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Article

Financial Inclusion or Financial Structure? Within- and Between-Country Evidence on Banking Stability in the QUAD Economies

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Abstract: Cross-country studies of financial inclusion and banking stability typically report a single coefficient estimated from panels that pool bank-based and market-based financial systems. This study asks what such a coefficient identifies when the inclusion index varies far more across countries than within them. An annual panel of the four Quadrilateral Security Dialogue (QUAD) economies—India, the United States, Japan, and Australia—covering 2004 to 2021 was assembled, and a principal component index of financial inclusion was constructed from International Monetary Fund and World Bank indicators of branch reach and credit and deposit depth and related to the country-level bank Z-score. The between-country variance of the index is approximately 40 times its within-country variance, so any estimator drawing on cross-sectional variation is identified from four country means rather than from 67 country-years. Consistent with this, the between-country association is large and negative (−1.60), whereas the within-country estimate is 0.10 and statistically indistinguishable from zero. A leave-one-country-out analysis traces the negative between-country result entirely to the United States, whose market-based system pairs low bank-based inclusion with the highest measured stability in the sample. A Hansen-type threshold model returns no significant split, and inspection of the regime assignment shows why: The residual-minimizing threshold separates India and the United States from Japan and Australia, with a single observation crossing it, so the model estimates a country grouping rather than a behavioral discontinuity. The one association surviving the within-country specifications is between banking-system capitalization and stability. In panels with few and structurally heterogeneous units, supply-side inclusion indices proxy financial architecture, and the resulting coefficient should not be interpreted as a behavioral parameter.
Keywords: financial inclusion, banking stability, Z-score, QUAD economies, principal component analysis, within-between estimation, identification

1. Introduction

Bank stability is a public good. When banks absorb shocks rather than transmit them, credit keeps flowing, payments clear, and the wider economy is spared the long shadow that follows a banking crisis. The turmoil of 2007–2009 made the cost of the alternative concrete, and in its aftermath policymakers across advanced and emerging economies pushed to widen access to formal financial services (Allen et al., 2016; Han &Melecky, 2013; Kaushal, V., Chauhan, M., & Pathania, K. S. 2026a). Financial inclusion—bringing households and small firms into the banking system as depositors and borrowers—became a shared objective, folded into national strategies and endorsed by the Group of 20 and the international financial institutions.

Whether wider inclusion helps or hinders the stability of the banks that deliver it is less settled than the policy enthusiasm suggests. One strand of argument is reassuring. A broader depositor base is cheaper and stickier than wholesale funding and tends to stay put in a crisis, lending spread across many small borrowers diversifies credit risk, and a deeper banking system transmits monetary policy more evenly (Han &Melecky, 2013; Khan, 2011; Morgan &Pontines, 2014; Kaushal, V., Singh, R., & Pathania, K. S. 2026b). A second strand is wary. Reaching new and less-documented borrowers can erode screening standards, and rapid credit growth that outruns supervision has a long history of ending badly (Čihák et al., 2016; Feghali et al., 2021). Cross-country evidence is correspondingly mixed, ranging from a stabilizing effect (Neaime&Gaysset, 2018; Siddik et al., 2018) to a destabilizing one (Ahamed & Mallick, 2019; Dang &Thi, 2025), with several studies reporting that the sign depends on market structure or on the level of inclusion itself (Feghali et al., 2021;Singh, R. K. 2013; Vo et al., 2019).

Much less attention has been paid to a prior question: What does a cross-country inclusion coefficient identify? Composite inclusion indices are built from supply-side banking indicators—branch density, credit depth, deposit depth—that differ enormously across financial systems and move slowly within them. When such an index is entered into a panel regression alongside country fixed effects, the estimator uses only the sluggish within-country component. When it is entered without them, the estimator uses the large cross-sectional component, which encodes financial architecture as much as access. The two specifications answer different questions, and a literature that reports one or the other without decomposing them can produce a stable-looking coefficient that is in fact a comparison of financial systems.

The present study examines that decomposition in a deliberately small and structurally heterogeneous panel: the four members of the Quadrilateral Security Dialogue (QUAD)—India, the United States, Japan, and Australia. The QUAD label carries no monetary, regulatory, or financial-integration logic, and no claim is made here that it constitutes an economically meaningful bloc for the purposes of banking research. Its usefulness is narrower and purely analytical. Four countries observed over 18 years place one large emerging economy beside three mature ones and span the full range of financial architecture, from the bank-based systems of Japan and India to the market-based system of the United States, with Australia in between. That structural spread, compressed into a very small cross-section, is what makes the identification problem visible rather than latent. A reader who prefers to view the sample as four economies selected on financial architecture, with the QUAD label incidental, loses nothing of the argument.

Three questions organize the analysis. First, how much of the variation in a standard supply-side inclusion index is between countries rather than within them, and what does that imply for the estimators commonly applied to it? Second, does the estimated inclusion–stability relationship survive when the comparison is moved inside countries, or when a single country is removed? Third, are the nonlinear and dynamic specifications that this literature routinely deploys—Hansen-type thresholds and system generalized method of moments (GMM) among them—identified at this panel width, and what do they estimate when they are not?

The contribution is methodological. This study offers neither a new dataset, nor a new estimator, nor a resolution of the inclusion–stability debate. It shows, in a setting where the mechanics can be inspected directly, that a strong cross-country inclusion coefficient can be produced entirely by financial structure, that a bootstrapped threshold can resolve into a country split, and that the diagnostic tools ordinarily used to adjudicate between specifications—the Hausman test in particular—degenerate at this sample size. These are not features of the QUAD. They are latent in any cross-country study that pools financial architectures, and they are simply easier to see with four units than with 40.

1.2 Objectives and Hypotheses

The study pursued three objectives: to measure financial inclusion consistently across the QUAD economies from official data, to decompose its association with banking stability into between- and within-country components, and to establish what the nonlinear and dynamic specifications common in this literature can and cannot identify at this panel width.

Because the competing channels reviewed above do not point to a single expected sign, the first hypothesis was framed to let the data adjudicate rather than to confirm a prior.

H1: Financial inclusion is associated with bank stability in the QUAD economies, with direction left open.

H2: The relationship is nonlinear, changing sign or strength once inclusion crosses a threshold.

The third element of the design is not a hypothesis about the world but a robustness objective, and it is labeled as such to avoid the appearance of testing a proposition that is close to definitionally true in a four-country panel.

Objective R: To establish whether the estimated relationship is stable across estimators and panel composition, and to diagnose the source of any instability.

1.3 Literature Review

The idea that access to finance and the safety of the financial system are linked predates the current policy interest, but the empirical literature is largely postcrisis. Han and Melecky (2013) showed that economies with broader deposit access saw more stable deposit growth through the 2008 shock and read that as evidence for a funding-side stability benefit. Morgan and Pontines (2014) found that a larger share of lending to small and medium enterprises is associated with lower bank nonperforming loans and lower default risk. In a wide cross-section, Neaime and Gaysset (2018) reported that inclusion lowers financial instability in the Middle East and North Africa, working partly through inequality. Siddik et al. (2018) reached a similar conclusion across countries. The mechanism common to these studies is the one set out by Khan (2011): diversification of assets, a stickier deposit base, and better policy transmission.

A countervailing literature stresses the risks. Čihák et al. (2016) and Singh, R. K., Sharma, T., Singh, Y., Kumar, A., & Kumar, S. (2025) documented trade-offs as well as synergies between inclusion and stability and warned that the balance depends on how inclusion is pursued. Feghali et al. (2021) drew a sharp distinction by product: Deeper credit inclusion is associated with more fragility, whereas deeper payment and deposit inclusion is not, so aggregate indices can hide offsetting effects. Ahamed and Mallick (2019), using a large bank-level panel, found that inclusion generally raises bank stability but that the effect is stronger where banks hold more market power and better assets, a conditioning result echoed in Ahamed et al. (2021). Dang and Thi (2025) and Singh, R. K., Kumar, A., & Kumari, J. (2022a), whose empirical pipeline the present study adapts, reported an average negative effect across 157 banks in eight Association of Southeast Asian Nations (ASEAN) countries over 2010–2020, estimated by fixed effects, a panel threshold model, and two-step system GMM, with the effect varying by bank and market structure.

