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Migration Of Smartphone Revolution On Economic Prosperity Of ASEAN Countries

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Abstract

In the early 21st century, an expansive technological paradigm transformed global economies and societies. This study assesses the impact of the mobile revolution on essential metrics in the telecommunications service sector, also investigates whether the mobile revolution correlates with improved individual incomes in the nations comprising the Association of Southeast Asian Nations (ASEAN). Through a meticulous examination of time-series and panel data spanning the years 1990 to 2023, the findings derived from the Interrupted-Time Series analysis (ITS) unveil that the pivotal year of 2007 marked a substantial escalation in mobile subscription density, employment within the telecommunications services sector, and investment in said sector across the majority of ASEAN countries. The panel Autoregressive Distributed Lag Cointegration (Panel ARDL) further elucidates a lasting and positive association among pivotal variables—employment in telecommunication, investment in the smartphone industry, market size for mobile communication services, and GDP per capita. These results highlight that advancements and active involvement in the smartphone industry significantly contribute to the income of residents in ASEAN countries.

Keywords: *Mobile revolution, Telecommunications service sector, Economic development, ASEAN countries, Interrupted-time series (ITS)*

1. Introduction

In the early 21st century, a technological wave swept across the globe, transforming economies and societies. At the forefront of this wave was the mobile phone, a powerful tool connecting individuals and unlocking access to information like never before. The rise of the mobile phone, particularly the smartphone, has not just reshaped communication, but also[1] revolutionized economies across the globe. This revolution, fueled by technological advancements and policy decisions, has permeated various aspects of economic activity, impacting entirely from productivity and growth to employment and inequality.

In terms of economic growth, it increased productivity and efficiency of businesses and individuals, enabling faster communication, collaboration, and access to information. This has led to improved efficiency in various sectors, from agriculture to healthcare, ultimately contributing to economic growth (Hübler & Hartje, 2016; Park & Oh, 2021; Romer, 1990; Zhao, 2019). It also allows for the expansion of new industries and services. The mobile ecosystem has spawned a plethora of new industries and services, from app development to mobile banking. These new ventures create jobs and contribute to GDP growth, diversifying economies and fostering innovation(Bezerra et al., 2015). In addition, it enhanced access to markets for all groups of citizens. Mobile technology empowers businesses, particularly in rural areas, to connect with customers and markets more easily.

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This expands their reach and sales potential, leading to economic development and poverty reduction (Rotondi et al., 2020).

2. Literature Review

2.1 Nexus between mobile revolution and economic growth

As in Romer (1990) endogenous growth model, technology assumes a pivotal role in driving sustained economic growth. Unlike traditional models, Romer's framework treats technological change as an integral part of the economic system, emphasizing the active accumulation of knowledge through investments in education, research and development, and innovation. The model introduces the concept of increasing returns to scale in the production of ideas, emphasizing that dedicating more resources to R&D leads to a compounding productivity of new ideas. Government policies are crucial in this context, playing a vital role in creating an environment conducive to technological innovation. The model also recognizes the dynamic nature of growth, with technology continuously fueling economic expansion and creating positive spillover effects across sectors. Empirically, the beginning of the smartphone revolution, sparked by the introduction of the first iPhone in 2007, has left an indelible mark on global economic development. A report from GSMA and (Hübler & Hartje, 2016) reveal that the mobile economy made a substantial contribution of approximately $2.4 trillion to the world economy in 2013, constituting 3.6% of the global GDP. This influence is evident in the creation of over 10 million jobs and a noteworthy $336 billion contribution to public funding in the United States alone. Projections indicate that the mobile economy could potentially grow to contribute 5.1% to the global GDP by 2020.

Smartphones have become instrumental in fostering economic globalization and growth (Hübler & Hartje, 2016). They have facilitated seamless communication and collaboration for businesses, connecting them with customers and suppliers worldwide. Additionally, the increased accessibility to information has driven productivity and innovation, empowering individuals, and businesses. Research conducted by Leslie et al., 2012) emphasizes the symbiotic relationship between mobile phone penetration and economic growth in developing nations, highlighting how increased access to mobile devices fuels communication, transactions, and entrepreneurial endeavors(Jack & Suri, 2014; Zhu & Li, 2018). Park & Oh, (2021) underscore the transformative power of mobile phone penetration, showcasing its role in enhancing market access, revolutionizing payment system, and fostering financial inclusion. Additionally, Kanyam et al., (2017)showed that mobile phones and the internet also help to reduce corruption in sub-Saharan Africa.

