Navigating the Green Frontier: The Impact of Digitalization on Environmental Pollution in Selected South East Asian Economies

Noor Zahirah Mohd Sidek[1], Alfiah Hasanah[2], Muhammad Hanif Othman[3]

[1,3]Department of Economics, Faculty of Business Management, Universiti Teknologi MARA, Malaysia

[2]Faculty of Economics and Management, Universitas Padjadjaran, Bandung, Indonesia

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ABSTRACT

The objective of this paper is to re-examine the impact of digitalization on environmental pollution. Past studies use CO2 as a representation of potential environmental harm. In this paper, environmental pollution is extended to cover other sources of pollution such as methane and nitrous oxide. Prior to the analysis, the cross-dependency and panel unit root tests were conducted to understand the underlying structure of the data and to examine the suitability of the econometrics method used. Given the absence of cross-dependency and the presence of unit roots, the panel ARDL estimation method is used to examine the interplay between digitalization and environmental pollution. In addition, CO2 is segregated into different categories of emission such as CO2 resulting from the production of electricity and heat, manufacturing, and emissions from transportation. The sample consists of ten Southeast Asian countries spanning from 2003 to 2022. Results indicate that digitalization amplifies environmental pollution irrespective of the proxy used. The surge in the number of internet users induces higher emissions due to increased production of electricity and heat, emissions from solid and liquid fuel usage, and transport. Similarly, an increase in mobile users increases CO2 emissions from fuel and liquid consumption, manufacturing, construction, and transportation. Moving forward, it is crucial to consider the adoption of green technology in production and explore alternative energy sources to curtail environmental pollution.

Keywords: Digitalization, environmental pollution, South East Asian economies, CO_2, green technology

INTRODUCTİON

Since the advent of the 2nd industrial revolution (IR) in the 19th century, global carbon dioxide (CO2) emissions have undergone a staggering increase, soaring from approximately 196.75 million tonnes in 1850 to a staggering 37.5 billion tonnes in 2022, primarily fueled by fossil fuel consumption (Global Carbon Budget, 2023). Notably, the geographical distribution of these emissions has undergone significant shifts over time. In the early 20th century, over 90% of emissions originated from Europe and the United States. However, the rapid industrialization and economic ascent of emerging economies, particularly in Asia, have reshaped this landscape, with China, Europe, and the United States collectively contributing less than a third of global emissions by 2022. In contrast, high-income countries such as the United States, New Zealand, Germany, France, Greece, Canada, and Australia, alongside oil-producing nations like Russia, Kazakhstan, and Turkmenistan, continue to account for substantial portions of CO2 emissions, with some oil-rich states exhibiting notably high per capita emissions rates.

Environmental degradation resulting from air pollution is intricately linked to the contamination effects of various pollutants, including not only CO2 but also nitrogen oxide (NOX), sulfur dioxide (SO2), and methane (CH4) (Zaidi and Saidi, 2018). The ramifications of this degradation extend far beyond localized impacts, encompassing global challenges such as the exacerbation of infectious diseases, the escalation of climate change-induced phenomena like global warming, and the heightened frequency of natural disasters such as floods and prolonged droughts. Such climate-related shifts disrupt ecosystems and imperil biodiversity, ultimately posing grave threats to both human populations and the natural world (Zaidi & Saidi, 2018).

Addressing environmental pollution necessitates a multifaceted approach that encompasses financial support for green production initiatives and decarbonization efforts across the entire production spectrum. While the theoretical appeal of attracting investment and financing for eco-friendly ventures is evident, practical considerations such as return on investment and profitability often take precedence in investment decisions. In this context, directive policies wield considerable influence in mitigating environmental pollution (Truby, 2018). For instance, China's decision to halt proof-of-work (PoW) digital currency mining operations had yielded substantial reductions in emissions, underscoring the efficacy of targeted regulatory interventions in curbing pollution (Xiao et al., 2023; Howson, 2021; Howson & de Vries, 2022; Browne, 2021). Conversely, the absence of comparable directives in nations like Iran or Kazakhstan has perpetuated alarming emissions levels stemming from digital currency mining activities (Browne, 2021; Vahia, 2021).

