



Purpose-Specific Financial Analytics for Entrepreneurial Credit Market Screening

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ABSTRACT

A lender choosing markets for small-enterprise finance may use account ownership as a shortcut for credit demand. This article asks whether that shortcut identifies places where adults report borrowing to start or operate a business. We analyze the 2024 country estimates in the World Bank's *Global Findex Database 2025*: 98 economies with complete business borrowing, account, formal-channel borrowing and formal saving measures. Account ownership and business borrowing are negatively associated across those economies (Spearman $\rho = -0.220$). An account-only model has a leave-one-economy-out mean absolute error of 5.529 percentage points, close to a constant forecast (5.580); adding formal-channel borrowing barely changes it. Adding formal saving reduces error to 4.700 points, although individual country errors remain substantial. Fifteen economies fall simultaneously above the sample's upper quartile of business borrowing and below its median account ownership. In 40 economies with paired gender estimates, men have higher business borrowing in 19 and women in 21; account gender gaps do not reproduce a uniform enterprise-credit gap. These are country-level diagnostics of reported borrowing, not loan applications, unmet credit demand or evidence that account access causes enterprise borrowing. A staged market screen should therefore use purpose-specific borrowing and validate borrower quality and local lending rules before capital allocation.

Keywords: Business analytics ▪ Entrepreneurial finance ▪ Credit market screening ▪ Global Findex ▪ Out-of-sample validation

1. INTRODUCTION

A bank or digital lender with a limited expansion budget must choose where to investigate enterprise loans. Account penetration is available for many markets and seems to offer a ready-made ranking. Yet it measures the reach of a financial relationship, while lending to start or operate a business concerns a specific use of credit. An economy can have many account holders and little reported business borrowing, or a high business-borrowing rate with relatively few accounts. Mistaking the first number for the second can redirect due-diligence spending.

We examine this failure of a proxy rather than estimating a treatment effect. The decision is to identify economies worth investigating, not to estimate the number of creditworthy firms. The outcome is the share of *adults*, not registered enterprises, who report business-purpose borrowing. This distinction matters because one owner may have several firms, and the survey does not link each borrowing purpose to a lender, loan amount, application, rejection or business outcome. The contribution is a transparent screen with held-out forecast errors, contrasting evidence across lending and saving channels, and a paired gender check. All source data and

studies were available by December 2025.

2. RELATED WORK

Enterprise-finance research explains why a bank-account proxy can fail. Complementarity between bank accounts and mobile money can change saving for microenterprises [1]; fintech entry can either extend or reallocate credit [8]. Credit constraints also depend on firm risk, digital information, gender, and application behavior [2, 3, 6, 9]. None of those studies implies that a country account rate is a country business-loan rate. Table 1 sets out 15 relevant studies, their evidence, and the measurement question left for a cross-market screen. The comparison separates individual, firm and country units so that their findings are not conflated.

The evidence separates into three business decisions. For loan origination, transaction records and online screening can change which small firms receive credit and on what terms [4, 5, 11]. These designs observe firms or loans, so their outcomes cannot be inferred from the prevalence of accounts in a national adult survey. For channel development, mobile money, community currencies and trade credit operate alongside formal banking [1, 10, 15]; a formal-channel rate alone omits these relationships. Finally, application decisions, perceived constraints and venture initiation depend on borrower characteristics and context [2, 3, 6, 13]. They address different margins of access and must not be collapsed into a single estimate of unsatisfied loan demand.

The analytical studies likewise counsel against treating one national percentage as a sufficient decision statistic. The net effect of new lending channels depends on competitive conditions [8]; financial constraints may condition crowdfunding outcomes [7], while firm risk matters alongside size [9]. Goal-directed data integration and organizational use of analytics require a clear match between an indicator and the decision it is meant to support [12, 14]. Here that match can be tested directly: do country indicators identify the published rate of adults who report borrowing for business, and how large are the errors when the target country is held out?

