Chapter 12

Investigating the Growth Effects of Sharing Health Data in ASEAN Member States

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1. Introduction

1.1. Background

The medical and healthcare industry has achieved considerable growth in the Association of Southeast Asian Nations (ASEAN) Member States (AMS), partly driven by demographic changes. Moreover, medical tourism has become a significant industry in countries such as Thailand (Thailand Convention and Exhibition Bureau, 2020). AMS might face challenges balancing investment in infrastructure and increasing healthcare expenditure while confronting a decline in tax revenues (ASEAN, 2020: 9). Yet, healthcare is also a source of innovation and growth. This chapter argues that improving health-related information data sharing can achieve further growth and productivity gains.[1]

This chapter focuses on identifying the impact of enhanced data sharing in healthcare on economic growth. In a recent report, the Asian Development Bank (ADB, 2022) highlighted the three core benefits of data sharing in healthcare: monitoring infectious diseases, preventing non-communicable diseases, and remote monitoring. Quantifying the benefits of data sharing is essential for formulating policy recommendations, as costs need to be considered (e.g. investment in cybersecurity, regulatory changes). The coronavirus disease (COVID-19) pandemic illustrated that data hold crucial health value in addition to economic and societal value. Health data, including COVID-19 pandemic data, can potentially inform policies that would, directly and indirectly, contribute to productivity and growth on the micro and macro level. Health data benefit individuals, health systems, as well as policies. Individual-level data can help individuals to monitor their health. For instance, the data are valuable in marketing health-based gadgets, including smartwatches and COVID-19 symptom trackers. Moreover, the ASEAN Digital Masterplan 2025 (ASEAN, 2020) highlighted that e-health will be central in enhancing access to healthcare and mitigating the impact of COVID-19 (deliverable DO5). In summary, this study focuses on the impact of data sharing on the productivity of the healthcare industry, which contributes to economic output. Arguably, there is a second channel through which data sharing increases output – by improving population health – which in turn drives labour productivity. However, this relationship is beyond the scope of this study. To analyse this effect properly, one needs to address dual causality as it is well documented that labour market outcomes affect health, leading to an endogeneity issue. Furthermore, many confounding effects affect population health apart from data sharing in healthcare settings.

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[1] Note that we use the terms 'data sharing' and 'data sharing in healthcare' interchangeably.

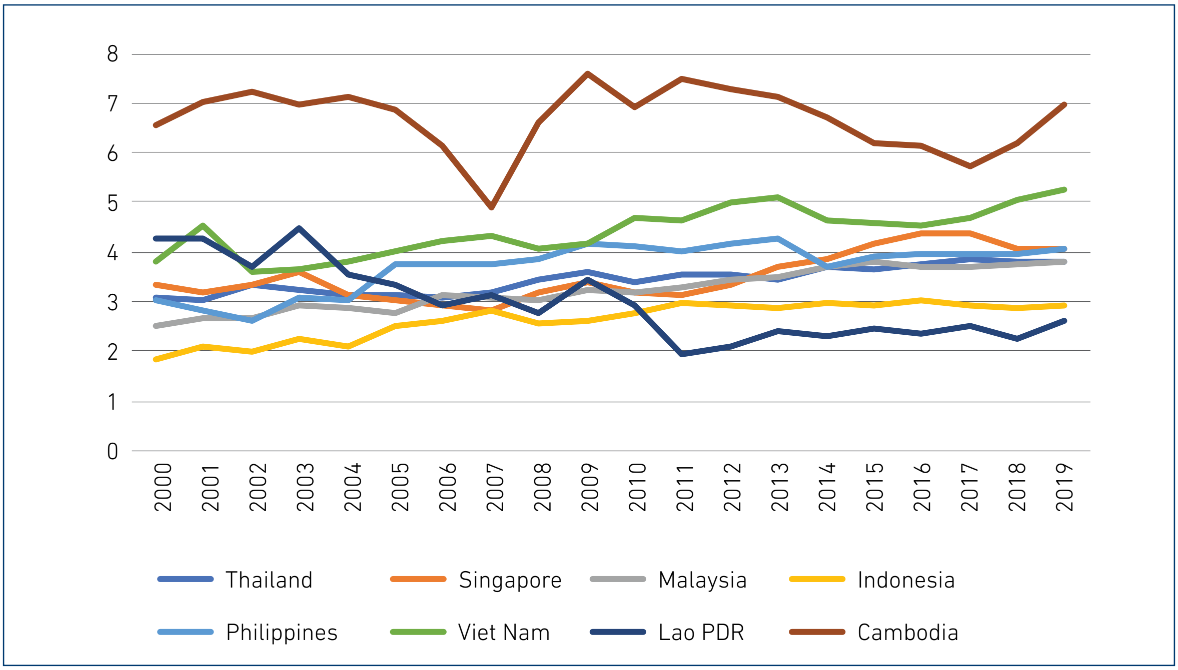
Beyond the urgency created by the pandemic, health data sharing has always benefited health systems and policymakers. For instance, AMS have the tradition of collating national-level representative data on maternal and child health, HIV/AIDS, family planning, and nutrition. This monitoring resulted in policies and programmes that could improve the health system and the health and well-being of populations at the national and subnational levels. Recently, most AMS joined the District Health Information Software (DIHS-2) partnership, which collates regular and timely data from health facilities to improve the health outcomes of patients. These sources of information strengthen health systems. Data-sharing activities and the information and communication technology (ICT) infrastructure support individuals and equip health providers and policymakers to make better decisions. However, very little is known about the impact of the health data infrastructure on economic growth. Our study fills this gap by assessing the economic argument for enhanced data sharing. We hypothesise that improved data sharing will contribute to the growth of the region, which in turn will support further growth of the e-health sector in AMS.

