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Entrepreneurship and Digital Financial Inclusion in Africa: Foundational Identity, Digitally Enabled Accounts and Business-Purpose Borrowing

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Abstract

This study examines whether reported foundational identity ownership and digitally enabled account ownership are associated with business-purpose borrowing in Africa. Drawing on 2024 Global Findex microdata for 29,883 adults aged 18–64 in 34 economies, it applies country-normalised survey weights so that each included economy contributes equal aggregate weight, together with logistic regressions with economy fixed effects and economy-clustered standard errors. The conceptual framework distinguishes institutional legibility, represented by reported foundational identity ownership, from transactional capability, represented by digitally enabled account ownership; it does not assume that these components form a causal or temporal pathway to borrowing. The primary specification omits income, which is structurally unavailable in Lesotho; income-adjusted sensitivity analyses use 29,037 respondents in the other 33 economies. Before account adjustment, the identity estimate is positive but statistically uncertain (average marginal effect [AME] 1.33 percentage points; 95% CI −0.09 to 2.76; $p = 0.066$); after account adjustment, it is 0.64 points (95% CI −0.92 to 2.20). Holding a digitally enabled account is associated with a 6.10 percentage-point higher predicted probability of reporting business-purpose borrowing (95% CI 4.62 to 7.59). A separate account/outcome model associates reported identity ownership with a 10.43 percentage-point higher account probability (95% CI 6.57 to 14.30). Null-imposed wild-cluster-bootstrap tests support the account-borrowing and identity-account coefficient associations, while the identity-borrowing estimate remains uncertain. The account association remains positive across the reported alternative samples and weights, while exploratory interaction analyses provide no statistically reliable evidence of variation by sex, residence, or income group. Because the outcome captures self-reported borrowing for business purposes rather than formal credit approval, source, price, or productive use, the findings are interpreted as conditional associations rather than evidence of mediation or causal sequencing. The strongest evidence-based implication is therefore narrow: identity coverage alone is not a reliable marker of business-purpose borrowing, whereas digitally enabled account ownership is a more robust correlate under the reported specifications.

Keywords: entrepreneurial finance; foundational identity; digitally enabled accounts; business-purpose borrowing; Africa; Global Findex

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1. Introduction

Entrepreneurial finance concerns the mobilisation and allocation of resources needed to start, operate and grow ventures. Although the field encompasses equity, venture capital, crowdfunding, and bootstrapping, debt and other forms of borrowing remain central to everyday enterprise formation and working-capital management (Cumming & Groh, 2018). In African markets, this financing problem is especially consequential because information asymmetry, limited collateral, short credit histories, and lender risk-assessment practices can restrict the financing options available to small firms and nascent entrepreneurs (Berger & Udell, 2006; Brixiová et al., 2020; Ogunmokun et al., 2026). Importantly, greater information does not automatically remove financing frictions because risk evaluation also depends on how information is interpreted by decision-makers; recent experimental evidence shows that perceived risk can vary with investor origin even when investors assess the same venture scenario (Solodoha, 2026b). The resulting constraint is therefore not only whether capital exists, but whether an individual can enter, use, and be recognised within the financial system and whether providers are willing to supply finance.

Digital finance has altered this entry problem. Mobile money, digital payments, and FinTech platforms can lower transaction costs, extend service reach, and create new transactional records (Jack & Suri, 2014; Ozili, 2018; Pelletier et al., 2020). Firm-level evidence from African countries links mobile money use with investment, access to finance, or productivity, although the relationship depends on complementary formal financial services and national context (Gosavi, 2018; Islam et al., 2018; Konte & Tetteh, 2023). A systematic review identifies a growing but still fragmented literature at the intersection of FinTech and SME finance (Sanga & Aziakpono, 2023). Recent cross-country evidence likewise associates digital finance and FinTech infrastructure with SME financial inclusion, while emphasising heterogeneous effects and complementary infrastructure across African economies (Olaoye et al., 2025; Sanga & Aziakpono, 2025; Umar et al., 2025).

An earlier institutional step has received less empirical attention in entrepreneurial-finance research: proof of identity. A recognised foundational identity can help a person satisfy customer due diligence requirements, authenticate claims, and become legible to formal institutions. Comparative financial-inclusion research identifies documentation and account-access barriers as important correlates of account ownership and use (Allen et al., 2016). Digital authentication can subsequently make verification cheaper and more remote, although innovation must remain compatible with know-your-customer, privacy, and consumer protection obligations (Elliott et al., 2022; Financial Action Task Force (FATF), 2020; Montes & Appaya, 2021). However, identity ownership is not equivalent to a digital identity, an account, a credit history, or an approved loan. Treating these stages as interchangeable risks turning a plausible policy narrative into an unsupported causal claim.

The distinction is empirically important. A pre-analysis audit of the 2024 Global Findex African microdata found broad coverage of foundational identity ownership but online digital identity questions in only Benin, Morocco, and Uganda. (World Bank, 2025a, 2025c, 2025d, 2025e; see Table S1). The present study therefore uses foundational identity ownership, not online digital identity, as its main identification measure, and explicitly treats digitally enabled accounts as a separate, more proximal financial interface. The outcome is whether an adult reported borrowing in the previous 12 months to start or operate a business. This measure captures entrepreneurial-purpose borrowing behaviour; it does not by itself establish formal credit access, loan approval, business ownership, or venture performance.

Throughout the manuscript, entrepreneurial finance is therefore used as the broader field of inquiry, whereas the measured dependent variable is referred to as business-purpose borrowing. The item captures one self-reported borrowing behaviour linked by the respon-

dent to starting or operating a business, but it cannot distinguish formal from informal finance or establish current business ownership, loan application or approval, lender, amount, price, repayment terms, or productive use. The empirical findings are therefore interpreted as evidence about business-purpose borrowing rather than as a general measure of entrepreneurial finance or formal credit access.