Against this backdrop, this paper aims to investigate the impact of digitalization on environmental pollution, using carbon dioxide (CO_2) emissions, methane, and nitrous oxide as proxies. Notably, recent data highlights Indonesia's emergence as a prominent CO_2 emitter in the Asia-Pacific region, with 619 million metric tonnes emitted in 2021, followed closely by Thailand (278.5 million metric tonnes), Malaysia (256.05 million metric tonnes), and the Philippines (144.26 million metric tonnes). At the forefront of this regional emissions landscape stands China, accounting for a staggering 10.5 billion metric tonnes of CO_2 emissions—more than half of the total emissions in the Asia-Pacific region. This paper probes into whether digitalization increases or help reduce CO_2 emissions. We hypothesize that digitalization could reduce CO_2 emissions if it leads to less travelling using private cars, and hence, less CO_2 emissions. On the other hand, digitalization may increase CO_2 emissions since digitalization is consumes electricity where traditional electricity generation of may increase CO_2 emissions.

This study delves into the question of whether digitalization contributes to an increase or reduction in CO_2 emissions. Our hypothesis posits that digitalization may result in a decrease in CO_2 emissions by potentially reducing the need for private car travel, thereby resulting in lower emissions. In addition, digitalization may reduce other monitoring costs and lead to higher efficiency. Conversely, digitalization could potentially exacerbate CO_2 emissions due to its electricity consumption, particularly if we rely on traditional electricity generation methods that contribute to CO_2 emissions.

LITERATURE REVIEW

The nexus between economic growth and environmental degradation has been a focal point of interest since the 1960s with mixed results but leans towards a positive relationship between the two where higher growth leads to higher environmental degradation (*inter alia* Wang, 2011; Arouri et al, 2012; Falahi & Ashena, 2010). With the emergence of different phases of the Industrial Revolution, IR 1.0 to IR4.0, more attention was given to sustainable production and revitalization of the environment. The Millennium Development Goals (MDGs) which precede the Sustainable Development Goals (SDGs) mark a new milestone where economic development and environmental sustainability receive equal footing.

Another intriguing aspect to consider is the disparities in CO_2 emissions. For instance, China's emission levels surpass those of India. Moreover, more developed regions such as Europe, North America, and Oceania emit greater amounts of CO_2 compared to less developed areas like Africa and South America. Similarly, per capita emissions in high-income countries are significantly higher, being approximately 30 times greater than those in low-income countries. For instance, in 2021, high-income countries accounted for 34% of emissions, whereas their population share was only 15.4%. Conversely, low-income countries contributed just 0.6% of emissions despite having an 8.8% share of the global population. These disparities highlight the inequality in emissions between high-income and low-income countries and across different regions (Richtie, 2023). In essence, approximately 80% of the world's emissions originate from high- and upper-middle-income countries with advanced levels of industrialization.

More recently, the literature has focused extensively on the impact of digitalization on CO_2 emissions. Broadly, the findings can be classified into two categories: digitalization leading to increased CO_2 emissions (e.g., Arshad et al., 2020; Lee and Brahmasrene, 2014; Charfeddine & Kahia, 2021; Ramzan et al., 2022; Godil et al., 2020) and digitalization resulting in decreased CO_2 emissions (e.g., Zhang & Meng, 2010; Nguyen et al., 2020; Chien et al., 2021; Shabani & Shahnazi, 2019; Anochiwa et al., 2022). Various variables commonly

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utilized to represent digitalization from an ICT infrastructure perspective include fixed broadband subscriptions, fixed telephone subscriptions, mobile phone subscriptions, and internet users (Ulucak & Khan, 2020; Moyer & Huges, 2012; Su et al., 2021). Different estimation methods have been employed to assess the impact of digitalization on CO2 emissions, with the panel quantile method being the most favoured (Anser et al., 2021; Nguyen et al., 2020; Chen et al., 2019; Chien et al., 2021; Ramzan et al., 2022; Godil et al., 2020). Other methodologies include the STRIPAT model (Anochiwa et al., 2020; Quaglione et al., 2023), cluster analysis (Arshad et al., 2019), DOLS (Shabani & Shanazi, 2019), and ARDL (Khan et al., 2022; Park et al., 2018).