3. Nexus between mobile revolution and employment in telecommunication services industry

The mobile revolution has brought up new business opportunities, particularly in the realms of mobile apps and e-commerce, generating revenue and employment(Hübler & Hartje, 2016). Moreover, businesses have experienced heightened efficiency, acknowledges to the ability of smartphones to enable remote work, and streamline operations through innovative mobile apps (Metu et al., 2020b). The International Telecommunication Union's recent research in 2022 and Metu et al., (2020) shed light on the profound influence of mobile technology on job markets in developing countries. Their findings highlight mobile tech's pivotal role in creating employment opportunities and empowering individuals across various. In this context, the mobile revolution emerges as a transformative force, poised to shape job markets and skill development (Krishnapillai, 2004). This revolution's potential lies in incentivizing mobile app development and fostering online training platforms, paving the way for a surge in job opportunities, especially in the tech sector (Chisnall, 2007; "The Mobile Revolution: The Making of Mobile Services Worldwide," 2006). In conclusion, the mobile revolution has created jobs through the growth of the app economy, expansion of e-commerce, increased demand for technology professionals, and the facilitation of remote work. Overall, it has been a key driver of employment across various industries, contributing to economic growth and innovation.

3. Research Methodology

3.1 Mobile revolution and improvement in telecommunication services sector

Interrupted Time Series (ITS) analysis is a quasi-experimental design commonly used in public health and other fields to evaluate the impact of interventions or exposures. Non-experimental designs are often more feasible in real-world settings where we cannot control the timing or nature of interventions. It provides valuable insights when experimental designs are impractical. Non-experimental designs are also useful for studying complex phenomena in real world complex settings characterized by the involvement of numerous variables. The mobile revolution, improvements in the ICT sectors, and economic prosperity, for example, are multifaceted developments with widespread implications, making them well-suited for non-experimental exploration. This study then opts for an ITS approach, leveraging existing data to evaluate the effects of the revolution. This method allows us to analyze the effects before and after revolution, capturing the authentic dynamics of the changing pattern.

The fundamental principle of Interrupted Time-Series Analysis (ITS), as depicted in Figure 1, centers on the comparison of data before and after an intervention to assess its influence over a continuous timeline. By applying this method to investigate the impact of the mobile phone revolution in 2007 on the communication service sector and economic development, it facilitates a comprehensive examination of trends or patterns within a single dataset. This approach enables the assessment of any discernible shifts, enhancements in economic prosperity, or consequences arising from the mobile phone revolution. Then the Segmented Linear Regression of ITS can be expressed as:

$$Y_t = \beta_0 + \beta_1 \text{Time} + \beta_2^* \text{Revolution} + \beta_3 \text{Postslope} + e_t \quad (1)$$

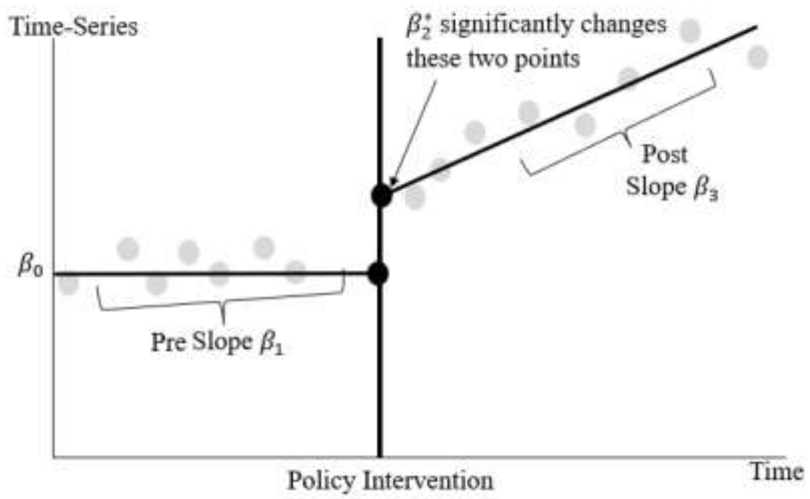

Figure 1 Single Interrupted Time Series (ITS)