The study asks whether reported foundational identity ownership and digitally enabled account ownership are associated with business-purpose borrowing among adults aged 18–64 across 34 African economies. Its primary equal-economy weighting targets the average included economy under the pooled model. It makes three contributions. First, it connects entrepreneurial finance with identification infrastructure, extending research that has mainly examined financing instruments, firms, or platforms. Second, it develops a stage distinction rather than claiming an empirically identified sequence: foundational identity represents institutional legibility, while digitally enabled account ownership represents a more proximal form of transactional capability. This distinction allows the analysis to examine whether these components of financial infrastructure display equally persistent associations with later business-purpose borrowing without claiming that identity causes account ownership, that accounts mediate borrowing, or that the observed variables occur in a known temporal order. Third, it explores whether the associations vary by sex, rural residence, and within-economy income position. Because directional subgroup hypotheses are not derived and several interaction tests are considered, this heterogeneity analysis is treated as exploratory rather than confirmatory. The empirical pattern indicates that digitally enabled account ownership is the more consistent correlate of business-purpose borrowing, while the post-adjustment identity estimate remains imprecise rather than demonstrating the absence of any relationship.

2. Literature Review and Conceptual Framework

2.1. Entrepreneurial Finance and Information Frictions in Africa

Entrepreneurial finance differs from general financial inclusion because the financial act is tied to venture creation or operation. The financing relationship is affected by uncertainty over the entrepreneur's ability, project quality, cash flow, and repayment. In classic credit-rationing theory, information asymmetry can prevent price from clearing the credit market because higher interest rates may worsen borrower selection and behaviour (Stiglitz & Weiss, 1981). SME-finance research therefore emphasises lending technologies, information production, collateral, and relationships rather than the mere presence of funds (Berger & Udell, 2006). More recent work further cautions that information is not interpreted mechanically. Investor characteristics can shape perceived venture risk, meaning that improved identification or account data may reduce some frictions without resolving lender evaluation or credit-supply decisions (Solodoha, 2026b).

Within this broader domain, business-purpose borrowing is treated as one observable financing behaviour rather than as a synonym for entrepreneurial finance. A positive response establishes only that the respondent reports borrowing for the purpose of starting or operating a business; it does not identify the financing contract, lender, venture status, approval process, or subsequent business outcome. This distinction is maintained in the empirical results and policy interpretation.

African evidence confirms that the financing constraint has both supply- and demand-side dimensions. Formal finance is associated with employment creation among SMEs, but affordability and loan size matter (Brixiová et al., 2020). Lenders' risk models may also reproduce exclusion even when more information is available (Ogunmokun et al., 2026). Consequently, business-purpose borrowing is best interpreted as an observed financing

behaviour within a broader opportunity structure, not as proof that a credit market is efficient or inclusive.

Demand-side studies add an important qualification. Across African surveys, income, education, employment, and demographic position are repeatedly associated with formal inclusion and financial resilience (Tinta et al., 2022), while institutional quality helps explain why similar individuals face different financial opportunities across countries (Nsiah & Tweneboah, 2023). These studies mostly examine account ownership or broad inclusion rather than borrowing for enterprise purposes. Firm-level panel evidence, by contrast, suggests that digital finance can widen SME access, but does not identify which individual adults borrowed to start or operate a business (Umar et al., 2025). The present outcome therefore occupies a narrower point between household financial inclusion and firm finance.

2.2. Foundational Identity as Institutional Infrastructure

Institutions structure exchange by defining recognised actors, rules, and enforcement arrangements (North, 1990). Foundational identification is one such institution: it enables a person to assert a legally recognised identity across public and private transactions. Identification can reduce documentary friction in onboarding and customer due diligence, while authentication can support remote or repeated verification (Financial Action Task Force (FATF), 2020; Gelb & Metz, 2018). From an entrepreneurial-finance perspective, identity may therefore be enabling infrastructure: it can make financial participation possible without resolving venture risk, repayment capacity, or lender incentives.

Identity systems also create risks. Inaccurate records, inaccessible enrolment, unauthorised surveillance, function creep, and weak redress can deepen rather than remove exclusion. International principles accordingly stress universal coverage, accessibility, data minimisation, security, user agency, and accountability (World Bank, 2022). The appropriate theoretical expectation is therefore conditional and non-deterministic: identity can lower one barrier, but the effect depends on whether financial institutions can use the credential lawfully, affordably, and inclusively.

Kromidha (2023) advances this discussion by showing how digital platforms mediate entrepreneurs' identities and reputations through connection-, familiarity-, and credibility-building strategies. That platform-level account demonstrates that identity is produced relationally in entrepreneurial finance. The present study addresses a prior layer: whether possession of a recognised foundational identity is associated with reported business-purpose borrowing across African economies.

The closest recent continent-wide evidence reinforces the need to distinguish stages without treating them as an observed temporal chain. Using 2025 Global Findex microdata, Kaulu and Kaulu (2026) find that national identity ownership is positively associated with formal account ownership and that there is substantial variation in inclusion between African countries. Their outcome is account ownership, whereas the present study examines whether a country-specific reported identity indicator and digitally enabled account ownership are each associated with the later, narrower behaviour of business-purpose borrowing. The comparison therefore motivates a stage-distinction question: whether institutional legibility remains informative at a behaviourally and commercially more specific point of financial participation. It does not establish that the same individuals move sequentially from identity to account ownership and then to borrowing.

2.3. Digitally Enabled Accounts as a Composite Transactional Interface

An identity credential establishes institutional legibility; an account can provide an interface through which value may be stored, transferred, and observed. Digitally enabled accounts may reduce geographic and temporal transaction costs, facilitate payments, and

create records that can support financial management or credit assessment. Mobile money evidence from Eastern and sub-Saharan Africa links related capabilities with firm investment and access to finance (Gosavi, 2018; Islam et al., 2018). However, Konte and Tetteh (2023) find that mobile money is most productive when combined with traditional finance, underscoring complementarity rather than technological substitution. In the present study, the released digitally enabled-account indicator combines mobile money account status with financial institution accounts used for digital payments by card or phone. Its definition therefore contains ownership and use components; it does not directly measure transaction frequency, account activation date, transaction histories, or whether the reported business-purpose borrowing passed through that account (World Bank, 2025c).

The composite should therefore be read as a heterogeneous indicator of digitally enabled financial connection. A respondent can qualify through mobile money account status or through use of a financial institution account for specified digital payments, so the indicator does not imply that these routes are economically equivalent, equally active, or used with the same intensity. The main analysis retains the composite because both routes provide a digitally enabled interface relevant to the conceptual framework, while robustness analyses separately examine financial institution accounts, mobile money accounts and reported digital payment use. Those alternatives are used to test the stability of the general interpretation, not to claim that the underlying forms of access and use are interchangeable. The framework therefore treats digitally enabled account ownership as a distinct and more proximal component of financial infrastructure rather than as a mediator. Foundational identity may reduce documentary or verification friction, while account ownership may indicate deeper connection to the financial and digital ecosystem; business-purpose borrowing still depends on credit demand, product availability, lender decisions, informal financing channels, and other individual and local conditions. Account ownership may precede a borrowing event, follow a borrowing attempt, or be jointly associated with entrepreneurial activity and financial capability. Cross-sectional data cannot determine that ordering, and changes in coefficients across nested models do not identify a pathway or mediation process. This restriction is consistent with methodological evidence showing that cross-sectional representations of longitudinal mediation processes can be seriously biased (Maxwell & Cole, 2007).