The direction of how digitalization affects CO2 emission can be summarized as follows: First, internet usage lowers the quality of the environment but increases electricity consumption (Park et al., 2018). Zhang and Meng (2019) echoed similar results for 115 developed and developing countries in which emissions are lower at the lower income threshold. Second, mobile phone subscriptions reduce CO2 emissions in production and consumption (Anochiwa et al., 2022) in Sub-Saharan African countries (1995-2017), whilst Anser et al. (2021) found that mobile phones increase CO2 emissions in twenty-six European Union countries (2000-2017). On the other hand, this study finds that fixed broadband has a positive effect in reducing CO2 emissions. In the provinces of China, Chen et al. (2019) suggest that an increase in both fixed broadband and mobile phone subscriptions increased CO2 emissions between 2001 and 2016. Using digital technologies in the form of big data and computing infrastructure to represent digitalization, Bianchini et al. (2022) show an increase in greenhouse gases (GHG) for selected areas in the UK for the period of 2007-2016. Another proxy used to represent digitalization is private investments in ICT, where Khan et al. (2022), Chien et al. (2021), and Ramzan et al. (2022) show that ICTs have reduced CO2 levels in the case of Morocco, BRICS countries, and Pakistan, respectively. On the other hand, the use of ICT in MENA countries from 1980 to 2019 shows an increase in environmental pollution (Charfeddine & Kahia, 2021). On a similar note, Lee and Brahmasrene (2014) and Arshad et al. (2020) show that CO2 increases with improvements in ICT in ASEAN countries (1991-2009) and South and Southeast Asia (1990-2014). However, Arshad et al. (2020) argue that advanced countries with robust financial development along with innovations in ICT can arguably lower CO2 emissions given greater financing in environmentally sustainable projects.

Given the discussions on the impact of digitalization on the environment, the primary focus has consistently been on carbon dioxide (CO2) emissions. This emphasis on CO2 emissions is attributed to the availability of comprehensive data on CO2 levels and their status as the most prevalent type of environmental pollution associated with digitalization. However, in this study, we aim to expand the scope of analysis beyond CO2 emissions. While CO2 remains a crucial indicator, we seek to introduce and incorporate various measurements of environmental pollution into our analysis. The main intention is to provide a more comprehensive understanding of the multi-layered impacts of digitalization on the environment, considering diverse forms of pollution beyond CO2 emissions. This broader approach allows for a more nuanced evaluation of the environmental consequences associated with digitalization, enabling us to explore additional dimensions of environmental degradation and assess the overall ecological footprint of digital technologies.

METHODOLOGY

Prior to determining the appropriate econometric specification model, a few preliminary tests, such as the cross-sectional dependency test and a few panel unit root tests (PUR), were conducted to examine the data.

A. Pre-Testing

Cross-sectional Dependency Test

The cross-sectional dependency (CSD) test is as follows:

$$CSD = \sqrt{}\,[\frac{2T}{N^2-1}\sum_{i=1}^{N-1}\sum_{i=j,t-1}^{N}\rho g] \qquad (1)$$

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where N denotes the cross-section unit of $\rho\hat{g}$ which measures the correlation of the residual, and T denotes the time dimension. The null hypothesis for CSD is no cross-sectional dependency.

Panel Unit Root Test

This study relies on the second-generation panel unit root test based on Im, Pesaran, and Shin (CIPS) and the Pesaran cross-sectional augmented Dickey-Fuller (CADF) tests proposed by Pesaran (2007). In addition, we add a third generation, which accounts for structural breaks in the panel data series. The third-generation panel unit root test with a structural break as proposed by Karavias and Tzavalis (2017) is expressed as follows:

$$Z_{it} = d_{it} + \vartheta_t f_t + \mu_{it} \tag{2}$$

where Z_{it}, d_{it}, f, ϑ and μ denote the aggregate deterministic segment, a common component, f_t, a polynomial movement, ϑ_t, a vector of $r \times 1$ common factors, a vector of loadings, and a white-noise stochastic term.