In our case, the model comprises two segments: Equation (2) represents the period before the intervention and equation (3) represents the period after the intervention:

$$Y_t = \beta_0 + \beta_1 \, T + \beta_2 \text{Revolution} + \beta_3 \, \text{Postslope} + \varepsilon_t \quad (2)$$

$$Y_t = \gamma_0 + \gamma_1 \, \text{Preslope} + \gamma_2 \, \text{Revolution} + \gamma_3 \, \text{Postslope} + \varepsilon_t \quad (3)$$

Where Y_t denotes smartphone penetration, investment, and employment in telecommunication industry. β_0 and γ_0 represent constant. T signifies time progression. Revolution represents a dummy variable for a mobile phone revolution in 2007, it is a dummy before (=0) or after (=1) the revolution $Preslope$ shows a continuous variable indicating time passed since the revolution has occurred (before revolution has occurred Postslope is equal to 0). $Postslope$ is a continuous variable indicating time passed since the revoultion has occurred (before intervention has occurred Postslope is equal to 0), and ε_t represents the residual or error terms.

Within Econometrical analysis, two prominent techniques stand out. The first is Ordinary Least Square estimation, which is effective but encounters challenges in managing autocorrelation issues. This arises when an outcome measured at a specific time is correlated with its past values—such as the temperature in January being linked to the temperature in the previous year's January, creating a correlation pattern (Woolrich et al., 2001). The second technique, Prais-Winsten Estimation, serves as a modification of the Cochrane-Orcutt method. It's specifically tailored for estimating parameters in a first-order autoregressive model, particularly adept at handling time series data characterized by autocorrelated errors, making it particularly advantageous in such scenarios(Anarfo et al., 2017).

Prais-Winsten Estimation Process

Basically, Prais-Winsten methodology is utilized in a linear regression model dealing with errors that display autocorrelation, described by the equation:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \quad (4)$$

where $Y_t$is the interested dependent variable (expansion in telecommunication market, employment, and investment in telecom sector) at time t, X_t denotes the revolution or the shock at time t where in this study t= mobile revolution in 2007, and ε_t represents the error term at time t. The error term εt is presumed to exhibit an autocorrelation structure. Autocorrelation Structure: Within Prais-Winsten, an assumption is made concerning a first-order autoregressive (AR(1)) model for the error term, articulated as:

$$\varepsilon_t = \rho\varepsilon(t-1) + u_t \quad (5)$$

In this formulation, ρ is the autocorrelation coefficient, ε(t-1) is the error at the previous time point, and u_t is the white noise error term at time t. Combining both elements, the model can be represented as:

$$Y_t = \beta_0 + \beta_1 X_t + \rho\varepsilon(t-1) + u_t \quad (6)$$

This iterative approach aims to estimate coefficients β_0 and β_1 alongside ρ, the autocorrelation coefficient. It starts with an initial Ordinary Least Squares (OLS) regression, moves to adjusting for autocorrelation using OLS residuals to estimate ρ, and iteratively refines the model's parameters until convergence. Diagnostic tests validate the model's adequacy, ensuring adherence to AR(1) assumptions.

3.2 Long run Cointegration between Mobile revolution and Economic Prosperitiy of ASEAN economies.

3.2.1 Cross-sectional dependence and Panel Unit Root Test

This study employed panel data analysis to explore interdependence or correlation among individual units, such as countries in a panel dataset. A novel approach involved the use of distinct measurements and a connection lattice to elucidate the descriptive relationship among the variables under consideration. Additionally, to identify potential cross-sectional issues within the data, the study applied the Cross-Sectional Dependence (CD) test proposed by Pesaran (2007). The formulation of the CD test is as follows:

$$CD = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij} \tag{7}$$

Where CD represents the measure of cross-sectional dependence. T signifies the number of time periods. N denotes the number of cross-sectional units. ρ ij represents the pairwise correlation between units i and j. ∑ denotes the summation across pairs of units i and j, where i ranges from 1 to N-1 and j ranges from i+1 to N. This formula will compute a measure of cross-sectional dependence by summing the pairwise correlations between different units, adjusted by the number of time periods and the number of units in the panel dataset. The square root term and the scaling factors aim to normalize this measure. Higher values of CD indicate stronger cross-sectional dependence among the units in the panel data. To ensure accurate results and minimize forecasting errors in ASEAN countries with diverse economic structures and series levels, it's crucial to verify the stationary properties as recommended by Kongbuamai et al., (2023) and Wang & Dong, (2019). This study, therefore, tests the panel utilizing second-generation estimators of the Cross-sectional LM, Pesaran, and Shin tests (CIPS) and Cross-sectional Augmented Dickey-Fuller (CADF).