Recent multilevel evidence shows that digital payment use varies both within and between African economies, with individual resources operating inside country-specific technological and institutional settings (Nyakurukwa et al., 2025). Macro-panel research similarly finds that FinTech deepens inclusion through channels such as mobile infrastructure and education rather than through technology alone (Olaoye et al., 2025). These findings support a complementary capabilities interpretation: identity can enable recognition, accounts can enable repeated transactions, and wider infrastructure can determine whether either capability becomes economically useful.

2.4. Stage Distinction and Competing Theoretical Logics

The theoretical contribution is a distinction among institutional legibility, transactional capability, and observed entrepreneurial-finance behaviour, not an assertion that they constitute interchangeable indicators of inclusion. This distinction matters because a person may possess a recognised identity without holding or using an account, and may hold an account without borrowing for a business. Although developed in the context of alternative-finance measurement rather than identification systems, Solodoha (2026a) similarly emphasises the analytical value of separating enabling or dispositional conditions from observable entrepreneurial action. Applied here, the implication is that ownership of infrastructure should not be treated as equivalent to later financing behaviour. For the

empirical analysis, that broader theoretical language is intentionally narrowed: the observed dependent variable is business-purpose borrowing, not entrepreneurial finance in its full sense. The stage distinction therefore concerns how two infrastructure indicators relate to one specific reported borrowing behaviour, without implying business ownership, formal credit access, or venture performance.

Two competing logics clarify what the data can speak to. A barrier-removal logic predicts that reported foundational identity ownership may retain a positive conditional association with business-purpose borrowing because legal recognition can lower onboarding and verification frictions even after account status is considered. A capability-proximity logic predicts that the identity association may weaken once digitally enabled account ownership is considered because institutional recognition can be necessary in some settings but remains more distal from financial use than a transactional interface. The observed pattern is more consistent with the second logic, but the post-adjustment identity estimate is imprecise, and its confidence interval includes both a modest negative association and a potentially meaningful positive association; the results therefore do not falsify the barrier-removal logic.

The distinction also separates evidence about individual-level finance correlates from evidence of institutional effects. Solodoha et al. (2023), using a natural experiment, show that an institutional incentive can alter entrepreneurial financing behaviour, illustrating the stronger identification required to make claims about institutional effects. The present cross-sectional study instead asks whether analytically distinct components of financial infrastructure display different conditional associations with reported business-purpose borrowing. Its theoretical value lies in locating a boundary between institutional legibility and transactional capability, not in demonstrating a causal sequence between them.

2.5. Research Questions

RQ1: Is reported foundational identity ownership associated with business-purpose borrowing among working-age adults across African economies?

RQ2: Is holding a digitally enabled account conditionally associated with business-purpose borrowing after reported foundational identity ownership and observed individual characteristics are considered, and how does the identity estimate differ when account status is included in the model?

Exploratory RQ3: Do the identity and digitally enabled account associations appear to differ by sex, rural residence, or bottom-40 within-economy income status?

3. Methodology

3.1. Research Design and Data Source

The study uses a cross-sectional associational design based on the 2024 individual-level data released with the Global Findex Database 2025. The World Bank and Gallup collect the Findex through randomly selected, nationally representative samples of the civilian, non-institutionalised population aged 15 years and older, typically interviewing approximately 1000 adults per economy and providing respondent weights (Klapper et al., 2025; World Bank, 2025b). The statistical analyses use the official labelled world file release WLD_2024_FINDEX_v02_M, findex_microdata_2025_labelled_update112425.dta, obtained on 4 October 2026; its African economy observations reproduce the original country file sample and descriptive estimates (World Bank, 2025a, 2025c). The design estimates contemporaneous associations; the conceptual stage distinction introduced above is not treated as an observed temporal sequence.

A variable-coverage audit preceded model specification. Among the African country files, 34 economies contained valid observations for the country-specific reported founda-

tional identity indicator and the business-borrowing outcome: Algeria, Benin, Botswana, Burkina Faso, Cameroon, Comoros, Côte d'Ivoire, Democratic Republic of the Congo, Egypt, Eswatini, Ethiopia, Gabon, The Gambia, Ghana, Guinea, Kenya, Lesotho, Libya, Malawi, Morocco, Mozambique, Namibia, Niger, Nigeria, Republic of the Congo, Senegal, Sierra Leone, South Africa, Tanzania, Togo, Tunisia, Uganda, Zambia, and Zimbabwe. Online digital identity ownership and use were observed only in Benin, Morocco, and Uganda and were not promoted to a continent-wide explanatory variable. Because online digital identity items are available in only three economies, they are excluded from all 34-economy explanatory models, robustness tests, policy conclusions, and primary substantive findings. They are referenced only as a coverage audit explaining why reported foundational identity, rather than online digital identity, is used for the continent-wide analysis.

3.2. Analytical Sample

The primary sample was restricted to adults aged 18–64. The 34 included economies contain 34,112 surveyed respondents of all sampled ages, of whom 30,087 fall within this working-age range. Sequential exclusions remove 34 respondents with an invalid business-borrowing response, a further 15 with an invalid identity response, 152 with missing education, and 3 with missing residence information. No additional exclusions arise from account status, sex, age, internet use, or workforce status at their respective stages. The resulting sample contains 29,883 respondents, including 5201 unweighted business-borrowing events. In total, 204 working-age respondents are excluded: 0.68% unweighted and 0.74% using equal-economy weights defined on the eligible sample. Table S2 distinguishes these non-overlapping exclusions from marginal variable missingness and compares included and excluded respondents.

Income quintile is unavailable for all Lesotho respondents: 865 in the working-age sample and 846 in the primary sample. Income is therefore omitted from the primary 34-economy models. Income-adjusted sensitivity models use 29,037 respondents with observed income in the other 33 economies and are compared with income-unadjusted models on exactly that common sample. No Lesotho respondent is assigned an observed income category, and no within-economy income distribution is imputed without supporting data.