Two threads matter for what follows. The first is nonlinearity. Vo et al. (2019) and Dang and Thi (2025) both argued that the relationship changes across levels of inclusion, which motivates a threshold test. The second is measurement. Because inclusion is multidimensional, researchers summarize it with composite indices, either by the distance-based construction of Sarma and Pais (2011) or by principal components, as in Cámara and Tuesta (2014) and Park and Mercado (2016). The choice matters: Distance indices impose weights, whereas principal components let covariation in the data set them. A separate literature on digital finance (Ozili, 2018; Kumar, R. 2012) extends these questions to mobile and platform-based access, which supply-side indicators capture only indirectly.

Three features of this literature bear directly on the design adopted here, and it is worth stating them plainly because they define what the present study can add.

First, the level of analysis conditions everything downstream. Bank-level studies such as those of Ahamed and Mallick (2019) and Dang and Thi (2025) obtain large samples and ample within-country heterogeneity, which is what fixed-effects and system-GMM machinery requires. They also inherit a mismatch that is rarely confronted: The inclusion index varies only by country and year, so every bank in a given country-year is assigned the same value of the key regressor. A bank-level outcome is regressed on a country-level treatment, and the effective number of independent observations on that treatment is the number of country-years, not the number of bank-years. Country-level designs make this constraint visible rather than removing it.

Second, the estimators travel less well than the pipelines that carry them. Two-step system GMM is consistent as the number of cross-sectional units grows large (Blundell & Bond, 1998), and a bootstrapped threshold requires enough units crossing the candidate split to identify separate regime slopes (Hansen, 2000; Singh, R. K., Kumar, A., Kumari, J., & Singh, Y. 2022b). Both are routinely transplanted into settings that cannot support them and reported without the diagnostics that would reveal the problem.

Third, the advanced-economy end of the sample is thinly represented in inclusion–stability work, which skews toward emerging markets where bank-based inclusion metrics move most. Including the United States, where household finance runs substantially through markets and nonbank intermediaries rather than bank branches, tests whether such metrics travel to systems they were not designed to describe. This is the specific gap the present sample fills.

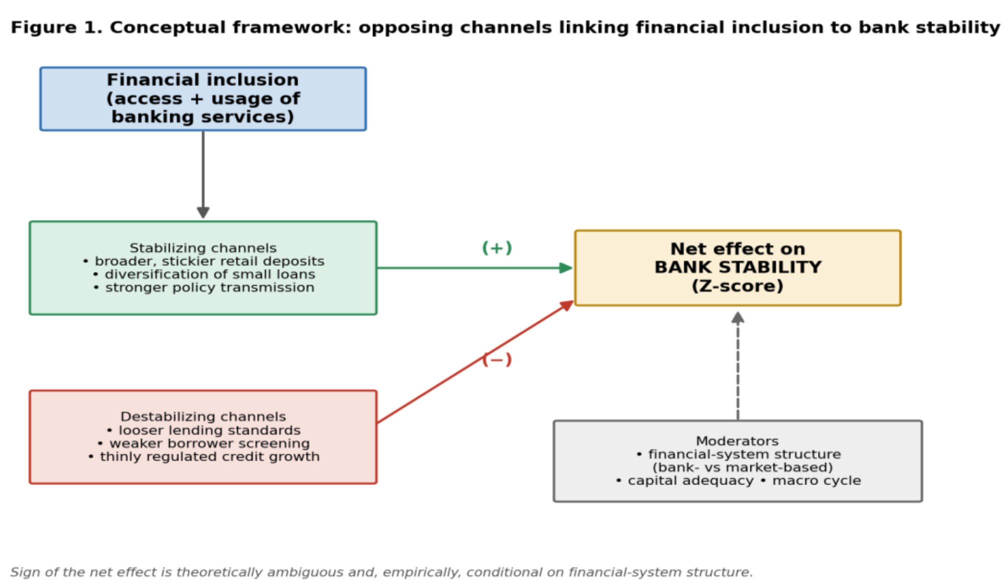
1.4 Theoretical and Conceptual Framework

The analysis rests on three theoretical footings. The first is intermediation and funding theory. Retail deposits gathered from many small savers are less flight-prone than wholesale funding, so a bank that draws in previously unbanked depositors lengthens and steadies its funding, which lowers liquidity risk and, through the denominator of the Z-score, earnings volatility (Han &Melecky, 2013). The second is portfolio theory. Spreading credit over a large number of small, imperfectly correlated borrowers reduces the variance of the loan book relative to a concentrated portfolio, provided screening holds (Khan, 2011). Working against both is information economics: New borrowers are by definition less documented, so expansion can raise adverse selection and moral hazard, and credit that grows faster than a bank's capacity to screen it tends to sour (Feghali et al., 2021).

The net of these forces is not a fixed quantity. It depends on how inclusion is achieved and on the structure of the system achieving it. In a bank-based economy, inclusion and banking depth are nearly the same quantity, so supply-side inclusion metrics rise together with intermediation. In a market-based economy, households can be substantially included through securities, funds, and nonbank channels while bank-branch and bank-credit metrics stay low. This structural point governs the interpretation of the results and is the reason the cross-country coefficient is treated here as a composite of access and architecture rather than as a behavioral parameter.

Figure 1 sets out the framework. Financial inclusion feeds two opposing channels: a stabilizing channel running through funding and diversification and a destabilizing channel running through weaker screening and unchecked credit growth. Their net effect on bank stability is moderated by financial-system structure, by capitalization, and by the macroeconomic cycle. The figure makes the central claim visible: The sign of the arrow into bank stability is not fixed by theory, and whether a system is bank-based or market-based is the moderator that the empirical work must hold up to the light.

Figure 1: *Conceptual Framework Linking Financial Inclusion to Bank Stability Through Opposing Channels*



Note. The net effect on stability is theoretically ambiguous and, empirically, contingent on financial-system structure.

1.5 Method

1.5.1 Sample and Study Period

The compiled panel covers the four QUAD economies annually from 2004 to 2021, giving 72 country-years. The estimation sample comprises 67 country-years, and the attrition is fully accounted for: The banking-sector controls in the Global Financial Development Database (GFDD) end in 2020, which removes the four 2021 observations, and the bank Z-score is unavailable for Australia in 2004, which removes one more. The inclusion index is missing for the United States in 2021 (Table A1), but that observation already lies outside the estimation window, so the gap does not affect any reported estimate. Descriptive statistics and the appendix tables use the full 2004–2021 window where data permit; all regression results use 2004–2020 with $N = 67$. This distinction is maintained consistently throughout.

The design is country level. The reference study is bank level because its authors used a proprietary bank database; that source is not openly available, and a country-level panel drawn from official aggregates is the standard alternative in the cross-country inclusion–stability literature (Han &Melecky, 2013; Neaime&Gaysset, 2018). The panel is small by construction, and its width is not incidental to the argument but constitutive of it: The study concerns what happens to standard estimators when the cross-section is thin and the units are structurally unlike.

1.5.2 Data Sources

All data are secondary and drawn from official sources. The bank Z-score and the banking-sector controls are from the World Bank's (2022) GFDD. The financial inclusion inputs—commercial bank branches per 100,000 adults, together with private credit and bank deposits relative to gross domestic product (GDP)—originate in the International Monetary Fund (2024) Financial Access Survey (FAS) and were retrieved in harmonized form from World Bank Open Data. Real GDP growth and consumer price inflation are from the World Development Indicators (World Bank, 2024). Two intended inputs could not be used: The United States discontinued reporting automated teller machine density to the FAS after 2009, and depositor and borrower counts per adult are not consistently reported for these advanced economies. No values were interpolated across those gaps.

1.5.3 Measures

The dependent variable is the natural logarithm of the bank Z-score, the standard country-level measure of banking-system soundness, with higher values indicating a larger distance to insolvency (Laeven& Levine, 2009). The regressor of interest is the financial inclusion index described below. Controls were kept few and were chosen to be conceptually distinct from inclusion and free of severe collinearity: regulatory capital to risk-weighted assets, nonperforming loans to gross loans, real GDP growth, and inflation. Bank-sector size, competition, diversification, and liquidity were considered but excluded from the main specification because at the country level they move almost one for one with the inclusion index; their variance inflation factors (VIFs) in the pooled data exceed conventional thresholds, and including them would render the inclusion coefficient uninterpretable. Table 1 lists each variable with its definition, source, and expected sign.

