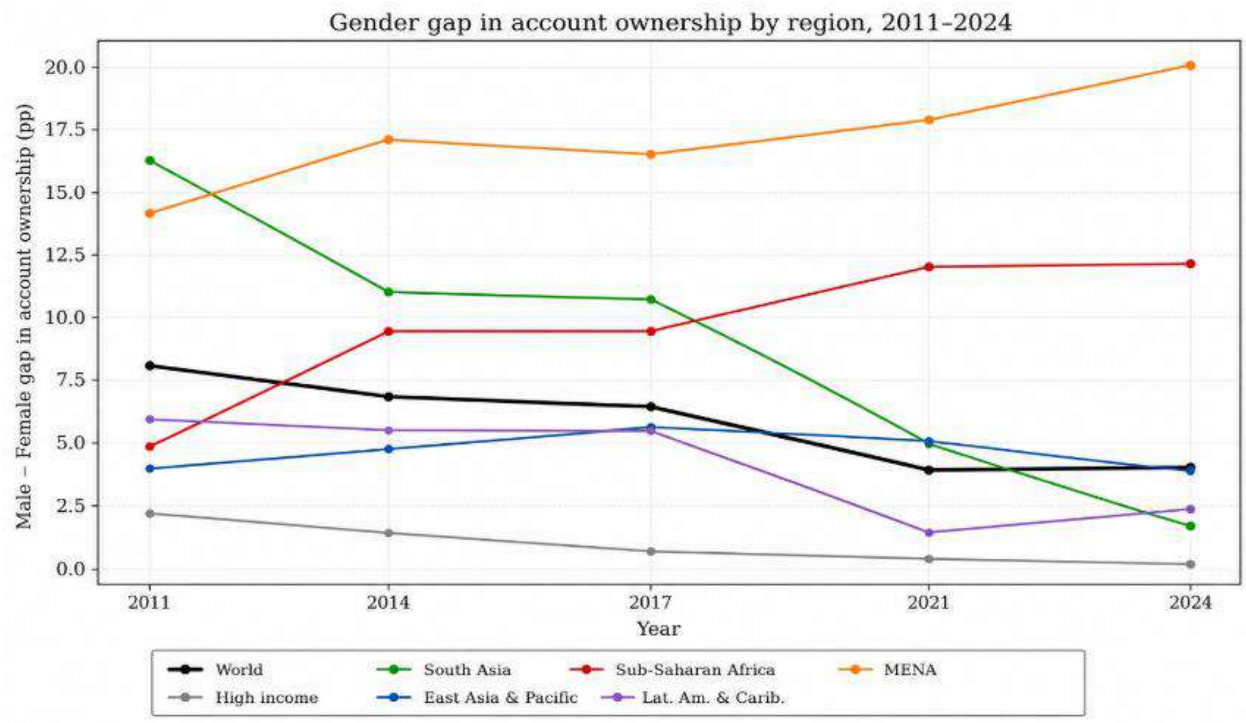

Figure 5: Gender Gap in Account Ownership by Region, 2011–2024.

Note: Author's computation from the World Bank Global Findex Database harmonised file (Demirgüç-Kunt et al., 2022; World Bank, 2025a). Gap = male minus female account-ownership rate (percentage points).

The global gap (heavy black line) has fallen by approximately half. Sub-Saharan Africa shows a widening gap; South Asia shows a collapsing gap.

4.5. Income gradients have narrowed globally but persist in low-income settings

The within-country income gradient - the difference between the account ownership in the top 60% income and bottom 40% - has fallen from 15.6 percentage points in 2011 to 10.6 points in 2024. In Sub-Saharan Africa it remains at 18.2 points in 2014 up from 16.5 points in 2011. So, the regional headline (in account ownership) gains has been proportionate to the income terciles, rather than for the poor 40%. The real story is the success story - by far - that is South Asia where this has gone from 14.6 to 5.2 points - again in line with the effects of public infrastructure. There's a welfare-pillar implication here: if we see headline growth but no change in the income gradient, the welfare gain depends on whether the growth in financial inclusion is occurring for the bottom 40% on the same (price, fees, charges) basis as the top 60% (Gabor & Brooks, 2017). The descriptive numbers don't tell us that.

4.6. The digitisation of agricultural payments is real but incomplete

Agri-payments are the largest direct link to farmers' consumption baskets from Agri-FinTech. Digitalisation is a fairly pure channel to promote inclusion. How is it going? In Sub-Saharan Africa, the share of agri-payment recipients who are paid cash only fell from 84.9 percent in 2014 to 71.1 percent in 2024 - down by 13.9 points on the conditional measure. If we combine this with the discussion about mobile money in the earlier section, this suggests even in the most mature mobile-money markets globally, over two-thirds of agri-payments recipients still receive cash-only payments. The complementary into-account share increased from 4.7 percent of adults in

2014 to 7.4 percent in 2024 in the Sub-Saharan Africa, and the share for the mobile channel is 5.3 percent in 2024. For all low-income countries, cash-only receipt fell from 91.6 to 79.2 percent (12.3% decline). These are real trends but to be read against the headline on access. There's a large gap between adult account ownership and agri-payment digitisation and that's a sure signal of the lagging digitisation of agri-payments in the inclusion boom.