Data sharing is essential in digital healthcare and, to a lesser extent, in more traditional healthcare settings. However, ensuring cybersecurity is paramount due to the sensitive nature of health-related private information. As stated in deliverable DO3 of the ASEAN Digital Masterplan 2025 (ASEAN, 2020), digital services must be trustworthy, and consumer protection cannot be compromised. Our report details security concerns and possible technology-based solutions while looking at the benefits of data sharing. Next, we discuss the country-specific context, followed by our research questions, data sources, methodology, and empirical findings. Finally, we outline policy recommendations and conclude our study. Our code, written in Python and Stata, is available on GitHub (Kling, 2023). The repository provides access to the repository with links to educational videos produced by Yunikarn Ltd.

1.2. Country-specific context

Figures 12.1, 12.2, and 12.3 show stylised facts for selected AMS, including health expenditure as a percentage of gross domestic product (GDP), internet servers per 1 million people, and mobile phone subscriptions per 100 people. All data are extracted from the World Development Indicators (WDI) database (World Bank, 2022). The general trend amongst AMS, based on the mean and median, indicates that health expenditures relative to GDP have increased from 2000 to 2019 – the median increased from 3.22% to 3.95%, whereas the mean rose from 3.56% to 4.19%. Moreover, the data do not suggest any decline from the 2010 levels, with a median of 3.30% and a mean of 3.90%.