Accordingly, Lesotho remains included in the primary 34-economy models because income is not entered in those specifications; Lesotho is excluded only from analyses that require observed income, namely the income-adjusted sensitivity models and income subgroup analyses.

3.3. Measures

The measurement strategy distinguishes the reported borrowing outcome from the two focal infrastructure indicators and from the variables used for adjustment and exploratory heterogeneity analysis. Business-purpose borrowing is the dependent variable, while reported foundational identity ownership and digitally enabled account ownership represent institutionally and transactionally distinct explanatory measures. Sex, residence and income position support the subgroup analyses; the remaining covariates provide the specified adjustment set. The analytical role, coding and interpretative limits of each measure are summarised in Table 1.

Table 1. Variables and operationalisation.

Variable	Role	Operationalisation
Business-purpose borrowing	Binary outcome	1 if the respondent reported borrowing in the previous 12 months to start or operate a business (fin22e); 0 for 'no'. The item is self-reported and does not identify business ownership, loan application or approval, lender/source, formality, amount, price, repayment conditions, or productive use.
Reported foundational identity ownership	Primary explanatory variable	1 for reported ownership of the foundational identity asked about in the country questionnaire (fin46); 0 for 'no'. The exact credential is country-specific, so the pooled measure is interpreted as a country-specific reported identity indicator rather than as a single legally identical credential across all economies. It is not labelled as online digital identity.
Digitally enabled account	Financial-interface variable	Released binary variable dig_account. The codebook defines it through mobile money account status or a financial institution account used for digital payments by card or phone. Mobile money status itself incorporates reported service use and some inferred payment receipt. This measure is not equivalent to nominal bank-account ownership, payment frequency, or a verified channel for the reported business borrowing. Alternatives use account_fin, account_mob, and anydigpayment (World Bank, 2025c).
Sex	Heterogeneity/control	Female = 1; male = 0, following the Findex value labels.
Rural residence	Heterogeneity/control	Rural = 1; urban = 0.
Income position	Heterogeneity/control	Within-economy household income quintiles; bottom 40% comprises quintiles 1–2. Income-adjusted models and income heterogeneity use the 33 economies with observed income. Income is omitted from primary 34-economy models.
Other controls	Covariates	Age centred at 40 and divided by 10, plus its square; primary, secondary, or tertiary education; sex; rural residence; workforce status; internet use; economy fixed effects. Income quintiles enter only observed-income sensitivity models.

Note. Coding follows the labelled microdata and official codebook. fin46 responses 1 and 2 are recoded to 1 and 0; responses 3 and 4 are treated as missing. The public English ID4D instrument uses a local-credential placeholder, so exact nationally administered wording and legal equivalence are not established by the released labels. Table S1 reports each economy's observed item universe, weighted ownership, missingness, and analytical sample. The released dig_account categories combine no, do not know, and refusal at zero; this aggregation cannot be fully undone from the constructed indicator alone (World Bank, 2025c, 2025d).

3.4. Analytical Strategy

Descriptive estimates and primary models use respondent weights normalised within the analytical sample so that each included economy receives total weight N/G, where N is the unweighted sample size and G is the number of included economies. The target is the average included economy under the pooled model, rather than all African adults. This substantive choice matches the comparative research question and prevents the largest economies from dominating. Unweighted and adult-population-weighted estimates are reported alongside it. The population-weighted sensitivity assigns economy totals in proportion to pop_adult, the released 2023 population aged 15 years or older; it is therefore not an exact population weighting of adults aged 18–64. All weight schemes are rescaled to sum to N. The main borrowing regressions are weighted binary logistic models with

economy fixed effects. Model 1 includes identity and the full non-income covariate set; Model 2 adds digitally enabled-account status. The specification is:

$$\text{logit}[\Pr(Y_{ic} = 1)] = \alpha_c + \beta_1 ID_{ic} + \beta_2 ACCOUNT_{ic} + \gamma X_{ic}.$$

Here, Y is business-purpose borrowing for individual i in economy c; α_c is an economy fixed effect; X contains the observed controls; and β_2 is omitted from Model 1. Model 1 estimates the adjusted identity-borrowing association before account adjustment, while Model 2 estimates both exposure associations conditionally on the other exposure. A separate Model A uses digitally enabled account status as the outcome, with identity and the same controls, to estimate the observable identity-account link. It uses the same primary sample for comparability; a maximal account-outcome sample is examined separately. Changes across models are descriptive and do not establish mediation or temporal ordering (Maxwell & Cole, 2007). Economy fixed effects absorb additive economy-level intercept differences, but not individual-level confounding or country-specific slopes. Binary-variable AMEs are weighted averages of the change in predicted probability when the relevant variable is set to one rather than zero while other observed covariates are retained (Mood, 2010).

Estimation uses weighted pseudo-likelihood scores and the CR1 economy-cluster sandwich covariance, multiplied by $G/(G-1) \times (N-1)/(N-k)$, where k includes all estimated slope and economy-intercept parameters. Confidence intervals and conventional tests use the t distribution with $G-1$ degrees of freedom, rather than normal critical values. Focal coefficient and log-odds product-term tests additionally use a null-imposed linearised wild cluster bootstrap with Rademacher multipliers, 9999 replications and seed 20261004. This Python implementation follows the score-and-information construction of WCLR-C, rather than claiming to have run Stata boottest (Roodman et al., 2019; MacKinnon et al., 2025). Python 3.12.14, NumPy 2.3.5, SciPy 1.17.0, pandas 2.2.3, and statsmodels 0.15.0 were used; numerical estimation and bootstrap components are independently checked against weighted GLM and artificial-regression calculations. Public files contain respondent weights but no PSU or stratum identifiers, so economy clustering does not reproduce the complete national survey variance design (Cameron & Miller, 2015; MacKinnon et al., 2023). For clarity, the value 20261004 is the reproducibility seed, not a date. Stata was not used; all analyses were conducted in Python 3.12.14 with the package versions reported above.

AME confidence intervals use the delta method with the full fitted-model covariance and the same cluster-based critical values. These intervals condition on the observed covariate distribution and fitted economy profiles. Since each economy intercept is identified within a single economy cluster, their uncertainty is difficult to recover fully through the cluster sandwich; country-deletion and refitted country-jackknife results are consequently reported as sensitivity checks, rather than presented as complete design-based survey uncertainty (MacKinnon et al., 2025).