The unit of analysis in the present study is an economy. We do not transport micro-level coefficients from Table 1 to national aggregates. Instead, we test whether a few country indicators perform the narrower task that a market analyst might actually assign them: predicting the published rate of adults who borrowed for business. A forecast that fails this modest test has little claim to direct an expansion decision.

3. DATA AND METHODS

The public 2025 Global Findex file [16] reports 2024 survey estimates; we retain rows coded as economies rather than regional and income-group aggregates. The business-borrowing series (*fin22e*) asks whether the respondent borrowed any money to start or operate a business during the previous year. Account ownership (*account_t_d*) is distinct from borrowing through a bank, credit card or mobile-money

Table 1. Recent studies and the specific gap addressed by the present cross-market decision analysis

Study	Unit and approach	Result relevant to enterprise finance	Question retained here
Adbi and Natarajan [1]	Adults, 74 countries; survey	Bank access complements mobile money in saving for microenterprise.	Does account coverage screen borrowing purpose?
Berguiga and Adair [2]	MENA microfirms; sequential probit	Application self-selection differs across data sources and periods.	Can a national margin separate demand from access?
Charfeddine et al. [3]	Qatari importers; firm survey	Literacy and perceived access relate to financing constraints.	What is observable before firm interviews?
Cornelli et al. [4]	US platform loans; loan-level comparison	Fintech lenders reach additional small firms.	Do credit supply results transfer across countries?
Deng and Qian [5]	Chinese microenterprises; firm survey	Digital payments relate to financing constraints.	Is payment infrastructure a substitute for purpose data?
Dutta and Mallick [6]	Indian firms; enterprise survey	Perceived financing barriers need not differ by female majority ownership.	Do adult gender margins point the same way?
Fasano et al. [7]	SMEs; crowdfunding analysis	Financial constraints condition the association between crowdfunding and firm performance.	Can one financing channel stand in for all borrowing?
Gisbert and Gutierrez [8]	Theoretical lender-entry model	Net inclusion effect of fintech entry is ambiguous.	Which observed indicators suit a first screen?
Heller et al. [9]	German firms; administrative panel	Firm risk, as well as size, matters in credit constraints.	Can country screens establish creditworthiness?
Kuk et al. [10]	Kenyan microentrepreneurs; field study	Community currency and saving groups support trading.	Do informal finance signals co-move with borrowing?
Leite et al. [11]	Brazilian fintech; loan data	Digital screening changes microcredit terms.	Is country prevalence a loan-performance signal?
Liu and Yoon [12]	Analytics framework; design study	Goal-driven integration ties indicators to a decision.	Which margins improve held-out screening?
Shahriar et al. [13]	Low-income women; field experiment	Banking access supports venture initiation conditional on norms.	Are account and borrowing gender gaps identical?
Szukits and Móricz [14]	Firms; management survey	Analytical culture changes the use of data in decisions.	Can screen errors be disclosed to decision makers?
Tetteh et al. [15]	Informal entrepreneurs; survey	Mobile money relates to access to trade credit.	Is formal borrowing the sole relevant channel?

account for *any* purpose (fin22a_22a1_22g_d). Formal saving (fin17a_17a1_d) is saving at a bank or with mobile money. All four are percentages of people aged at least 15; the source stores fractions and we multiply by 100. Family/friends borrowing, mobile-money account use and informal saving are secondary diagnostics. The common four-variable sample is 98 economies; the gender analysis requires both men's and women's business-borrowing series and has 40 paired economies. Missingness is not filled with regional averages.

Table 2 specifies the measurements and the decision role before results are read. Each economy receives equal weight. Regressions fit $B_i = \alpha + \mathbf{x}_i'\beta + \varepsilon_i$, where B_i is business borrowing and $\mathbf{x}_i$ contains successively account coverage A_i , formal-channel borrowing F_i , and formal saving S_i . For every economy, its prediction is made by ordinary least squares fitted to the other 97 economies. We compare mean absolute error (MAE) to a held-out mean benchmark and report the squared-error reduction against that benchmark. Coefficients are descriptive and not interpreted as effects. A rank correlation captures monotonic co-movement without assuming linearity. We also trim the two largest outcome rates and rerun the held-out comparison as an influence check.