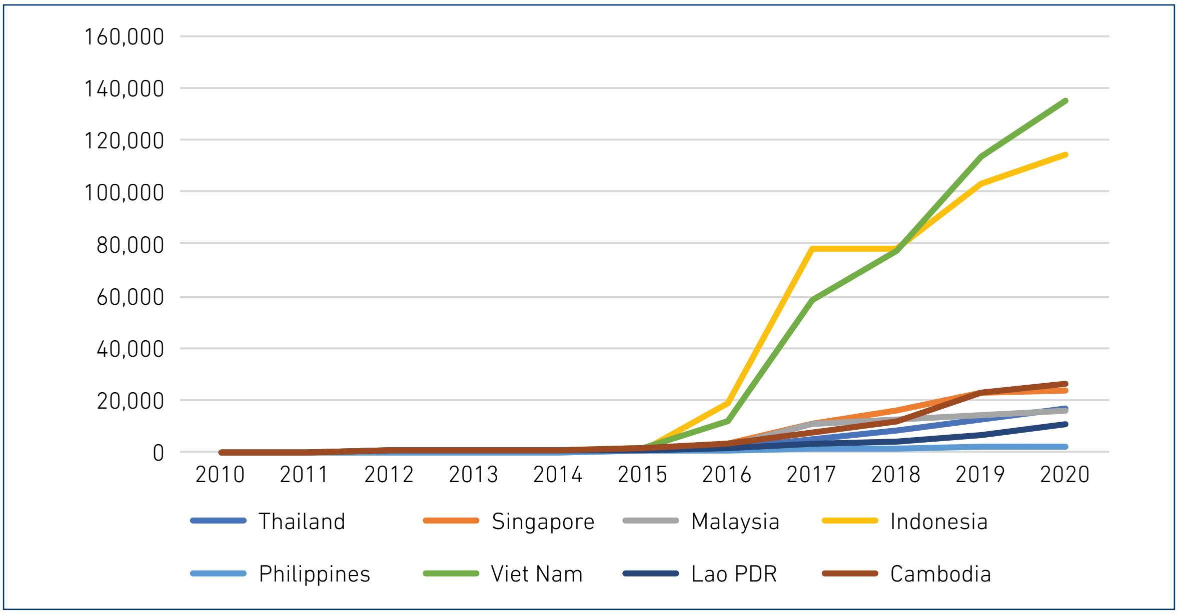
Figure 12.1. Current Health Expenditure in Selected ASEAN Member States
(% of GDP)



ASEAN = Association of Southeast Asian Nations, GDP = gross domestic product.
Source: World Bank (2022).

It is evident that ICT infrastructure has developed rapidly in AMS, while healthcare has witnessed a sustained increase relative to GDP, driven by population ageing and higher living standards. Figure 12.2 illustrates the relative expansion of the internet from 2010 to 2020. Singapore exhibits the highest number of secure internet servers per 1 million inhabitants due to the high concentration of international businesses. However, Viet Nam and Indonesia have improved the most compared with their 2010 starting positions.

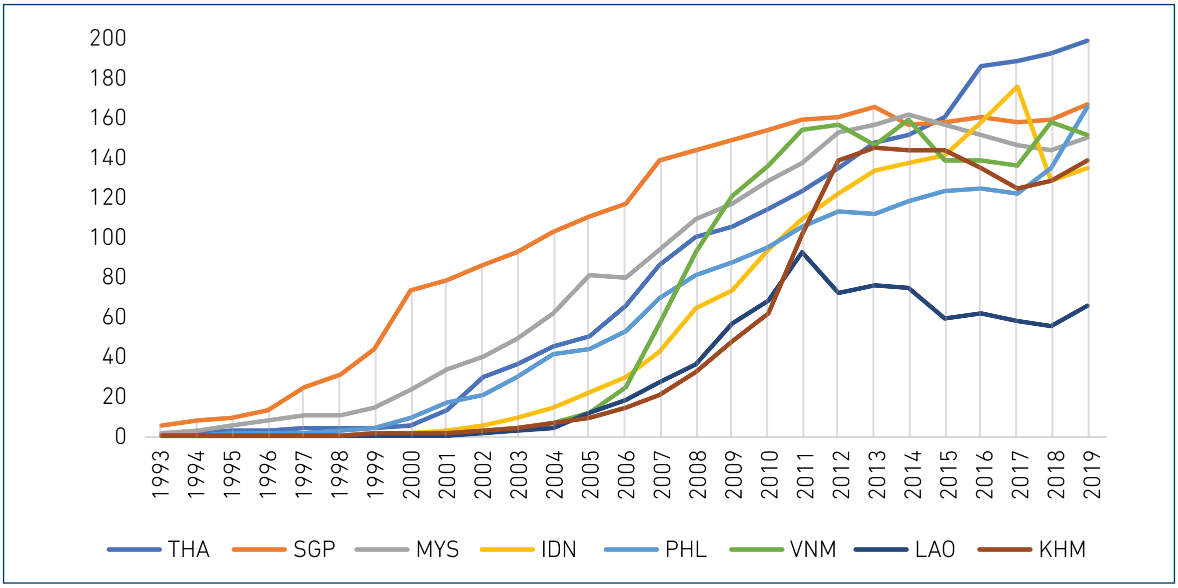
Figure 12.2. Secure Internet Servers in Selected ASEAN Member States
(per 1 million people, indexed)



ASEAN = Association of Southeast Asian Nations.