Progressively adjusted borrowing models first include age, age-squared, and sex, then add education and rural residence, then internet use, and finally workforce status. They are compared on the common primary sample; maximal samples for earlier stages are also examined. Age and sex are demographic antecedents, while contemporary education, residence, and income are socioeconomic proxies whose temporal positions are not fully observed. Internet use and workforce status may reflect prior characteristics, consequences of digital inclusion, or entrepreneurial activity, or shared causes. Their inclusion is therefore conditional adjustment, not a verified causal adjustment set; attenuation cannot be assigned to a particular mechanism (Schisterman et al., 2009). Income quintiles are added only on the 33-economy common-support sample.

Exploratory heterogeneity models interact both identity and account status with sex, rural residence, and bottom-40 income status. For income heterogeneity, the observed-income sample is used, and binary income group replaces the quintile indicators. Subgroup AMEs are standardised over the same model sample's covariate distribution by setting the modifier to each group in turn and updating all product terms. Differences are group 1 minus group 0; their confidence intervals and tests use the covariance of the difference. Probability-scale contrasts are the basis for subgroup interpretation, because a logit product coefficient tests a different null (Ai & Norton, 2003). Holm adjustment is applied to the six probability-scale contrasts (Holm, 1979). Product-term bootstrap tests are reported separately. Approximate detectable differences at 80% power are calculated from contrast standard errors; they are precision diagnostics, not retrospective observed-power estimates or evidence of equivalence.

Further checks compare weights, workforce, and eligible all-adult samples, financial-institution accounts, mobile money accounts, and reported digital payment use. Countries with identity ownership of at least 95% or below 60% are excluded in separate descriptive sensitivity analyses, and every economy is omitted in turn with weights renormalised and the model refitted. These coverage thresholds are transparent sensitivity screens, not legal harmonisation criteria. Formal causal omitted-variable bounds are not reported because the temporal ordering and causal contrast needed to interpret them are not identified by these data. The full outputs, component audit and country-specific descriptive contrasts are supplied in Tables S1–S9.

3.5. Ethics and Reproducibility

The study analyses anonymised public-use secondary data and reports only pooled or economy-level aggregates; no new participants were recruited, and no identifiable records were accessed. The files were used under the World Bank Microdata Library access terms. The accompanying analytical package contains the reproducible scripts, software versions, source-file checksum, coding decisions, sample audit, and aggregate model output. Respondent-level records are not redistributed; replication requires obtaining the licensed microdata from the World Bank Microdata Library.

4. Results

4.1. Descriptive Results

Business-purpose borrowing was reported by 16.33% of the equal-economy weighted sample. Reported foundational identity ownership was substantially more common (83.17%) than holding a digitally enabled account (48.99%). The economy-level borrowing rate ranged from 3.29% in Morocco to 32.26% in Uganda, with a median of 16.86%. This dispersion supports controlling for additive economy-level intercept differences rather than interpreting the pooled mean as a homogeneous continental rate. The unweighted borrowing rate is 17.40%, compared with 14.58% under the adult-population weighting. These differences demonstrate that the three weighting schemes represent different targets; they do not establish that one target is intrinsically preferable. Table S3 reports all four identity-by-account cells and economy-specific descriptive borrowing contrasts. The characteristics of the primary analytical sample under the three weighting schemes are summarised in Table 2.

Table 2. Characteristics of the primary analytical sample under three weighting schemes.

Characteristic	Equal Economy	Unweighted	Adult Population
Business-purpose borrowing	16.33%	17.40%	14.58%
Reported identity	83.17%	85.86%	86.24%
Digitally enabled account	48.99%	55.11%	47.41%
Female	52.53%	52.08%	52.03%
Rural residence	64.85%	62.66%	59.66%
Internet use	48.15%	56.39%	44.44%
In workforce	61.88%	64.47%	64.65%
Age in years	34.24 years	33.75 years	34.15 years
Secondary education	41.93%	54.60%	43.68%
Tertiary education	5.06%	8.92%	5.36%

Note. N = 29,883 adults aged 18–64 in 34 economies; 5201 unweighted business-borrowing events. Each economy receives equal aggregate weight in the primary scheme. Population weights use the released 2023 population aged 15+ as economy totals, not exact 18–64 population counts. Primary-or-less education is the remaining category. Source. Authors' recalculations using the official Global Findex 2025 microdata.

4.2. Identity, Digitally Enabled Accounts and Business-Purpose Borrowing

In Model 1, reported identity ownership corresponds to an AME of 1.33 percentage points (95% CI −0.09 to 2.76; $p = 0.066$); the coefficient bootstrap p-value is 0.0957. After account adjustment, the identity AME is 0.64 points (95% CI −0.92 to 2.20; $p = 0.409$), with a coefficient bootstrap p-value of 0.4282. The conditional account-borrowing AME is 6.10 points (95% CI 4.62 to 7.59; $p < 0.001$), and the coefficient bootstrap p-value is 0.0001. In Model A, identity ownership is associated with a 10.43-point higher account probability (95% CI 6.57 to 14.30; $p < 0.001$; coefficient bootstrap $p = 0.0002$). Thus, the observable identity-account association is positive, while the identity-borrowing estimate remains imprecise. These pairwise associations do not establish mediation or a known temporal ordering. The complete primary model estimates and focal probability contrasts are reported in Table 3.

The small-cluster bootstrap leaves the substantive inference unchanged: the account-borrowing coefficient remains statistically well supported, whereas the identity-borrowing coefficient remains uncertain. This robustness check is reported in the current analysis rather than deferred to future work because inference with 34 economy clusters is consequential for distinguishing the strong account result from the borderline identity estimate.

To place the attenuation of the identity estimate in context, Table S3 cross-tabulates the four possible identity/account combinations and reports their weighted prevalence and business-purpose borrowing rates. This makes the overlap between the two infrastructure indicators transparent rather than treating digitally enabled account ownership as if it were mechanically nested within reported identity ownership. Together with Model A, where reported identity ownership is associated with a 10.43 percentage-point higher predicted probability of digitally enabled account ownership, the cross-tabulation supports treating institutional legibility and account capability as related but non-equivalent constructs. The reduction in the borrowing AME from 1.33 to 0.64 percentage points is therefore interpreted only as a descriptive change in conditional association, not as evidence that account status mediates or explains a fixed proportion of an identity effect. Because both reported identity ownership and digitally enabled account status are binary, Model A and the four-cell cross-tabulation provide the paper's direct empirical assessment of their association; a simple bivariate correlation is not treated as evidence of temporal sequencing or mediation.

