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The Digital Gender Gap in ASEAN-10: Causes, Economic Consequences, and Spatial Spillovers

Duy Hung Bui
Faculty of Economics, Banking Academy of Vietnam, Hanoi, Vietnam

ABSTRACT: This study provides the first comprehensive empirical analysis of the digital gender gap (DGG) and its economic consequences across the ten member states of the Association of Southeast Asian Nations (ASEAN-10) over 20102024. Because conventional System GMM is inadmissible at N=10, we deploy Cross-Sectionally Augmented ARDL (CS-ARDL) as our primary estimator, with Pooled Mean Group, Mean Group, and fixed-effects with Driscoll-Kraay standard errors as robustness checks. To capture cross-border externalities, we estimate Spatial Durbin Models with five alternative weighting matrices. A one-percentage-point reduction in the composite DGG index is associated with a long-run 0.81% rise in real GDP per capita, a 0.19 percentage-point rise in female labour force participation, and a 0.06 point decline in the Gini coefficient. Spatial decomposition attributes 32-38% of total effects to cross-border spillovers, and Hansen threshold tests identify a critical broadband penetration of 9.4 subscriptions per 100 inhabitants above which DGG effects intensify. Findings call for embedding genderdisaggregated targets in the successor to the ASEAN Digital Masterplan 2025, leveraging the Digital Economy Framework Agreement to harmonize affordability provisions, and prioritizing infrastructure expansion in Cambodia, Lao PDR, and Myanmar.

KEYWORDS: Digital gender gap, ASEAN, CS-ARDL, Spatial Durbin Model, female labour force participation, income inequality, spillovers.

JEL: J16, O33, O47, L86, R11, F15.

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**Corresponding Author: Duy Hung Bui*

1. INTRODUCTION

ASEAN is simultaneously the world's most rapidly digitalizing region and one of its most digitally unequal. Between 2015 and 2023, internet access in ASEAN expanded from 27% to 65% for women and from 37% to 70% for men (UN Women and ASEAN Secretariat, 2024). The Boston Consulting Group projects the region's digital economy to reach US$2 trillion by 2030 under full Digital Economy Framework Agreement (DEFA) implementation. Yet the GSMA (2024, 2025) reports that women in low- and middle-income Asia-Pacific economies remain 14-15% less likely than men to use mobile internet, with the gap reaching 24% in Cambodia, and the 2025 edition documents a stalling of progress.

Following Van Dijk (2020), the DGG is multidimensional, motivational, material, skills, and usage access, with Hargittai's (2002) second-level divide and van Deursen and Helsper (2015) third-level divide showing that equalized access does not guarantee equal economic returns. In a region defined by the ASEAN Digital Masterplan 2025 (ADM 2025), the Bandar Seri Begawan Roadmap (BSBR, 2021), and the impending DEFA, understanding how the DGG affects growth, employment, and distribution is both academic and policy imperative.

The empirical evidence base for ASEAN remains fragmentary. Existing studies address the broader Asian context with global samples (Antonio & Tuffley, 2014), examine individual ASEAN economies cross-sectionally (UNCTAD-ESCAP, 2025), or study ASEAN aggregates without gender focus (Sugiharti et al., 2022; Sihombing et al., 2024). No study has jointly estimated the effect of the DGG on real GDP per capita, female labour force participation (FLFP), and income inequality for the full ASEAN-10 panel with cross-border spillovers.

Three methodological gaps compound this. First, System GMM (Blundell & Bond, 1998), the workhorse of the gender-ICT literature, is derived for large-N, small-T asymptotics; at N=10, its Hansen and AR(2) diagnostics are severely size-distorted (Roodman, 2009). Second, standard fixed effects ignore the cross-sectional dependence from common shocks (global cycles, COVID, commodity swings). Third, existing ASEAN work treats countries as isolated despite AEC and RCEP integration and cross-border digital payment linkages (e.g., PromptPay-PayNow).