Source: World Bank (2022).

Figure 12.3. Mobile Phone Subscriptions in Selected ASEAN Member States
(per 100 people)



ASEAN = Association of Southeast Asian Nations, IDN = Indonesia, KHM = Cambodia, LAO = Lao PDR, MYS = Malaysia, PHL = Philippines, SGP = Singapore, THA = Thailand, VNM = Viet Nam.

Source: World Bank (2022).

This chapter explores current practices in AMS and tries to quantify the economic impact of sharing health-related data using a growth accounting framework. Policy implications will focus on achieving the alleged benefits by mitigating and managing inherent barriers and risks. The ASEAN Digital Masterplan 2025 is highly ambitious and names e-health as one of the four key industries amongst finance, education, and e-government (ASEAN, 2020).

In a report on the digital health industry in ASEAN, the Hong Kong Trade Development Council outlined recent collaborations with the private sector to tackle the pandemic (HKTDC, 2021). These initiatives include an expansion of telemedicine, which is the dominant business segment in e-health, according to a recent study by McKinsey (Baur, Yew, and Xin, 2021). Providing remote healthcare to treat milder cases of COVID-19 has reduced the pressure on the healthcare system. Providing access to COVID-19 data through the open-data COVID-19 tracker in the Philippines and similar apps developed in other AMS helps plan capacity and inform decision-makers. HKTDC (2021) outlined that regulation related to data protection has focused on telemedicine in AMS.

1.3. Research questions and analytical steps

The section reviews the literature, modifies existing methods, combines secondary data sources, and estimates the economic impact of improved sharing of health-related data. Based on our quantitative analysis, we derive policy recommendations aimed at achieving the expected benefits by mitigating risks and barriers. Our overarching research question is: how can enhanced data sharing of health-related information generate economic growth?

To address this question, we have to break down the underlying relationships into several smaller steps. First, we can relate different types of capital accumulation and labour supply to economic growth using growth accounting. Economic growth occurs by efficiently combining capital and labour through a production function affected by technological progress. We split investment into ICT and non-ICT investment. Infrastructure like broadband or mobile networks is central to reducing the digital divide and is a prerequisite for data sharing (ASEAN, 2020).

Second, after demonstrating the importance of ICT capital and its partial impact on growth in AMS, we estimate the size and growth potential of e-health based on industry and company reports. Using secondary data (i.e. the WDI provided by the World Bank), we can relate the size of the nascent e-health market to overall health spending. Using additional data on health expenditure, we estimate a panel vector autoregression (VAR) to explain economic growth. The panel VAR model focuses on the short-term dynamics of changes in health spending, ICT and non-ICT capital accumulation, and economic growth.

Third, based on the panel VAR model, we obtain the system's dynamics, captured in impulse-response functions. These are used to simulate the likely impact of data sharing and e-health on future economic growth. We calculate impulse responses over 10 steps to obtain midterm forecasts, simulating a 10-year period.

Finally, we provide practical policy implications based on our estimates, including privacy-preserving technologies, which can enable data sharing by mitigating associated risks. These technologies could increase trust in the system, which is essential for participation. Moreover, our analysis suggests that a data gap exists as current practices of data sharing in healthcare settings are not reported at the country level. It would be prudent to monitor data sharing more closely to mitigate risks and understand the current state of technology.