Table 1: *Variable Definitions, Measurement, Sources, and Expected Signs*

Variable	Symbol	Definition and measurement	Source	Exp. sign
Bank stability	LNZ	Natural log of bank Z-score = (ROA + equity/assets)/*SD*(ROA)	World Bank GFDD	—

Financial inclusion	FI	PCA index of branch access and credit/deposit depth (0–1)	IMF FAS; World Bank	+/−
Capital adequacy	CAP	Regulatory capital to risk-weighted assets (%)	World Bank GFDD	+
Credit risk	NPL	Nonperforming loans to gross loans (%)	World Bank GFDD	−
GDP growth	GDPG	Annual growth of real GDP (%)	World Bank WDI	+
Inflation	INF	Consumer price inflation (%)	World Bank WDI	−

Note. GFDD = Global Financial Development Database; FAS = Financial Access Survey; WDI = World Development Indicators; ROA = return on assets; PCA = principal component analysis; IMF = International Monetary Fund; GDP = gross domestic product. Expected sign refers to the effect on bank stability.

1.5.4 Two Measurement Caveats

Two properties of the measures deserve statement before any results are read, because both bear directly on the interpretation of the cross-country estimate.

The first concerns the inclusion index. Two of its three inputs—private credit to GDP and bank deposits to GDP—are conventionally understood as measures of financial *depth* rather than of access breadth, and private credit to GDP in particular is a well-established correlate of financial fragility in its own right. Only branch density is unambiguously an access measure. The index constructed here is therefore best described as a composite of bank-based access and bank-based depth, and a reader who prefers to interpret the results as bearing on depth rather than on inclusion will not be misreading them. This limitation is shared with much of the cross-country literature, which uses the same FAS supply-side inputs; it is stated here because the central interpretive claim of the present study depends on it.

The second concerns the dependent variable. The GFDD country-level Z-score is computed from aggregated sector-wide return on assets, equity to assets, and the standard deviation of returns. Aggregate profitability across a banking system containing several thousand institutions is mechanically less volatile than that of any single institution, because idiosyncratic variation nets out in the aggregate. The denominator of the Z-score therefore shrinks with the number and heterogeneity of banks being aggregated, and the measured Z-score rises. The United States, with by far the largest and most fragmented banking population in the sample, is exposed to this more than Japan or Australia. Its Z-score of approximately 32 on the raw scale should not be read as a clean statement that American banks are twice as far from insolvency as Japanese banks. This matters for the results reported below: The United States is a candidate outlier on *both* sides of the regression, for reasons of aggregation on one side and financial architecture on the other. The implication is taken up in the Discussion.

1.5.5 Construction of the Financial Inclusion Index

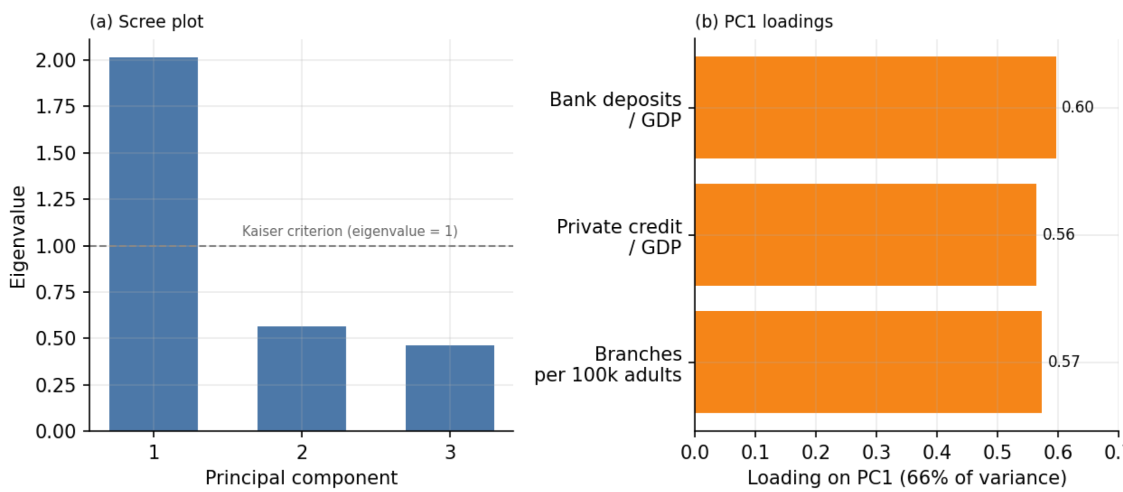
The inclusion index follows the approach now standard in this literature (Cámara & Tuesta, 2014; Park & Mercado, 2016). Three subindicators enter: branches per 100,000 adults, capturing the reach of the physical network; private credit to GDP; and bank deposits to GDP, capturing the depth of use. The three indicators were standardized and combined by principal component analysis (PCA). The first principal component accounts for 66% of the joint variation and is the only component with an eigenvalue above 1, so it alone defines the index; its loadings are close to equal across the three inputs (.57, .56, and .60), so the index is a balanced summary rather than a single indicator in disguise. The component scores were then rescaled to a 0-to-1 range for readability. Table 2 reports the loadings and variance shares, and Figure 2 shows the scree plot and loadings. A four-indicator variant that adds geographic branch density was retained for robustness; it correlates .81 with the main index but is dominated by land area and is therefore not preferred. Results using this variant are reported in Table 12.

Table 2: *Principal Component Analysis of the Financial Inclusion Subindicators*

Subindicator	PC1	PC2	PC3
Bank branches per 100,000 adults	.572	−.650	−.501
Private credit to GDP (%)	.564	.755	−.336
Bank deposits to GDP (%)	.596	−.090	.798
Eigenvalue	2.014	0.566	0.463
Variance explained (%)	66.2	18.6	15.2
Cumulative (%)	66.2	84.8	100.0

Note. N = 71 country-years (2004–2021). PC = principal component; GDP = gross domestic product. PC1 is the only component with an eigenvalue above 1 and defines the index. Loadings on PC1 are balanced across the three inputs.

Figure 2: *Principal Component Analysis of the Financial Inclusion Index: Scree Plot and PC1 Loadings*



Note. PC = principal component. PC1 accounts for 66% of joint variation; the three subindicators load almost equally.

One property of the index governs everything that follows and is therefore stated before any estimate is presented. Almost all of its variation is between countries rather than within them: The between-country variance of the index is approximately 40 times its within-country variance. Japan sits highest and India lowest, with the United States and Australia in between (Figure 4). The consequence is arithmetic rather than interpretive. A fixed-effects estimator uses only the scarce within-country movement. A pooled, random-effects, or panel-corrected estimator leans on the abundant between-country spread, and with four units that spread contains four independent pieces of information about the regressor of interest, regardless of how many country-years are stacked beneath them. Any conventional standard error attached to a between-country coefficient in this panel will therefore be too small, and no heteroscedasticity- or dependence-robust correction repairs the problem, because such corrections address the shape of the error process rather than the number of independent draws on the regressor.

1.5.6 Analytic Strategy

The empirical workflow is set out in Figure 3. Given the decomposition just described, the estimators are presented in two tiers rather than as a single ladder.

The inferential tier consists of the within-country estimators: country fixed effects, estimated with clustered and with Driscoll–Kraay (1998) standard errors. These use only within-country variation in inclusion and are the only specifications from which inferential conclusions are drawn. The baseline relates the log Z-score of country *i* in year *t* to its inclusion index and controls, with country effects absorbing time-invariant structural differences:

$$\ln Z(i,t) = \alpha(i) + \beta \times \mathrm{FI}(i,t) + \gamma \times \mathbf{X}(i,t) + \varepsilon(i,t),$$