This paper makes four contributions. First, we construct a balanced panel for ASEAN-10 over 2010-2024, combining ITU DataHub, GSMA Mobile Gender Gap microdata, ILOSTAT, and SWIID, with a composite DGGPCA index spanning access, mobile internet, and skills dimensions. Second, we deploy CS-ARDL (Chudik et al., 2016) which absorbs unobserved common factors, corroborated by PMG (Pesaran, Shin, & Smith, 1999), MG, and FE with Driscoll-Kraay standard errors (Driscoll & Kraay, 1998), all with wild cluster bootstrap inference (Cameron, Gelbach, & Miller, 2008). Third, we estimate Spatial Durbin Models (LeSage & Pace, 2009) with five alternative W matrices and decompose direct, indirect, and total effects. Fourth, we apply Hansen (1999) threshold regression and panel local projections (Jordà, 2005).

Results are economically substantial. A one-percentage-point reduction in the internet usage gap raises long-run GDP per capita by 0.81%, FLFP by 0.19 percentage points, and reduces the Gini by 0.06 points, robust across estimators and DGG measures. The SDM attributes 32–38% of effects to spillovers. Thresholds at ~9.4 broadband subscriptions per 100 inhabitants mirror Asongu and Odhiambo's (2023) African finding. Marginal returns are largest in CLMV (Cambodia, Lao PDR, Myanmar, Vietnam), with output elasticities roughly twice the ASEAN-6 average.

Section 2 reviews the literature; Section 3 develops the framework and hypotheses; Section 4 presents data and methodology; Section 5 reports diagnostics; Sections 6, 7 present CS-ARDL and SDM results; Section 8 provides robustness and heterogeneity; Sections 9, 10 discuss and conclude.

2. LITERATURE REVIEW

2.1 Conceptualizing the digital gender gap

Van Dijk (2020) distinguishes motivational, material, skills, and usage access as sequential resources: weakness in any link generates persistent exclusion. Hargittai (2001) formalized the second-level divide in online skills, and van Deursen and Helsper (2015) articulated the third-level divide, in which equivalent online engagement yields unequal tangible benefits stratified by gender. Ragnedda (2018) frames digital capital as a Bourdieusian resource convertible into human, economic, and social capital, with gendered conversion rates yielding unequal returns. Antonio and Tuffley (2014) identify socioeconomic, sociocultural, and institutional barriers that interact in developing contexts. Peláez-Sánchez, George Reyes, and Glasserman-Morales (2023) systematically review gendered barriers in digital education; Mariscal, Mayne, Aneja, and Sorgner (2019) develop an access-use-skills-agency measurement framework we adopt.

2.2 Determinants

Economic constraints are foundational: entry-level smartphones cost 24% of women's vs. 12% of men's monthly income in LMICs (A4AI, 2021). Educational disparities: UNESCO (2019) finds women 25% less likely to possess basic ICT skills and 4× less likely to have advanced programming abilities; tertiary STEM enrolment remains stratified across ASEAN (UNESCO UIS, 2024). Sociocultural norms are context-specific, the mediating pattern differs across Muslim-majority Indonesia/Malaysia/Brunei, Buddhist-majority Thailand/Cambodia/Lao PDR/Myanmar, and Catholic-majority Philippines (Antonio & Tuffley, 2014). Institutional quality and gendermainstreamed national strategies, Singapore's SG Women in Tech, the Philippines' Magna Carta, Vietnam's alignment of digital and gender strategies, correlate with narrower gaps (UNCTAD-ESCAP, 2025).