3.2.2 Panel ARDL cointegration

The Autoregressive Distributed Lag (ARDL) bounds test for cointegration is also used to determine the presence of a long-term relationship among smartphone revolution and economic growth in a regression model with mixed order of integration. It involves estimating an unrestricted error correction model (ECM) that includes lagged levels and differences of the variables. ARDL bounds testing is advantageous as it allows for the inclusion of variables with different orders of integration in the same model, making it useful for analyzing economic relationships among variables that may have mixed properties in terms of stationarity (Narayan, 2005). Our empirical model for long term cointegration is specified as:

$$\begin{aligned} \Delta LNGDPPC_t = \alpha_0 &+ \sum_{i=1}^{n} \beta_i \Delta LNGDPPC_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta \mathrm{LNEMP}_{t-i} + \sum_{i=1}^{n} \delta_i \Delta \mathrm{LNINT}_{t-i} \\ &+ \sum_{i=1}^{n} \theta_i \Delta \mathrm{LNINV}_{t-i} + \sum_{i=1}^{n} \vartheta_i \Delta \mathrm{LNMCS}_{t-i} + \sum_{i=1}^{n} \rho_i \Delta \mathrm{HDI}_{t-i} + \varepsilon_t \end{aligned} \tag{8}$$

Where Δ denotes the first difference operator, t represents time. LNGDPER t is the dependent variable (GDP per capita). LNEMP, LNINT, LNINT, LNINV, and LNMCS are the independent variables (employment, internet subscription density , investment in telecommunication, mobile cellular subscriptions, and human development index respectively). HDI signifies the human development index is included in the model to control for the socio-economic and education factors that might affect the GDP per capita. $\beta_i, \gamma_i, \delta_i, \theta_i, \vartheta_i$, and ρ_i represent the coefficients for the respective lagged terms. ε_t is the error term and the α_0 signifies the constant term. The Error Correction Term (ECT) or the coefficient associated with the first-differenced dependent variable represents the speed of adjustment toward the long-run equilibrium. Negative and statistically significant coefficient on the ECT indicates the presence of a long-term relationship among the variables and how quickly the system returns to equilibrium after short-term shocks.

3.4 Data

The dataset presented in table 1 includes key variables related to telecommunications and economic indicators of nine ASEAN countries namely, Thailand, Myanmar, Malaysia, Lao PDR, Cambodia, Philippines, Vietnam, and Indonesia. MCS embodies the prevalence of Mobile Cellular Subscriptions per 100 people, observed in 100-person units from 1970 to 2023, drawing insights from the World Bank. INV delves into Investment in communication service, quantified in USD and chronicled from 1970 to 2023, sourced from International Telecommunication Union (ITU). EMP captures the realm of Full-time employees in the telecommunication service, measured in 1000 people according to ITU records. INT quantifies internet subscription density as a percentage, with data spanning. The Revolution variable dichotomizes data into epochs pre- (0) and post- (1) the Mobile revolution in 2007. GDPPC charts the trajectory of Real GDP per capita in USD from 1970 to 2023, referencing the World Bank. Lastly, HDI measures Human Development Index on a scale of 0 to 1, extending from 1970 to 2023 and drawing data from the United Nations. This array of variables offers a comprehensive narrative, enabling a nuanced exploration of the transformative impact of the mobile revolution on economic and telecommunications landscapes.

Table 1 List of Variables

Variable	Description	Sample	Unit	Source
MCS	Mobile Cellular Subscriptions per 100 people	1970 - 2023	100 persons	World Bank
INV	Investment in communication services	1970 - 2023	USD	ITU
EMP	Full-time employee in telecommunication service	1970 - 2023	1000 persons	ITU
INT	internet subscription density	1970 - 2023	%	ITU
Revolution	Mobile revolution	2007	0 = before 1= after	
GDP	Real GDP	1970-2023	USD	World Bank
GDPPC	Real GDP per capita	1970-2023	USD	World Bank
HDI	Human Development Index	1970-2022	0-1	United Nation

3.2 Descriptive Statistic

The descriptive statistics, as depicted in Table 4, serve as a brief overview of key aspects such as central tendency, spread, and distribution shape for each variable in the dataset. The result shows that our data set appears to be generally well-structured and complete for further in-depth analyses and interpretations.