Table 3. Complete primary logistic-model estimates and focal probability contrasts.

Panel A Odds ratios and 95% confidence intervals			
Term	**Model 1 Borrowing**	**Model 2 Borrowing**	**Model A Account**
Reported identity	1.112 [0.990, 1.250]	1.052 [0.928, 1.193]	1.858 [1.467, 2.353]
Digitally enabled account	Not included	1.625 [1.439, 1.836]	Not included
Female	1.177 [1.012, 1.370]	1.205 [1.038, 1.400]	0.747 [0.687, 0.813]
Age centred at 40 per decade	0.923 [0.861, 0.989]	0.914 [0.853, 0.981]	1.126 [1.071, 1.185]
Centred age squared	0.919 [0.893, 0.947]	0.923 [0.896, 0.950]	0.959 [0.933, 0.986]
Rural residence	1.021 [0.897, 1.162]	1.046 [0.919, 1.192]	0.733 [0.644, 0.836]
Secondary education	1.001 [0.881, 1.138]	0.939 [0.828, 1.064]	2.068 [1.834, 2.332]
Tertiary education	1.018 [0.817, 1.268]	0.912 [0.741, 1.122]	4.865 [3.556, 6.655]
Internet use	1.357 [1.241, 1.483]	1.215 [1.110, 1.330]	3.403 [2.950, 3.925]
In workforce	2.185 [1.950, 2.449]	2.067 [1.845, 2.316]	2.005 [1.798, 2.234]
Respondents	29,883	29,883	29,883
Outcome events	5201	5201	16470
Economies	34	34	34
McFadden pseudo R-squared	0.077	0.083	0.271
Economy intercepts	Included	Included	Included
Panel B Focal average marginal effects and bootstrap coefficient tests			
Model and Exposure	**AME pp [95% CI]**	**AME *p***	**Wild Coefficient *p***
Model 1 identity	1.33 [−0.09, 2.76]	0.066	0.0957
Model 2 identity	0.64 [−0.92, 2.20]	0.409	0.4282
Model 2 account	6.10 [4.62, 7.59]	<0.001	0.0001
Model A identity	10.43 [6.57, 14.30]	<0.001	0.0002

Note. Models 1 and 2 have business-purpose borrowing as the outcome; Model A has digitally enabled account status as the outcome. Primary education, male sex, urban residence, no internet use, and outside-workforce status are reference categories. Age is (age-40)/10 and its square is included, so the two age terms must be interpreted jointly. All primary models omit income and use equal-economy weights, CR1 economy-cluster covariance, and t(33) critical values. AME intervals are model-conditioned delta-method intervals. Bootstrap *p*-values concern the zero logit coefficient, which corresponds to a zero binary-variable AME in these non-interacted models; they are not bootstrap AME confidence intervals. WCLR-C uses 9999 Rademacher draws and seed 20261004. Full log-odds coefficients, standard errors, *p*-values, economy-intercept point estimates, and fit diagnostics are in Table S7 and the accompanying output files.

4.3. Heterogeneity and Robustness

The standardised account AMEs are positive in each subgroup, but none of the six probability-scale differences excludes zero at the 5% level before or after Holm adjustment. The account difference is −0.12 points for women versus men (95% CI −2.00 to 1.75), 1.67 points for rural versus urban residents (−0.83 to 4.16), and 1.15 points for the bottom 40% versus top 60% income groups (−1.19 to 3.49). Country-jackknife contrast intervals are also compatible with zero. Approximate 80% power detectable account differences are 2.65, 3.53, and 3.31 points, respectively, before multiplicity adjustment; detectable identity differences are larger, at 5.81, 6.16, and 5.31 points. These precision limits preclude treating non-significance as evidence of equal associations or distributive equality. The subgroup AMEs and the corresponding between-group contrasts are summarised in Table 4.

Table 4. Standardised subgroup average marginal effects and between-group contrasts.

Panel A Subgroup effects in percentage points with 95% confidence intervals			
Group	**Identity AME [95% CI]**	**Account AME [95% CI]**	**N/Economies**
Men	1.91 [−1.42, 5.24]	6.19 [4.54, 7.84]	29,883/34
Women	−0.39 [−2.07, 1.28]	6.06 [4.23, 7.90]	29,883/34
Urban	−1.45 [−4.72, 1.82]	4.95 [2.52, 7.39]	29,883/34
Rural	1.43 [−0.68, 3.54]	6.62 [5.01, 8.22]	29,883/34
Top 60% income	0.47 [−1.96, 2.91]	5.86 [4.00, 7.72]	29,037/33
Bottom 40% income	1.05 [−1.40, 3.49]	7.02 [5.14, 8.90]	29,037/33
Panel B Differences between groups and probability-scale tests			
Comparison	**Identity Difference [95% CI]**	**Account Difference [95% CI]**	**Comparison**
Women minus men	−2.31 [−6.42, 1.80] $p = 0.262$	−0.12 [−2.00, 1.75] $p = 0.895$	Women minus men
Rural minus urban	2.88 [−1.47, 7.24] $p = 0.187$	1.67 [−0.83, 4.16] $p = 0.184$	Rural minus urban
Bottom 40% minus top 60%	0.57 [−3.18, 4.33] $p = 0.758$	1.15 [−1.19, 3.49] $p = 0.323$	Bottom 40% minus top 60%

Note. Each subgroup effect is standardised over the same covariate distribution within its model, with sex, residence, or income group set to the stated value and product terms updated. Differences are group 1 minus group 0, with the covariance between subgroup estimates incorporated. Income heterogeneity excludes Lesotho and adjusts for binary bottom-40 status instead of quintile indicators. Confidence intervals and raw p-values use the model-conditioned cluster delta method with t(G−1) critical values. Holm-adjusted p-values for all six probability-scale contrasts are 1.000. Wild-bootstrap product-term tests are reported separately in Table S8 and do not test the same probability-scale null. Table S9 provides detectable-difference and country-jackknife sensitivities.