2.3 Economic consequences

A4AI (2021) estimates 32 LMICs lost approximately US$1 trillion cumulative GDP over 2011-2020 from women's digital exclusion, with annual losses of US$126 billion and approximately US$24.7 billion in forgone tax revenue. UN Women (2025) projects closing the gap could raise global GDP by US$1.5 trillion annually and lift 30 million women from poverty. Asongu and Odhiambo (2024) in sustained work on Sub-Saharan Africa, establish positive ICT-FLFP (2018), negative ICT-inequality (2019), and a critical 9.187 broadband threshold (2023). Tunçsiper (2025) documents OECD cointegration between digitalization and women's employment.

ASEAN-specific evidence is thinner: Adeleye et al. (2025) apply CS-ARDL to ASEAN-5 growth without gender focus; Xu, Qiu, Rahman, Bhuiyan, and Hasan (2025) document China-ASEAN spillovers. None jointly address gender, growth, distribution, and spatial dimensions for the full ASEAN-10 panel.

2.4 Channels

Three channels link DGG to aggregate outcomes. (i) Labour participation: mobile internet lowers job-search costs and enables remote work (Shuangshuang, Zhu, Mughal, Aparcana, & Muda, 2023). (ii) Entrepreneurship: digital platforms lower transaction costs (e.g., Shopee, Tokopedia, Lazada), though gendered platform dynamics can reimpose stratification (Ticona & Mateescu, 2018). (iii) Income distribution: skill-biased technological change (Acemoglu & Autor, 2011) widens earnings distributions when digital skills are unequally acquired by gender.

2.5 Spatial spillovers and regional integration

Spillover channels include knowledge diffusion through online communities; network effects as connected user bases grow; demonstration effects via cross-border media and diaspora; and trade–investment linkages. These are amplified by ASEAN's institutional density: AEC (2015), RCEP (2022), BSBR (2021), ADM 2025, and DEFA, plus cross-border payment linkages (PromptPay-PayNow 2021; multilateral Regional Payment Connectivity 2022).

Despite this, no prior study has employed spatial econometrics to quantify gender-related digital spillovers within ASEAN.

2.6 Research gap

Three gaps motivate this study: the regional gap (no gender-focused ASEAN-10 analysis), the methodological gap (System GMM is inappropriate at N=10 and heterogeneous panel time-series methods have not been applied to this question), and the spatial gap (existing work treats ASEAN countries as isolated).

3. THEORETICAL FRAMEWORK AND HYPOTHESES

We synthesize four traditions: Van Dijk's resources-and-appropriation framework (sequential exclusion), (Becker, 2002) human capital theory extended to digital skills and spatial economics (LeSage & Pace, 2009). The framework generates three transmission channels, human capital, labour participation, and distribution, plus a spatial mechanism that transmits effects through knowledge diffusion, demonstration effects, and trade-investment linkages within ASEAN integration.

H1 (Growth). The long-run elasticity of real GDP per capita with respect to DGG is negative.

H2 (Participation). The long-run effect of DGG on FLFP is negative.

H3 (Distribution). The long-run effect of DGG on the Gini coefficient is positive.

H4 (Spillovers). Spatial indirect effects of DGG on domestic outcomes are statistically significant.

H5 (Non-linearity). DGG effects intensify above a critical broadband penetration threshold (following Asongu and Odhiambo, 2023).

4. DATA AND METHODOLOGY

4.1 Sample and data

Our balanced panel covers ASEAN-10, Brunei, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam, over 2010-2024 (150 country-years). Gender-disaggregated digital indicators come from the ITU DataHub (2024 release), GSMA Mobile Gender Gap Reports (2018-2025), and the Oxford Digital Gender Gaps project (Fatehkia et al., 2018; Kashyap et al., 2020) for imputation. Outcomes: log real GDP per capita (WDI, constant 2015 USD), FLFP 15+ (ILOSTAT modelled), Gini of disposable income (SWIID v9.6 primary; PIP and WIID for robustness). Controls: trade openness, FDI/GDP, urbanization, mean years of schooling, gender parity in tertiary, IMF financial development index, and the first principal component of six WGI dimensions.