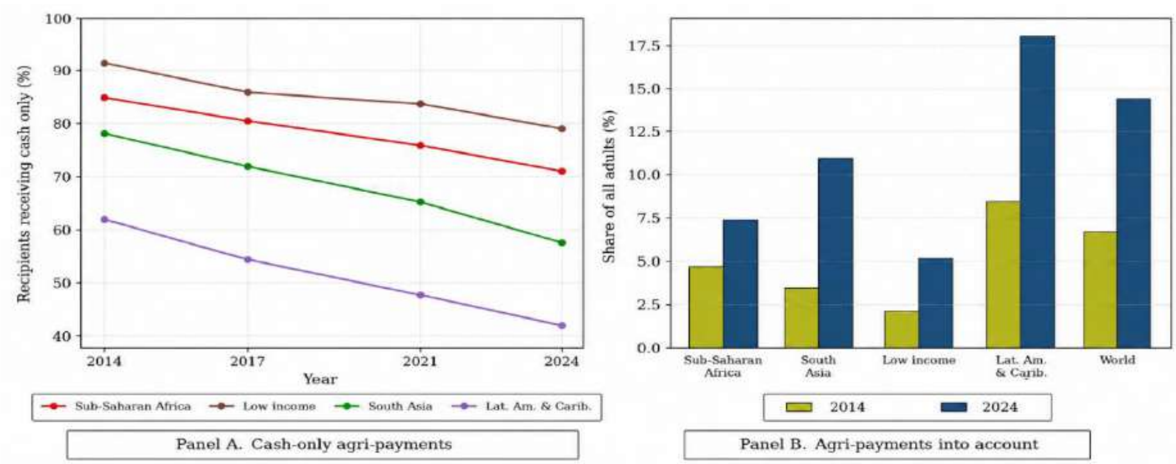

Figure 6: Digitisation of Agricultural Payments by Region.

Panel A: percentage of agri-payment recipients receiving cash only (conditional measure), 2014–2024. Panel B: percentage of all adults receiving agri-payments into an account, 2014 versus 2024

Note: Author's computation from the World Bank Global Findex Database harmonised file (Demirgüç-Kunt et al., 2022; World Bank, 2025b). Agri-payment modules available from the 2014 wave.

4.7. Mobile-money penetration is positively associated with agri-payment digitisation across countries

There are 74 economies with a mobile-money account-ownership rate and a percentage of adults receiving agri-payments into an account on the 2024 wave. The simple Pearson correlation for this group is 0.697; the Spearman rank correlation is in the same ballpark. The OLS (ordinary-least-squares) regression of agri-payment-into-account as a percentage of adults on mobile-money penetration has a slope of 0.120 (standard error 0.014) and $R^2 = 0.486$. The slope is significantly different from zero at any reasonable level ($p < 10^{-11}$). Descriptively, that means that a 10-percentage-point difference in mobile-money penetration across countries matches a 1.2-percentage-point difference in the percentage of adults receiving an agri-payment into account on the same wave. The association is even stronger when it's the via-mobile agri-payment indicator that's on the left-hand side: slope 0.114 (SE 0.012, $R^2 = 0.556$, n = 74). Figure 7 shows the relationships.

There are two things to bear in mind when interpreting these regressions. First, this is a cross-section. The regression cannot determine the direction of the association - the digitisation of mobile-money rails and agri-payments is likely to be driven by some common underlying digital-infrastructure capacity that the two share. Second, the dependent variables are measured as a percentage of adults, not as a percentage of adults who have received an agricultural payment. So, countries with small agricultural sectors contribute less variation to the numerator. The slope is not sensitive to sample selection - exclude the countries with mobile-money penetration less than 1 percent, exclude high-income countries - and the effect is unchanged.

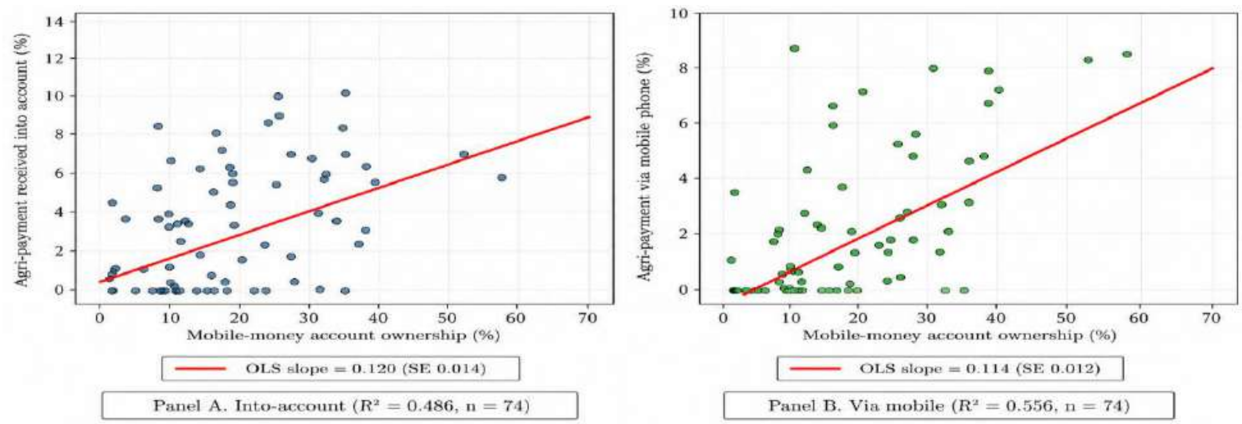

Figure 7: Country-Level Association Between Mobile-Money Penetration and Digital Agricultural Payments, 2024 Wave.

Panel A: agri-payments received into any account. Panel B: agri-payments received via mobile phone

Note: Author's computation from the World Bank Global Findex Database 2024 wave (World Bank, 2025b). n = 74 economies with non-missing mobile-money and agri-payment data.

