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Push–Pull Factors and Entrepreneurial Activity: Digital Access, Human Capital, and Self-Employment in Indonesia and the United Kingdom

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ABSTRACT

Entrepreneurial activity is widely regarded as a central driver of economic development through its contribution to innovation, employment creation, and productivity growth. This study examines the long-run and short-run relationships between internet usage, human capital, gross domestic product (GDP) per capita, unemployment, and self-employment as a proxy for entrepreneurial activity in Indonesia and the United Kingdom, within the push–pull entrepreneurship framework. Annual time-series data covering 1994–2023 for Indonesia and 2001–2023 for the United Kingdom are analyzed using country-specific Autoregressive Distributed Lag (ARDL) bounds testing models. The results reveal pronounced heterogeneity in the long-run determinants of self-employment across the two economies. In Indonesia, internet usage is positively and significantly associated with self-employment in the long run ($\beta = 0.223$, $p < 0.01$), whereas human capital ($\beta = -0.493$, $p < 0.10$) and GDP per capita ($\beta = -0.006$, $p < 0.01$) are negatively associated with self-employment, with a rapid error-correction adjustment of 96.7 percent per period. In the United Kingdom, unemployment is the only variable exhibiting a statistically significant long-run association with self-employment ($\beta = 0.892$, $p < 0.10$), while internet usage, human capital growth, and GDP per capita show no significant long-run relationship; instead, internet usage, human capital growth, and unemployment exert significant short-run effects, with a comparatively gradual adjustment of 31.7 percent per period. The novelty of this study lies in providing the first direct, country-specific ARDL comparison of a developing and a developed economy within a unified push–pull framework, demonstrating that identical macroeconomic factors operate through opposing directions of association and fundamentally different temporal horizons depending on a country's stage of economic development. Given the observational nature of the study and the use of self-employment as a proxy for entrepreneurial activity, these findings should be interpreted as macro-level associations rather than definitive causal effects.

Keywords: Entrepreneurial Activity; Self-Employment; Internet Usage; Human Capital; ARDL.

1. INTRODUCTION

Entrepreneurship is widely recognized as a key contributor to economic development through its association with innovation, employment creation, productivity growth, and structural transformation. It also enhances economic resilience by encouraging business creation and supporting structural transformation. However, entrepreneurial activity is influenced by a broad range of economic, institutional, and structural conditions, including labour market opportunities, income levels, human capital, institutional quality, and digital access. Although entrepreneurship is a multidimensional concept encompassing innovation, opportunity recognition, and business creation, comparable macro-level measures are often unavailable across countries and over extended periods. Consequently, empirical research has widely employed self-employment as a proxy for entrepreneurial activity because of its consistent availability in international datasets (Blanchflower, 2000; Parker & Robson, 2004; Bjuggren et al., 2012; OECD, 2021). Nevertheless, self-employment is an imperfect proxy, as it does not distinguish between opportunity-driven and necessity-driven entrepreneurship and therefore

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should be interpreted as an aggregate indicator of entrepreneurial activity rather than a direct measure of entrepreneurial motivation (Bjuggren et al., 2012).

One influential perspective, the push–pull framework, explains entrepreneurial entry through necessity-driven ("push") versus opportunity-driven ("pull") motivations (Gilad & Levine, 1986; Dawson & Henley, 2012). Push factors unemployment, job insecurity, limited income, drive individuals toward self-employment as an alternative livelihood, while pull factors market opportunities, innovation potential, financial reward, independence attract new business creation (Giacomin et al., 2023). Motivations are, however, often more complex than this binary suggests, involving multiple overlapping factors (Giacomin et al., 2023). The framework thus serves as a conceptual foundation for this study, while self-employment remains an aggregate proxy rather than a direct measure of entrepreneurial motivation (Bjuggren et al., 2012).

Building on the push–pull framework, entrepreneurial activity is further shaped by human capital and technological conditions. Human Capital Theory holds that education strengthens individuals' capacity to recognize and pursue entrepreneurial opportunities (Becker, 1964), while the opportunity recognition perspective emphasizes the ability to discover and exploit them (Shane & Venkataraman, 2000). Digital technologies reinforce this by reducing information asymmetries and transaction costs and expanding market access (Nambisan, 2017; Camps et al., 2026), though without directly shaping motivation. Macroeconomic conditions matter too: favourable conditions encourage opportunity-driven business creation, while weak labour markets push individuals toward self-employment as an alternative income source (Martínez-Cañas et al., 2023). Accordingly, digital access, human capital, economic development, and unemployment are expected to shape self-employment differently across contexts.

Indonesia and the United Kingdom provide two contrasting economic settings for examining the macro-level correlates of self-employment. Indonesia is a rapidly developing economy characterized by a large labour force, expanding digital adoption, and a relatively high prevalence of self-employment, whereas the United Kingdom represents a mature, high-income economy with advanced digital infrastructure, higher educational attainment, and more established labour market institutions. These contrasting structural characteristics provide a valuable comparative setting for examining whether the associations between digital access, human capital, macroeconomic conditions, and self-employment differ across economies at different stages of development. Rather than presuming that self-employment reflects either necessity- or opportunity-driven entrepreneurship, this study examines whether common macroeconomic factors are associated with self-employment across two contrasting economic and institutional contexts.

Recent empirical research has expanded the traditional push–pull perspective by demonstrating that entrepreneurial behaviour is influenced by a combination of economic, institutional, and individual factors rather than by a single dominant motivation. For example, Martínez-Cañas et al. (2023) found that pull factors influence entrepreneurial engagement primarily through opportunity awareness, whereas push factors are more closely associated with perceptions of risk and limited employment alternatives. Similarly, Giacomin et al. (2023) show that entrepreneurial decisions are often driven by multiple and overlapping motivations, suggesting that the conventional distinction between necessity-driven and opportunity-driven entrepreneurship may oversimplify entrepreneurial behaviour. Collectively, these studies suggest that entrepreneurial activity is shaped by multiple economic and institutional conditions rather than by a single dominant motivation, where digital access, human capital, and labour market conditions jointly shape the environment in which self-employment occurs.

Evidence from recent entrepreneurship research further suggests that entrepreneurial outcomes vary considerably across different economic and institutional settings. For instance, Yu and Lu (2023) show that both push and pull factors influence entrepreneurial engagement beyond traditional self-employment by shaping individuals' career choices and perceptions of innovation opportunities. Likewise, Batz Liñeiro et al. (2024) report that opportunity-driven entrepreneurs generally exhibit stronger entrepreneurial intentions, higher growth aspirations, and greater innovation orientation than necessity-driven entrepreneurs. Earlier evidence by Block and Sandner (2009) also indicates that opportunity- and necessity-driven entrepreneurs may experience different business trajectories and survival outcomes over time. Although these studies advance understanding of entrepreneurial motivations and outcomes, they primarily rely on individual-level measures that directly capture entrepreneurial motives, intentions, or business characteristics. Consequently, their findings are not directly comparable to macro-level analyses based on internationally consistent self-employment data. Accordingly, the present study employs self-employment as a macro-level proxy for entrepreneurial activity and examines how macroeconomic factors are associated with self-employment across two contrasting economic contexts.

Despite growing interest in entrepreneurship research, three important gaps persist. First, existing studies predominantly examine entrepreneurial activity within single-country settings, limiting evidence on whether macro-level determinants of self-employment operate similarly across different stages of economic development. Second, digital access, human capital, unemployment, and economic development are typically analysed in isolation or at the micro level, with few studies integrating them within a unified macro-level push–pull framework using long-term time-series data. Third, the absence of consistent cross-country motivation measures leaves self-employment underexplored as a comparative proxy for entrepreneurial activity between developed and developing economies. This study addresses these gaps by applying the push–pull framework to compare Indonesia and the United Kingdom over an extended annual time-series period.