Table 2 Descriptive statistics of variables

	LNGDPPC	LNEMP	LNINT	LNINV	LNMCS	HDI
Mean	5.029	4.154	0.119	8.630	0.811	0.605
Median	5.246	4.267	0.786	9.028	1.461	0.610
Maximum	6.086	5.131	2.062	9.702	2.260	0.810

	LNGDPPC	LNEMP	LNINT	LNINV	LNMCS	HDI
Minimum	3.703	2.602	-4.282	4.194	-2.941	0.333
Std. Dev.	0.637	0.633	1.777	1.022	1.453	0.115
Skewness	-0.538	-0.676	-0.944	-2.387	-0.892	-0.328
Kurtosis	1.999	2.672	2.720	9.522	2.614	2.386
Jarque-Bera	23.780	21.293	40.072	78.810	36.646	8.804
Probability	0.000	0.000	0.000	0.000	0.000	0.012
Observations	264	264	264	264	264	264

4. Empirical Results

4.1 Panel Unit Root Tests

The findings from the unit root tests are encapsulated in Table 3. Both the CIPS and CADF panel unit root tests outcomes converge on the conclusion that the null hypothesis (indicating non-stationarity) remains accepted at the level. However, at the initial difference I(1), the null hypothesis is rejected, signaling the stationarity and integration at I(1).

Table 3 Panel Unit Root Tests

Variables	**CIPS Statistics**		**CADF test statistic**	
	Level	**First difference**	**Level**	**First difference**
LNMCS	-2.088	-2.153*	-2.789	-3.355*
LNINV	-2.223	-5.993***	-2.371	-6.485*
LNEMP	-2.308	-2.907***	-2.970	-4.049*
LNINT	-1.709	-3.214*	-0.949	-3.230*
LNGDP	-1.687	-3.431***	-1.632	-3.723*
LNGDPPC	-2.417*	-3.202***	-3.003	-4.279***
HDI	-2.278	-5.735***	-2.729	-6.367***

***,**, and * are statistically significant at 1%, 5%, and 10%, respectively

Table 4. Ordinary Least Squares (OLS) and Prais-Winsten regression for Mobile revolution and Mobile Cellular Subscriptions

	Thailand		**Malaysia**		**Vietnam**		**Indonesia**	
Variables	OLS	Prais	OLS	Prais	OLS	Prais	OLS	Prais
Time	1.123***	2.136***	1.588***	2.330***	0.390*	1.441*	0.446***	1.095*
	(0.294)	(0.754)	(0.316)	(0.693)	(0.197)	(0.859)	(0.152)	(0.589)
Revolution	65.61***	7.436	75.29***	11.52**	113.4***	32.02***	64.31***	13.53***
	(8.763)	(5.482)	(10.50)	(4.886)	(12.22)	(7.610)	(9.364)	(4.448)
Post Rev.	4.667***	3.160*	0.225	0.253	0.349	1.700	5.250***	4.876***
	(0.665)	(1.593)	(0.691)	(1.430)	(0.974)	(2.057)	(0.882)	(1.279)
Constant	-13.40***	-8.356	-18.30***	-7.344	-4.906*	-9.142	-5.476**	-4.137
	(4.292)	(29.39)	(4.953)	(29.66)	(2.662)	(25.26)	(2.129)	(21.07)
R-	0.961	0.246	0.940	0.177	0.971	0.372	0.975	0.471

squared

	Philippines		**Myanmar**		**Lao**		**Cambodia**	
Variables	OLS	Prais	OLS	Prais	OLS	Prais	OLS	Prais
Time	0.949***	1.729***	0.007***	0.0536	0.229**	0.719	0.210***	0.678
	(0.238)	(0.544)	(0.002)	(0.403)	(0.0992)	(0.498)	(0.0700)	(0.794)
Revolution	60.63***	7.978**	-13.86*	-6.248	54.13***	8.234	61.64***	5.682
	(7.545)	(3.800)	(7.916)	(6.784)	(9.218)	(6.031)	(17.17)	(7.374)
Post Rev.	1.430***	0.980	8.536***	6.935***	-0.276	1.216	4.987***	5.918***
	(0.507)	(1.114)	(0.851)	(1.211)	(0.750)	(1.363)	(1.502)	(1.947)
Constant	-11.34***	-5.519	-0.0794***	-0.497	-2.873**	-6.070	-2.558**	-2.832
	(3.510)	(24.05)	(0.0288)	(9.803)	(1.346)	(12.77)	(0.985)	(22.58)
Observations	54	54	54	54	54	54	54	54
R-squared	0.953	0.190	0.921	0.582	0.940	0.203	0.938	0.312