$$\omega = \frac{\sum_{i=}^{N} Q_m^{br} Z_t}{\sum_{i=}^{N} Z_{t-1}^{I} Q_m^{br} Z_{t-1}} \quad m = (M_1, M_2) \tag{3}$$

where Z_i and Z_{i-1} are $T \times 1$ vectors Q_m is the orthogonal features matrix which is a $T \times T$ identity matrix; the superscript br in Q_m denotes the degree of reliance in the breakpoint. This unit root test with structural breaks uses 100 bootstraps for each period of time. The null hypothesis is that the panel time series are non-stationary (Karavias and Tzavalis, 2017).

Panel ARDL

The link between environmental pollution, GDP, and digitalization is expressed using the panel autoregressive distributed lag (ARDL) for the Southeast Asian economies. The basic model is based on Sikder et al. (2022), which is expressed as follows:

$$EP_{it} = f(Dig_{it}, GDP_{it}, inf_{it}, open_{it}, pop_{it}) \tag{4}$$

where *t* denotes the time period from 2003 to 2022, *E*P represents environmental pollution, which will be captured by CO2 and other proxies discussed in the following subsection, *dig* represents digitalization within the country, *GDP* captures the size of the economy, *inf* captures the price level and *pop* represents the size of the demand in the country. The econometric specification or the long-run model is written as,

$$EP_{it} = \beta_0 + \beta_{1i} GDP_{it} + \beta_{2i} Dig_{it} + \beta_{3i} inf_{it} + \beta_{4i} open_{it} + \beta_{5i} pop_{it} + \varepsilon_{it} \tag{5}$$

Following Anwar et al. (2020), data on environmental pollution, GDP, digitalization, and population were transformed into logarithmic form to estimate the coefficients more efficiently. Whilst *t* represents the time element, *i* captures the cross-section effect and *e* represents the error term. The β coefficient symbolizes the long-run relationship between the dependent and independent variables in the equation. The short-run model is shown below:

$$\Delta EP_{it} = \sum_{k=1} M_{ij} \Delta EP_{it-j} + \sum_{k=0}^{q} Z_{ij} \Delta DV_{it-j} + \varphi_{ij} ect_{t-i} + \varepsilon_{it} \tag{6}$$

where DV represents digitalization, GDP, population, trade openness, and inflation.

Data and Sources

Environmental pollution is represented by a host of proxies, which include carbon dioxide emission kg per 2015 US$ of GDP (*CO2*), agriculture methane emissions based on thousand metric tonnes of CO2 equivalent

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(methane), and agriculture nitrous oxide emission based on thousand metric tonnes of CO2 equivalent (*NOX*). In the case of CO2, this proxy is categorized into different types of CO2 emissions, such as CO2 emissions from solid fuel consumption (*CO2_fuel*), electricity and heat production (*CO2_elec*), gaseous fuel consumption (*CO2_gas*), liquid fuel consumption (*CO2_liq*), manufacturing, industries, and construction (CO2_man), as well as other sectors excluding residential buildings, commercial and public services (CO2_res), and transport (*CO2_trans*).

Digitalization is represented by fixed broadband subscriptions (*Fixed_BB*), fixed broadband subscriptions per 100 people (*Fixed_BB_100*), mobile cellular subscriptions (*Mobile*), mobile cellular subscriptions per 100 people (*Mobile_100*), individuals using the internet as a percentage of the population (*Internet Users*), secure internet servers (*SIS*), and secure internet servers per 1 million people (*SIS_100*). The control variable includes gross domestic product at constant 2015 US$ (GDP) to control for the size of the economy and income level, total trade as a ratio of GDP (open) to capture the size of trade and globalization, inflation (inf), and population to capture the size of demand. All data were derived from the World Development Indicator (WDI).