Against this background, the present study contributes to the entrepreneurship literature by providing a comparative macro-level analysis of the relationships between digital access, human capital, selected macroeconomic factors, and self-employment in Indonesia and the United Kingdom. By comparing two economies with distinct levels of economic development, labour market structures, and digital transformation, the study examines whether these macroeconomic factors exhibit different short-run and long-run relationships with self-employment across contrasting economic contexts. To achieve this objective, the study employs the Autoregressive Distributed Lag (ARDL) approach, which enables the simultaneous estimation of both short-run dynamics and long-run equilibrium relationships. Rather than attempting to identify entrepreneurial motivations directly, self-employment is adopted as a comparable macroeconomic proxy for entrepreneurial activity and interpreted accordingly. Specifically, this study addresses the following research questions: (i) What are the short-run and long-run relationships between internet usage and self-employment in Indonesia and the United Kingdom? (ii) What are the short-run and long-run relationships between human capital and self-employment in the two countries? (iii) What are the short-run and long-run relationships between GDP per capita, unemployment, and self-employment in Indonesia and the United Kingdom? By addressing these questions, the study extends the comparative entrepreneurship literature by providing empirical evidence on the macroeconomic determinants of self-employment across developed and developing economies, while offering policy insights for promoting entrepreneurship and digital transformation under different economic conditions.

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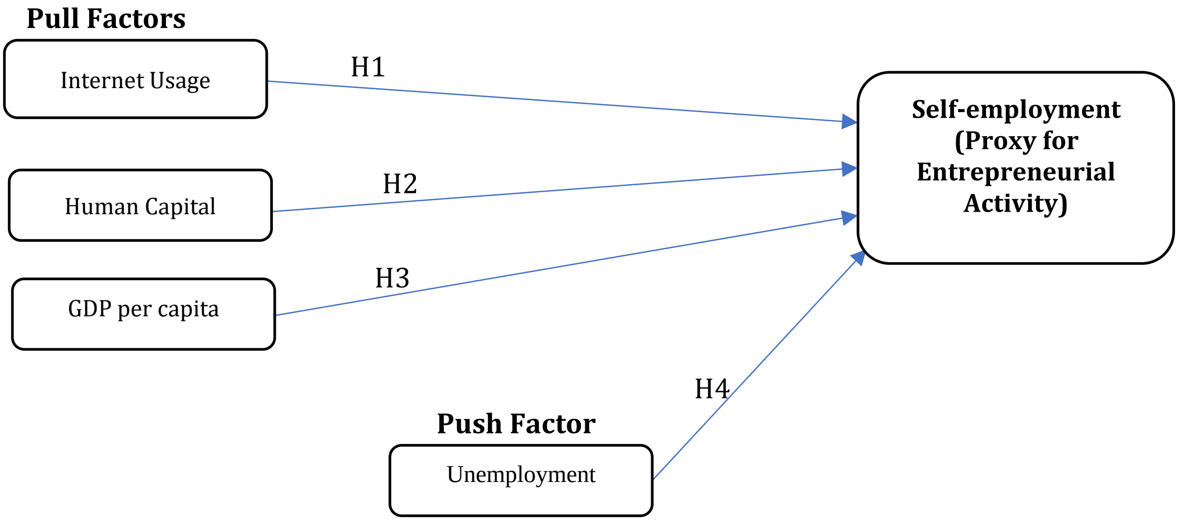

Figure 1. Conceptual Framework of the Study

Based on the push–pull framework and the entrepreneurship literature, this study develops four hypotheses regarding the relationships between digital access, human capital, macroeconomic conditions, and self-employment. As a key pull factor, digital access enhances entrepreneurial ecosystems by reducing information asymmetries, lowering transaction costs, facilitating market access, and expanding opportunity recognition Nambisan (2017). Previous studies further suggest that greater internet usage is associated with higher entrepreneurial participation by creating a more supportive environment for self-employment (Martínez-Cañas et al., 2023; Camps et al., 2026). Accordingly, the following hypothesis is proposed:

H1: Internet usage is positively associated with self-employment.

Human Capital Theory suggests that education enhances individuals' knowledge, skills, and capabilities, thereby improving their ability to identify and exploit entrepreneurial opportunities (Becker, 1964). Similarly, the opportunity recognition perspective argues that entrepreneurship depends on individuals' capacity to discover and evaluate opportunities, which is strengthened by higher levels of human capital Shane and Venkataraman (2000). Consistent with these theoretical arguments, recent empirical evidence indicates that human capital promotes entrepreneurial competencies and entrepreneurial engagement (Giacomin et al., 2023). Accordingly, the following hypothesis is proposed:

H2: Human capital is positively associated with self-employment.

Economic development influences entrepreneurial activity by shaping market opportunities, resource availability, and the relative attractiveness of self-employment. Higher levels of economic development generally improve access to knowledge, finance, infrastructure, and markets, thereby creating a more supportive environment for entrepreneurial activity (Acs et al., 2014; Audretsch & Keilbach, 2004). However, previous studies report heterogeneous findings, suggesting that the direction and magnitude of this relationship may vary across different economic and institutional contexts. Accordingly, the following hypothesis is proposed:

H3: GDP per capita is significantly associated with self-employment, although the direction of this relationship may vary across different economic contexts.

Within the push–pull framework, unemployment is widely recognized as a push factor that encourages individuals to enter self-employment when wage-employment opportunities are limited (Gilad & Levine, 1986). Recent empirical evidence further suggests that labour market constraints increase entrepreneurial engagement through necessity-driven mechanisms

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Martínez-Cañas et al. (2023). Although the magnitude of this relationship may vary across different economic and institutional contexts, the prevailing theoretical expectation is that higher unemployment is associated with greater self-employment. Accordingly, the following hypothesis is proposed:

H4: Unemployment is positively associated with self-employment.

2. METHOD

2.1 Research Design, Data Source, and Study Period

This study adopts a quantitative comparative design using annual secondary time-series data from the World Bank's World Development Indicators (WDI), a consistent and internationally comparable source. Indonesia and the United Kingdom were selected as contrasting cases a developing economy with historically necessity-driven self-employment versus a developed economy with opportunity-driven entrepreneurship providing a meaningful setting to examine whether digital access, human capital, and economic development relate to self-employment differently across contexts. The Indonesian sample covers 1994–2023 (30 annual observations) and the UK sample covers 2001–2023 (23 annual observations), based on data availability; these are reduced to 28 and 22 observations, respectively, in the ARDL estimation due to first-differencing and lag adjustments. Human capital is measured as tertiary enrolment in level form for Indonesia and as its growth rate for the UK, following the stationarity assessment, without affecting comparability since each country is estimated separately. These periods, spanning major digital and economic transformations, suit the ARDL approach, which accommodates a mix of I(0)/I(1) variables and estimates both short- and long-run dynamics.

2.2 Variables and Measurement

The dependent variable is the self-employment rate (% of total employment), used as a macroeconomic proxy for entrepreneurial activity: since internationally comparable indicators capturing entrepreneurship's full dimensions (innovation, opportunity recognition, venture growth) remain limited, self-employment is widely adopted in cross-country research (Parker & Robson, 2004; Bjuggren et al., 2012), though it does not distinguish necessity- from opportunity-driven entrepreneurship. The explanatory variables are human capital (tertiary school enrolment, % gross in level form for Indonesia, annual growth rate for the UK following the stationarity assessment in Section 2.1), internet usage (% of population, reflecting digital connectivity), GDP per capita (constant 2015 US$, reflecting economic development), and the unemployment rate (% of labour force, reflecting labour market pressure toward self-employment). All variables retain their original units except UK human capital, expressed as a growth rate; Table 1 summarizes full definitions and sources.