2. Research Approach

2.1. Prior research

Prior research fundamentally stresses two important perspectives. First, we discuss the contribution of information technology to economic development via productivity, research, innovation, and technological development. Previous literature documented the positive impact of the internet of things (IoT) on economic value (productivity) by using interconnected devices and transmitting data and information (Espinoza et al., 2020). In a similar line of research, Vasileiadou and Vliegenthart (2009) highlighted the impact of internet use on sharing research information, coordination, meetings, and team management. These factors contribute to enhancing research productivity. However, they stressed the challenges of data security and privacy. These challenges are relevant in healthcare settings. Bozeman and Rogers (2002) investigated the historical perspective of knowledge transformation through the internet and technological innovation, where social configurations contributed to the knowledge value. Using longitudinal surveys of 94 internet ventures in Beijing, Batjargal (2007) examined internet entrepreneurship relations in China and found that the interaction of social capital and entrepreneurs positively affects the survival of internet firms and creates value by combining their social and human capital. Using 356 internet-related firms listed on the NASDAQ, Wagner and Cockburn (2010) found that information and the effect of patents are essential determinants of the signal of the firm's quality and survival.

Second, we highlight the importance of new technology in healthcare settings, such as applications of blockchain technology. Theodouli et al. (2018) explained the importance of blockchain technology and its contribution to private and auditable healthcare data sharing and healthcare data access permission. In addition, applications of machine learning and artificial intelligence (AI) have been studied in the literature extensively. This issue is fundamentally important for both developed and developing countries. During the COVID-19 pandemic, data sharing and learning from data have received great attention and prominence in academic research and policy debates. However, the challenges to the privacy of health-related data are crucial and costly, and high-level technological innovation is required, as discussed in our policy recommendations. Using health expenditure data for 20 Organisation for Economic Co-operation and Development (OECD) countries, Devlin and Hansen (2001) explained the bi-directionality between healthcare expenditure and GDP. They found that increasing healthcare spending causes output using the Granger causality testing approach. Our panel VAR confirms this dual causality, as GDP growth affects health spending – but health spending also drives economic growth.

Mobile applications, blockchain, and information technology amplify the potential value of healthcare, benefiting care providers and medical research, as documented by Liang et al. (2017). These advances supported the integrity and validity of the health data and shared them with healthcare providers and health insurance companies. Information sharing in the healthcare sector is vital for healthcare providers and patients. Shen, Guo, and Yang (2019) highlighted the importance of blockchain, digest chain, and structured peer-to-peer (P2P) network techniques, which MedChain can use to achieve higher efficiency and satisfy the security requirements in data sharing in the health sector. However, innovative design technology and transparency can transform healthcare information sharing by incorporating the protection of sensitive health information and deploying and installing software across health systems amongst providers and electronic health record systems (Cyran, 2018).

Banerjee, Hemphill, and Longstreet (2018) studied the importance of wearable devices and their competency in relation to healthcare data sharing and privacy risks. Recent literature in the healthcare sector has showed the importance and implementation of AI. For instance, Aggarwal et al. (2021) conducted a study in the United Kingdom with a cross-sectional survey of 408 patients, which was based on the views of patients and the public about sharing health data for AI-based research. Despite these developed strands of literature, a systematic approach that attempts to quantify the economic impact of enhanced data-sharing in healthcare is missing.

2.2. Growth accounting

In line with recent research on IoT and its impact on growth, we use a growth accounting framework to evaluate the impact of data sharing in healthcare on productivity (Espinoza et al., 2020). This methodology was developed by Jorgenson and Griliches (1967); Jorgenson et al. (2003); and Jorgenson, Gollop, and Fraumeni (1987). Following this methodology, each industry, including healthcare, achieves its gross output as a function of capital, labour, and technology. We define aggregate input, say capital, as a Törnqvist quantity index of individual capital types (Espinoza et al., 2020).[2] To capture the impact of data sharing, which requires broadband and mobile access, we distinguish between ICT and non-ICT capital.

The growth accounting methodology requires a set of assumptions, including competitive factor markets, full input utilisation, and constant returns to scale. Constant returns to scale imply that doubling all inputs increases the output twofold. Accordingly, output growth can be expressed as the cost-share weighted growth of inputs and technological change, using the translog functional form. In line with Espinoza et al. (2020), we use two types of capital: ICT capital (*C*), which refers to investment in ICT; and non-ICT capital (*K*). Data sharing requires adequate infrastructure to collect, store, transmit, and analyse data. Hence, we argue that the availability of ICT infrastructure determines the growth impact of data sharing. Understanding the contribution of ICT capital to growth is central to assessing the likely effect of enhanced data sharing.