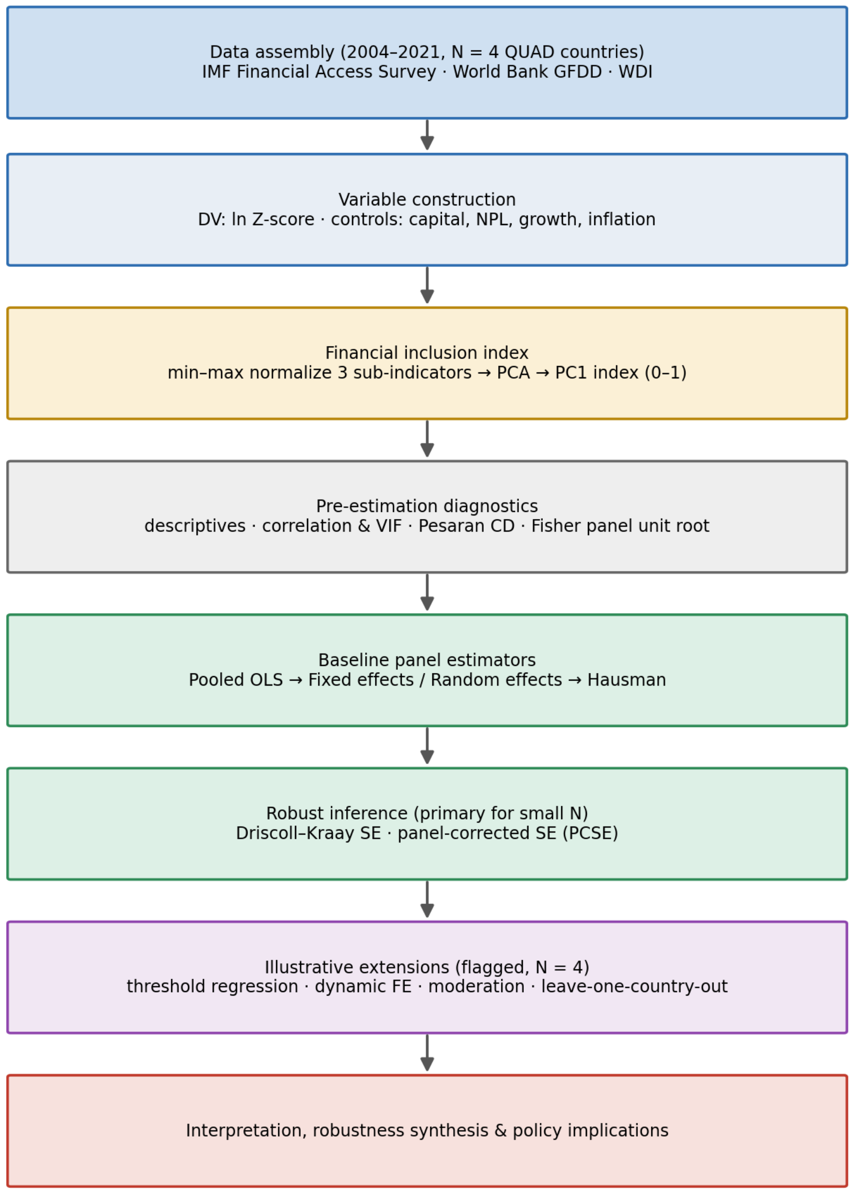
where FI is the inclusion index, **X** collects capital adequacy, credit risk, growth, and inflation, and $\alpha(i)$ is a country fixed effect.

The descriptive tier consists of the estimators that draw on cross-country variation: pooled ordinary least squares (OLS), random effects, and panel-corrected standard errors (PCSE; Beck & Katz, 1995). These are reported because the literature reports them and because the contrast with the within-country estimates is the central object of interest. They are *not* interpreted as tests. Point estimates are reported, but their significance levels are treated as uninformative, for the reason given above: They describe a comparison of four country means.

Three further specifications probe particular questions and are reported with their identification limits attached. A Hansen-type (2000) threshold regression searches for a level of inclusion at which the slope changes, with significance judged by a residual bootstrap; the composition of the resulting regimes is inspected directly in Table 11, and that inspection proves more informative than the bootstrap. A dynamic fixed-effects model adds a lagged dependent variable to allow for persistence in stability. An interaction of inclusion with capital tests whether capitalization conditions the relationship. Two-step system GMM (Blundell & Bond, 1998), which the reference study uses, is not appropriate here: Its consistency relies on a large number of cross-sectional units, and with four countries the instrument count overwhelms the group count and the overidentification test degenerates. It is reported as not estimable rather than presented as a result.

Figure 3: *Empirical Research Design and Estimation Workflow*

Figure 2. Empirical research design and estimation workflow



Note. Within-country estimators carry the inferential weight; between-country estimators are reported descriptively; threshold, dynamic, and moderation models are reported with identification limits attached.

1.6 Results

1.6.1 Descriptive Statistics

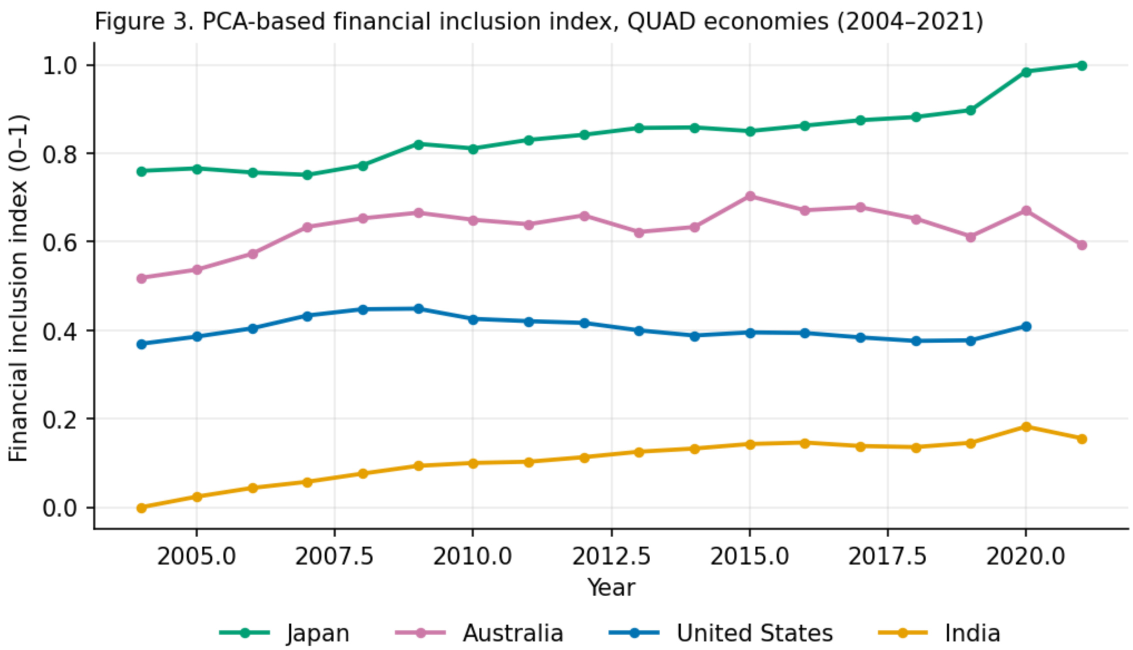
Table 3 summarizes the variables over the full 2004–2021 window. The log Z-score averages 2.91, so the geometric mean Z-score is approximately 18.4, and it ranges from about 2.29 to 3.56. The inclusion index has a sample mean of 0.50 and spans the full 0-to-1 range; the endpoints are fixed at 0 and 1 by the rescaling, but the mean of approximately one half is an empirical feature of the data rather than a construction artifact. The country pattern behind these averages is telling. The United States records by far the highest Z-score, near 32 on the raw scale, alongside the second lowest inclusion index; Japan and India post moderate Z-scores with, respectively, the highest and lowest inclusion. That configuration—high measured stability paired with low bank-based inclusion in the United States—anticipates the central result. Figure 4 plots the index by country over the sample period.

Table 3: *Descriptive Statistics*

Variable	*n*	*M*	*SD*	Min	Max
Financial inclusion index	71	0.50	0.28	0.00	1.00
Branches per 100,000 adults	72	26.83	9.26	8.88	35.66
Private credit/GDP (%)	71	83.08	33.16	36.19	143.14
Bank deposits/GDP (%)	71	113.50	59.24	53.76	259.61
Bank Z-score	71	19.67	7.78	9.89	35.17
ln Z-score	71	2.91	0.35	2.29	3.56
Capital adequacy (%)	68	13.61	1.79	10.10	17.56
Credit risk, NPL (%)	68	2.60	2.31	0.20	9.98
GDP growth (%)	72	2.92	3.13	−5.94	9.69
Inflation (%)	72	2.84	2.83	−1.35	11.99

Note. Sample: four QUAD economies, 2004–2021. GDP = gross domestic product; NPL = nonperforming loans. Z-score and controls from World Bank Global Financial Development Database; inclusion inputs from International Monetary Fund Financial Access Survey; macroeconomic series from World Development Indicators. Regression estimates use the 2004–2020 subperiod with $N = 67$; see the Method section for the attrition account.

Figure 4: *Principal Component Analysis–Based Financial Inclusion Index for the QUAD Economies, 2004–2021*



Note. QUAD = Quadrilateral Security Dialogue. Index rescaled to 0–1. Japan scores highest and India lowest; the United States and Australia lie in between.