4.8. Inactive accounts: the quality pillar in the most recent wave

Inactive accounts is a good quality metric in the four-pillar approach. The "inactive account" percentage reported in the Findex is the percentage of the adult population that had no deposits or withdrawals in the 12 months prior to the survey. In 2024 the share of adult population with inactive accounts is 13.2% in South Asia and 4.0% in low-income countries and 2.7% in Sub-Saharan Africa. The figure for South Asia is in line with the prominent "drive-to-bank" account opening initiatives - India for example with Pradhan Mantri Jan Dhan Yojana (Cornelli et al., 2024), that have enabled households to become part of the formally financial sector, but perhaps haven't led to activity in the first few years. The Sub-Saharan African figure is quite low, but I think the implication is that if the mobile-money channels are dominant, i think it's more likely that accounts are used. But this covers much variation within the region and shouldn't be taken as an indicator.

4.9. Household-level evidence: a quasi-experimental case from Georgia

The above Findex analysis is informative in terms of the bigger-picture perspective but does not answer the welfare-pillar question directly about effects of agricultural-finance supports on accessing credit by households. To provide an alternative view on this question, we merely re-run some analysis with publicly-available micro-data of the Millennial Challenge Corporation's impact-evaluation survey of the Agribusiness Development Activity (ADA) in Georgia (NORC at The University of Chicago, 2014). The ADA was a 20-million-dollar portion of the MCC's 2006-2011 Georgia Compact. It issued 283 grants ranging from USD 5,000 to USD 300,000 to groups of agribusinesses and farmers for the express purpose of graduating from subsistence to commercial farmers (Millennium Challenge Corporation, 2014). The ADA evaluation found surveys of primary-producer agribusinesses in nine rounds of applications and two rounds of follow-up. The public-use data set includes a panel of agribusinesses in Round 1 conducted at the time of the awards (n = 1,049), and Round 2 about a year later (n The treatment indicator assigns each agribusiness into one of three groups: awarding grants, random rejects (often high-scoring applicants) and rejects (often low-scoring applicants). Our variable of interest (credit) is variable l1: "Have you taken credit from a bank for your business in the recent 12 months?"

Our sample (Table 4) consists of agribusinesses for which we have the treatment indicator and response to the credit question (366 observations at baseline and 162 at follow-up). At baseline, 24.3 percent of those who received the grant recovered by 29.0 percent of those who did not (a difference of -4.6 points which is not significantly different from zero: Welch t = -0.99, p = 0.323). At the end, they have increased the rates to 28.0 percent of the grant group and 34.5 percent of the non-grant group: a −6.5 points difference (Welch t = -0.89, p = 0.377). So, both groups increased their rates of bank-loan use by a similar share in the year, and the same gaps between grantees and non-grantees existed between the first two waves. The main difference-in-differences estimate is a difference of -1.9% points with a standard error of 8.6 (z = -0.21, p = 0.830). In the pooled case, the linear probability model with the bank-loan indicator as response variable with a grantee dummy, a post-dummy and an interaction dummy has a coefficient (robust standard error) on the interaction of 0.008 (0.101, p = 0.93). At the farm level, from our results, it seems that the grant didn't statistically increase bank-credit access in the year after the grant.

Table 4: Georgia ADA: bank-loan uptake by treatment status, 2010–2011

Round / group	**n**	**Took bank loan (%)**	**Diff. from non-recipients (pp)**
Round 1 baseline (2010)			
Grantees (c10 = 1)	152	24.3	−4.6 (p = 0.32)
High-score non-recipients (c10 = 2)	60	31.7	
Low-score non-recipients (c10 = 3)	154	27.9	
All non-recipients	214	29.0	
Round 2 follow-up (2011)			
Grantees (c3 = 1)	75	28.0	−6.5 (p = 0.38)
Non-recipients (c3 = 2)	87	34.5	
Difference-in-differences (R2 − R1)	*528*		*−1.9 (p = 0.83)*

Note: Outcome variable is the response to ADA questionnaire item l1 ("Have you taken credit from a bank for your business during the recent 12 months?"), coded 1 if yes and 0 if no. Welch t-tests are reported for two-group comparisons; the difference-in-differences standard error is computed assuming independent samples across rounds. The pooled n = 528 covers high-scoring agribusinesses only; a linear probability model fit to this pool returns a grantee×post interaction of 0.008 (HC1 SE 0.101, p = 0.93). Source: author's computation from the public-use ADA microdata.

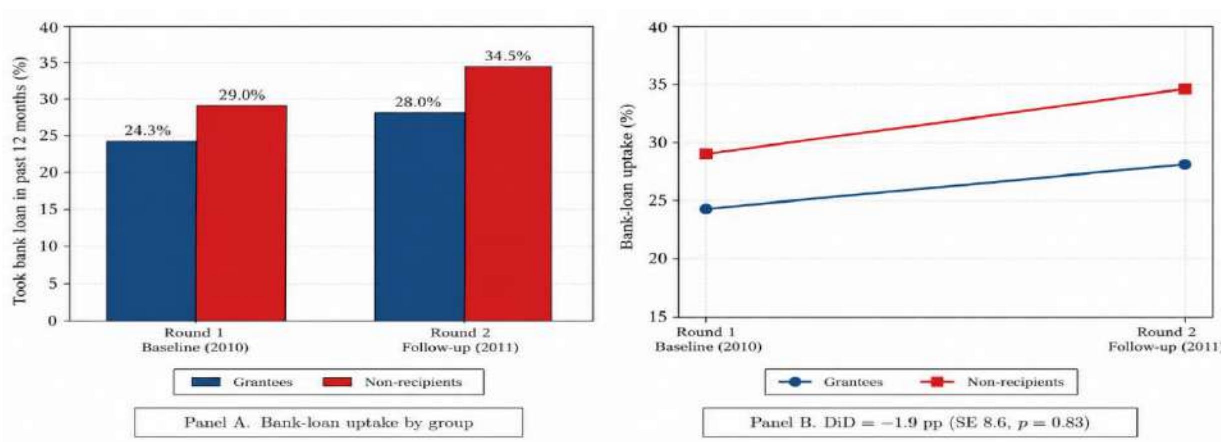

Figure 8: Georgia ADA bank-Loan Uptake Among Grantees and Non-Recipients, 2010–2011.