Note: Dependent variable is mobile cellular subscriptions per 100 people. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.3 Mobile revolution and investment in telecommunication service

Table 5 and figure A.2 presents findings from Ordinary Least Squares (OLS) and Prais-Winsten regression methods to examine the post-revolution effect of mobile revolution and the expansion in telecommunications service investment. The finding confirms that the Mobile revolution in 2007 suddenly indicates positive and statistically significant in Myanmar, Lao PDR, and Cambodia. The post revolution also shows positive and significant in Thailand, Vietnam, and Cambodia.

The positive and significant relationship across these countries likely stems from ongoing technological advancements, fostering increased connectivity within the countries, evolving consumer behavior favoring communication services, and the global trend towards digitalization, collectively driving the growing importance and investment demand for improved communication infrastructure over time (Chisnall, 2007; Hübler & Hartje, 2016; Park & Oh, 2021; "The Mobile Revolution: The Making of Mobile Services Worldwide," 2006).

Table 5 OLS and Prais-Winsten Regression on Mobile Revolution and Telecom Investment

	Thailand		Malaysia		Vietnam		Indonesia	
Variables	OLS	Prais	OLS	Prais	OLS	Prais	OLS	Prais
Time	0.108***	0.010***	0.094***	0.087***	0.042***	0.037***	0.138***	0.159***
	(0.009)	(0.017)	(0.0056)	(0.012)	(0.005)	(0.012)	(0.029)	(0.04)
Revolution	-0.508*	-0.137	-0.123	0.0731	-0.273	-0.120	-0.0698	-0.0738
	(0.295)	(0.423)	(0.249)	(0.283)	(0.202)	(0.278)	(0.381)	(1.007)

Post Rev.	0.045***	0.0604	0.121***	0.117**	0.0482*	0.0518	0.108***	0.149
	(0.0201)	(0.0627)	(0.0208)	(0.0436)	(0.0274)	(0.0433)	(0.0330)	(0.152)
Constant	17.20***	17.35***	18.07***	18.15***	17.85***	17.96***	16.78***	16.21***
	(0.161)	(0.398)	(0.110)	(0.297)	(0.0903)	(0.281)	(0.786)	(0.977)
R-squared	0.860	0.870	0.883	0.974	0.775	0.945	0.639	0.330
	Philippines		Myanmar		Lao		Cambodia	
Variables	OLS	Prais	OLS	Prais	OLS	Prais	OLS	Prais
Time	0.0718***	0.061***	0.132***	0.145***	0.051***	0.053**	0.139***	0.133***
	(0.0057)	(0.017)	(0.030)	(0.041)	(0.009)	(0.020)	(0.007)	(0.012)
Revolution	-0.0771	-0.0302	2.745***	1.678	4.449***	4.346***	0.529***	0.0808
	(0.153)	(0.252)	(0.936)	(1.478)	(1.009)	(0.843)	(0.137)	(0.354)
Post Rev.	0.038***	0.0224	-0.37***	-0.30*	-0.92***	-0.92***	-0.14***	-0.16***
	(0.0085)	(0.055)	(0.131)	(0.171)	(0.098)	(0.087)	(0.007)	(0.05)
Constant	18.21***	18.50***	14.15***	13.94***	14.67***	14.66***	16.52***	16.62***
	(0.137)	(0.425)	(0.495)	(0.933)	(0.160)	(0.432)	(0.170)	(0.283)
Observations	52	52	52	52	49	49	52	52
R-squared	0.817	0.943	0.585	0.311	0.746	0.734	0.936	0.893

Note: Dependent variable is investment in communication service (USD). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.4 Mobile revolution and full-time employee in telecommunication

Table 6 and figure A.3 The relationship between the mobile revolution and full-time employment in the telecommunications sector across Southeast Asian countries is complex and varied. While the Mobile revolution has influenced employment in this sector, the impact differs among these nations. Table 6 shows that most countries show a negative and significant correlation between the Mobile revolution in 2007 and employment, indicating the sustained effects and time lagging in general industry growth. However, the positive effects of the Mobile revolution itself and the post-revolution period on employment are more significant among these countries. Influences such as technological efficiency, market maturity, shifting service demands, regulatory policies, economic conditions, and industry-specific trends collectively contribute to the diverse outcomes observed in employment levels within the telecommunications sector across these regions.