4.2 DGG index

Following Mariscal et al. (2019), we construct the internet usage gap DGG_int = (Male - Female)/Male × 100; analogously for mobile internet and digital skills. Our preferred measure, DGG-PCA, is the first principal component of the three normalized indicators (73.4% of variance; loadings 0.62, 0.59, 0.51), standardized to mean 0 and SD 1. Robustness uses each component separately and a recoded gender parity score.

4.3 Econometric strategy

With N=10 and T=15, System GMM is statistically inadmissible (Roodman, 2009; Bun and Sarafidis, 2015). We instead deploy heterogeneous panel time-series estimators. Our primary specification is CS-ARDL (Chudik et al., 2016), which augments the country-specific ARDL with cross-sectional averages of y and x to absorb unobserved common factors. At T=15 we report CS-DL as the preferred headline and CS-ARDL for comparison. Robustness: Pooled Mean Group (Pesaran, Shin, and Smith, 1999), Mean Group (Pesaran and Smith, 1995), and FE with Driscoll-Kraay (1998) standard errors. Inference uses wild cluster bootstrap-t (9,999 replications; Cameron et al., 2008) via the Roodman et al. boottest procedure, validated at 5 clusters (MacKinnon & Webb, 2018). The Spatial Durbin Model (LeSage & Pace, 2009) is estimated by ML with (Lee & Yu, 2010) bias correction; we compute direct, indirect, and total effects via the LeSage-Pace partial derivatives with 1,000 simulation draws. Specifications:

$$\Delta y_{it} = c_i - \phi_i [y_{i,t-1} - \theta_i' x_{i,t-1} - \delta_i' \bar{z}_{t-1}] + \Sigma \psi_{ij} \Delta y_{i,t-j} + \Sigma \beta_{ij}' \Delta x_{i,t-j} + \gamma_i' \bar{z}_t + \varepsilon_{it} \quad (1)$$

$$y_{it} = \rho \Sigma_j w_{ij} y_{jt} + \beta' x_{it} + \theta' \Sigma_j w_{ij} x_{jt} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Five spatial weighting matrices: (i) binary land-border contiguity; (ii) inverse great-circle distance; (iii) k-nearest neighbours (k=3); (iv) bilateral-trade weights (IMF DOTS); (v) CLMV/ASEAN-6 block-diagonal. Pre-estimation diagnostics: Pesaran (2004, 2021) CD; CIPS unit-root (Pesaran, 2007, validated at N=T=10); (Westerlund, 2007) cointegration with 1,000 bootstrap replications; Pesaran and Yamagata (2008) $\tilde{\Delta}$_adj with Blomquist and Westerlund (2013) HAC correction; global Moran's I for spatial autocorrelation.

5. DESCRIPTIVE STATISTICS AND DIAGNOSTICS

Table 1 reports 2023 country-level DGG indicators. Singapore, Malaysia, and Indonesia (where women's mobile internet adoption now exceeds men's) show near-parity. Cambodia (24.0% mobile internet gap), Lao PDR (21.7%), and Myanmar (26.3%) exhibit the largest gaps.

Table 1. Digital gender gap indicators by ASEAN-10 country, 2023

Country	Internet gap (%)	Mobile internet gap (%)	Skills gap (%)	DGG-PCA	Subregion
Brunei	3.4	4.7	5.2	-0.42	ASEAN-6
Cambodia	21.8	24.0	28.1	1.78	CLMV
Indonesia	4.1	-6.4	8.3	-0.51	ASEAN-6
Lao PDR	19.4	21.7	23.8	1.42	CLMV
Malaysia	2.7	3.1	4.6	-0.58	ASEAN-6
Myanmar	24.5	26.3	31.4	2.04	CLMV
Philippines	5.3	4.2	7.1	-0.34	ASEAN-6
Singapore	1.2	2.1	3.4	-0.71	ASEAN-6
Thailand	3.8	4.6	6.2	-0.43	ASEAN-6
Vietnam	4.5	5.8	9.7	-0.27	CLMV

Source: Authors' calculations from ITU Data Hub, GSMA Mobile Gender Gap Report 2024, and ITU skills indicators. DGG-PCA standardized across the 2010-2024 panel.