1.6.2 Correlations and Multicollinearity

Table 4 reports pairwise correlations and Table 5 the VIFs. In the pooled data the inclusion index is highly collinear with bank-sector size, competition, and liquidity, with inflation factors well above 10, which is why those variables were held out. More importantly, the inclusion index itself carries a pooled VIF of 39.7. This figure is not a peripheral diagnostic: It is a second expression of the between-within decomposition, and it means that the pooled specification cannot support an interpretable coefficient on inclusion. It is reported here so that the descriptive status assigned to the pooled results in Table 7 is understood as following from the data rather than from analytical preference. Once the between-country variation is removed—that is, on data demeaned within countries—every retained regressor has a VIF below 2.5, so the fixed-effects specification that carries the argument is free of the collinearity that afflicts the pooled cross-section.

Table 4: *Correlations Among Model Variables*

Variable	1	2	3	4	5	6
1. ln Z-score	—					
2. FI index	−.29	—				
3. Capital adequacy	.25	.20	—			
4. NPL	−.05	−.56	−.03	—		
5. GDP growth	−.06	−.63	−.31	.31	—	
6. Inflation	−.01	−.77	−.18	.30	.59	—

Note. Pearson correlations, pooled sample. FI = financial inclusion; NPL = nonperforming loans; GDP = gross domestic product.

Table 5: *Variance Inflation Factors, Pooled Versus Within-Country*

Regressor	Pooled VIF	Within VIF
Financial inclusion	39.70	2.24
Capital adequacy	1.90	1.54
Credit risk (NPL)	4.20	2.48
GDP growth	2.30	1.23
Inflation	5.60	1.95

Note. VIF = variance inflation factor; NPL = nonperforming loans; GDP = gross domestic product. Pooled VIFs reflect between-country collinearity; within-country VIFs, which apply to the fixed-effects model, are all below 2.5. Bank-sector size, competition, diversification, and liquidity were excluded for pooled VIF > 10.

1.6.3 Panel Diagnostics

Table 6 collects the panel diagnostics. The Pesaran (2015) test rejects cross-sectional independence for the inclusion index and for GDP growth, which is expected among four financially and commercially linked economies and which motivates the use of Driscoll–Kraay standard errors. Fisher-type panel unit-root tests give a mixed picture: The log Z-score and the inclusion index are stationary in levels at conventional sizes, whereas capital adequacy and credit risk appear closer to integrated and are stationary after differencing. With a time dimension of approximately 18 years, unit-root tests have limited power, so the levels specification was retained and read alongside robust standard errors rather than pushed toward a differenced or cointegration design that four countries could not support.

Table 6: *Cross-Sectional Dependence and Panel Unit-Root Tests*

Variable	CD	*p*	ADF-Fisher *p* (level)	ADF-Fisher *p* (Δ)
ln Z-score	0.92	.359	.032	<.001
FI index	3.33	.001	.025	.048
GDP growth	6.05	<.001	.013	<.001
Inflation	1.08	.280	.099	<.001

Note. CD = Pesaran cross-sectional dependence test statistic (null hypothesis: cross-sectional independence); ADF-Fisher = Maddala–Wu panel unit-root test (null hypothesis: unit root); FI = financial inclusion; GDP = gross domestic product. Values for capital adequacy and nonperforming loans indicate near-integration in levels; see text.

1.6.4 Between- and Within-Country Estimates

Table 7 presents the core estimates, and Figure 5 places the inclusion coefficient from each estimator on a single scale. The contrast is the central finding.

Estimators that draw on cross-country variation return a large negative point estimate: Pooled OLS puts it at −1.60, and the random-effects and panel-corrected estimates coincide with it. Read literally, a move from the least to the most included system in the sample would cut the log Z-score by more than 1.5 units. It is not read literally here. As established above, this coefficient is identified from four country means; its nominal standard error of 0.21 treats 67 stacked country-years as independent draws on a regressor that takes essentially four values. Conventional significance levels are therefore reported in the table for completeness and comparability with the literature, but they are not interpreted, and no inference in this article rests on them.

The fixed-effects estimator tells a different story. Once only within-country variation is used, the coefficient is +0.10 and statistically indistinguishable from zero, whether standard errors are clustered or computed by the Driscoll–Kraay method. The nested specifications in Table 8 add texture: Inclusion enters positively and significantly when it sits alone or with macroeconomic controls (Model 2: $b = 0.62$, $p < .01$), then fades to nonsignificance once capital adequacy and credit risk are added, which suggests that whatever within-country signal exists runs through bank fundamentals rather than through inclusion directly.

Three qualifications attach to Table 7 and should be read with it.

First, the random-effects column reproduces the pooled OLS estimates. This occurs when the estimated variance of the country-specific effect is driven to its boundary of zero, in which case the generalized least squares transformation parameter is zero and random effects collapses onto pooled OLS. That outcome sits uneasily beside the fixed-effects results, which imply substantial country heterogeneity, and it is a known small-sample pathology at this number of groups. It is also the most likely source of the negative Hausman statistic reported below. The column is flagged as degenerate rather than treated as independent corroboration of the pooled result, and random effects is not counted as a third estimator agreeing with the first two.

Second, the panel-corrected standard errors reported here were computed without a Prais–Winsten AR(1) correction, which is why the PCSE coefficients are identical to pooled OLS and the standard errors are smaller. With a persistent dependent variable constructed from a rolling volatility window, uncorrected PCSE will understate uncertainty, and the column should be read accordingly.

Third, the Hausman test does not adjudicate. Its statistic is negative here, a recognized small-sample outcome arising when the estimated covariance difference is not positive semidefinite, so it cannot be read as a vote for either model. Rather than lean on a degenerate test, the two estimators are treated as answering different questions—between country versus within country—and both are reported. A correlated random-effects specification in the manner of Mundlak (1978), which enters the country mean of inclusion alongside its within-country deviation and delivers a direct test of their equality, would be the appropriate replacement for the Hausman comparison here; it is only weakly identified with four groups, but it would state the decomposition in a single regression rather than across two columns, and it is recommended for extensions of this design.

Among the controls, capital adequacy carries a positive coefficient in every specification, but its statistical significance is not uniform. In the within-country model it is $b = 0.02$ with a clustered standard error of 0.02, which does not reach conventional significance; the same point estimate reaches $p < .01$ under Driscoll–Kraay standard errors. Because that shift rests on a threefold contraction of the standard error under a dependence-robust correction, and because such corrections more commonly widen than narrow intervals when cross-sectional dependence is present, the significance of the capital coefficient in the Driscoll–Kraay column should be treated as sensitive to the lag-truncation choice rather than as established. What can be said without qualification is that the point estimate is positive in all five columns and that its magnitude is stable: A 1-percentage-point increase in the capital ratio is associated with a Z-score higher by approximately 2%. Credit risk and the macroeconomic variables enter with small and less stable coefficients; inflation is weakly positive within countries, which reflects the coincidence of Japan's low-inflation decades with its banking-sector weakness rather than any general stabilizing role of inflation.

Table 7: *Financial Inclusion and Bank Stability: Within- and Between-Country Estimates*

Variable	FE	FE (D–K)	Pooled OLS	RE	PCSE
FI index	0.10 (0.45)	0.10 (0.53)	−1.60 (0.21)	−1.60 (0.21)	−1.60 (0.14)
Capital adequacy	0.02 (0.02)	0.02** (0.01)	0.05 (0.02)	0.05 (0.02)	0.05 (0.02)
Credit risk (NPL)	0.01 (0.01)	0.01 (0.01)	−0.07 (0.02)	−0.07 (0.02)	−0.07 (0.01)
GDP growth	0.01 (0.01)	0.01 (0.01)	−0.03 (0.02)	−0.03 (0.02)	−0.03 (0.01)
Inflation	0.02* (0.01)	0.02* (0.01)	−0.08 (0.02)	−0.08 (0.02)	−0.08 (0.01)

Constant	2.45** (0.08)	2.45** (0.27)	3.46 (0.35)	3.46 (0.35)	3.46 (0.27)
N	67	67	67	67	67
R^2 / within R^2	.196	.196	.484	.484	—

Note. The dependent variable is the natural log of the bank Z-score. Standard errors appear in parentheses. FE = fixed effects; D–K = Driscoll–Kraay standard errors; OLS = ordinary least squares; RE = random effects; PCSE = panel-corrected standard errors, computed without an AR(1) correction; FI = financial inclusion; NPL = nonperforming loans; GDP = gross domestic product. The first two columns constitute the inferential tier; the last three constitute the descriptive tier. The RE column reproduces pooled OLS because the estimated variance of the country effect lies at its zero boundary; it is reported as degenerate and does not constitute independent corroboration. Significance levels are omitted for the descriptive tier because those coefficients are identified from four country means and their nominal standard errors understate uncertainty; see the Analytic Strategy section.