Table 6 OLS and Prais-Winsten Regression on Mobile Revolution and Telecom Full-Time Employment

	Thailand		Malaysia		Vietnam		Indonesia	
Variables	OLS	Prais	OLS	Prais	OLS	Prais	OLS	Prais

Time	0.855***	0.717***	0.757***	0.816***	2.869***	2.100***	0.946***	0.929
	(0.0705)	(0.205)	(0.131)	(0.276)	(0.281)	(0.718)	(0.163)	(2.548)
Revolution	-29.09***	-17.26***	-0.260	0.0170	-37.54***	-0.990	-111.2*	-19.34
	(7.106)	(5.798)	(6.017)	(6.838)	(6.910)	(7.341)	(56.69)	(69.06)
Post Rev.	5.674***	5.223***	-0.448	-0.738	-2.174***	-1.973	27.62**	13.55
	(0.621)	(0.735)	(0.469)	(0.957)	(0.312)	(1.902)	(10.56)	(9.041)
Constant	-1.174	0.466	6.757**	5.196	-2.901	4.155	13.02***	11.79
	(1.359)	(4.770)	(3.266)	(6.484)	(5.389)	(19.44)	(3.952)	(59.50)
R-squared	0.934	0.772	0.566	0.125	0.767		0.582	0.117
	Philippines		Myanmar		Lao		Cambodia	
Variables	OLS	Prais	OLS	Prais	OLS	Prais	OLS	Prais
Time	0.384***	0.494**	0.317***	0.325***	0.0511***	0.0508***	0.0379***	0.0496**
	(0.106)	(0.226)	(0.0247)	(0.0425)	(0.00394)	(0.00704)	(0.00701)	(0.0201)
Revolution	-4.59***	0.297	1.885***	0.691	-0.294	-0.307	3.021***	1.829**
	(1.599)	(3.180)	(0.640)	(1.379)	(0.361)	(0.266)	(1.099)	(0.726)
Post Rev.	-0.50***	-0.936	-0.44***	-0.344**	0.457***	0.458***	0.0129	0.0844
	(0.144)	(0.677)	(0.0692)	(0.159)	(0.0279)	(0.0277)	(0.0925)	(0.078)
Constant	9.509***	5.384	-1.273**	-1.312	-0.382***	-0.368**	-0.376***	-0.509
	(3.073)	(5.634)	(0.544)	(0.978)	(0.0780)	(0.160)	(0.110)	(0.458)
Observations	53	53	53	53	53	53	53	53
R-squared	0.288		0.874	0.648	0.983	0.966	0.842	0.644

Note: Dependent variable is full-time employee in telecommunication (Thousand people). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.5 Correlation in telecommunications and economic variables

The correlation matrix reveals positive relationships among ICT improvements and citizen income. Strong correlations are observed, notably between LNGDPER (Log of GDP per capita) and HDI (Human Development Index) at 0.931, indicating a close link between economic prosperity and human development. Additionally, positive correlations exist between LNGDPER and other ICT-related variables, such as LNEMP (Log of Employment), LNMCS (Log of Mobile Cellular Subscriptions), LNINV (Log of Investment), and LNINT (Log of Internet Subscription Density). These findings suggest a positive association between ICT advancements and various indicators of economic well-being and connectivity.