Table 2 reports descriptive statistics. Real GDP per capita averages US$8,487 but ranges from US$1,180 (Myanmar) to US$66,800 (Singapore). FLFP averages 56.7% (Lao PDR >75%, Indonesia: 53%). Gini averages 37.8.

Table 2. Descriptive statistics, ASEAN-10 panel 2010–2024 (N=150)

Variable	Mean	SD	Min	Max	Source
DGG-PCA	0.00	1.00	-0.84	2.41	Authors
Internet gap (%)	11.21	9.83	-2.4	38.7	ITU
Mobile internet gap (%)	9.34	11.42	-6.4	32.1	GSMA
Skills gap (%)	13.78	10.94	0.0	36.5	ITU
Log GDP p.c.	8.45	1.32	6.94	11.11	WDI
FLFP (% 15+)	56.74	14.32	28.4	78.9	ILOSTAT
Gini (disposable)	37.81	4.18	30.6	46.2	SWIID
Trade (% GDP)	123.8	91.3	21.5	388.4	WDI
FDI (% GDP)	5.84	4.47	-0.6	21.4	WDI
Urbanization (%)	50.18	22.07	19.7	100.0	WDI
Schooling (years)	8.13	2.41	3.8	12.6	UNESCO
Gender parity tertiary	0.97	0.06	0.81	1.18	UNESCO
Financial development	0.41	0.21	0.08	0.86	IMF
Institutional quality	0.00	1.68	-2.34	3.21	WGI
Broadband (per 100)	8.92	9.46	0.1	32.8	ITU

Table 3 reports pre-estimation diagnostics. Pesaran (2004, 2021) CD tests reject cross-sectional independence for all variables (CD statistics 8.4-24.7, $p<0.001$), confirming the appropriateness of cross-sectional augmentation. CIPS tests find log GDP per capita, FLFP, Gini, DGG-PCA, and most controls I(1); institutional quality is I(0). The mixed I(0)/I (1) configuration is precisely where the ARDL family is appropriate. Westerlund (2007) bootstrap cointegration tests ($P\tau$ p-values 0.003, 0.011, 0.018) reject no-cointegration for all three outcomes. Pesaran– Yamagata (2008) $\tilde{\Delta}$_adj rejects slope homogeneity ($p<0.05$), motivating heterogeneous-coefficient estimation.

Table 3. Pre-estimation diagnostics

Variable	Pesaran CD	CIPS (level)	CIPS (Δ)	Order
Log GDP per capita	24.71***	-1.42	-4.18***	I(1)
FLFP rate	18.43***	-1.74	-3.94***	I(1)
Gini coefficient	12.84***	-1.83	-3.71***	I(1)
DGG-PCA	21.07***	-1.91	-4.32***	I(1)
Trade openness	16.32***	-1.67	-3.86***	I(1)
Schooling (years)	19.83***	-1.58	-3.94***	I(1)
Financial development	17.24***	-1.79	-4.07***	I(1)
Institutional quality	14.61***	-2.84***	-	I(0)
Broadband (per 100)	22.94***	-1.41	-4.27***	I(1)

Notes: CIPS with one lag and constant; critical values at N=10, T=15 (Pesaran, 2007): 10% = -2.07, 5% = -2.21, 1% = -2.45. *** p<0.01.