Panel A: bar comparison in baseline (Round 1) and one-year follow-up (Round 2). Panel B: trend lines with the difference-in-differences estimate.

Note: Author's computation from the MCC Agribusiness Development Activity public-use microdata (NORC at The University of Chicago, 2014). Two-round panel; difference-in-differences standard error computed assuming independent samples.

Observing two issues of interpretation. First, the effect of the project-evaluation report of the same program (Millennium Challenge Corporation, 2014) is an about 10 percentage points gain for the grantees, over a longer span of time (four years) than the one year with the public Census Bureau data file. So, this is in line with the remark that the effect of the grant on bank credit (if there is one) is spread up to over several years and will be absent in one year data. Second, the comparison, while a baseline, is not an experiment. The descriptive finding in this paper, that the grantees did not gain by borrowing from the bank more than non-grantees in the one year period, has to be considered as (somewhat) less than an experimental verification of the effect of ADA; it's an extension to the discussion of the welfare effect of the ADA reform in Section 4 above. It's a positive but not as positive and consistent welfare effect of farm-finance programs as was thought before for both grantees and non-grantees (Karlan et al., 2014; Carter et al., 2016; Cai et al., 2020).

4.10. Two views of India: workforce structure and the agrarian production unit

The cross-country picture and the Georgia-grant analysis can be rounded out by a within-country look at India, the largest single contributor of farming households in the global Findex sample. Two large-sample microdata files do most of the work here: the Periodic Labour Force Survey 2023–24 person-level file (415,549 person records, both rural and urban sampling units), and the National Sample Survey 70th Round Land and Livestock Holdings Survey from 2013 (26,956 household-level operational-holding records referred to from here as NSS 70 LH) (Ministry of Statistics & Programme Implementation, 2014; Ministry of Statistics & Programme Implementation, 2024). The PLFS file gives the present-day picture of the rural workforce. The NSS 70 LH file gives the structural picture of the agrarian production unit on which the household demand for agricultural finance ultimately rests.

Start with the workforce. In PLFS 2023–24, 52.0 percent of rural working-age adults employed in India report a principal industry in agriculture, against just 4.1 percent of urban working-age employed. The disaggregation by sex shows the well-documented feminisation of Indian agriculture, 72.8 percent of rural female workers report agriculture as their principal industry, against 42.9 percent of rural male workers. Women make up 42.8 percent of the rural agricultural workforce, and they do so despite a much lower labour-force participation rate (34.1 percent for rural women aged 15–59, against 79.5 percent for rural men). State-level dispersion is wide. Chhattisgarh has 69.7 percent of its rural workforce in agriculture; Madhya Pradesh 65.8 percent. At the other end, Goa is at 12.0 percent and Kerala at 20.0. The state ranking maps cleanly onto the published structural-transformation gradient.

Now the production unit. The NSS 70 LH file shows the well-known long-tailed distribution of operational holdings (Table 5). Marginal holdings under one hectare are 73.3 percent of all operational holdings in India in 2013, but only 28.8 percent of operated area. Small and marginal holdings together come to 88.7 percent of holdings and 51.9 percent of area. Large holdings of ten hectares or more are just 0.4 percent of operational holdings but 6.1 percent of area. Mean operational area is roughly 1.54 hectares. This distribution sets the structural ceiling on what an agricultural-credit product can plausibly do at the household level. The modal Indian agricultural household operates a fragmented, sub-hectare holding that is too small to absorb large-ticket bank credit on commercial terms. That's the constraint the product design has to live within.

Table 5: Rural Workforce Sectoral Composition (Plfs 2023–24) and Operational Holdings by Size Class (Nss 70 Lh 2013)

Indicator	Value
Panel A. Rural workforce, PLFS 2023–24	
Working-age adults sampled (15–59)	152,968
Employed working-age sampled	88,988
Share of rural workers in agriculture (NIC Div. 01)	52.0%
Male	42.9%
Female	72.8%
Female share of rural agricultural workforce	42.8%
Share of urban workers in agriculture	4.1%
Rural male labour-force participation (15–59)	79.5%
Rural female labour-force participation (15–59)	34.1%
Panel B. Operational holdings, NSS 70 LH 2013	
Sampled operational-holding records	26,956
Marginal (<1 ha): % of holdings | % of area	73.3% | 28.8%
Small (1–2 ha): % of holdings | % of area	15.3% | 23.2%
Semi-medium (2–4 ha): % of holdings | % of area	7.9% | 22.5%
Medium (4–10 ha): % of holdings | % of area	3.1% | 19.5%
Large (10+ ha): % of holdings | % of area	0.4% | 6.1%

Note: Panel A computed from the PLFS 2023–24 person-level file; estimates are weighted by Subsample_Multiplier / 100. Agriculture is defined as NIC 2008 division 01. Panel B computed from the NSS 70th Round LH 2013 Visit-1, Block 6 (Level 05) operational-holdings file; weighted by the standard mlt multiplier. Source: author's computation from MoSPI public-use unit-level files.