*$p < .05$. **$p < .01$.

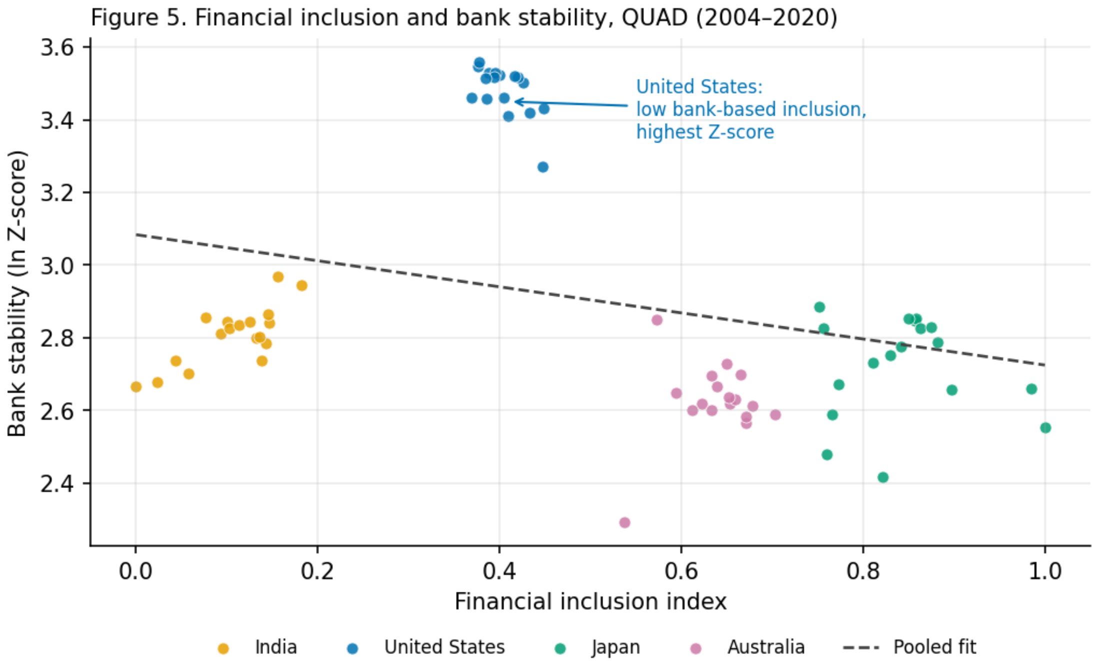
Table 8: *Nested Fixed-Effects Specifications*

Variable	Model 1	Model 2	Model 3	Model 4
FI index	0.46† (0.27)	0.62** (0.14)	0.18 (0.67)	0.10 (0.45)
Macroeconomic controls	No	Yes	No	Yes
Bank controls	No	No	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Within R^2	.043	.116	.095	.196

Note. The dependent variable is the natural log of the bank Z-score. Standard errors appear in parentheses. FI = financial inclusion. The coefficient on inclusion is positive with macroeconomic controls (Model 2) but fades once bank fundamentals enter (Models 3 and 4).

†$p < .10$. **$p < .01$.

Figure 5: *Financial Inclusion Coefficient Across Estimators With 95% Confidence Intervals*



Note. Between-country estimators cluster near −1.6; within-country estimators lie near zero. Intervals for the between-country estimators are nominal and understate uncertainty for the reason given in the Method section.

1.6.5 Leave-One-Country-Out Analysis

Table 9 reports the leave-one-country-out estimates. Dropping India, Japan, or Australia leaves the between-country inclusion coefficient large and negative, between −1.63 and −1.87. Dropping the United States flips it to +0.37. The entire negative cross-country association is produced by one country.

The interpretation follows directly from the structural argument. The United States pairs the highest measured bank stability in the sample with a low bank-based inclusion index, because American households are included substantially through markets and nonbank channels that supply-side banking indicators do not observe, and because its Z-score is computed by aggregating over an unusually large and fragmented banking population. Both of these are measurement features rather than behavioral ones, and they push in the same direction. The negative coefficient is not evidence that inclusion undermines stability; it is what a bank-based inclusion index and a sector-aggregated stability measure jointly produce when a market-based system is placed in a panel with bank-based systems.

The proper weight to place on this analysis should be stated. With four units, removing one leaves three, and no leave-one-out replication here has the properties of an influence diagnostic in a conventional sample. The analysis does not establish that the United States is an outlier in a statistical sense. What it establishes is narrower and sufficient: that the sign of the between-country coefficient is determined by a single unit and therefore that the coefficient cannot be interpreted as a population parameter. The within-country estimates are, by contrast, small and nonsignificant across all four replications, which is consistent with the absence of a robust time-series relationship inside these countries over the sample period.

Table 9: *Leave-One-Country-Out Estimates of the Financial Inclusion Coefficient*

Sample	Pooled OLS (descriptive)	Fixed effects
Excluding India	−1.87	0.12

Excluding United States	0.37	0.28
Excluding Japan	−1.78	0.45
Excluding Australia	−1.63	−0.39

Note. The dependent variable is the natural log of the bank Z-score. OLS = ordinary least squares. Dropping the United States reverses the sign of the between-country coefficient, showing that it is determined by a single unit. Pooled estimates are reported without significance markers, consistent with their descriptive status. All fixed-effects estimates are nonsignificant at $p < .10$; standard errors are reported in the online supplemental material.

1.6.6 What the Threshold Model Estimates

Table 10 reports the threshold, dynamic, and moderation results. The threshold search locates its residual-minimizing split at an inclusion value of $\gamma = 0.54$, but the bootstrap does not support it: The *p* value against a linear alternative is .221, so the null hypothesis of no threshold cannot be rejected, and neither regime slope is individually significant.

Reporting this as an inconclusive test would understate what the analysis shows. Because the estimated threshold and the underlying index values are both observable, the regime assignment can be inspected directly, and Table 11 does so. In the estimation sample, the split at $\gamma = 0.54$ places all 17 Indian observations and all 17 United States observations below the threshold, together with Australia in 2005, and all 17 Japanese observations together with Australia from 2006 onward above it. Exactly 1 observation out of 67 crosses the threshold within a country. The two regimes are therefore the country pair India and the United States versus the country pair Japan and Australia, and the threshold model is estimating a two-group country split with a single crossing observation to identify the location of the break.

This is the substantive result of the analysis, and it is stronger than the bootstrap *p* value. A Hansen-type threshold model requires units to cross the candidate split so that regime slopes are identified from within-unit variation in regime membership. When the threshold variable is almost entirely between unit, as an inclusion index is, regime membership is a fixed country attribute and the model reduces to an interaction with a country grouping. The failure of the bootstrap to reject is not a finding about nonlinearity in the inclusion–stability relationship. It is a symptom of a specification that was not identified in the first place.

The point generalizes beyond this sample. Any panel threshold model applied to a slow-moving country-level index will assign most units to a single regime for their entire observed history and will therefore estimate a partition of countries rather than a behavioral discontinuity—a partition whose composition is rarely reported. The diagnostic proposed here is simple, requires no additional data, and can be applied to any published threshold estimate for which the threshold value and the index series are available: Tabulate regime membership by unit and count the crossings.

The dynamic fixed-effects model adds a lagged log Z-score whose coefficient of 0.17 is not statistically significant, indicating weak year-to-year persistence at the country level. In that specification the inclusion coefficient turns negative and marginally significant, $b = -0.65$, $p = .038$. This estimate requires direct comment because it is the only within-country specification that returns a significant coefficient and it points in the opposite direction to the static within-country result. Three considerations bear on it. The Nickell bias induced by a lagged dependent variable in a within estimator is of order $1/T$ and is therefore modest at $T = 17$, so it is not on its own a sufficient explanation. More relevant is that the lagged dependent variable is weakly identified with four groups and that the Z-score is constructed from a rolling volatility window, which induces mechanical serial correlation between the outcome and its own lag independently of any economic persistence. The dynamic estimate is therefore treated as further evidence that the sign is specification dependent rather than structural, which is the argument of this article; a reader could equally treat it as evidence against the null reported here, and no claim is made to have ruled that reading out.