6. CS-ARDL AND PANEL TIME-SERIES RESULTS

Table 3 reports CS-DL (preferred) and CS-ARDL long-run estimates. A one-SD increase in DGG-PCA reduces long-run real GDP per capita by 8.1% (β=-0.081, p<0.01), FLFP by 1.94 pp (p<0.01), and raises the Gini by 0.62 points (p<0.05). Expressed per percentage-point of internet usage gap (SD=9.83), these correspond to -0.81% GDP, 0.19 pp FLFP, and 0.06 Gini. Error-correction speeds (ϕ) are -0.38, -0.42, and -0.34, implying half-lives of 1.3-1.7 years. Pesaran CD on residuals cannot reject no-dependence, confirming that cross-sectional augmentation absorbed common factors.

Table 3. CS-DL and CS-ARDL long-run estimates

	Log GDP p.c.	FLFP	Gini
Panel A. CS-DL			
DGG-PCA	-0.081*** [0.002]	-1.943*** [0.004]	0.624** [0.027]
Schooling (years)	0.103*** [0.000]	1.247*** [0.003]	-0.418*** [0.008]
Financial development	0.247*** [0.001]	4.728** [0.018]	-1.046 [0.142]
Trade (log)	0.084** [0.024]	-1.234* [0.071]	0.317 [0.213]
Gender parity tertiary	0.142** [0.027]	8.943*** [0.003]	-2.318** [0.024]
Panel B. CS-ARDL			
DGG-PCA (long-run)	-0.084*** [0.003]	-2.014*** [0.006]	0.671** [0.024]
Adjustment ϕ	-0.382*** [0.001]	-0.418*** [0.000]	-0.341*** [0.004]
CD residuals	0.84 [0.401]	1.13 [0.259]	0.91 [0.363]
Observations	130	130	130

Notes: Wild cluster bootstrap-t p-values (9,999 replications) in brackets. Cross-sectional averages of y and x (and lags) included throughout. *** p<0.01, ** p<0.05, * p<0.10.

Table 4 compares estimators. PMG yields point estimates close to CS-DL but the Hausman test rejects poolability (p<0.05 for all outcomes), confirming our preference for CS-DL/CS-ARDL and MG. MG yields larger estimates with wider intervals; FE-DK yields more conservative estimates. All four converge on the same sign and comparable magnitude.

Table 4. Long-run DGG-PCA coefficient: estimator comparison

Estimator	Log GDP p.c.	FLFP	Gini
CS-DL (preferred)	-0.081*** (0.026)	-1.943*** (0.673)	0.624** (0.281)
CS-ARDL	-0.084*** (0.028)	-2.014*** (0.731)	0.671** (0.297)
PMG	-0.075*** (0.022)	-1.812*** (0.604)	0.583** (0.244)

MG	-0.094*** (0.034)	-2.183*** (0.812)	0.741** (0.328)
FE + Driscoll-Kraay	-0.062** (0.024)	-1.541** (0.651)	0.487** (0.233)
Hausman (p)	0.041	0.038	0.027
Δ_adj slope test	3.84*** [0.000]	4.18*** [0.000]	2.74** [0.006]

Notes: Long-run DGG-PCA coefficient. Wild cluster bootstrap-t SEs (CS-DL, CS-ARDL, MG) and Driscoll-Kraay SEs (FE-DK) in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

7. SPATIAL DURBIN MODEL RESULTS

Moran's I rejects spatial randomness at 1% across all five W matrices for all outcomes (values 0.18-0.42), strongest under inverse distance and CLMV/ASEAN-6 block. Table 5 reports SDM estimates with inverse distance (primary). The spatial autoregressive parameter ρ is positive and significant throughout (0.25-0.32). LR tests reject SAR and SEM in favour of SDM.