In line with the growth accounting literature,[3] economic output in a country at time t (Yt) is achieved through a combination of the two types of capital (ICT and non-ICT), labour input (Lt), and technology (At). Equation 1 captures these model assumptions:

$$Y_t = A_t\, C_t^{a} K_t^{\beta} L_t^{1-\alpha-\beta}, \alpha > 0,\ \beta > 0 \qquad (1)$$

Equation (1) is often expressed in per capita form by dividing by the level of population at time t (P_t). Let $y_t = Y_t / P_t$ denote GDP per capita, and let δ be the employment rate as a share of the total population, i.e. Lt = lt Pt with 0 ≤ lt ≤ 1. Capital is expressed in per capita terms and denoted ct and kt, respectively. Hence, we obtain Equation (2) in per capita terms:

$$y_t = A_t\, C_t^{a} K_t^{\beta} L_t^{1-\alpha-\beta}, \alpha > 0,\ \beta > 0 \qquad (2)$$

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[2] See Kohli (2004) for a detailed discussion of the Törnqvist index.

[3] See Jorgenson and Griliches (1967); Jorgenson et al. (2003); and Jorgenson, Gollop, and Fraumeni (1987).

Accordingly, growth occurs if technology (total factor productivity) increases, capital deepens (i.e. more capital per person), and the employment rate increases. Several assumptions must be imposed to obtain this simplified functional form, including competitive factor markets, full input utilisation, and constant returns to scale. Hence, if all inputs are multiplied by a factor, say m, outputs increase by the same factor m due to assuming constant returns to scale. This implies that any further increase in output would be attributed to technological progress.

Taking the natural logarithm on both sides of Equation (2) and first-differencing yields Equation (3), where variables refer to log returns. The statistical model adds an error term, where $\varepsilon_t \sim N(0, \sigma^2)$ is identically and independently distributed.

$$\hat{y}_t = \hat{A}_t + \alpha\hat{c}_t + \beta\hat{k}_t + \gamma\hat{l}_t + \varepsilon_t, \gamma = 1 - \alpha - \beta \qquad (3)$$

Equation (3) is estimated with our panel data set using various specifications. We modify Equation (3) using an intercept dummy for AMS and interaction terms. The intercept dummy and interaction terms can determine whether ICT-related investment benefits AMS more than other countries.

2.3. Linking data sharing to e-health and growth

Historically, global pandemics have been shown to impact productivity due to labour shortages arising from the death of adults. The double impact of pandemics, i.e. mortality and the economic fallout, has remained the main concern globally. For instance, responses to combat the spread of COVID-19 have had a considerable economic impact. While most countries devised some local interventions in addition to the World Health Organization (WHO) global recommendations, different models emerged. Sweden tried keeping the economy open, which impacted mortality and the economy. The United Kingdom followed stricter regulations and largely relied on data to make lockdown decisions. Interventions such as the furlough scheme were launched to mitigate the impact of the lockdowns on the economy. But the public finances of several countries have been directly and indirectly affected by the pandemic. Most governments made record budget deficits due to increased pandemic spending and decreased tax revenues.

As the pandemic and the economy are closely connected, the big question every country seeks an answer to is what are the best mitigating strategies. While test and trace, improved vaccination, and cure will continue to play an important role, the pandemic clearly shows that our data systems require strengthening.

Methodologically, data sharing in healthcare is difficult to measure directly. However, data sharing is a core component of business models in digital healthcare (e-health). Our research strategy uses three main types of data sources to explore the relationship between data sharing and growth. First, country-level data are provided by The Conference Board and the World Bank. Second, industry reports focused on healthcare in Asia and AMS. These reports also focused on e-health and its dominant business segments. Third, firm-level reports are challenging to obtain due to the nascent nature of the e-health industry. However, firm-level reports provide insights into business models to identify the importance of data sharing.