The interaction of inclusion with capital is nonsignificant, $b = -0.03$, $p = .458$, so the data do not support the view that capitalization conditions the inclusion–stability relationship in this sample. System GMM could not be estimated, as anticipated.

Table 10: *Extensions: Dynamic, Threshold, Moderation, and Generalized Method of Moments Models*

Model and parameter	Estimate	Inference
Dynamic FE: lagged ln Z-score	0.17	$p = .150$
Dynamic FE: FI index	−0.65	$p = .038$
Threshold: estimated γ	0.54	Bootstrap $p = .221$
Threshold: FI below γ	−0.47	$p = .242$
Threshold: FI above γ	0.01	$p = .974$
Moderation: FI × capital adequacy	−0.03	$p = .458$
System GMM	Not estimable	Instruments > groups

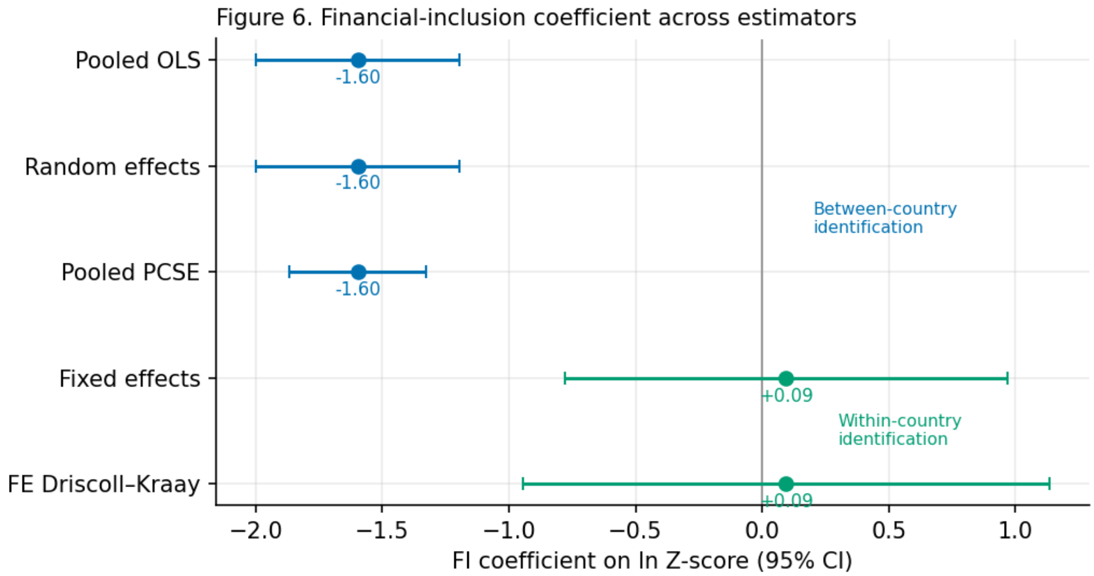
Note. The dependent variable is the natural log of the bank Z-score. FE = fixed effects; FI = financial inclusion; GMM = generalized method of moments. The threshold model is not identified at this panel width; see Table 11. System GMM is not identified with four cross-sectional units.

Table 11: *Composition of the Estimated Threshold Regimes (γ = 0.54), Estimation Sample 2004–2020*

Country	Observations below γ	Observations above γ	Years crossing γ
India	17	0	None
United States	17	0	None
Japan	0	17	None
Australia	1	15	2005 to 2006
Total	**35**	**32**	**1 of 67**

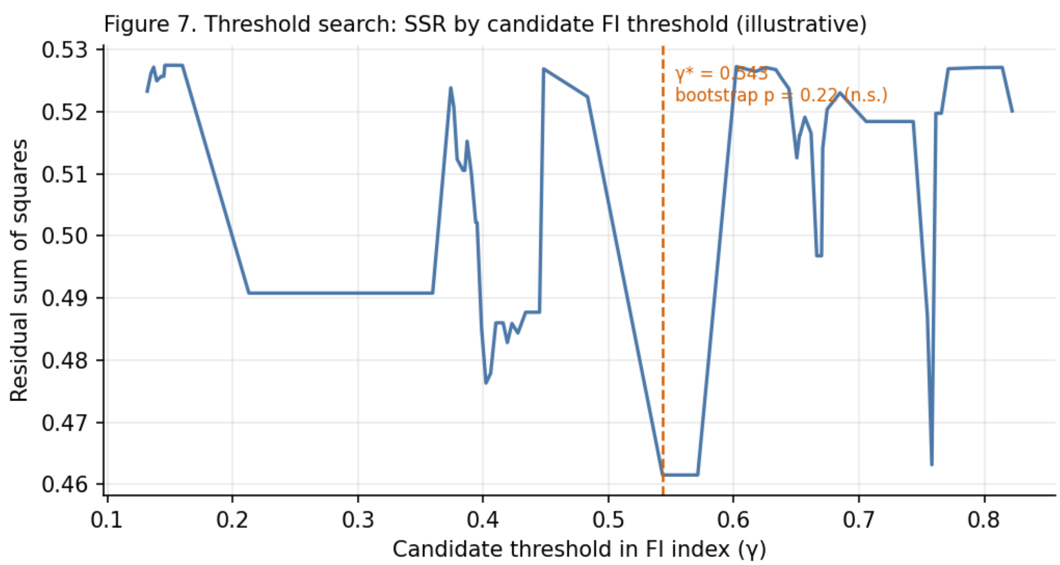
Note. Regime membership was computed from the inclusion index in Table A1 at the estimated threshold. Three of four countries never cross the threshold, so regime membership is a fixed country attribute and the regime slopes are not separately identified from within-country variation. Australia in 2004 is excluded from the estimation sample because the Z-score is unavailable.

Figure 6: *Financial Inclusion and Bank Stability Across the QUAD Economies, 2004–2020*



Note. QUAD = Quadrilateral Security Dialogue. The United States combines the highest Z-scores with a low bank-based inclusion index, driving the negative between-country slope.

Figure 7: *Threshold Search: Residual Sum of Squares by Candidate Inclusion Threshold*



Note. The residual-minimizing threshold is not statistically significant (bootstrap $p = .221$) and is not identified; see Table 11.

1.6.7 Robustness

Table 12 reports estimates using the four-indicator index variant described in the Method section, which adds geographic branch density to the three main inputs and correlates .81 with the preferred index. Consistent with the main specification, the fixed-effects coefficient on the four-indicator index is small and statistically indistinguishable from zero (0.42, ns), whereas the pooled coefficient is negative and significant (−0.75, $p < .01$). The between- and within-country contrast that anchors the paper therefore does not depend on excluding geographic branch density from the index.

Table 12: *Robustness: Estimates Using the Four-Indicator Financial Inclusion Index*

Variable	Fixed effects	Pooled OLS (descriptive)
FI index (four-indicator)	0.42 (0.42)	−0.75** (0.16)
Capital adequacy	0.02 (0.02)	0.07** (0.03)
Credit risk (NPL)	0.01 (0.01)	−0.01 (0.01)
GDP growth	0.01 (0.01)	−0.02 (0.01)
Inflation	0.02† (0.01)	−0.03* (0.01)
N	67	67
R^2 / within R^2	0.21	0.33

Note. The dependent variable is the natural log of the bank Z-score. Standard errors appear in parentheses. OLS = ordinary least squares; FI = financial inclusion; NPL = nonperforming loans; GDP = gross domestic product. The four-indicator index adds geographic branch density to branch density per 100,000 adults, private credit to gross domestic product, and bank deposits to gross domestic product.

1.7 Discussion

Read together, the results deliver a message about identification rather than about inclusion. Across the QUAD economies there is no evidence of a robust within-country association between financial inclusion, measured from official supply-side sources, and banking stability. The large negative between-country coefficient that a conventional pooled specification would report is not a behavioral estimate: It is determined by a single unit, it is attached to a regressor with a pooled VIF near 40, and it is identified from four country means. On the hypotheses, H1 finds no robust within-country relationship; H2 finds no significant threshold and, more importantly, no identified threshold model; and Objective R is met in the sense that the source of the instability has been diagnosed.