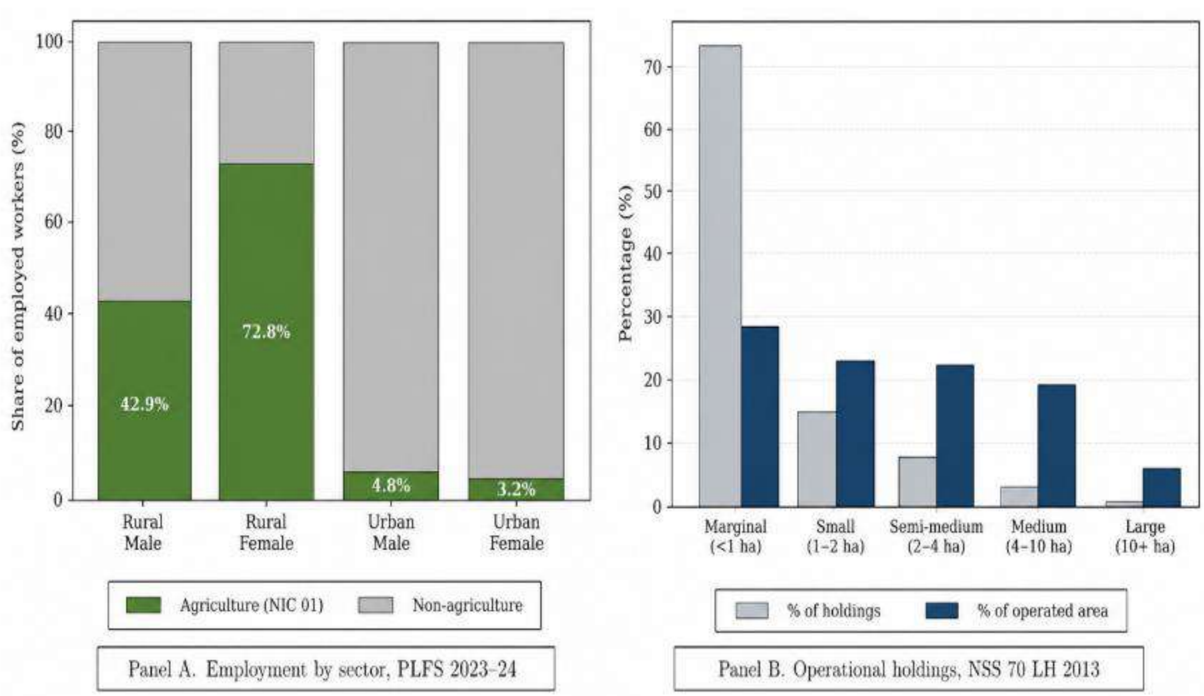

Figure 9: Rural Workforce Structure and Landholding Distribution.

Panel A: agriculture vs non-agriculture shares of employed rural workers aged 15–59, by sex, PLFS 2023–24. Panel B: operational landholdings by size class, NSS 70 LH 2013.

Note. Panel A: author's computation from PLFS 2023–24 person-level file, weighted by Subsample_Multiplier / 100 (Ministry of Statistics & Programme Implementation, 2024). Panel B: author's computation from NSS 70th Round LH 2013, weighted by standard mlt multiplier (Ministry of Statistics & Programme Implementation, 2014).

Two implications fall out of this for the Agri-FinTech discussion. First, the female-concentration result implies that any product designed around the idea of a single male household head as the credit decision-maker will systematically under-serve the population that does most of the agricultural labour (FAO, 2023; Roessler et al., 2018). Second, the landholding distribution implies that the value chain of an Indian Agri-FinTech product has to be designed to work at sub-hectare scale, with average ticket sizes that are correspondingly small. This, in turn, is the structural reason that the Findex agri-payment indicators show India with substantial digital-payment penetration on the headline account-ownership measure but more modest penetration on the agri-payment-into-account measure.

4.11. India: rural finance outcomes, agricultural-payment digitisation, and structural change

The PLFS and the NSS LH gives a structural assessment of the Indian agriculture but lacks rural financial-inclusion indicators. We use three supplement data sets to get these measures. First is the National Bank for Agriculture and Rural Development (NABARD) All India Rural Financial Inclusion Survey 2016-17 (NAFIS-I) that provides state-level data of rural household variables on rural debt, household savings, micro-finance, landholding and household income, broken out between agricultural and non-agricultural households. Second, is the Government's monthly food-distribution data set which include district-specific volume of rice, wheat, coarse-grain and fortified-rice allocated and distributed (in two parts: the quantity of food items through automated electronic-point-of-sale (e-PoS) machines and quantity through unautomated channels) from food-Public Distribution System (PDS) outlets monthly during January 2017 through September 2023 (Department of Food and Public Distribution, 2024). The third is the Agricultural Census of India (AcI) that reports state-by-social group-by-operational holding-by-crop tables of area devoted to irrigated cultivation, un-irrigated cultivation and operational holding sizes for the last two Agricultural Censuses (AcIs; year 2010-11 and 2015-16), allowing for direct computation of changes in land-partitions between recent AcIs (Ministry of Agriculture & Farmers Welfare, 2014; Department of Agriculture, Cooperation & Farmers Welfare, 2019).

Consider the rural finances (NAFIS 2016-17). The unweighted average for the state sample is: 59.1 percent report savings, 44.0 percent report credit indebtedness, 20.0 percent report microfinance and 1.10 hectares is average operational holdings. The association most evident on state-to-state basis is between microfinance and indebtedness (Pearson $r = +0.720$, $p < 0.001$). The signs and the sizes are consistent with the results of evidence from the empirical rural-credit literature; states with high rate of microfinancing are not states with low rate of indebtedness, they are states with high indebtedness and microfinancing loans (micro-leases) complement the existing formal and informal credit markets. Gujarat is one such big example with highest indebtedness (79%) rate and also highest rate of penetration (65%) in the field of microfinancing. The other end of the spectrum is Bihar with lower indebtedness (34%) and lower rate of penetration from microfinancing (less than 20%). Across states, there is certainly a strong negative correlation between the average landholding size and the savings rate ($r = -0.426$, $p = 0.021$) - the smaller the average landholdings, the higher the savings rate is as per the precautionary savings hypotheses for the rural households with the land constraint. One more point from a look at the NAFIS data: in 23 out of 29 states that have reported so far, the average monthly income per household is higher for Agriculture households than the average monthly income (overall average: average monthly income of agricultural households is ₹10,292 while, that of other rural households is ₹9,259).