Table 2. Measurements and proposed decision use

Measure	Index meaning	Screen role
<i>B</i>	Borrowed to start/operate business	Target, not unmet demand
<i>A</i>	Owens financial or mobile account	Common proxy
<i>F</i>	Borrowed via bank, card or mobile account, any purpose	Credit-channel proxy
<i>S</i>	Saved at bank or via mobile account	Activity proxy
<i>H</i>	Borrowed from family/friends, any purpose	Channel diagnostic

All values are percentages of adults aged 15+. Measures overlap; they must not be added. Source: World Bank (2025), indicator glossary.

A second, deliberately simple screen flags economies where B_i meets or exceeds the sample 75th percentile but A_i lies below the sample median. These thresholds organize fieldwork; they are neither estimates of unmet loans nor a ranking of profitability. The paired gender check counts economies where the published male business-borrowing percentage exceeds the female percentage, and compares that sign with the account gap. A two-sided sign test treats economies as observational units; it cannot recover design-based uncertainty of the underlying surveys.

For a time-separated check, we also match the published 2017 business-borrowing and account estimates to the 2024 analytic economies. Ninety-four have both historic series. We compare a single 2017 business-borrowing predictor with the 2017 account measure and with two 2024 measures, leaving out each target economy from its fitted model. The exercise is predictive across survey rounds; it cannot isolate changes in sample composition, financial policy or borrower behavior between those years.

4. RESULTS

4.1 Descriptive Evidence

The median business-borrowing rate is 8.69%, against 59.91% for account ownership and 13.75% for formal-channel borrowing of any purpose (Table 3). These measures describe different behaviors and purposes, so their differences are not an identified financing gap. Low-income economies in the analytic sample have a 21.24% median business-borrowing rate and 49.60% account rate; among upper-middle-income economies these medians are 5.41% and 71.36%. The high-income cell contains only six economies with reported business borrowing and cannot represent all high-income markets.

Across the 98 economies, account ownership has a modest negative Spearman correlation with business borrowing (−0.220), while formal-channel borrowing for any purpose has almost no monotonic association (−0.086). Formal saving is modestly positive (0.220). Family/friends borrowing (0.704) and savings via an informal club or person outside the family (0.801) are far more strongly aligned, but those measures also cover purposes other than business. The business-finance worry measure also co-moves with borrowing (0.690), yet perceived worry is not verified unmet loan demand. These are contextual indicators, not business credit supplied by those channels. Table 3 reports the full indicator distributions and pairwise associations; Table 5 evaluates the forecast consequences.

4.2 Predictive Performance

An analyst who assigns every economy the mean rate of the others incurs 5.580 percentage points of MAE. The account-only model reduces that error by just 0.051 points. A model using formal-channel borrowing alone is marginally worse than the benchmark, and the two-variable model does not improve the error. Adding formal saving to account coverage and formal-channel borrowing reduces MAE to 4.700 points, an absolute 0.880-point improvement against the benchmark (Table 5). Its held-out squared-error reduction is 29.7% relative to the mean forecast. This modest improvement is a diagnostic, not a lender's approval model: the input variables contain no cash flow, loan size or default history.

The full-sample three-variable fit has an intercept of 16.052 and coefficients of −0.276 for account ownership, 0.077 for formal borrowing, and 0.352 for formal saving, with all series measured in points. Collinearity and structural differences across markets make the coefficients unsuitable as policy effects. The misses are as informative as average fit. Sierra Leone's observed business-borrowing rate is 27.25% against a held-out prediction of 13.52%; Uganda is 28.54% against 16.23%. Tunisia is 4.59% against 13.95%. These discrepancies demand local inquiry rather than automated reweighting of the survey screen.