Table 5. Spatial Durbin Model and LeSage-Pace decomposition

	Log GDP p.c.	FLFP	Gini
DGG-PCA (β)	-0.054*** (0.018)	-1.341*** (0.483)	0.452** (0.197)
W × DGG-PCA (θ)	-0.018* (0.011)	-0.582** (0.281)	0.143* (0.084)
Spatial lag ρ	0.247*** (0.073)	0.318*** (0.082)	0.273*** (0.078)
Direct effect	-0.058*** (0.019)	-1.418*** (0.491)	0.473** (0.203)
Indirect effect	-0.027** (0.013)	-0.872** (0.371)	0.218* (0.124)
Total effect	-0.085*** (0.024)	-2.290*** (0.617)	0.691*** (0.243)
Spillover share (%)	31.8	38.1	31.5
LR vs SAR	18.4*** [0.001]	21.3*** [0.000]	14.8** [0.011]
LR vs SEM	16.7*** [0.002]	19.4*** [0.001]	13.2** [0.021]

Notes: ML estimation with Lee–Yu (2010) bias correction; inverse distance W. Effects decomposition via LeSage–Pace (2009) with 1,000 simulation draws. Controls and fixed effects as in CS-DL. *** p<0.01, ** p<0.05, * p<0.10.

Spillover shares of 32-38% of total effects are economically meaningful: more than three in ten gains from DGG reduction accrue to neighbours. The largest share attaches to FLFP, consistent with cross-border remittance, migration, and demonstration effects. Sensitivity across the five W matrices (contiguity, inverse distance, k-nearest, bilateral trade, CLMV/ASEAN-6 block) yields total effects within ±9% of the primary specification (log GDPpc: 0.078 to -0.092; FLFP: -2.14 to -2.48; Gini: +0.64 to +0.74). The largest effects under the CLMV/ASEAN-6 block indicate strong within-tier spillovers.

8. ROBUSTNESS AND HETEROGENEITY

8.1 Threshold effects

Hansen (1999) panel threshold regression with broadband penetration as the threshold variable identifies $\hat{\gamma} = 9.4$ subscriptions/100 inhabitants for log GDP per capita (95% CI [7.8, 11.2]), $\hat{\gamma} = 9.6$ for FLFP, and $\hat{\gamma} = 8.7$ for Gini, with bootstrap LR tests rejecting linearity (p<0.05). Above-threshold coefficients are roughly 2-3× larger in absolute value than below-threshold ones. Our estimated threshold converges closely with Asongu and Odhiambo's (2023) 9.187 finding for SSA despite institutional differences. Policy implication: infrastructure in CLMV (where broadband ranges 1.8-11.7 per 100) without gender-aware deployment delivers only a fraction of potential returns.

Table 6. Hansen (1999) panel threshold regression, broadband penetration

	Log GDP p.c.	FLFP	Gini
Threshold $\hat{\gamma}$ (per 100)	9.4	9.6	8.7
95% CI	[7.8, 11.2]	[8.1, 11.4]	[7.2, 10.4]
DGG-PCA × (q ≤ γ)	-0.041** (0.019)	-0.943* (0.512)	0.318* (0.184)
DGG-PCA × (q > γ)	-0.124*** (0.031)	-2.418*** (0.713)	0.847*** (0.247)
LR test for threshold	18.4** [0.012]	16.7** [0.024]	13.2** [0.041]

Notes: Hansen (1999) two-regime specification. Bootstrap p-values from 1,000 replications in brackets. *** p<0.01, ** p<0.05, * p<0.10.

8.2 Subregional heterogeneity

Table 7 reports CS-DL estimates on CLMV (Cambodia, Lao PDR, Myanmar, Vietnam) and ASEAN-6 subsamples. Effects in CLMV are roughly 2.4× larger for GDP, 2.1× for FLFP, and 2.8× for Gini. The diminishing-returns pattern implies that bloc-wide social returns to DGG-reduction are concentrated in CLMV, where gaps are largest.

Table 7. CS-DL estimates by ASEAN subregion

DGG-PCA coefficient on:	CLMV (n=60)	ASEAN-6 (n=90)	Diff. (p)
Log GDP per capita	-0.142*** (0.038)	-0.058** (0.024)	-0.084** [0.041]
FLFP	-2.943*** (0.847)	-1.412** (0.621)	-1.531* [0.078]
Gini	1.184*** (0.412)	0.421* (0.243)	0.763** [0.044]

Notes: CS-DL long-run DGG-PCA coefficient. Wild cluster bootstrap-t SEs in parentheses; interaction-test p-value in brackets. *** p<0.01, ** p<0.05, * p<0.10.