And now to payments digitalisation The PDS data show a very short period and almost complete transformation from the paper (or cash) distribution of food grain to the Point of Sale (PoS) electronic distribution between 2018 and 2023. In the first full reporting month (January 2018) 39.9 percent of food grain is distributed electronically. This goes up to 100 percent in September 2023. The annual averages tell the same story: 53.9 percent in 2018, 73.0 in 2019, 92.9 in 2020, 92.6 in 2021, 97.6 in 2022, 99.7 in 2023. The dramatic jump in 2018-2020 coincides with the national roll-out of e-PoS with Aadhaar. Eventually, all major states get close to 100% digitisation. The big thing is that, in 2018-2023 India has largely digitised the most important one-off agricultural-payments-related transaction in the rural areas - the monthly food ration payments given through the more than 500,000 PDS (food security) outlets to 800 million rural beneficiaries.

Then, the bigger-picture. In the past 5 years since the last Agricultural Census (2010-11) we have witnessed a reduction in the size of area. The proportion of total area cultivated in the marginal class (less than 1 ha) has increased from 22.8 to 27.5 over 5 years (2010-11 to 2015-16) in that period (4.7% increase). The area of large holdings (10 ha or more) has fallen from 10.3 to 8.3 percent. Irrigation share has grown in all classes and here observe that the irrigation share of small farmers (55.4) is actually bigger than that of large (48.6). This was not the case when the large had an irrigation advantage (due to being able to afford costly tubewells) - now the small can afford cheap tubewells. The AgCens contrast (read the NSS 70th LH 2013 cross-sectional in Section 3.10) suggests that, structurally, the Indian agricultural farm is getting smaller, irrigated and numerous. This is a structural change - not a policy monkey - that has led to the increase in demand for small-ticket digitised credit and for small-ticket transactions with the help of digital wallets.

Table 6: Rural Finance Outcomes (Nafis 2016–17), PDS Digitisation (2018–2023), and Agcensus Structural Change (2010–11 Vs 2015–16)

Indicator	Value
Panel A. NAFIS 2016–17 (state-level, n = 29 states)	
Households reporting savings (state mean)	59.1%
Households reporting indebtedness (state mean)	44.0%
Households with microfinance (state mean)	20.0%
Average landholding (state mean)	1.10 ha
Mean monthly income, all rural households	₹9,259
Mean monthly income, agricultural households	₹10,292
States where agri-HH income exceeds all-HH income	23 of 29
Cross-state Pearson r: microfinance ↔ indebtedness	+0.720 ($p < 0.001$)
Cross-state Pearson r: savings ↔ landholding size	−0.426 ($p = 0.021$)
Panel B. PDS digitisation, monthly 2018–2023 (n = 69 months)	
Districts reporting	706
Automated share, Jan 2018	39.9%
Automated share, Sep 2023	100.0%
Annual mean: 2018	53.9%
Annual mean: 2020	92.9%
Annual mean: 2023	99.7%
Panel C. Agricultural Census 2010–11 vs 2015–16 (cropped-area shares)	
Marginal (<1 ha) area share, 2010–11 → 2015–16	22.8% → 27.5%
Small (1–2 ha) area share, 2010–11 → 2015–16	21.9% → 22.5%
Large (≥10 ha) area share, 2010–11 → 2015–16	10.3% → 8.3%
Marginal-holdings irrigation rate, 2015–16	55.4%
Large-holdings irrigation rate, 2015–16	48.6%

Note. Panel A from NAFIS 2016–17 state-level public file (one row dropped for missing state name); state means are unweighted. Panel B from monthly food-distribution data, restricted to months with at least 500 districts reporting; shares are quantity-weighted across districts within each month. Panel C from Agricultural Census of India 2010–11 and 2015–16 state-by-farm-size-by-crop tabulations. Sources: Department of Food and Public Distribution (2024) for PDS (Department of Food and Public Distribution, 2024); Ministry of Agriculture and Farmers Welfare (2014, 2019) for AgCensus (Ministry of Agriculture & Farmers Welfare, 2014; Department of Agriculture, Cooperation & Farmers Welfare, 2019).