Table 1. Definition and Measurement of Variables

No.	Variable	Conceptual Definition	Operational Measure	Transformation	Data Source (WDI Indicator)
1	Entrepreneurial Activity	The extent of independent economic activity undertaken by individuals within the labour market.	Self-employment (% of total employment).	None	World Bank, WDI (SL.EMP.SELF.ZS)

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No.	Variable	Conceptual Definition	Operational Measure	Transformation	Data Source (WDI Indicator)
2	Human Capital	The stock of knowledge, skills, and competencies acquired through higher education that enhance individuals' productive and entrepreneurial capabilities.	Gross tertiary school enrolment (% gross).	Indonesia: Original series. United Kingdom: Annual logarithmic growth rate of tertiary school enrolment following the stationarity assessment.	World Bank, WDI (SE.TER.ENRR)
3	Internet Usage	The level of digital connectivity that facilitates access to information, communication, and entrepreneurial opportunities.	Individuals using the Internet (% of population).	None	World Bank, WDI (IT.NET.USER.ZS)
4	GDP per capita	The level of economic development and productive capacity that shapes entrepreneurial opportunities and incentives.	GDP per capita (constant 2015 US$).	None	World Bank, WDI (NY.GDP.PCAP.KD)
5	Unemployment	Labour market conditions measured by the proportion of the labour force actively seeking but unable to obtain employment.	Unemployment rate (% of total labour force).	None	World Bank, WDI (SL.UEM.TOTL.ZS)

Source: World Bank Indicators

2.3 Empirical Model and Estimation Strategy

Separate country-specific models were estimated for Indonesia and the United Kingdom (UK) to account for differences in economic development, labour market structures, and entrepreneurial environments. Estimating separate models allows the analysis to examine whether the macroeconomic determinants of self-employment differ between a developing and a developed economy while avoiding the restrictive assumption of homogeneous parameter estimates across countries. The long-run ARDL models are specified as follows:

$$SELFEMP_{ID,t} = \beta_0 + \beta_1 HC_{ID,t} + \beta_2 INT_{ID,t} + \beta_3 GDPPC_{ID,t} + \beta_4 UNEMP_{ID,t} + \varepsilon_t \quad (1)$$

$$SELFEMP_{UK,t} = \beta_0 + \beta_1 HCG_{UK,t} + \beta_2 INT_{UK,t} + \beta_3 GDPPC_{UK,t} + \beta_4 UNEMP_{UK,t} + \varepsilon_t \quad (2)$$

where SELFEMP denotes the self-employment rate, HC represents tertiary school enrolment (% gross), HCG is the annual logarithmic growth rate of tertiary school enrolment, INT denotes internet usage (% of the population), GDPPC represents GDP per capita (constant 2015 US$), UNEMP is the unemployment rate (% of the total labour force), and ε is the random disturbance term. Following the stationarity assessment described in Section 2.1, the United Kingdom model employs the annual logarithmic growth rate of tertiary school enrolment, calculated as

$$HCG_t = 100 * [\ln(HC_t) - \ln(HC_{t-1})] \quad (3)$$

where the terms denote the annual logarithmic growth rate of human capital and gross tertiary enrolment in the current and preceding year; multiplying by 100 yields an approximate percentage growth rate a scale-independent, stationary measure suitable for ARDL estimation.

Stationarity was assessed using ADF and PP tests, complemented by KPSS and Ng–Perron for robustness; because these tests differ in null hypotheses and finite-sample properties, ADF/PP served as the primary basis for classifying variables as I(0) or I(1), with KPSS/Ng–Perron confirming these classifications and ruling out I(2) variables.

The ARDL bounds testing approach (Pesaran, Shin & Smith, 2001) was adopted for its suitability with mixed I(0)/I(1) variables and small samples. Given the limited sample sizes (28 observations for Indonesia, 22 for the UK), significance was evaluated using Narayan's (2005) finite-sample critical values. Optimal lag structure was selected via AIC in EViews 13, with a maximum lag of two per variable, yielding ARDL (2,2,1,0,0) for Indonesia and ARDL (1,1,2,1,1) for the UK. Reflecting each dataset's deterministic properties, Case 4 (restricted trend, unrestricted intercept) was used for Indonesia and Case 2 (restricted intercept, no trend) for the UK. Following confirmed cointegration, long-run coefficients and the ECM were estimated as:

The short-run error correction specification for Indonesia is expressed as

$$\begin{aligned}\Delta SELFEMP_{ID,t} = \quad & \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \Delta SELFEMP_{ID,t-i} + \sum_{j=0}^{q_1} \beta_j \, \Delta HC_{ID,t-j} \\ & + \sum_{k=0}^{q_2} \gamma_k \, \Delta INT_{ID,t-k} + \sum_{l=0}^{q_3} \delta_l \, \Delta GDPPC_{ID,t-l} \\ & + \sum_{m=0}^{q_4} \phi_m \, \Delta UNEMP_{ID,t-m} + \lambda ECT_{ID,t-1} + u_t\end{aligned} \tag{4}$$

Similarly, the short-run ECM for the United Kingdom is

$$\begin{aligned}\Delta SELFEMP_{UK,t} = \quad & \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \Delta SELFEMP_{UK,t-i} + \sum_{j=0}^{q_1} \beta_j \, \Delta HCG_{UK,t-j} \\ & + \sum_{k=0}^{q_2} \gamma_k \, \Delta INT_{UK,t-k} + \sum_{l=0}^{q_3} \delta_l \, \Delta GDPPC_{UK,t-l} \\ & + \sum_{m=0}^{q_4} \phi_m \, \Delta UNEMP_{UK,t-m} + \lambda ECT_{UK,t-1} + u_t\end{aligned} \tag{5}$$

where Δ is the first-difference operator, ECT_{t-1} is the lagged error correction term, and λ is the speed of adjustment; a negative, significant λ confirms long-run equilibrium. Lag orders were selected via AIC. Model adequacy was verified using the Breusch–Godfrey LM (serial correlation), Breusch–Pagan–Godfrey (heteroskedasticity), ARCH LM, Jarque–Bera (normality), and Ramsey RESET (specification) tests.

3. RESULTS AND DISCUSSION

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3.1 Results

Table 2. Descriptive Statistics for Indonesia

Variable	Obs.	Mean	Std. Dev.	Min	Max
Self-employment (%)	30	59.457	5.825	51.499	67.274
Human Capital (%)	30	24.154	10.787	10.496	44.881
Internet Usage (% of population)	30	17.627	21.877	0.001	69.208
GDP per capita (Constant US$)	30	2,701.267	796.297	1,767.515	4,192.652
Unemployment rate (%)	30	5.299	1.407	3.308	8.060

Source: Author's calculations
Notes: *The sample consists of 30 annual observations covering 1994–2023. Standard deviation measures the dispersion of each variable around its mean.*

Table 2 shows internet usage and GDP per capita exhibiting the widest variation over 1994–2023, reflecting Indonesia's rapid digital and economic expansion, while self-employment and unemployment remained comparatively stable.

Table 3. Pearson Correlation Matrix (Indonesia, 1994–2023)

Variable	(1)	(2)	(3)	(4)	(5)
(1) Self-employment (%)	1.000	-0.936	-0.780	-0.941	0.610
(2) Human Capital (%)	-0.936	1.000	0.933	0.990	-0.670
(3) Internet Usage (% of population)	-0.780	0.933	1.000	0.934	-0.664
(4) GDP per capita (Constant US$)	-0.941	0.990	0.934	1.000	-0.687
(5) Unemployment rate (%)	0.610	-0.670	-0.664	-0.687	1.000

Source: Author's calculations
Notes: *The table reports Pearson correlation coefficients based on 30 annual observations (1994–2023). Correlation coefficients range from −1 to +1, where values closer to ±1 indicate stronger linear relationships between variables.*

Table 3 shows self-employment strongly and negatively correlated with human capital, internet usage, and GDP per capita, but positively with unemployment. The high correlation among explanatory variables (notably human capital–GDP per capita, r = 0.990) signals potential multicollinearity, formally assessed via VIF in Table 4.