B. Digitalization and environmental pollution

Since data on digitalization is not available for an extended time period and proxies were used to capture the digitalization, results may be biased since they only account for one specific definition. A better option would be taking a combination of a few variables that could capture digitalization. For this purpose, four dimensions were chosen to represent digitalization which include fixed broadband subscriptions, internet users, mobile subscriptions, and secure internet servers. We applied the principal component analysis (PCA) method to actively produce a new dataset to represent digitalization. PCA is a preferable method due to its simplicity in exploring interrelationships or summarizing data (Stevens, 1996; Tabachnick & Fidell, 2013). PCA involves three major steps. First, the assessment of suitability, which considers the sample size and the strength of the relationship among the variables. The strength of the relationship is tested using the Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity, which are also measures for sampling adequacy. Bartlett's test should be significant ($p < 0.05$), while the KMO index should be more than 0.6. Our results show that the KMO test is 0.83, indicating the suitability of the data to be combined using PCA, and Bartlett's test is significant, signalling sample adequacy.

The second step involves factor extraction to determine the smallest number of factors to represent the relationship of the variables. Three methods can be used to examine the number of factors to retain. Kaiser's criterion uses the eigenvalue, where factors with eigenvalues of more than one would be retained. Normally, Kaiser's criterion is supplemented with parallel analysis and the scree test. In parallel analysis, a random dataset with the same size as the original dataset is generated. The eigenvalues will be compared, and those with eigenvalues that exceed the randomly generated values will be retained. Arguably, parallel analysis is more accurate since Kaiser's criteria and the scree plots tend to overestimate the number of components that should be retained. The results show that the optimal number of components is one (1), which confirms that the four proxies previously identified to represent digitalization can be a single variable to represent digitalization. The third step involves factor rotation. In this study, we rely on orthogonal (uncorrelated) rotation since it is easier to interpret and report. In terms of the rotational approach, we used the Varimax factor rotation since it minimizes the number of components. This approach identifies and allows a reduction in the number of variables to only those with high loadings on a single component.

The same method is applied to construct a new variable for environmental pollution based on the source. In this study, we resort to two classifications where (i) environmental pollution (*pollution*) constitutes (i) agriculture methane, (ii) agriculture nitrous oxide, and (iii) carbon dioxide. The second combination (*pollution_CO2*) focuses on seven (7) different components of CO2 emissions, including emissions from solid fuel consumption, electricity and heat production, gaseous fuel consumption, liquid fuel consumption, manufacturing, transport, and other sectors.

FINDINGS

Table 1 reports the descriptive statistics for the variables used in this paper. The panel unit root tests show that the variables are either I(0) or I(1) and the dependent variable (s) are I(1), which corroborates the use of panel ARDL. Panel unit root tests with structural breaks show no signs of major structural breaks, and the CSD test shows no evidence of cross-section dependency, hence not reported.

Table1descrıptıve Statıstıcs

Variable	Mean	Max	Min	Std. Dev.	PUR
METHANE	8.991	11.414	0.520	3.700	I(0)
NOX	8.122	11.090	2.6416	2.455	I(0)
CO2	0.566	0.920	0.148	0.247	I(1)
CO2_elec	44.920	73.041	26.202	11.343	I(1)
CO2_fuel	22.829	45.934	0.029	13.603	I(1)
CO2_gas	26.287	71.129	6.241	15.435	I(1)
CO2_liq	48.309	111.719	13.484	15.747	I(1)
CO2_man	22.206	35.007	11.501	6.390	I(1)
CO2_res	2.486	10.526	-0.025	2.509	I(1)
CO2_trans	25.684	44.465	13.654	6.518	I(1)
Fixed_BB	13.295	15.607	5.493	2.033	I(0)
FBB _100	5.388	27.261	0.001	7.645	I(0)
GDP	26.113	27.433	23.935	0.741	I(0)
Inf	5.690	35.024	-0.845	5.899	I(0)
Internet_User	29.314	82.100	0.065	24.418	I(0)
Mobile	17.002	19.601	11.765	1.764	I(0)
Mobile _100	81.940	154.035	0.269	48.870	I(0)
Open	125.334	343.488	27.090	85.015	I(1)
Pollution	0.126	0.815	-2.280	1.051	I(1)
Pollution_CO2	-0.013	2.932	-1.330	1.014	I(0)
Population	17.730	19.361	15.230	1.187	I(0)
Digitalization	0.015	1.443	-2.164	1.000	I(0)