The finding speaks to a measurement problem that the inclusion–stability literature has not fully confronted. Bank-branch density and bank-credit depth are reasonable proxies for inclusion in economies where banks are the main channel of finance, but they understate inclusion where markets and nonbank intermediaries do the work. Pooling bank-based and market-based systems and reading a single inclusion coefficient therefore risks mistaking a structural difference for a behavioral effect. Two features of the present design compound this and should be acknowledged rather than argued away. The inclusion index is, as noted in the Method section, substantially a measure of bank-based financial depth, and the sector-aggregated Z-score is mechanically higher for the largest and most fragmented banking population in the sample. The United States is therefore mismeasured on both sides of the regression in the same direction, and the between-country coefficient is best understood as a ratio of two measurement artifacts rather than as a noisy estimate of a true parameter. The QUAD group makes this visible because it deliberately spans the structural range; the same confound is latent in any cross-country study that mixes financial architectures.

The threshold result carries the same lesson in sharper form. A model that appears to test for a behavioral nonlinearity turns out, on inspection of its regime assignment, to be estimating a partition of countries. Because the diagnostic is a matter of tabulating regime membership, it is available to any study reporting a threshold estimate on a slow-moving country-level index, and its routine reporting would be a useful convention. Threshold estimates in this literature that do not report regime composition cannot be assessed on this point by their readers.

Two things this study does not establish should be stated. First, it does not show that financial inclusion has no effect on banking stability. The within-country estimates are null, but a four-country panel with a slow-moving regressor has limited power to detect a modest effect, and one within-country specification—the dynamic model—

returns a significant negative coefficient. Second, the analysis is associational throughout. Reverse causality is plausible: Banking systems that are stable and well capitalized may be better placed to extend access, so the direction of any relationship is not settled by the design. The usual remedy in this literature is dynamic-panel internal instrumentation, which is unavailable at this panel width, and no substitute is offered. Readers should treat every coefficient reported here as a conditional association.

The one result that recurs across specifications is the positive point estimate on capital, which aligns with a large body of work (Beck et al., 2013; Laeven& Levine, 2009) and with the direction of postcrisis regulation. As noted above, its statistical significance within countries is sensitive to the standard-error choice, so it is best described as a consistent and economically plausible association rather than as a firmly established one.

How do these results sit beside the reference study and the wider evidence? Dang and Thi (2025) reported an average destabilizing effect of inclusion across 157 ASEAN banks, with the effect varying by bank and market structure. The QUAD evidence neither confirms nor contradicts that pattern so much as it shows that the pipeline is not portable: In a small sample of structurally diverse economies, the same sequence of estimators yields a between-country coefficient that is a structural artifact, a within-country null, and a threshold model that is not identified. That is consistent with the product-level nuance reported by Feghali et al. (2021) and with the conditioning results of Ahamed and Mallick (2019), both of which caution against a single universal effect.

1.7.2 Policy Implications

The implications that follow are correspondingly modest, and they concern the reading of evidence more than the setting of policy.

First, the apparent cross-country trade-off between inclusion and stability in these four economies is a measurement artifact and should not be read as a warning. Nothing in these data shows that widening access has destabilized the QUAD banking systems. That is a weaker statement than an affirmative finding of no tension, and it should not be strengthened.

Second, supervisors and international bodies should read cross-country inclusion league tables with care. A low bank-based inclusion score in a market-based economy signals financial structure, not exclusion, and rankings that ignore this will mislead. Where inclusion is pursued through credit expansion, the product-level evidence still counsels attention to lending standards, but that is a matter of how credit grows rather than of inclusion as such (Feghali et al., 2021).

Third, the recurring positive association between capitalization and stability is consistent with the central thrust of the postcrisis regulatory agenda and offers no support for trading capital standards away in the name of expanding access.

1.7.3 Limitations

The limitations are substantial and shape what can be claimed. The most important is the width of the panel: Four countries cannot support dynamic panel or threshold inference and cannot deliver a well-powered test of a modest within-country effect. The null reported here is therefore consistent both with a true zero and with a small effect the design cannot detect.

The second is measurement, in two directions. The inclusion index rests on supply-side banking indicators, two of the three of which are conventionally measures of financial depth; it omits automated teller machine density, which the United States stopped reporting after 2009, and account-level penetration, which is not consistently available for these economies. It therefore understates inclusion delivered through markets, financial technology, and nonbank channels. Separately, the sector-aggregated Z-score is sensitive to the number and heterogeneity of institutions being aggregated, which is not constant across these four systems.

The third is the level of analysis: Country aggregates cannot capture the bank-level heterogeneity that a proprietary database would, so the estimates describe banking systems rather than individual banks. The fourth is identification. The design is associational, no instrument or natural experiment is available at this panel width, and reverse causality is untreated. Finally, the estimation window closes in 2020, so the pandemic period and its aftermath fall outside it.

1.7.4 Future Research

Four extensions would sharpen the picture, and the first two are those on which the argument most depends.

Validating the mismeasurement claim against a demand-side benchmark is the most direct next step. The World Bank Global Findex database reports account ownership for all four economies in 2011, 2014, 2017, and 2021. If the supply-side index ranks the United States close to India while Findex separates them sharply, the structural interpretation offered here would be confirmed empirically rather than argued. Four waves across four countries do not constitute a panel, but they constitute a validation exercise, and it is one this design cannot do without.

Broadening the cross-section—to the Group of 20, or to a matched set of bank-based and market-based systems—would give the threshold and dynamic models the cross-sectional mass they need while preserving the structural contrast that makes the question interesting. It would also permit the correlated random-effects specification recommended above to be estimated with adequate power.

Moving to bank-level data where it can be obtained would let the within-country question be asked with the heterogeneity it deserves, although the mismatch between a bank-level outcome and a country-level treatment would remain and should be handled explicitly. Extending the window past 2021 would bring the pandemic and its aftermath into view, a period during which inclusion and stability may have moved together in new ways.

Appendix A

Constructed Financial Inclusion Index and Bank Z-Score by Country-Year

The values below are the compiled inputs and outputs used in estimation. They are reproduced so that the index and the outcome variable can be inspected directly and so that the regime composition reported in Table 11 can be verified. All figures derive from the official sources cited in the text; none were interpolated.

Table A1

Financial Inclusion Index (0–1) by Country and Year

Year	India	United States	Japan	Australia
2004	0.000	0.370	0.760	0.519
2005	0.024	0.386	0.766	0.537
2006	0.044	0.404	0.757	0.573
2007	0.057	0.433	0.751	0.634
2008	0.076	0.447	0.773	0.653
2009	0.093	0.449	0.821	0.666
2010	0.100	0.426	0.811	0.650
2011	0.103	0.420	0.830	0.640
2012	0.113	0.417	0.842	0.660

Year	India	United States	Japan	Australia
2013	0.125	0.400	0.857	0.622
2014	0.133	0.388	0.858	0.633
2015	0.143	0.395	0.850	0.703
2016	0.146	0.394	0.863	0.671
2017	0.138	0.384	0.875	0.678
2018	0.136	0.376	0.882	0.652
2019	0.146	0.377	0.898	0.612
2020	0.182	0.409	0.985	0.670
2021	0.156	—	1.000	0.594

Note. Author's calculation (principal component analysis of branch access and credit and deposit depth). Source data: International Monetary Fund Financial Access Survey and World Bank. The United States value for 2021 is unavailable; that observation lies outside the estimation window and does not enter any reported estimate.

Table A2

Bank Z-Score by Country and Year

Year	India	United States	Japan	Australia
2004	14.39	31.81	11.93	—
2005	14.56	31.73	13.30	9.89
2006	15.47	31.84	16.89	17.31
2007	14.91	30.54	17.89	14.83
2008	17.39	26.37	14.48	13.71
2009	16.65	30.94	11.20	14.84
2010	17.18	33.21	15.36	15.33
2011	16.89	33.66	15.69	14.40
2012	17.02	33.75	16.08	13.90
2013	17.17	33.93	17.22	13.74
2014	16.45	34.11	17.33	13.49
2015	16.18	34.14	17.35	13.33
2016	17.14	33.67	16.87	13.00
2017	15.45	33.62	16.95	13.64
2018	16.49	34.68	16.27	13.97

Year	India	United States	Japan	Australia
2019	17.57	35.17	14.28	13.47
2020	19.00	30.30	14.28	13.25
2021	19.44	31.06	12.86	14.15

Note. Source: World Bank Global Financial Development Database. Higher values indicate greater distance to insolvency. The Australian value for 2004 is unavailable, which together with the 2021 control gap accounts for the estimation sample of $N = 67$.

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