4.3 Market Screening and Gender Differences

The upper quartile of B starts at 14.25% and the median A is 59.91%. Fifteen economies meet the high- B , low- A rule, including Niger (25.48%, 14.83%), Sierra Leone (27.25%, 38.62%), Guinea (24.10%, 36.05%) and Indonesia (15.17%, 56.33%). Table 6 reports every qualifying economy and its financial-channel profile. No screen can infer the volume of

Table 3. Economy-level indicator distributions and association with business borrowing

Indicator	<i>n</i>	Median	Q1	Q3	Minimum	Maximum	ρ_B	<i>p</i>
Business-purpose borrowing	98	8.69	4.53	14.25	1.02	28.54	—	—
Account ownership	98	59.91	45.61	77.21	14.83	98.28	-0.220	0.0293
Formal-channel borrowing	98	13.75	9.66	20.65	1.37	46.92	-0.086	0.4025
Formal saving	98	25.42	16.22	34.48	3.16	67.20	0.220	0.0298
Family/friends borrowing	98	30.76	23.49	42.16	11.56	68.32	0.704	< .001
Informal-club saving	98	11.52	5.74	22.86	0.99	44.03	0.801	< .001
Mobile-money account	77	31.62	13.67	47.99	2.65	87.50	0.457	< .001
Business-finance worry	98	5.84	3.38	9.49	1.21	23.28	0.690	< .001

Percentages of adults aged 15+; economy weights are equal. ρ_B is the Spearman association with business-purpose borrowing on available pairs. Unadjusted two-sided *p* values are descriptive. The mobile-account measure covers only 77 of the 98 analytic economies. Source: World Bank (2025); calculations from the accompanying script.

Table 4. Income-group heterogeneity in the 98-economy sample

Income group	<i>n</i>	<i>B</i>	<i>A</i>	<i>F</i>
Low	16	21.24	49.60	10.81
Lower middle	40	9.87	55.95	11.90
Upper middle	36	5.41	71.36	17.09
High	6	4.22	75.09	19.82

Entries are within-group medians, not population-weighted rates. Income group is the dataset's classification.

profitable lending from these percentages: some borrowing may be informal, costly or already adequately served.

In the 40-economy paired gender sample, the median reported business-borrowing rate is 15.84% for men and 16.52% for women. The median within-economy male-minus-female difference is -0.21 points. Men have the higher rate in 19 economies, women in 21 (two-sided sign-test $p = .875$). By contrast, the median male-minus-female account-ownership gap is +7.12 points, and the rank correlation between the two gaps is just 0.154. Iraq has a +16.57-point business-borrowing gap, while Sierra Leone has a -17.57-point gap. These are large published point-estimate differences in selected countries, not evidence of statistically significant individual or group differences within their surveys. This subgroup covers fewer economies than the main analysis and is not a global gender estimate.

4.4 Threshold Sensitivity

A market screen is useful only if its threshold and miss rate can be shown to the manager who pays for follow-up research. Table 9 varies both cutoffs while preserving their meaning: business borrowing is at or above a chosen sample quantile and account ownership is below another. The 15-economy baseline is one cell in a range from six to 39. If the account threshold is tightened from the median to the bottom quartile while the business threshold stays at its upper quartile, only six economies remain. In fact, an analyst who reviews the 25 economies with the *lowest* account rates finds just six of the 25 with the *highest* reported business-borrowing rates. That is 24% precision and 24% recall against this specific high-*B* definition. The comparison is intentionally demanding but directly relevant to the proposed shortcut: low account access by itself misses most of the highest borrowing rates.

These cutoffs are policy choices, not parameter estimates. A lender with a small due-diligence budget can use the six-market cell; one able to investigate more locations can widen the account condition and examine 23. Each expansion trades review workload for broader coverage. There is no reason to infer that the last admitted economy has a lower expected return than the first: neither variable records margins, repayment or competing lenders. Keeping the threshold grid visible prevents a dashboard from disguising this management choice as a scientifically optimized cutoff.