The presence of unit roots in some of the variables (Table 1) and the absence of cross-section dependency and structural breaks corroborates the use of panel ARDL. Table 2 shows the benchmark results of how digitalization affects environmental pollution, proxied by CO2. The first regression combines the proxies for digitalization – fixed broadband subscribers, internet users, mobile subscriptions, and secure internet servers. Regression 2-4, on the other hand, runs the proxy for digitalization individually. Results show that digitalization is positively correlated to CO2 emission, where more digitalization is associated with higher CO2 emission. Interestingly, GDP is negatively related to CO2, which indicates the size of the economy does not necessarily result in higher CO2 emissions. The sign of the coefficients for trade openness and population is positive, which supports the fact that a higher population leads to higher CO2 emissions. A classic example would be the use of transportation to work, which emits CO2. Since the Southeast Asian economies are still short on public transportation, the use of private cars would increase CO2 emissions. Trade is also positively

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related to CO2 since trade increases both production and consumption, which later lead to higher CO2 emissions. Inflation is negatively associated with CO2 but is only significant in the second regression

Table 2 Dependent Varıable: Co2

Long-run				
Variable	All	Fixed BB	Int User	Mobile
Digital	0.448*** (0.062)	0.018** (0.009)	0.002* (0.001)	0.132*** (0.031)
GDP	-0.360*** (0.052)	-0.183** (0.075)	-0.008 (0.053)	-0.295*** (0.072)
Inflation	0.001 (0.005)	-0.006** (0.002)	-0.004 (0.004)	-0.007 (0.005)
Open	0.003*** (0.001)	0.002*** (0.000)	0.004*** (0.001)	0.006*** (0.000)
Pop	0.141 (0.091)	0.151*** (0.042)	0.239*** (0.087)	0.041 (0.029)
Constant	9.626*** (1.360)	2.916** (1.149)	-3.885*** (0.684)	4.684*** (1.098)
Short run				
ect_{t-1}	-0.219 (0.138)	-0.207** (0.172)	-0.005 (0.049)	-0.160 (0.098)
LL	347.25	342.87	342.53	352.68

Note: ***, **, and * denote 1%, 5%, and 10% significant levels.

For robustness, we run the same set of regression using categorical CO2 emissions, which include emissions from electricity consumption, solid fuel consumption, liquid fuel consumption, emissions from manufacturing, construction, and other services, and emissions from transportation activities.

We also use different proxies to represent environmental pollution. The first proxy is the combination of CO2, methane, and nitrous oxide (pollution), and the second proxy is the combination of all categories of CO2 emission (pollution_CO2). For the robustness test, we use the number of mobile subscriptions and the number of internet users to represent digitalization. Table 3 illustrates the results when CO2 is replaced with other proxies—pollution based on the three main gas emissions and by segmented CO2 emissions. Digitalization is represented by the number of internet users. Table 4 repeats the same process but changes the proxy for digitalization with the number of mobile subscriptions. The results are consistent with Bianchini et al. (2022) and Chen et al. (2019), where the higher penetration of fixed broadband and mobile subscriptions leads to higher CO2 emissions. Our study contradicts the findings by Park et al. (2018), Nguyen et al. (2020), and Anochiwa et al. (2022), which suggested that the internet lowers electricity consumption. Based on our results, we argue that the increase in the number of internet users will definitely increase electricity consumption, leading to higher CO2 emissions. We also argue that the use of the internet and other ICT-type solutions leads to cost reductions. For example, online meetings reduce the need to travel, which is a cost-savings element. Cost savings equate to more revenue and profits, leading to higher salaries, wages, or even bonuses. This

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would lead to greater demand for goods and services, which in turn would lead to more production. Given the lack of green production mechanisms in Southeast Asian countries, more production leads to higher CO2 emissions and other forms of pollution.