The account association remains positive under workforce restriction (AME 6.82 points; 95% CI 4.65 to 8.99), unweighted estimation (6.05; 4.87 to 7.22), adult-population weighting (4.66; 2.20 to 7.11), income adjustment on the 33-economy sample (6.36; 4.84 to 7.87), and the eligible all-adult sample (6.09; 4.73 to 7.45). Across the 34 leave-one-economy-out fits, its AME ranges from 5.81 to 6.32 points; identity AMEs range from 0.27 to 0.94 points and remain statistically uncertain. Progressive adjustment changes the account AME from 7.80 points with demographic controls to 7.88 after socioeconomic adjustment, 7.28 after internet use, and 6.10 after workforce status. This change underscores the relevance of the control set without identifying whether any variable is a confounder, consequence, or proxy. Financial institution accounts, mobile money accounts, and reported digital payment use also have positive conditional associations, with coverage and samples shown explicitly in

Tables S5 and S7. Weighted within-economy variance inflation factors for the main model range from 1.06 to 1.35, and its scaled condition index is 1.94; sparse identity-by-account cells and country coverage are documented in Tables S3–S5.

Because the component measures capture different forms of access and use and do not have identical coverage, their positive direction is interpreted as a robustness check on the broader digital connection result rather than as evidence that mobile money accounts, financial institution accounts, and digital payment use are substantively equivalent. The composite dig_account measure therefore remains useful for the primary specification, but its internal heterogeneity is treated as a limitation rather than hidden behind the aggregate label.

4.4. Cross-Country Comparative Pattern

The cross-country structure is substantively important because average business-purpose borrowing differs sharply across the included economies, from 3.29% in Morocco to 32.26% in Uganda under the reported economy-specific descriptives. Table S3 therefore reports economy-specific identity and account coverage together with descriptive borrowing contrasts, allowing the pooled result to be read alongside national variation rather than as a homogeneous African pattern. These country-level contrasts are descriptive: the national samples are modest after restriction and some identity/account combinations are sparse, so 34 separate adjusted slope estimates would be imprecise and would create a substantial multiple-testing problem.

The influence analysis nevertheless provides a useful comparative robustness check. Re-estimating the main model after omitting each economy in turn produces account AMEs ranging from 5.81 to 6.32 percentage points, while the identity AMEs range from 0.27 to 0.94 percentage points and remain statistically uncertain. This stability indicates that the pooled account association is not driven by any single included economy, but it should not be interpreted as evidence that the account slope is identical across countries. Regional, financial development, and mobile money environments remain plausible sources of slope heterogeneity; formally estimating those contextual differences would require pre-specified country-level measures and adequate higher-level statistical power, and is therefore treated as a priority for subsequent multilevel research rather than inferred from the present pooled cross-sectional model.

4.5. Exploratory Online Digital Identity Coverage

Because online digital identity ownership and use are observed in only Benin, Morocco, and Uganda, these variables are not used in the 34-economy inferential analysis and no 3-economy estimate is used to support the study's substantive findings or conclusions. This subsection is retained only as a measurement-coverage note documenting why online digital identity was excluded from the continent-wide analysis.

5. Discussion

5.1. Interpretation of the Findings

The central finding is not that identity is irrelevant. Rather, after digitally enabled account status is considered, the estimate for reported foundational identity ownership is small and imprecise. Foundational identity can reduce documentary and verification barriers, but it does not create a suitable credit product, demonstrate business cash flow, lower venture risk, or guarantee that a lender will supply finance. The observed pattern is therefore more consistent with the capability-proximity logic than with a strong barrier-removal interpretation at the borrowing stage: account ownership is more closely associated with reported financial behaviour than identity ownership alone. However, the post-adjustment

confidence interval for identity includes both a modest negative association and a potentially meaningful positive association, so the analysis cannot establish that identity has no relationship with business-purpose borrowing. This interpretation is consistent with information-friction theory and with arguments that lender risk-assessment technologies, not simply missing borrower information, shape SME debt constraints in sub-Saharan Africa (Berger & Udell, 2006; Ogunmokun et al., 2026; Solodoha, 2026b).

This stage-specific interpretation helps reconcile the result with Kaulu and Kaulu (2026), who report a positive association between national identity and formal account ownership in a closely related African Findex sample. Their result concerns entry into an account relationship, whereas the present paper examines a later and narrower observed behaviour: borrowing for a business purpose. Taken together, the studies suggest that institutional legibility and transactional capability should be analysed as distinct components of financial inclusion rather than treated as interchangeable indicators. This comparison does not establish that individuals move sequentially from identity to account ownership and then to borrowing; it instead locates a possible boundary around where an identity association is empirically detectable.

Digitally enabled account ownership is more closely connected to participation in the financial and digital ecosystem, and the 6.10 percentage-point adjusted association accords with African firm-level studies linking mobile money use with investment or finance and with evidence that digital and traditional services can be complementary (Gosavi, 2018; Islam et al., 2018; Konte & Tetteh, 2023). The result should nevertheless not be interpreted as the effect of opening or using an account, nor as evidence that the account enabled, carried, or mediated the reported borrowing. The Findex indicator does not identify the source of the borrowing or whether funds moved through the observed account, and the borrowing item may include formal, informal, family, or other channels. Reverse selection is also plausible: people seeking business finance may obtain or activate an account as part of that process, while entrepreneurial motivation, digital capability, local credit supply, and unmeasured business ownership may influence both variables. The defensible interpretation is therefore that adults who hold a digitally enabled account are more likely, conditional on the observed covariates, to report business-purpose borrowing.

The exploratory sex, rural, and income interaction tests do not provide statistically reliable evidence of subgroup differences, but they should not be interpreted as evidence of distributive equality or common effects. The same probability of reporting borrowing can mask differences in source, amount, price, maturity, collateral, coercion, repayment stress, and the quality of financial products. The heterogeneity results therefore motivate continued disaggregated measurement rather than a conclusion that the account-borrowing relationship is substantively identical across social groups. For clarity, these are statistical interaction terms between the focal exposure variables and sex, rural residence, or income group; they do not describe interpersonal interactions.

Country context remains consequential even after economy fixed effects account for time-invariant economy-level intercept differences that enter additively. Nyakurukwa et al. (2025) document meaningful within- and between-country variation in digital financial inclusion, and Nsiah and Tweneboah (2023) associate institutional quality with African inclusion outcomes. The fixed effects used here do not remove unobserved individual-level differences, do not identify the effects of country institutions, and do not allow the identity or account slopes to vary by economy unless that heterogeneity is modelled explicitly. The paper therefore treats the pooled coefficients as conditional average associations within the chosen specification rather than as evidence that institutional context has been fully controlled. The additional cross-country checks sharpen this interpretation. Economy-specific descriptives retain visibility of national variation, and the leave-one-economy-out

estimates show that no single economy is responsible for the pooled account association. These checks assess influence and context, not slope equality: the present study does not claim that the account-borrowing relationship is identical across African economies, and formal explanation of regional or institutional slope variation remains a multilevel research question.