Table 4. Variance Inflation Factor (VIF) Analysis for Multicollinearity Assessment

Multicollinearity Test (VIF)	Centered VIF
Human Capital (%)	51.914
Internet Usage (% of population)	8.141
GDP per capita (Constant US$)	54.614
Unemployment rate (%)	1.931

Source: Author's calculations

Note: *VIF > 10 indicates severe multicollinearity. Robustness checked via ARDL (Case 4) excluding collinear variables separately.*

Table 4 shows severe multicollinearity between human capital and GDP per capita (VIF > 10), reflecting their shared association with long-run development, while internet usage and unemployment remain within acceptable limits. Robustness checks excluding each collinear variable separately (Case 4) are reported in Tables 5 and 6.

Table 5. Robustness Analysis of the Long-Run ARDL Estimates

Variable	Baseline Model	Excluding GDP per capita	Excluding Human Capital
Human Capital (%)	−0.493* (0.0580)	−0.433 (0.2788)	—
Internet Usage (% of population)	0.223*** (0.0000)	0.217*** (0.0002)	0.194*** (0.0000)
GDP per capita (Constant US$)	−0.0056*** (0.0067)	—	−0.0059*** (0.0008)
Unemployment (%)	−0.052 (0.9112)	0.770 (0.2548)	0.632** (0.0144)
Trend	−0.026 (0.9204)	−0.500 (0.1921)	−0.462*** (0.0006)

Source: Author's calculations
Notes: *Values in parentheses are p-values. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

Table 6. Error Correction Estimates and Model Diagnostics

Statistic	Baseline Model	Excluding GDP per capita	Excluding Human Capital
Error Correction Term (ECTt−1)	−0.967*** (0.0000)	−0.699*** (0.0000)	−1.158*** (0.0000)
Speed of Adjustment (%)	96.7	69.9	115.8
R^2	0.725	0.625	0.714
F-statistic	11.596***	7.341***	10.998***
Observations	28	28	28

Source: Author's calculations
Notes: *p-values in parentheses. ***, **, * = significant at 1%, 5%, 10%.*

Tables 5 and 6 report robustness checks excluding GDP per capita and human capital separately. Internet usage's positive, significant long-run coefficient remains stable across specifications (0.194–0.223), and the error correction term stays negative and significant throughout, confirming the main findings are not driven by the multicollinearity flagged in Table 4.

Table 7. Unit Root Test Results for Indonesia

Variable	ADF (Level)	ADF (1st Difference)	PP (Level)	PP (1st Difference)	Order of Integration
Self-employment (%)	-1.3458 (0.8554)	-3.6371** (0.0452)	-1.3458 (0.8554)	-4.5020*** (0.0066)	I(1)
Human Capital (%)	-1.1993 (0.8919)	-4.5115*** (0.0068)	-1.1126 (0.9094)	-4.7722*** (0.0035)	I(1)
Internet Usage (%)	-1.8885 (0.6327)	-3.2883* (0.0888)	0.4614 (0.9986)	-3.3318* (0.0818)	I(1)
GDP per capita (constant 2015 US$)	-1.5582 (0.7846)	-4.5074*** (0.0066)	-1.6438 (0.7499)	-4.4726*** (0.0071)	I(1)

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Variable	ADF (Level)	ADF (1st Difference)	PP (Level)	PP (1st Difference)	Order of Integration
Unemployment (%)	-3.1002 (0.1270)	-5.2725*** (0.0011)	-1.8500 (0.6540)	-5.3163*** (0.0010)	I(1)

Source: Author's calculations
Notes: *Test statistics with MacKinnon p-values in parentheses. Estimated with intercept and trend; ADF uses SIC lag selection, PP uses Newey–West (Bartlett kernel). H0: unit root. *, **, *** = significant at 10%, 5%, 1%.*

Both tests were estimated with intercept and trend, consistent with the macroeconomic nature of the series. As shown in Table 7, all variables are non-stationary at levels but stationary after first differencing significant at 1–5% except internet usage (10%) confirming that all variables are I(1) with none I(2), satisfying the ARDL bounds-testing requirement.

Table 8. Additional Stationarity Tests (KPSS and Ng–Perron) for Indonesia

Variable	KPSS (Level)	KPSS (1st Diff.)	Ng–Perron (Level)	Ng–Perron (1st Diff.)	Conclusion
Self-employment (%)	0.095	0.139	Unit Root	Stationary	I(1)
Human Capital (%)	0.170	0.076	Unit Root	Stationary	I(1)
Internet Usage (%)	0.182	0.106	Stationary	Stationary	I(0)/I(1)*
GDP per capita (constant 2015 US$)	0.168	0.122	Unit Root	Stationary	I(1)
Unemployment (%)	0.150	0.100	Unit Root	Stationary	I(1)

Source: Author's calculations
Notes: *KPSS: intercept + trend, Newey–West (Bartlett kernel), H0: stationarity. Ng–Perron: intercept + trend, Spectral GLS detrending, SIC lag selection, H0: unit root.*

Table 8 reports KPSS and Ng–Perron tests as robustness checks against ADF/PP. As these tests differ in null hypothesis and finite-sample properties, ADF/PP results were treated as primary, with KPSS/Ng–Perron confirming that all variables remain I(0) or I(1) satisfying the ARDL integration requirement.

Table 9. ARDL Bounds Test for Cointegration

ARDL Bounds Test for Cointegration	F-statistic	10%	5%	1%
Computed F-statistic	**6.0690**			
Lower Bound, I(0)		3.378	4.048	5.666
Upper Bound, I(1)		4.274	5.090	6.988

Source: Author's calculations.
Notes: *H0: no long-run relationship. Critical values from Narayan (2005), n = 30 (closest to actual n = 28). Case 4 specification (restricted trend, unrestricted intercept). Cointegration confirmed if F-statistic exceeds upper bound.*

As shown in Table 9, the computed F-statistic (6.069) exceeds the 5% upper bound, confirming cointegration among the variables at the 5% level and justifying estimation of the long-run ARDL coefficients and ECM.

Table 10. Long-Run ARDL Estimates for Self-Employment in Indonesia

Variables	Coefficient	Std. Error	t-Statistic	p-value
Human Capital (%)	-0.4930*	0.2471	-1.9953	0.0580
Internet Usage (%)	0.2234***	0.0314	7.1093	0.0000
GDP per capita (constant 2015 US$)	-0.0056***	0.0019	-2.9776	0.0067
Unemployment (%)	-0.0517	0.4587	-0.1128	0.9112

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Variables	Coefficient	Std. Error	t-Statistic	p-value
Trend	-0.0261	0.2581	-0.1010	0.9204

Source: Author's calculations.
Notes: *Dependent variable: Self-employment (% of total employment). Derived from the ARDL cointegrating equation, Case 4 (restricted trend, unrestricted intercept). ***, **, * = significant at 1%, 5%, 10%.*

As shown in Table 10, internet usage is positively and significantly associated with self-employment in the long run, while human capital and GDP per capita show significant negative associations the latter two counterintuitive given theoretical expectations. Unemployment and the trend term are not significant.

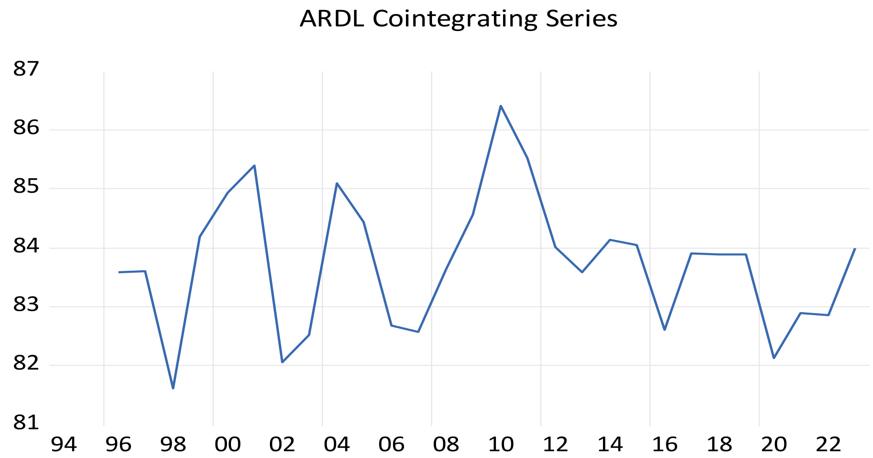

Figure 2. Long-Run Equilibrium Relationship Estimated from the ARDL Model for Indonesia

Figure 2 presents the estimated long-run equilibrium path obtained from the selected ARDL model for Indonesia. The equilibrium series exhibits moderate fluctuations over the sample period, reflecting changes in the underlying economic environment. Despite these short-term variations, the estimated long-run path remains stable without evidence of persistent divergence or structural instability. This visual evidence is consistent with the ARDL bounds test, which confirms the existence of a long-run cointegrating relationship among self-employment, human capital, internet usage, GDP per capita, and unemployment.