Table 7 Correlation matrix among variables

	LNGDPER	LNGDP	HDI	LNEMP	LNMCS	LNINV	LNINT
LNGDPER	1.000						
LNGDP	0.714	1.000					
HDI	0.931	0.736	1.000				
LNEMP	0.581	0.923	0.614	1.000			
LNMCS	0.680	0.336	0.762	0.309	1.000		
LNINV	0.366	0.481	0.434	0.398	0.336	1.000	
LNINT	0.653	0.387	0.755	0.335	0.889	0.271	1.000

4.6 Long run Cointegration between ICT improvement and GDP per capita

Table 8 presents the results of a cointegration analysis among key variables related to telecommunications and economic indicators using Panel ARDL bound testing. The outcomes suggest the potential existence of co-integration relationships among the variables across the panel. A negative and statistically significant coefficient on the Error Correction Term (ECT) in the ARDL model indicates the existence of a long-term relationship among the variables included in the model. Furthermore, the magnitude of this coefficient illustrates the speed at which the system converges back to its long-run equilibrium following short-term disturbances or shocks.

Table 8 Cointegration between ICT sectors and GDP per capita

Long Run Equation				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LNEMP	0.511922	0.074272	6.892504	0.0000
LNHDI	0.297834	0.179218	1.661853	0.0993
LNINT	0.100684	0.007508	13.41002	0.0000
LNINV	0.090666	0.021126	4.291745	0.0000
LNMCS	-0.018082	0.014354	-1.259768	0.2104
ECT	-0.354329	0.107999	-3.280851	0.0014
C	0.123216	0.057426	2.145644	0.0341

Note: Dependent Variable: D(LNGDPER), Included observations: 237 , Maximum dependent lags: 3. Model selection method: Akaike info criterion (AIC), Akaike info criterion -3.732, Schwarz criterion -1.670, Hannan-Quinn criter. -2.915

The analysis reveals a positive long-term relationship between key variables like employment in telecommunication (LNEMP), investment in the smartphone industry (LNINV), market size for mobile communication services (LNMCS), and GDP per capita. This implies that the progress and engagements within the smartphone industry have a favorable impact on the income of ASEAN residents. Developments and involvement in the smartphone industry positively affect the earnings or income of individuals residing in the ASEAN region. When the smartphone industry experiences advancements, growth, or increased activity, it tends to generate opportunities that contribute to the income of people within the ASEAN community. These advancements could create various job opportunities directly within the industry, such as manufacturing, software development, marketing, and sales.

Moreover, as the industry expands, it stimulates ancillary sectors like transportation, retail, and services, fostering additional employment opportunities and income sources for people indirectly linked to the smartphone industry(Escamilla et al., 2021; Roessler, 2018). Additionally, increased engagement with smartphones often leads to greater connectivity, access to information, and avenues for entrepreneurship or online businesses (Giachetti & Mensah, 2023; Sousa & Rocha, 2019). These factors can boost economic participation, potentially resulting in higher income levels among ASEAN residents as they leverage these technological advancements to their advantage.

5. Conclusion and Policy Implications

The analysis underscores a positive and enduring association between crucial variables such as employment in the telecommunication sector (LNEMP), investment in the smartphone industry (LNINV), market size for mobile communication services (LNMCS), and GDP per capita within the ASEAN region. This indicates that the advancements and active participation in the smartphone industry significantly contribute to the income of residents in ASEAN countries. The positive impact extends beyond direct employment in the smartphone industry, encompassing various sectors such as manufacturing, software development, marketing, and sales. Moreover, the industry's growth creates ripple effects, fostering additional job opportunities in ancillary sectors like transportation, retail, and services. The increased connectivity and access to information facilitated by smartphones also open avenues for entrepreneurship and online businesses, further enhancing economic participation and potentially elevating income levels among ASEAN residents.

The policy implication indicates that the progress and active involvement within the smartphone industry contribute positively to the income levels of residents in the ASEAN region. The advancements in smartphone technology and increased participation in the industry generate favorable conditions for economic growth. As the smartphone sector evolves, it not only creates direct employment opportunities within the industry but also fosters a broader economic ecosystem. This, in turn, leads to increased income opportunities for individuals in the ASEAN community. The expansion of the smartphone industry stimulates various sectors, triggering a ripple effect that enhances overall economic activity. The resulting opportunities for employment and income generation extend beyond the immediate confines of the industry, influencing ancillary sectors and fostering a more robust economic landscape within the ASEAN region.

However, for some developing countries like Myanmar and Lao, integrating into this digital landscape presented unique challenges. Affordability, infrastructure, and access remained critical hurdles, creating a digital divide that threatened to widen the gap between developed and developing nations. Closing the digital divide through infrastructure development and affordability initiatives is crucial for ensuring inclusive economic growth and social development.

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