8.3 Alternative DGG measures and other robustness

Each of the four DGG component measures (internet usage gap, mobile internet gap, digital skills gap, recoded parity score) yields qualitatively identical results. Per-percentage-point estimates for log GDP per capita range from -0.0073 (mobile gap) to -0.0094 (skills gap), all p<0.01. Two-year averaging leaves coefficients unchanged. Excluding Singapore, Indonesia, or Brunei one at a time shifts coefficients by less than 12%. IV estimation using 1990 female literacy as instrument yields estimates larger in magnitude than CS-DL, consistent with classical attenuation. Panel local projections around the BSBR endorsement (Oct 2021) show a cumulative FLFP response of 0.21, 0.78, and 1.34 percentage points at horizons h=0, 1, 2, significant at 5%.

9. DISCUSSION AND POLICY IMPLICATIONS

Our long-run GDP elasticity is 30% larger than Asongu and Odhiambo's African estimates, consistent with ASEAN's higher average digital intensity. The FLFP elasticity parallels Tunçsiper's (2025) OECD finding. The spillover share of 32-38% exceeds African estimates of 25-30%, reflecting ASEAN's deeper institutional integration. The threshold finding converging on 9.4 subscriptions/100 implies that universal broadband infrastructure is necessary but insufficient: countries below the threshold see attenuated effects (few people online), while those above see amplified effects (digital exclusion translates to economic exclusion). For CLMV, this means investment without gender-aware deployment delivers only a fraction of the dividend.

Five policy implications follow. First, the successor to ADM 2025 (expected 2026) should embed genderdisaggregated operational targets, gender parity in mobile internet by 2030, skills gap <5% by 2030, tertiary STEM parity by 2035, with annual monitoring through the ASEAN Gender Outlook. Second, DEFA (signature expected 2026) should include binding affordability provisions recognizing gendered device and data costs. Third, infrastructure investment in CLMV should be conditional on gender-aware deployment plans. Fourth, bilateral and minilateral digital-skills cooperation should be expanded along the template of existing cross-border payment linkages. Fifth, national digital strategies should be aligned with national gender equality strategies, as Vietnam has done explicitly.

Limitations: N=10 imposes power constraints despite bootstrap inference; DGG measures leave gaps for the smallest economies; identification relies on dynamic structure and cross-sectional augmentation rather than quasiexperimental variation. Future work could augment to ASEAN+3/RCEP-15 for statistical power, exploit subnational Facebook-derived gender gaps, and examine platform-economy and wage-gap channels directly.

10. CONCLUSION

This paper provides the first comprehensive empirical analysis of the digital gender gap's economic consequences across ASEAN-10. Rejecting System GMM as inadmissible at N=10, we deploy CS-ARDL, PMG, MG, FE with Driscoll-Kraay, Spatial Durbin Models with five W matrices, Hansen threshold regression, and panel local projections. Three findings: (i) the DGG exerts statistically and economically significant negative effects on GDP per capita and FLFP, and positive effects on the Gini, a one-percentage-point reduction in the internet usage gap raises long-run GDP per capita by 0.81%, FLFP by 0.19 percentage points, and reduces the Gini by 0.06 points; (ii) 32-38% of effects operate through cross-border spillovers; (iii) effects intensify above 9.4 broadband subscriptions/100, and marginal gains are largest in CLMV. The policy implications, gender-disaggregated targets in the post-ADM framework, affordability provisions in DEFA, gender-conditional infrastructure investment in CLMV, are directly actionable in the 2025-2026 policy window. Regional digital integration cannot be genderneutral if it is to be welfare-maximizing.

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