Table 11. Error Correction Model (Short-Run Dynamics)

Variables	Coefficient	Std. Error	t-Statistic	p-value
COINTEQ	-0.9670***	0.1409	-6.8647	0.0000
Δ Self-employment (-1)	0.4599***	0.1311	3.5087	0.0020
Δ Human Capital	-0.3192**	0.1407	-2.2695	0.0334
Δ Human Capital (-1)	0.5550***	0.1479	3.7515	0.0011
Δ Internet Usage	-0.0173	0.0584	-0.2964	0.7697

Source: Author's calculations.
Notes: *Δ = first difference; COINTEQ = error correction term. ***, **, * = significant at 1%, 5%, 10%.*

Table 11's error correction term is negative and highly significant, with about 96.7% of disequilibrium corrected within one period a rapid adjustment. In the short run, human capital's effect reverses sign between the contemporaneous and lagged terms, self-employment shows positive persistence, and internet usage is insignificant; GDP per capita and unemployment were excluded from the AIC-selected specification entirely.

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Table 12. Diagnostic Tests for the Estimated ARDL Model

Diagnostic Test	Null Hypothesis	Test Statistic	p-value	Decision
Breusch–Godfrey LM Test	No serial correlation	$\chi^2 = 2.702$	0.259	No serial correlation
Breusch–Pagan–Godfrey Test	Homoskedastic residuals	$\chi^2 = 16.640$	0.083	Homoskedasticity not rejected
ARCH LM Test	No ARCH effects	$\chi^2 = 1.102$	0.294	No ARCH effects
Jarque–Bera Normality Test	Residuals are normally distributed	JB = 0.541	0.763	Residuals are normally distributed
Ramsey RESET Test	Model is correctly specified	F = 0.081	0.780	No specification error

Source: Author's calculations.
Notes: *Obs*R^2 (Chi-square) statistics reported for LM/ARCH tests. $p > 0.05$ = fail to reject H0. All tests pass no serial correlation, heteroskedasticity, ARCH effects, non-normality, or misspecification.*

As shown in Table 12, the estimated ARDL model passes all diagnostic checks no serial correlation, heteroskedasticity, ARCH effects, non-normality, or specification error confirming the model's validity for reliable inference.

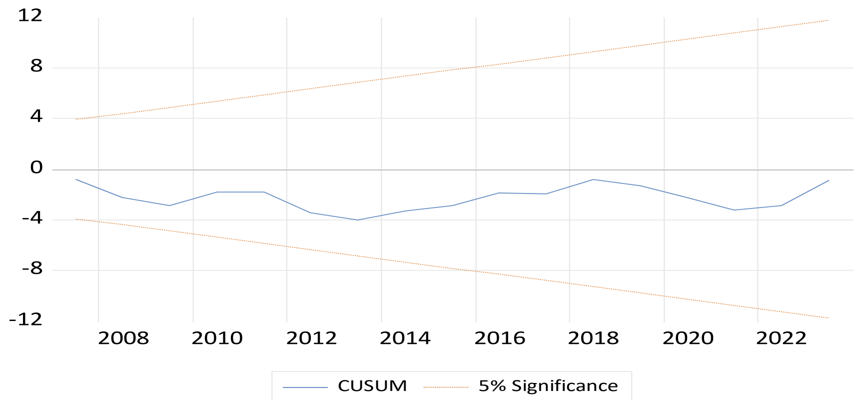

Figure 3. CUSUM Stability Test for the Indonesian ARDL Model
Notes: *The dashed lines represent the 5% significance bounds. Parameter stability is supported when the cumulative sum (CUSUM) statistic remains within the critical bounds throughout the sample period.*

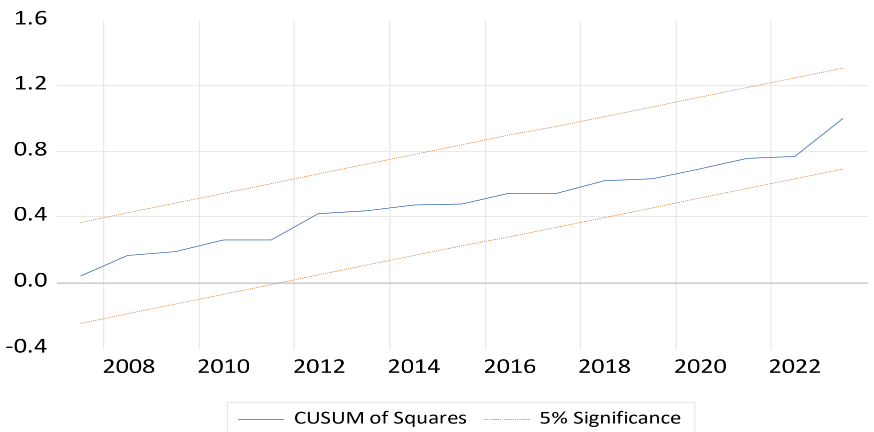

Figure 4. CUSUM of Squares (CUSUMSQ) Stability Test for the Indonesian ARDL Model

Notes: *The dashed lines represent the 5% significance bounds. Parameter stability is supported when the cumulative sum of squares (CUSUMSQ) statistic remains within the critical bounds throughout the sample period.*

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Parameter stability was assessed using CUSUM and CUSUMSQ tests (Figures 3–4); both statistics remain within the 5% critical bounds throughout the sample, confirming stable coefficients and no structural instability in the model.

Table 13. Descriptive Statistics of the Variables (United Kingdom, 2001–2023)

Variable	Obs.	Mean	Std. Dev.	Min	Max
Self-employment (%)	23	13.920	0.962	12.238	15.353
Human Capital Growth (%)	23	1.469	3.388	-4.096	10.061
Internet Usage (%)	23	81.648	15.667	33.481	96.197
GDP per capita (constant 2015 US$)	23	44,343.63	2,384.36	40,082.14	48,433.01
Unemployment (%)	23	5.513	1.471	3.657	8.279

Source: Author's calculations
Notes: Sample: 23 annual observations (2001–2023). Human Capital Growth = annual log growth rate of gross tertiary school enrolment (% gross), used for the UK following the stationarity assessment.

Table 13 shows self-employment remained stable over 2001–2023, while human capital growth exhibited the greatest volatility, reflecting fluctuating tertiary enrolment. Internet usage and GDP per capita confirm the UK's high-income, digitally advanced profile.

Table 14. Correlation Matrix of the Variables (United Kingdom, 2001–2023)

Variables	(1)	(2)	(3)	(4)	(5)
(1) Self-employment (%)	1.000				
(2) Human Capital Growth (%)	0.076	1.000			
(3) Internet Usage (%)	0.752	0.263	1.000		
(4) GDP per capita (constant 2015 US$)	0.514	0.298	0.732	1.000	
(5) Unemployment (%)	0.136	-0.413	0.069	-0.454	1.000

Source: Author's calculations
Notes: Pearson correlations based on 23 annual observations (2001–2023). All explanatory-variable pairs remain below 0.80, indicating low multicollinearity risk.

Table 14 shows self-employment moderately-to-strongly correlated with internet usage and GDP per capita, while human capital growth and unemployment show weak associations. The highest pairwise correlation (internet usage–GDP per capita) stays below 0.80, suggesting low multicollinearity confirmed by VIF in the next table.