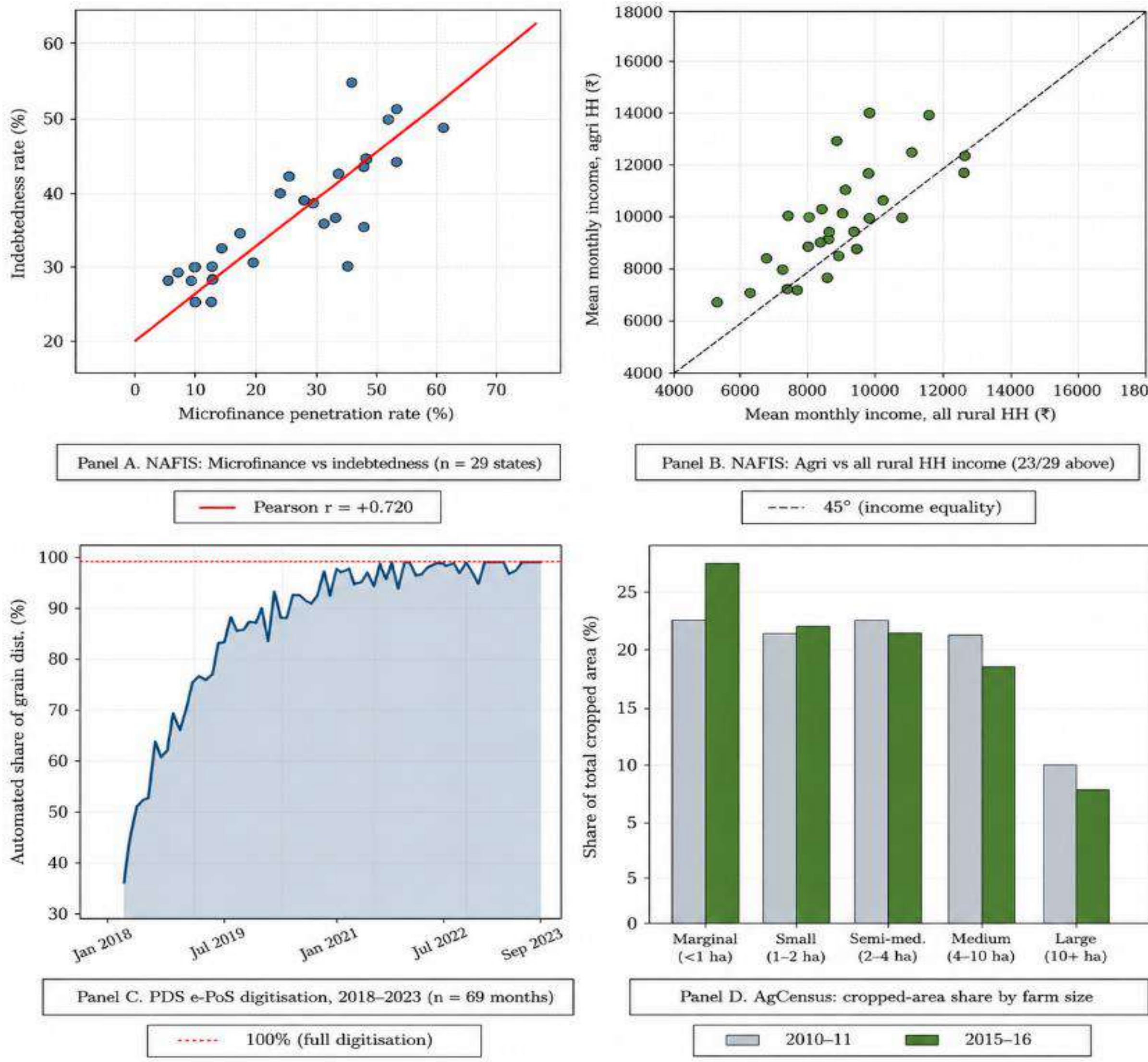

Figure 10: Rural Finance Outcomes, Agricultural-Payment Digitisation, and Structural Change.

Panel A: cross-state scatter of household microfinance penetration against household indebtedness, NAFIS 2016–17. Panel B: agricultural-household monthly income against all-rural-household monthly income. Panel C: percentage of food-grain quantity distributed through automated (e-PoS) channels by month. Panel D: share of total cropped area by farm-size class, Agricultural Census 2010–11 and 2015–16.

Note. Panel C: monthly PDS food-distribution data (Department of Food and Public Distribution, 2024). Panel D: Agricultural Census of India 2010–11 and 2015–16 (Ministry of Agriculture & Farmers Welfare, 2014; Department of Agriculture, Cooperation & Farmers Welfare, 2019).

Agri-FinTech has three implications First, the positive sign on the level of micro-finance and the level of household debt among the Indian states suggest that in terms of distributional effects, the roll-out of the microfinance in India is more likely to be characterised with a credit-stacking effect than a credit-substitution effect; and the descriptive data is in support of the latter. Second, by 2023 in India, the Public-Distribution-System (PDS) is likely to be digitised i.e. the agri-adjacent (agri-payment) is not the private agri-payment in India (Section 3.6). Thus, the cross-country regression suggested in Section 3.7 is likely to be a mis-priced level of digitisation of the agri-payment (it's an inference from the private sector). Third, the marginalisation in the comparison section in the above quote could be explained with the insight of the VRIO analysis in Section 3.10; that the Agri-FinTech product is likely to be on the back of the sub-hectare level and have a market in India, and the recent pentennial (five-year) census suggests that it's being ploughed down.

5. Discussion

So the findings look good on the four-pillar test, with minor reservations. On access, the descriptive results in Sections 4.1 and 4.2 are confirmation and extension of the access headline gains in Sub-Saharan Africa via mobile-money. And they add to it - the absolute gain in mobile-money in Latin America and the Caribbean in the past two waves is now bigger than Africa's. On the usage pillar, the regional percentages of dormant accounts in Section 4.8 are consistent with the view that nominal account usage and ownership is not the same and should be measured separately - not least because they are different in South Asia. On the second pillar of quality, the current study cannot compute effective annual percentage rates (EAPRs) or debt over-burden - in both cases, we would need the micro-data of surveys which are not part of the aggregates harmonised across banks. The latter is only a measure of quality and should be computed in conjunction with, for instance, aggregate data.

The last pillar (welfare) may be misleading. The review literature shows that the emphasis in the Kenyan literature is primarily on a welfare Pillarschannel that includes lower remittance costs (Ky et al., 2021; Suri & Jack, 2016). The 4.7 regression adds another regularity (across countries) to the regression: the digitalisation of agricultural payments into accounts occurs simultaneously to the level of mobile-money-penetration. This is consistent with there being a value-chain level channel as well as a remittance Pillarschannel (though, as noted above, the cross-section cannot separate. The slope (0.120 percentage points of agri-payment-into-account per percentage point of mobile-money penetration) is low, so the digitalisation of agri-payments has occurred after the penetration of mobile-money, even if the platform for mobile-money is available. Another is the household level study of Georgia (in Section 4.9): even a cash-stipend payment (that would help to sell smallholder farms) did not result in increased bank credit in the first year. The India case study (Section 4.10) is another. In this society where 57.7 per cent of the rural workforce is agricultural, where 73 per cent of the operational holdings are less than a hectare, and 43 per cent of farm labour is female, the aggregate, cross-country measures of payments systems are hiding a world where the average size of the agricultural transaction is small, farmers are constrained by their holding capacity, and the gender composition of the workforce makes the design of any product offered to a mythical male household head unsustainable.