The number of internet users is positively associated with emissions from electricity and heat production, solid fuel consumption, liquid fuel consumption, and transportation. Using mobile subscriptions as a proxy for digitalization, its impact on environmental pollution is significant, especially for the emission of CO2 from electricity, transport, fuel, manufacturing, and residential usage. On a similar note, trade openness and population are positively related to environmental pollution in the majority of the results. In other words, an increase in population inevitably leads to higher CO2 emissions. Similarly, the movement of goods, services, and financial and physical investments leads to a higher trade-to-GDP ratio, rendering more production, which in turn leads to higher emissions of CO2 and other pollutants. Hence, it is imperative for the policymaker to engage in green production to assuage the impact of production on the environment.

Table 3a Dependent Variable: Environmental Pollution by Source

	1	2	3
DV	Pollution	Pollution CO2	CO2 electric
Long run			
Int_User	0.056*** (0.014)	0.045*** (0.007)	0.251*** (0.036)
GDP	-0.452*** (0.014)	-2.301*** (0.343)	2.265* (0.036)
Inflation	0.0001 (0.001)	-0.006*** (0.002)	-0.050 (0.074)
Open	0.001* (0.001)	0.003** (0.001)	0.050*** (0.013)
Pop	0.735*** (0.001)	1.133*** (0.230)	4.230*** (1.229)
Constant	-1.656 (1.402)	57.744*** (8.559)	61.21*** (16.266)
Short run			
ect_{t-1}	-0.112 (0.075)	-0.302** (0.149)	-0.412*** (0.141)
LL	604.83	52.34	-202.05

Note: ***, **, and * denote 1%, 5%, and 10% significant levels.

Table 3b Dependent Variable: Environmental Pollution By Source

	4	5	6
DV	CO2 fuel	CO2 gas	CO2 liq

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Long run			
Int_User	0.291*** (0.087)	0.001 (0.088)	0.122** (0.049)
GDP	-8.617*** (2.449)	-7.245** (3.617)	-7.789 (4.757)
Inflation	-0.318* (0.1397)	0.710* (0.362)	-0.589* (0.342)
Open	0.016 (0.011)	0.015 (0.023)	0.332*** (0.064)
Pop	4.828*** (0. 942)	6.452** (2.717)	12.408*** (2.644)
Constant	-72.37* (42.423)	31.268*** (4.801)	12.159 (82.539)
Short run			
ect_{t-1}	-0.1631 (0.1078)	-0.332** (0.141)	-0.374** (0.160)
LL	-280.28	-249.66	-363.66

Note: ***, **, and * denote 1%, 5%, and 10% significant levels.

Table 3c Dependent Variable: Environmental Pollution by Source

	7	8	9
DV	CO2 man	CO2 res	CO2 trans
Long run			
Int_User	-1.262 (0.969)	-0.008 (0.021)	0.268*** (0.033)
GDP	-32.87 (78.89)	-1.750** (0.787)	-21.05*** (1.048)
Inflation	-13.85 (16.23)	-0.091 (0.071)	0.085*** (0.016)
Open	-5.046 (5.525)	0.012 (0.013)	0.129*** (0.020)
Pop	65.067 (90.187)	1.667 (1.348)	14.774*** (1.601)
Constant	450.69	18.47*	279.77**

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	(166.51)	(9.317)	(23.0184)
Short run			
ect_{t-1}	-0.0385 (0.0395)	-0.142*** (0.054)	-0.425* (0.243)
LL	-164.2	-15.35	-121.44

Note: ***, ** and * denote 1%, 5% and 10% significant level.

Table 4a Dependent Variable: Environmental Pollution by Source

	1	2	3
DV	Pollution	Pollution CO2	CO2 electric
Long run			
Mobile	0.056*** (0.014)	0.048*** (0.017)	-5.764*** (0.640)
GDP	-0.452*** (0.106)	0.119 (0.081)	34.919*** (3.44)
Inflation	0.001 (0.001)	-0.003** (0.001)	0.133*** (0.035)
Open	0.001* (0.0006)	0.001** (0.001)	0.064*** (0.018)
Pop	0.735*** (0.067)	1.377*** (0.138)	7.267*** (2.476)
Constant	-1.656 (1.402)	20.212*** (2.769)	-640.328*** (72.214)
Short run			
ect_{t-1}	-0.112 (0.075)	-0.454*** (0.163)	-0.112 (0.073)
LL	604.83	62.21	604.83

Note: ***, **, and * denote 1%, 5%, and 10% significant levels.