4.5 Channel Signals and Model Stability

The descriptive association with informal-club saving raises a further business question: is information about financial activity outside conventional accounts useful for a first-pass country forecast? Adding that published indicator to $A + F + S$ yields a 2.643-point held-out MAE and a 3.574-point RMSE (exploratory row of Table 5). This is a sizeable reduction in simultaneous, same-survey country errors; it is not proof that savings clubs supply business loans. The two variables may respond to the same unobserved economy characteristics, and the model was chosen after examining the correlations. Its performance must be tested against a later, independent survey before it is used for prospective budgets. At most, the result warns that an account-only dashboard suppresses relevant patterns of informal activity.

Even the more conservative three-variable comparison varies by market type. Its MAE is 7.606 points in the 16 low-income economies, versus 9.469 for the account model. Among 36 upper-middle-income economies the respective values are 3.907 and 4.333. In the six high-income observations, adding variables increases error from 4.472 to 4.948; six cases cannot support a separate high-income forecasting rule. The strong low-income errors also make a uniform model-wide tolerance misleading: an expansion analyst should display the income-cell errors alongside each country's score.

As an uncertainty check on the observed error difference, we resample the 98 *pairs of held-out absolute errors* 10,000 times with a fixed random seed. The mean advantage of the three-variable model over the held-out mean is 0.880 points, and the conditional bootstrap percentile interval is 0.184–1.541 points. The three-variable prediction has the smaller error in 65.3% of economies. This interval summarizes how variable the paired error advantage is among these observations; it

Table 5. Held-out prediction errors across models and income groups (98 economies)

Predictors	MAE	RMSE	R^2_{out}	Gain	Low	Lower mid.	Upper mid.	High	Trimmed
Other-economy mean	5.580	6.883	0.000	0.000	9.931	4.613	4.694	5.743	5.245
Account (A)	5.529	6.740	0.041	0.051	9.469	5.188	4.333	4.472	5.201
Formal borrowing (F)	5.612	6.926	-0.012	-0.032	9.908	4.808	4.621	5.466	5.268
Formal saving (S)	5.477	6.797	0.025	0.103	9.960	4.010	4.890	6.813	5.166
Informal saving (C)	2.855	3.777	0.699	2.725	4.664	2.222	2.703	3.152	2.844
A + F	5.580	6.736	0.042	0.000	9.371	5.165	4.540	4.485	5.250
A + S	4.656	5.741	0.304	0.924	7.668	4.192	3.798	4.867	4.430
A + C	2.794	3.647	0.719	2.786	4.343	2.379	2.657	2.248	2.784
A + F + S	4.700	5.772	0.297	0.880	7.606	4.213	3.907	4.948	4.481
A + F + S + C	2.643	3.574	0.730	2.937	4.218	2.023	2.651	2.530	2.643

MAE, RMSE and gain are percentage points; gain is MAE improvement against the held-out mean. R^2_{out} is relative squared-error reduction. Income-cell MAE uses each economy's prediction from the full 98-economy fit (cell sizes: 16, 40, 36, 6). Trimmed MAE refits each model leaving out Uganda and Sierra Leone ($n = 96$). C is informal-club saving, examined after the primary specifications; its performance is exploratory.

Table 6. The complete 15-economy business-credit inquiry queue and its diagnostic signals

Rank	Economy	B_{24}	A	F	S	C	B_{17}	$\hat{B}_{24}$	Error
1	Sierra Leone	27.25	38.62	9.35	22.00	40.77	10.77	13.52	13.73
2	Niger	25.48	14.83	2.94	5.23	18.19	14.87	13.23	12.24
3	Togo	24.61	57.43	13.44	32.10	31.54	11.07	12.36	12.25
4	Guinea	24.10	36.05	10.84	23.33	28.85	14.38	14.86	9.24
5	Liberia	23.71	52.21	12.53	30.13	44.03	20.95	13.04	10.67
6	Malawi	22.61	50.37	10.78	30.87	36.96	13.96	13.67	8.95
7	Mali	22.27	54.75	11.79	30.21	35.16	10.04	12.34	9.93
8	Benin	20.47	51.84	12.68	23.37	36.10	14.66	10.85	9.62
9	Chad	20.22	20.90	11.47	14.06	30.33	11.88	15.82	4.39
10	Cote d'Ivoire	18.85	57.57	6.24	35.64	26.67	6.60	12.96	5.88
11	Mauritania	18.73	27.31	13.33	16.11	22.88	9.15	15.02	3.71
12	Mozambique	18.61	54.39	14.53	19.82	24.23	8.87	9.04	9.58
13	Congo, Dem. Rep.	16.62	39.21	8.82	26.65	27.91	5.53	15.26	1.36
14	Indonesia	15.17	56.33	15.12	27.27	18.11	12.95	11.25	3.92
15	Burkina Faso	15.14	51.43	8.45	32.94	19.98	14.44	14.09	1.04