Table 15. Variance Inflation Factor (VIF) Test

Variable	Centered VIF
Human Capital Growth (%)	1.462
Internet Usage (%)	4.536
GDP per capita (constant 2015 US$)	5.199
Unemployment (%)	2.957

Source: Author's calculations.
Notes: *Centered VIF < 10 indicates severe multicollinearity is unlikely.*

Table 15 shows all VIF values well below 10 (max 5.199 for GDP per capita), confirming multicollinearity is not a concern for the UK model.

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Table 16. Unit Root Test Results for the United Kingdom

Variable	ADF (Level)	ADF (1st Difference)	PP (Level)	PP (1st Difference)	Order of Integration
Self-employment (%)	-1.5815 (0.4756)	-3.8535*** (0.0083)	-1.6159 (0.4588)	-3.9068*** (0.0074)	I(1)
Human Capital Growth (%)	-2.6050 (0.1070)	-6.2340*** (0.0000)	-2.6050 (0.1070)	-6.1853*** (0.0001)	I(1)
Internet Usage (%)	-4.9122*** (0.0011)	-3.1352** (0.0385)	-9.1071*** (0.0000)	-3.0140** (0.0491)	I(0)/I(1)
GDP per capita (constant 2015 US$)	-1.8005 (0.3708)	-5.4746*** (0.0002)	-1.6256 (0.4540)	-7.0433*** (0.0000)	I(1)
Unemployment (%)	-2.6394 (0.1020)	-3.4356** (0.0206)	-1.2361 (0.6405)	-3.4590** (0.0196)	I(1)

Source: Author's calculations.
Notes: *Test statistics with MacKinnon p-values in parentheses. Estimated with intercept only; ADF uses SIC lag selection, PP uses Newey–West (Bartlett kernel). H0: unit root. *, **, *** = significant at 10%, 5%, 1%.*

Table 16 was estimated with intercept only. Self-employment, human capital growth, GDP per capita, and unemployment are I(1), while internet usage is stationary at level, I(0). This I(0)/I(1) mix, with no I(2) variables, satisfies the ARDL bounds-testing requirement.

Table 17. KPSS and Ng–Perron Unit Root Test Results for the United Kingdom

Variable	KPSS (Level)	KPSS (1st Diff.)	Ng–Perron (Level)	Ng–Perron (1st Diff.)	KPSS Classification	Ng–Perron Classification
Self-employment (%)	0.3996	0.3890	Unit Root	Stationary	I(0)	I(1)
Human Capital Growth (%)	0.3669	0.1540	Stationary	Stationary	I(0)	I(0)
Internet Usage (%)	0.6384	0.5131	Unit Root	Unit Root	I(1)	I(1)
GDP per capita (constant 2015 US$)	0.6235	0.2950	Unit Root	Stationary	I(1)	I(1)
Unemployment (%)	0.1868	0.1568	Stationary	Stationary	I(0)	I(0)

Source: Author's calculations.
Notes: Constant-only specification. KPSS H0: stationarity; Ng–Perron H0: unit root. Ng–Perron uses SIC lag selection; KPSS uses Newey–West (Bartlett kernel). Complementary robustness checks to Table 16.

Table 17's KPSS/Ng–Perron results show minor classification differences from Table 16, expected given their differing null hypotheses. ADF/PP remained the primary basis for integration order; critically, no variable is classified I (2), confirming the dataset satisfies the ARDL requirement.

Table 18. ARDL Bounds Test for Cointegration (United Kingdom)

ARDL Bounds Test for Cointegration	F-statistic	10%	5%	1%
Computed F-statistic	**4.3579**			
Lower Bound, I(0)		2.525	3.058	4.280
Upper Bound, I(1)		3.560	4.223	5.840

Source: Author's calculations.
Notes: *Critical values from Narayan (2005), n = 30 (closest to actual n = 22). Case 2 specification (restricted constant, no trend).*

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As shown in Table 18, the F-statistic (4.358) exceeds the 5% upper bound, confirming cointegration at the 5% level and justifying estimation of the long-run ARDL coefficients and ECM.

Table 19. Long-Run ARDL Estimates for Self-Employment in the United Kingdom

Variables	Coefficient	Std. Error	t-Statistic	p-value
Human Capital Growth (%)	0.0472	0.1180	0.4002	0.6940
Internet Usage (%)	-0.0740	0.0698	-1.0606	0.3037
GDP per capita (constant 2015 US$)	0.0006	0.0004	1.3769	0.1864
Unemployment (%)	0.8924*	0.5044	1.7692	0.0948
Constant	-9.7822	16.2794	-0.6009	0.5558

Source: Author's calculations.
Notes: *Long-run coefficients from the ARDL cointegration model. ***, **, * = significant at 1%, 5%, 10%.*

As shown in Table 19, unemployment is the only variable with a significant long-run association with self-employment (positive, at 10%); human capital growth, internet usage, and GDP per capita are not significant.

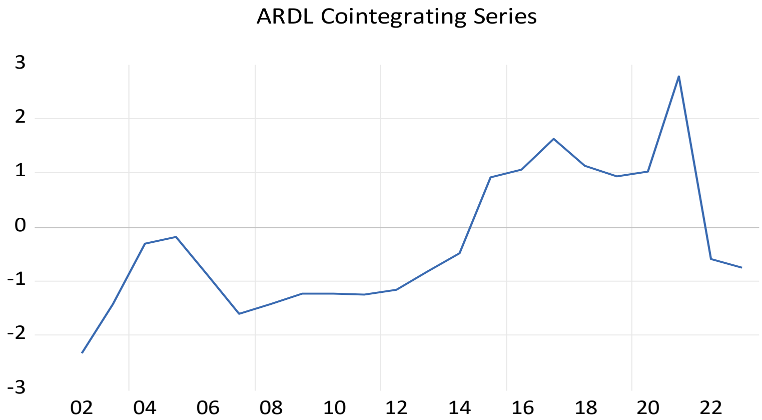

Figure 5. Long-Run Equilibrium Relationship Estimated from the ARDL Model for the United Kingdom

Figure 5 shows the UK's estimated long-run equilibrium path fluctuating with macroeconomic and digital changes, but without persistent divergence visually confirming the stable long-run relationship supported by the bounds test.

Table 20. Error Correction Model (Short-Run Dynamics) for the United Kingdom

Variables	Coefficient	Std. Error	t-Statistic	p-value
COINTEQ	-0.3167***	0.0513	-6.1671	0.0000
Δ Human Capital Growth	0.0882***	0.0206	4.2740	0.0006
Δ Internet Usage	-0.0575***	0.0138	-4.1554	0.0007
Δ Internet Usage (-1)	0.0430***	0.0110	3.9180	0.0012
Δ GDP per capita (constant 2015 US$)	-0.00006	0.00004	-1.5455	0.1418
Δ Unemployment	-0.2887***	0.0872	-3.3109	0.0044

Source: Author’s calculations.
Notes: *Δ = first difference; COINTEQ = error correction term. ***, **, * = significant at 1%, 5%, 10%.*

Table 20's error correction term is negative and highly significant, with about 31.7% of disequilibrium corrected per period a notably slower adjustment than Indonesia's. In the short run, human capital growth and unemployment show significant negative-direction effects, internet usage reverses sign between its contemporaneous and lagged terms, and GDP per capita remains insignificant.

Table 21. Diagnostic Tests for the Estimated ARDL Model (United Kingdom)

Diagnostic Test	Null Hypothesis	Test Statistic (χ^2)	p-value	Decision
Breusch–Godfrey LM Test	No serial correlation	2.366	0.306	No serial correlation
Breusch–Pagan–Godfrey Test	Homoskedastic residuals	13.985	0.174	Homoskedasticity not rejected
ARCH LM Test	No ARCH effects	0.074	0.786	No ARCH effects
Jarque–Bera Normality Test	Residuals are normally distributed	1.081	0.582	Residuals are normally distributed
Ramsey RESET Test	Model is correctly specified	F = 0.270	0.614	No specification error

Source: Author's calculations.
Notes: Obs*R^2 (Chi-square) statistics reported for LM/ARCH tests. p > 0.05 = fail to reject H0. All tests pass no serial correlation, heteroskedasticity, ARCH effects, non-normality, or misspecification.