In Section 4.4, I offer what I think should be considered in their gender-gap debate. Worldwide it's closing. It's widening in Sub-Saharan Africa. I think it could be both as the gender gap in mobile-money adoption is greater than the gender gap in the financial institution account in some African countries (Roessler et al., 2018). So, inclusion strategies that are heavily dependent on the mobile-money rails for inclusion may lead to an increased gender gap unless the female specific impediments to mobile-money adoption are addressed.

The findings on the structural gap (Section 4.3) have an interesting implication for the rural-urban discussion, I think. The distribution of the gap across countries in 2024 is a bit bimodal: the mode is a 4-6 percentage point gap but there are long tails of fragile states and post-war countries with over 20 percentage point gap, and a few South Asian economies with negative gaps. Universal strategies will be better to the mind of the gap and not the tail. The latter point of the success of South Asia and failure of East Africa is as per the argument in the case study that that infrastructure strategies (public-rail vs telco-rail) are distributional. Behavioural credit-scoring strategies that take advantage of mobile-phone data (Björkegren & Grissen, 2019) is a complementary inclusion strategy in the absence of collateral, while remote-sensing techniques of large-scale agricultural monitoring (Burke et al., 2021) is a clue on how other Agri-FinTech products can be tailored to the systemic physiology of production. Index-insurance will have to do with the residual-risk-management aspect of the welfare pillar (Jensen et al., 2017).

6. Limitations

There are eight caveats. First, Findex is a survey of financial behaviour of households - the self-reported data is likely to be subject to recall and social-desirability biases, and these biases may vary between countries. Second, the World Bank aggregates across the regions (with population weighting) from the country level estimates, so they may vary with the sample designs of countries in the region. Third, the coverage of the agri-payment indicators is lower than that of the headline account-ownership indicators, particularly the mobile-indicator - and this could influence the result of the cross-country regression in Section 4.7. Fourth, this is a cross-sectional regression. Even if the correlation is high, it cannot be said that higher mobile-money coverage caused digitisation of the agri-payments.

Fifth, the results are not connected to farm-level impacts - the welfare pillar (one of the four pillars of the ADA) cannot be evaluated in the Findex data, and the paper should be seen as an addition to what we know from household panel data and randomised trials. Sixth, the microdata used in Section 4.9 from the Georgia ADA are for the short (1-year) horizon only and only contain a single binary (yes/no) credit-uptake variable. The published evaluation is about the effects on longer (four-year) horizons and these aren't in the public-use file. Seventh, the Section 4.10 results on India are on two years' cross-sections (PLFS 2023-24 and NSS 70 LH 2013) to provide the same structural information - that's all right, but the holding structure may have changed over the 10 years since 2013. Eighth, the results in Section 4.11 are on small samples on NAFIS panel (n = 29 states) and the PDS time series (which is missing in the first quarter of 2017 for some states, which did not report nationwide data) and the Census aggregations (reported as cropped-area shares but not as holding shares).

7. Conclusion

The descriptive results from the new release of the Global Findex Database (Findex) show that there were substantial increases in financial accessibility in most countries - and particularly in Sub-Saharan Africa, South Asia and the low-income category - between 2011 and 2024. The Sub-Saharan African (and increasingly in Latin America and the Caribbean) Findex gains are via mobile-money rails. But there remain major inequalities in 2024. The average rural-urban gap of low- and middle-income countries is 4-7%, the world's overall gender gap is 4.2% and the Sub-Saharan African gender gap is now 12.1%, in spite of accepting all the headlines. The econometric analysis, which uses the 2024 data, shows mobile-money penetration to be significantly and positively associated with the digitalisation of farmers' payments with 1.5% points higher rate of receiving agricultural payments into an account with 10% points higher mobile-money penetration.

The subsidiary household analysis using the public-use ADA micro-data from Georgia reveal no change in the access to bank loans gap between the ADA-recipient households and "failed" ADA-recipient households, a year later - which is in line with the thesis that overall welfare gains from agricultural-finance interventions are moderate and more concentrated than the headline gains in access. The India case study using the periodic labour force surveys (PLFS) 2023-24 and National Survey of Employment and Unemployment (NSS) 70 LH 2013 provides an update on the operating environment with more than 50 per cent of the rural workforce engaged in farming, 43 per cent of the workforce being women, and 73 per cent of the farming area covered by under 1hectare farms. The lesson is: unless Agri-FinTech products are implemented to be small-value, and gender-inclusive in such a context, they will under-serve their beneficiaries.

Overall, it confirms the headlines of inclusion literature on the access pillar, the headlines of gender pillars, lays the quantitative foundation to its value-chain (on channel-ing the agricultural payments), and to its welfare-caution discussion, and it provides the Indian farm unit context to the latter. The second wave of this analysis made possible by the linked Living Standards Measurement Study Integrated Surveys on Agriculture (LSMS-ISA) data that the World Bank makes available for some Sub-Saharan African countries (World Bank, 2025a), can begin to discuss some longer-term welfare pillar issues that cannot be addressed by the cross-country level aggregates, or household level year-on follow-up.

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Declaration: AI-assisted tools (LLMs) were used to prepare figures/illustrations and to improve the language and grammar of this chapter. The authors reviewed and approved all content and assume full responsibility for its accuracy.