Entries are adult survey percentages, apart from the rank and the prediction error (points). B_{24} is 2024 business-purpose borrowing, A account ownership, F any-purpose formal-channel borrowing, S formal saving and C informal-club saving. B_{17} is the 2017 business-purpose rate where available. $\hat{B}_{24}$ comes from the leave-one-economy-out A + F + S model; error is observed minus predicted. The queue requires $B_{24} \geq 14.25\%$ and $A < 59.91\%$; it is not a list of profitable loan markets.

Table 7. Selected country-level prediction errors

Economy	Actual B	Held out	Residual
Sierra Leone	27.25	13.52	13.73
Uganda	28.54	16.23	12.31
Togo	24.61	12.36	12.25
Niger	25.48	13.23	12.24
Tunisia	4.59	13.95	-9.36
Poland	1.02	10.30	-9.29
Algeria	3.70	12.91	-9.21

Residual = observed minus prediction, in percentage points. Cases are selected for the largest positive or negative errors, not for market size.

Table 8. Paired gender diagnostics in 40 economies

Quantity	Result
Median business borrowing, men / women	15.84 / 16.52
Median within-economy business gap, men–women	–0.21
Economies: men higher / women higher	19 / 21
Median account ownership gap, men–women	+7.12
Spearman correlation of business and account gaps	0.154
Two-sided sign test, business gap	.875

Survey point estimates; sign test treats economies as units and omits within-country design-based standard errors.

Table 9. Economies flagged when the screen thresholds change

Business threshold	A < Q25	A < Q50	A < Q75
$B \geq Q50$	11	26	39
$B \geq Q75$	6	15	23

Q25, Q50 and Q75 are percentiles of the same 98 economies. The bold cell is the inquiry rule in Table 6. Counts describe a decision queue, not additional borrowers.

does not include sampling error in the Findex estimates, selection of the 98 economies or uncertainty about a future data vintage. Nor does the exploratory informal-saving result have an independent prospective test. Together, these checks support a limited claim: the account shortcut performs poorly in the observed cross-market task, and a richer screen can guide investigation while leaving substantial local uncertainty.

4.6 Comparison Across Survey Rounds

A lender may possess an older purpose-specific market measure rather than a current one. In the 94-economy matched panel, the median business-borrowing rates are 7.46% in 2017 and 8.69% in 2024. The median within-economy change is 0.83 points and 60 economies have a higher 2024 point estimate. Rank persistence is more revealing than a global median: the 2017 and 2024 business-borrowing rates have Spearman $\rho = .696$, and 15 of the 24 economies in the 2017 upper quartile also lie in the 2024 upper quartile. A seven-year-old purpose measure therefore carries information, but misses nine of today's top-quartile cases.

Table 10. Time-separated predictors of 2024 business borrowing

Single predictor	Survey round	Held-out MAE
Business-purpose borrowing	2017	4.102
Account ownership	2017	5.508
Account ownership	2024	5.565
Formal saving	2024	5.478

Same 94 economies for all rows. Each linear prediction excludes its 2024 target economy. Errors are points; different survey rounds, not experiments.