5.2. Theoretical Contribution

The study's theoretical contribution is a stage distinction rather than an empirically identified infrastructural sequence. Foundational identity is conceptualised as institutional legibility: it can establish that an individual is recognised by formal institutions. Digitally enabled account ownership is conceptualised as a more proximal form of transactional capability: it places an individual closer to routine participation in financial and digital systems. Business-purpose borrowing is an observed financing behaviour that remains contingent on demand, product availability, lender assessment, and other conditions. Treating these constructs separately avoids collapsing infrastructure ownership and entrepreneurial action into a single measure of inclusion. This logic is consistent with Solodoha's (2026a) broader argument that enabling or dispositional conditions should be distinguished analytically from observable entrepreneurial behaviour.

The empirical pattern is more consistent with the capability-proximity logic because the account association is larger and more precisely estimated than the identity association after adjustment, but the evidence does not establish a mechanism. Solodoha (2026b) shows that venture risk evaluation depends not only on available information but also on who interprets it, reinforcing the point that identity or account data can reduce some frictions without resolving lender judgement or credit supply. By contrast, Solodoha et al. (2023) use a natural experiment to identify how an institutional incentive altered angel financing behaviour, illustrating the stronger design needed for causal claims about institutional effects. The present paper therefore extends entrepreneurial-finance theory by separating institutional legibility, transactional capability, and financing behaviour and by showing that their conditional associations need not persist equally at a later stage of financial participation. It does not claim that the estimated attenuation demonstrates mediation or a longitudinal process.

6. Practical and Policy Relevance

The findings suggest that foundational identity ownership alone is not a reliable indicator of business-purpose borrowing, whereas digitally enabled account ownership shows a stronger and more consistent association. Although this does not establish that accounts cause borrowing, it highlights the importance of looking beyond identity coverage towards meaningful financial participation. Policymakers may therefore consider affordable digital financial services, accessible payment systems, and proportionate customer due diligence as part of broader financial-inclusion strategies (Financial Action Task Force (FATF), 2020). Equally important are data protection, cybersecurity and accessible consumer-redress mechanisms, although these were not directly examined in this study (Elliott et al., 2022; World Bank, 2022). Future policy evaluations should assess actual account use, credit availability, borrowing costs, and repayment outcomes rather than assuming that identity or account ownership automatically improves entrepreneurial finance.

7. Limitations and Future Research

Several limitations should be considered when interpreting the findings. First, the cross-sectional design cannot establish causality or the sequence between identity ownership, account ownership, and borrowing, while unobserved factors such as financial

literacy, entrepreneurial experience, and local credit conditions may influence the observed associations (Maxwell & Cole, 2007). Second, the dependent variable captures self-reported business-purpose borrowing without identifying loan sources, approval, amounts, or business outcomes. The composite account measure and differences in country-specific identity documentation also limit measurement precision and comparability (World Bank, 2025c, 2025d, 2025e). Although economy fixed effects and robustness tests strengthen the analysis, they cannot eliminate unobserved confounding or fully reproduce the national survey designs. Furthermore, the 34 economies do not represent all African countries, online digital identity data cover only three economies, and Lesotho is excluded from income-adjusted analyses because income information is unavailable. Future research should employ longitudinal or quasi-experimental approaches, incorporate detailed borrowing and account-use measures, and examine how national financial and institutional conditions shape these relationships.

8. Conclusions

Across 29,883 working-age adults in 34 African economies, reported foundational identity ownership had a small and statistically uncertain conditional association with business-purpose borrowing after digitally enabled account status was considered. Holding a digitally enabled account was associated with a materially higher adjusted probability of reporting business-purpose borrowing, and that relationship remained positive across the alternative samples and weighting choices reported in the manuscript. The evidence therefore supports an analytical stage distinction rather than an identified sequence: institutional legibility and transactional account capability are distinct components of financial infrastructure, and their associations need not persist equally at the later behaviour of borrowing for a business purpose. The account result does not show that the account caused, enabled, or carried the borrowing, while the imprecise identity estimate does not prove that identity is irrelevant. The strongest evidence-based implication is that identity coverage alone is not a sufficient marker of entrepreneurial financial participation. Broader proposals concerning interoperable identity, account design, responsible business credit, and consumer safeguards remain policy and research propositions that require direct evaluation.

For interpretation, the conclusion is deliberately confined to the observed outcome. Business-purpose borrowing is one self-reported financing behaviour within the broader domain of entrepreneurial finance; the analysis does not establish business ownership, formal credit access, loan approval, borrowing terms, or productive use. The stronger account association should therefore be read as a robust correlate of this specific reported behaviour, not as evidence that digitally enabled accounts generate entrepreneurial finance generally.

These conclusions remain bounded by the cross-sectional design, the self-reported and source-unspecific borrowing outcome, the composite nature of the digitally enabled account measure, residual confounding from unobserved individual and market characteristics, and the fact that the 34 economies do not represent every African country. Future research should therefore prioritise longitudinal or quasi-experimental designs, harmonised measures of online digital identity and actual account use, and multilevel data linking individuals to business ownership, financial literacy, local banking, and mobile money penetration, credit-market development and loan terms. Such designs would allow the stage distinction developed here to be tested more directly without treating contemporaneous associations as causal sequences.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijfs14110310/s1, Table S1: Identity coverage and analytical sample by economy; Tables S2A–S2D: Sequential sample construction, marginal missingness, missing-data exclusions by economy, and observed characteristics of included and excluded respondents; Tables S3A–S3B:

Identity by digitally enabled account status and descriptive within-economy borrowing contrasts; Tables S4A–S4B: Weighted associations and multicollinearity diagnostics; Tables S5A–S5B: Account-indicator component coverage and alternative operationalisations; Tables S6A–S6B: Identity-coverage sensitivity and leave-one-economy-out analyses; Tables S7A–S7D: Covariate roles, focal effects across specifications, model fit, and income-adjusted slope estimates; Table S8: Wild-cluster coefficient and product-term tests; Tables S9A–S9C: Probability-scale contrast precision and country-jackknife sensitivities; Figure S1: Standardised subgroup effects with conditional 95% confidence intervals.

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