Table 4b Dependent Variable: Environmental Pollution By Source

	4	5	6
DV	CO2 fuel	CO2 gas	CO2 liq
Long run			
Mobile	4.715*** (1.6115)	-1.378 (1.005)	-5.148*** (0.640)
GDP	-1.744	-8.7431***	-22.224**

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	(3.447)	(2.928)	(4.799)
Inflation	0.601 (0.394)	-0.080 (0.098)	-0.261*** (0.088)
Open	-0.025 (0.039)	0.020 (0.024)	0.103** (0.042)
Pop	1.984 (3.431)	5.861** (2.397)	23.203*** (3.869)
Constant	-49.366 (36.261)	387.86*** (48.99)	335.437*** (67.614)
Short run			
ect_{t-1}	-0.094 (0.122)	-0.497*** (0.151)	-0.685*** (0.230)
LL	-287.16	-236.74	-324.91

Note: ***, **, and * denote 1%, 5%, and 10% significant level.

Table 4c Dependent Variable: Environmental Pollution by Source

	7	8	9
DV	CO2 man	CO2 res	CO2 trans
Long run			
Mobile	-3.800*** (1.362)	-1.200*** (0.237)	1.877*** (0.323)
GDP	-9.403* (4.944)	-1.385*** (0.169)	-16.378*** (1.800)
Inflation	0.142** (0.064)	-0.071*** (0.033)	-0.008 (0.029)
Open	0.226*** (0.074)	0.009** (0.004)	0.052*** (0.017)
Pop	-1.301 (6.898)	2.592*** (0.285)	12.702*** (3.524)
Constant	335.43*** (87.99)	16.365*** (3.037)	598.733*** (78.523)
Short run			
ect_{t-1}	-0.2995*** (0.0793)	-0.225** (0.093)	-0.269 (0.175)
LL	-159.52	-147.31	-147.87

Note: ***, ** and * denote 1%, 5% and 10% significant level.

CONCLUSION

Southeast Asia is home to 690.28 million people or approximately 8.4% of the total world population. Although the total CO2 emission is not as large as China or any other developed country, early efforts need to be brought into practice to ensure a healthy and sustainable environment. This paper delves into the impact of digitalization on environmental pollution. Although extensive studies have been undertaken on this subject, there is still room to deepen our understanding of the interplay between digitalization and environmental pollution. This paper offers another insight into digitalization where the common proxy for digitalization such as internet users, fixed broadband subscriptions, and mobile subscriptions are combined to capture the impact of digitalization. We offer both individual proxy analysis and the combined analysis to further understand its impact. Similarly, the definition of environmental pollution is extended by incorporating agriculture methane emissions and nitrous oxide emissions apart from the conventional use of CO2 to represent environmental pollution. In addition, CO2 is further segmented into different types of emissions such as emissions from electricity and heat production, transport, manufacturing, services, liquid and gas consumption, solid fuel consumption, construction, and residential usage.

The results show that digitalization as proxied by the number of internet users, fixed broadband penetration, mobile cellular subscription, and secure internet servers, aggravates environmental pollution. The use of digitalization improves production and other related services via cost reduction. This spillover effect extends to other parts of the economy where an increase in wages and salary from the consumer perspective and an increase in revenue and profits for companies lead to higher aggregate demand (AD). As a result, production increases but leads to higher CO2 emissions.

The results point to several policy directions. First, digitalization can lead to lower CO2 emissions via a reduction in transport usage. However, if production is not energy efficient or green and circular economy production is absent, CO2 and other pollution-related gases such as methane and nitrous oxide would continue to rise. Hence, digitalization policy must be complemented with green production and circular economy policies. Second, since digitalization consumes a high amount of electricity, renewable energy such as solar should gradually replace fossil fuels to generate electricity. Therefore, the way forward is to have a greener, cleaner production routine alongside recycling, upcycling, and downcycling.

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