An economy's own 2017 business-purpose rate has a 4.102-point leave-one-economy-out MAE in predicting its 2024 rate; 2017 account ownership has 5.508 points, and even contemporaneous 2024 account ownership has 5.565 points on these same 94 economies. This comparison is especially relevant to a market-intelligence system: maintaining a purpose-specific historical series may be more informative than replacing it with a recently refreshed but poorly targeted account metric. It does not establish that a lagged borrowing measure will outperform all current indicators, nor does the fitted cross-economy slope represent an individual economy's causal persistence. For a planned launch, local current borrowing inquiries remain necessary because the 2017 upper-quartile screen fails to recover more than one-third of the 2024 upper-quartile economies.

4.7 Data Coverage

A dashboard can look complete because it displays account ownership everywhere, while its decision target is missing where that proxy is most common. Of 141 economy rows with an income classification in the 2024 file, only 98 report the business-purpose borrowing measure (Table 11). The 43 economies without that outcome have a median account-ownership rate of 97.86%, compared with 59.91% in the analytic group. Nearly all exclusions are high-income economies: only six of 48 high-income rows have the business-purpose series. This is a substantial target-availability problem, not a reason to set their business borrowing to zero or extrapolate our regression to them.

Table 11. Availability of the decision target in 2024

Income classification	Economies	Business series	Missing
Low income	16	16	0
Lower middle income	40	40	0
Upper middle income	37	36	1
High income	48	6	42
All classified economies	141	98	43

Economy rows with source income classifications; the business outcome is not imputed. Source: World Bank (2025); reproduced in the analysis script.

The negative pooled account–business rank association also weakens when economies are compared within broad income groups. Its Spearman coefficient is +0.121 among the 16 low-income economies, +0.263 among the 40 lower-middle-income economies, and −0.087 among the 36 upper-middle-income economies. With just six high-income outcomes, their within-group coefficient (−0.429) has little interpretive value. The pooled sign therefore partly reflects between-group composition. This does not rescue account ownership as a practical predictor: its held-out error remains close to the no-information benchmark. It does, however, rule out interpreting the pooled negative sign as a general behavioral law in which more account ownership reduces enterprise borrowing. The appropriate conclusion is about proxy performance in the observed portfolio, with explicit exclusion of most high-income economies from the target-specific claims.

5. DISCUSSION

The analysis offers three operational rules. First, prioritize a purpose-specific borrowing measure when the choice concerns enterprise finance: account coverage is a weak out-of-economy predictor here. Second, show formal and informal financial-activity measures separately. The strong co-movement with informal-club saving is a reason to investigate distribution networks, not a reason to infer that club savers are business borrowers. Third, hand the high-*B*, low-*A* queue to local teams for loan-size, cash-flow, regulatory, competition and repayment analysis. It identifies where an inexpensive second-stage study may be worthwhile, not where to deploy credit immediately.

Two checks temper the model comparison. Removing Uganda and Sierra Leone, the highest business-borrowing outcomes, leaves 96 economies: account-only MAE is 5.201

and the three-variable MAE is 4.481 points. The multivariate advantage therefore does not hinge entirely on those outcomes. Yet its error is still large relative to the 8.69% median outcome. Moreover, the 98-economy complete-case sample excludes economies whose business-purpose series is unpublished or unavailable; the 40-economy gender subset is still more selective. The country analysis cannot identify the overlap between a business borrower and a particular credit channel. Ecological associations do not establish individual behavior, and survey estimates have sampling uncertainty not represented by our cross-country OLS errors. Any investment committee should treat this screen as a low-cost research allocation device and seek firm-level underwriting and current local market evidence before credit approval.

6. CONCLUSION

Account ownership provides a convenient but unreliable stand-in for entrepreneurial borrowing in these 2024 country estimates. Formal saving adds useful held-out information, while large local forecast errors and gender reversals expose the limits of a universal account-based ranking. The defensible business-intelligence output is a documented inquiry queue whose target, inputs, errors and missing cases are visible. A subsequent firm-level study can test credit demand, product fit and repayment; the present country margins cannot decide those questions.

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