As shown in Table 21, the UK ARDL model passes all diagnostic checks no serial correlation, heteroskedasticity, ARCH effects, non-normality, or specification error confirming its validity for reliable inference.

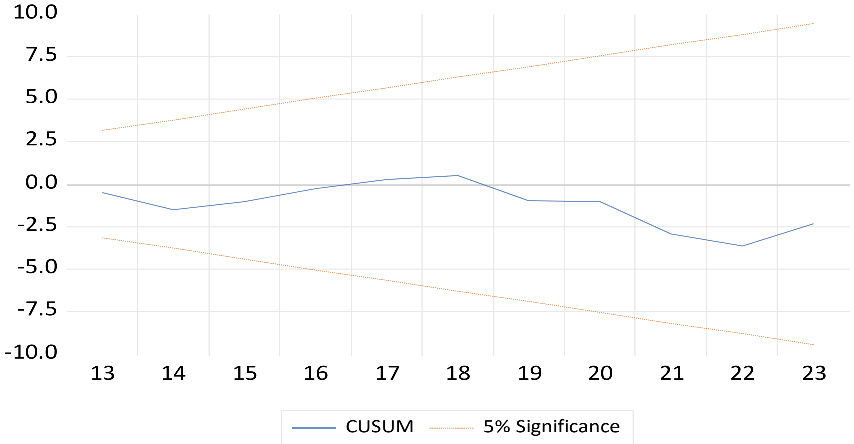

Figure 6. CUSUM Stability Test for the United Kingdom
Notes: *The dashed lines represent the 5% significance bounds. Parameter stability is supported when the cumulative sum (CUSUM) statistic remains within the critical bounds throughout the sample period.*

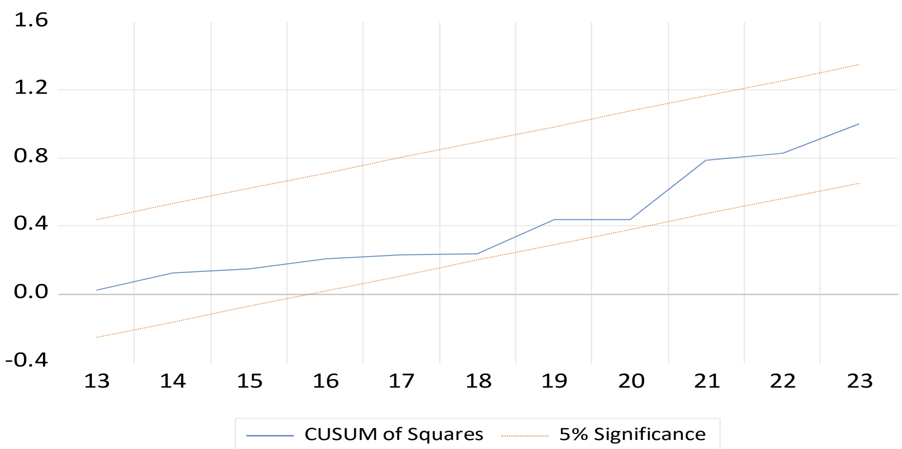

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Figure 7. CUSUM of Squares (CUSUMSQ) Stability Test for the United Kingdom
Notes: *The dashed lines represent the 5% significance bounds. Parameter stability is supported when the cumulative sum of squares (CUSUMSQ) statistic remains within the critical bounds throughout the sample period.*

Parameter stability was assessed using CUSUM and CUSUMSQ tests (Figures 6–7); both remain within the 5% bounds throughout the sample CUSUMSQ shows a gradual upward drift in later years but does not breach the limit confirming a structurally stable model.

Table 22. Comparative Summary of Push and Pull Factors Affecting Self-Employment in Indonesia and the United Kingdom

Factor	**Theory**	**Indonesia**	**United Kingdom**	**Comparative Insight**
Internet Usage	Pull	Long Run (+***)	Short Run (−, +)	Digital infrastructure is associated with long-run entrepreneurial activity in Indonesia, whereas in the UK the association is confined to short-run adjustments, with an initial negative association followed by a positive lagged association.
Human Capital	Pull	Long Run (−), *Short Run (−, +)*	Short Run (+***)	Human capital exhibits a weak negative long-run association but mixed short-run effects in Indonesia, whereas human capital growth's influence in the UK is confined to the short run and remains positive.
GDP per capita	Pull	Long Run (−***)	Not Significant	Rising income levels in Indonesia are associated with a gradual shift from self-employment toward formal employment, whereas no significant long-run relationship is observed in the UK.
Unemployment	Push	Not Significant	Long Run (+), *Short Run (−**)*	Self-employment in the UK shows a statistically significant association with unemployment in both the long run and short run, whereas no significant association is observed in Indonesia.
Error Correction Term	Adjustment	Fast (96.7%)	Moderate (31.7%)	Indonesia returns to its long-run equilibrium considerably faster following economic shocks than the United Kingdom.

Notes: ****, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

Table 22 contrasts the two economies: Indonesia's self-employment is driven by long-run pull factors, with internet usage positive and GDP per capita negative (suggesting a shift toward formal employment as the economy develops). The UK instead shows stronger short-run dynamics, with unemployment as its only significant long-run (push) factor. Indonesia also corrects short-run disequilibrium far faster (96.7% vs. 31.7%) a statistical property of the models, not evidence of stronger entrepreneurial dynamics.

Table 23. Summary of Hypothesis Testing Results

Hypothesis	**Theoretical Expectation**	**Indonesia**	**United Kingdom**	**Overall Decision**
H1. Internet usage is positively associated with self-employment.	Positive	Supported	Partially Supported*	Partially Supported
H2. Human capital is positively associated with self-employment.	Positive	Not Supported	Not Supported	Not Supported

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Hypothesis	Theoretical Expectation	Indonesia	United Kingdom	Overall Decision
H3. GDP per capita is significantly associated with self-employment, although the direction may vary across economic contexts.	Context-dependent	Supported	Not Supported	Partially Supported
H4. Unemployment is positively associated with self-employment.	Positive	Not Supported	Supported	Partially Supported

As summarized in Table 23: H1 (internet usage) receives partial support positive long-run in Indonesia, but mixed short-run signs in the UK. H2 (human capital) is not supported, showing a negative or insignificant association in both countries. H3 (GDP per capita) receives partial support, significant only in Indonesia. H4 (unemployment) receives partial support, significant long-run in the UK but with an opposite-signed short-run effect, and insignificant in Indonesia. Overall, push–pull associations vary by country and time horizon.

3.2 Discussion

This study examined the macro-level associations between digital access, human capital, macroeconomic conditions, and self-employment in Indonesia and the United Kingdom within the push–pull framework. In Indonesia, internet usage shows a positive long-run association, while human capital and GDP per capita are significantly negative. In the UK, unemployment is the sole significant long-run factor, with internet usage and human capital growth acting mainly through short-run dynamics. These findings should be read as associations involving self-employment as a proxy for entrepreneurial activity, not causal evidence.

3.2.1 Pull Factors and Digital Entrepreneurship

Digital access relates to self-employment through different temporal patterns: a significant positive long-run association in Indonesia, versus mixed short-run dynamics in the UK (a negative contemporaneous effect followed by a significant positive lag), with no long-run effect there reflecting differing economic and institutional contexts rather than stronger or weaker associations.

These findings are consistent with the digital entrepreneurship literature, which argues that digital technologies reduce information asymmetries, lower transaction costs, facilitate communication, improve market access, and strengthen entrepreneurial ecosystems (Nambisan, 2017; Camps et al., 2026; Yáñez-Valdés & Guerrero, 2024). Similarly, Gomes and Lopes (2022), using panel data from OECD countries, found that greater ICT access is associated with higher entrepreneurial activity by strengthening digital connectivity and innovation-oriented business environments. Ramos-Poyatos et al. (2025) further reported that digital infrastructure and digital human capital jointly support the adoption of information and communication technologies, reinforcing the view that well-developed digital ecosystems create favourable conditions for entrepreneurial activity.

The Indonesian long-run findings align with prior evidence: Gustina et al. (2020), using IFLS data, link internet use and cognitive/non-cognitive skills to entrepreneurial success via improved information and market access; Firdaus and Mustika Dewi (2024), Iskandar et al. (2024), and Lubis DS et al. (2024) similarly associate digital technologies, e-commerce, and digital capabilities with greater entrepreneurial participation; and in developed economies, Chen et al. (2023) link broadband infrastructure to business formation through stronger local ecosystems. Digital access thus appears to be an important pull-related condition for self-employment, though expressed differently across contexts a significant long-run association in Indonesia versus mixed short-run dynamics with no long-run effect in the UK. These remain macro-level associations, not evidence of causality or uniform effects across countries or time horizons.

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3.2.2 Human Capital and Education

The findings indicate that the relationship between human capital and self-employment differs across the two country-specific models and between the short run and the long run. In Indonesia, human capital exhibits a statistically significant negative long-run association with self-employment, although the short-run estimates reveal mixed dynamics, with a negative contemporaneous association and a positive lagged association. By contrast, no statistically significant long-run association is observed in the United Kingdom, whereas human capital growth is positively associated with self-employment in the short run. These findings suggest that the relationship between human capital and self-employment is context-dependent and may evolve differently over time rather than following a single uniform pattern. This interpretation is consistent with Arshed et al. (2021), who argue that the relationship between human capital and entrepreneurship depends on the surrounding economic and institutional environment. Likewise, Ramos-Poyatos et al. (2025) suggest that although human capital strengthens digital capabilities and entrepreneurial competencies, its contribution to entrepreneurial activity depends on broader labour market and institutional conditions.

The Indonesian long-run findings may reflect the gradual structural transformation of the labour market, whereby improvements in educational attainment are associated with greater participation in formal wage employment rather than self-employment. This interpretation is broadly consistent with evidence showing that entrepreneurship education enhances entrepreneurial knowledge, skills, and intentions, although these improvements do not necessarily translate into higher levels of entrepreneurial participation (Indriyarti et al., 2025; Syahrin et al., 2024). Similarly, Pradana and Kartawinata (2020) and Ridwan and Zaki (2023) report that formal employment continues to represent an attractive career option for many highly educated individuals because of its greater employment stability and career opportunities. In contrast, the absence of a statistically significant long-run relationship, together with the positive short-run association observed in the United Kingdom, suggests that human capital is associated primarily with short-run adjustments in self-employment rather than persistent long-run changes. Accordingly, these findings should be interpreted as evidence of macro-level associations between human capital and self-employment rather than as evidence that educational attainment directly determines individual entrepreneurial decisions or motivations.

3.2.3 Macroeconomic Conditions and Self-employment

The findings indicate that macroeconomic conditions are associated with self-employment through different patterns across the two country-specific models. In Indonesia, GDP per capita exhibits a statistically significant negative long-run association with self-employment, suggesting that economic development is accompanied by structural changes in the labour market that coincide with lower levels of self-employment over time. This interpretation is consistent with evidence indicating that economic development may gradually shift labour from self-employment toward more productive formal-sector employment, particularly in developing economies where self-employment represents an important source of income generation (Tran et al., 2025). Likewise, Rusu and Roman (2017) argue that the relationship between macroeconomic development and entrepreneurial activity is shaped by broader institutional and economic conditions and therefore varies across countries. In contrast, GDP per capita does not exhibit a statistically significant long-run or short-run association with self-employment in the United Kingdom, suggesting that changes in income levels alone are not systematically associated with self-employment within the estimated model.

The findings for unemployment also differ across the two country-specific models. In Indonesia, unemployment does not exhibit a statistically significant association with self-employment in either the long run or the estimated short-run dynamics. By contrast, unemployment exhibits a positive long-run association with self-employment in the United Kingdom, which is broadly consistent with the push–pull framework, where unemployment may act as a push factor encouraging self-employment when wage-employment opportunities become more limited (Gilad & Levine, 1986). However, the short-run estimates reveal a negative and statistically significant contemporaneous association, indicating that increases in unemployment are associated with lower self-employment in the short run. This contrast suggests that the relationship between unemployment and self-employment differs across time horizons rather than remaining uniform over time.

These findings are broadly consistent with recent studies emphasizing that entrepreneurial activity is influenced by a combination of institutional, technological, and macroeconomic conditions rather than by labour market conditions alone (Mai et al., 2025; Skica et al., 2025). Accordingly, the results suggest that the macroeconomic correlates of self-employment vary across different economic contexts and temporal horizons. Nevertheless, these findings should be interpreted as evidence of macro-level associations with self-employment rather than as direct evidence of necessity-driven or opportunity-driven entrepreneurial behaviour.

3.2.4 Comparative and Mixed-Motivation Perspectives

The findings should be interpreted within the broader push–pull entrepreneurship framework while recognising the limitations of self-employment as a proxy for entrepreneurial activity. Because the empirical analysis is based on separate country-specific ARDL models, the results identify macro-level associations within each country rather than statistically testing whether the estimated relationships differ between Indonesia and the United Kingdom. Nevertheless, the findings illustrate that the patterns of association vary across the two country-specific models and across the short run and the long run. This is consistent with recent studies suggesting that entrepreneurial activity is shaped by multiple and interacting economic, technological, and institutional factors rather than by a simple distinction between push and pull motivations (Tapsi & Rahman, 2025; Huang et al., 2026). Likewise, Kim and Parker (2021), using longitudinal evidence from the United Kingdom, show that different forms of self-employment respond differently to changing labour market conditions and business characteristics, highlighting the heterogeneous nature of self-employment.

The country-specific findings also align with the view that the relationship between macroeconomic conditions and self-employment is influenced by the broader institutional environment. Studies from Europe suggest that opportunity-oriented entrepreneurship is more likely to emerge in economies characterised by stronger innovation systems and supportive institutions (Resta et al., 2024). Similarly, Muggleton et al. (2025) report that entrepreneurial activity in the United Kingdom is associated with the availability of skills, experience, and entrepreneurial resources, even during periods of economic uncertainty. In the present study, however, these studies are used as theoretical perspectives rather than as direct explanations of the estimated coefficients. Accordingly, the results should be interpreted as evidence that the macro-level correlates of self-employment are context-dependent and may evolve differently across economic settings and over time, rather than as evidence that one country exhibits stronger entrepreneurial drivers than the other.

These policy implications warrant caution: for Indonesia, they point toward continued investment in digital infrastructure; for the UK, toward labour-market policy given unemployment's long-run relevance, with human capital and digital access mattering mainly in the short run. As macro-level associations, they do not imply causality.

4. CONCLUSIONS AND SUGGESTIONS

Using country-specific ARDL models, this study finds that the macro-level correlates of self-employment are context-dependent: in Indonesia, internet usage is positively associated with self-employment in the long run while human capital and GDP per capita are significantly negative, with rapid adjustment to equilibrium; in the United Kingdom, unemployment is the sole significant long-run factor, with internet usage and human capital growth operating mainly through slower-adjusting short-run dynamics. These associations should be interpreted cautiously, as self-employment is only a macro-level proxy for entrepreneurial activity, and the small samples and aggregate data preclude causal inference or formal cross-country comparison. Policy priorities should therefore be context-specific expanding digital infrastructure and digital entrepreneurial capacity in Indonesia, and strengthening innovation capacity and entrepreneurial finance in the United Kingdom while future research should incorporate broader entrepreneurship measures (e.g., TEA, GEM), firm-level data, and pooled cross-country models with formal coefficient-comparison procedures.

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