2.4. Panel VAR and simulation

As Van Beveren (2012) outlined, there are many statistical concerns regarding the estimation of total factor productivity (TFP) using the growth accounting approach. By default, TFP is a residual, which makes it prone to biases due to model specification problems. Furthermore, the growth accounting approach does not explicitly consider any feedback processes, e.g. current growth could affect subsequent infrastructure spending. These feedback effects matter when considering healthcare spending and economic growth (Devlin and Hansen, 2001). Hence, we follow Devlin and Hansen (2001) and estimate a panel VAR in reduced form, which permits that health-related and economic variables can both be dependent. The system of equations can be written as follows, where all dependent variables and their lagged independent variables are in log returns.

$$\hat{y}_{it} = r_0 + \sum_{j=1}^{j} r_j \, \hat{y}_{it-j} + \varepsilon_{it} \qquad (4)$$

We estimate this system of equations using Generalized Method of Moments (GMM). The coefficient matrices can be used to construct impulse-response functions (Holtz-Eakin, Newey, and Rosen, 1988). These illustrate the short-term dynamics of the system triggered by small changes in variables. Hence, we simulate the expected expansion of e-health on growth using these transmission matrices.

3. Data Sources

We follow a threefold data strategy. First, country-level data are obtained from The Conference Board's Total Economy Databases (CBTED1 and CBTED2) and the World Bank's WDI database. The databases cover most AMS, except Brunei and the Lao People's Democratic Republic (Lao PDR). Second, industry reports provide estimates of the e-health market in Asia and AMS. These reports identify business segments and dominant players in the e-health market of each country. Third, we obtain company reports from various sources. Most companies operating in the e-health market are at a nascent stage of development; hence, larger data providers such as Bloomberg or Datastream do not provide any financial information. Therefore, we had to rely on smaller data providers and mandatory disclosure requirements, which are minimal for private limited companies (Table 12.4). Table 12.1 introduces the variable names, their definitions, and data sources.

Table 12.1. Variables, Definitions, and Data Sources

Variable	Definition	Data sources
r_gdp	Real GDP, in billions of 2020 international dollars, converted using purchasing power parity	CBTED1
n_gdp	Nominal GDP, in billions of current international dollars, converted using purchasing power parity	CBTED1
Emp	Persons employed (millions)	CBTED1
Hours	Average annual hours worked per worker	CBTED1
t_hours	Total annual hours worked (millions)	CBTED1
Pop	Midyear population (millions)	CBTED1
out_p	Labour productivity per person employed in 2020 international dollars, converted using purchasing power parity	CBTED1
out_h	Labour productivity per hour worked in 2020 international dollars, converted using purchasing power parity	CBTED1
inc_pc	GDP per capita in 2020 international dollars, converted using purchasing power parity	CBTED1
gdp_g	Growth of GDP, percentage change	CBTED1
emp_g	Growth of employment, percentage change	CBTED1
t_hours_g	Growth of total hours worked, percentage change	CBTED1
pop_g	Growth of population, percentage change	CBTED1
out_p_g	Growth of labour productivity per person employed, percentage change	CBTED1
out_h_g	Growth of labour productivity per hour worked, percentage change	CBTED1

Variable	Definition	Data sources
inc_pc_g	Growth of GDP per capita, percentage change	CBTED1
Gdp	GDP	CBTED2
l_quant	Labour input – quantity	CBTED2
l_qual	Labour input – quality	CBTED2
c_total	Capital input – total	CBTED2
c_ict	Capital input – ICT	CBTED2
c_non_ict	Capital input – non-ICT	CBTED2
l_quant_c	Labour quantity contribution	CBTED2
l_qual_c	Labour quality contribution	CBTED2
c_total_c	Total capital contribution	CBTED2
c_ict_c	ICT capital contribution	CBTED2
c_non_ict_c	Non-ICT capital contribution	CBTED2
Tfp	Total factor productivity	CBTED2
l_share	Labour share	CBTED2
c_share	Capital share	CBTED2
ict_share	ICT capital share	CBTED2
non_ict_share	Non-ICT capital share	CBTED2
Health	Current health expenditure (% of GDP), 2000–2018	WDI
h_growth	Log return of health expenditure ($ current)	WDI

CBTED = The Conference Board Total Economy Database, GDP = gross domestic product, ICT = information and communication technology, WDI = World Development Indicators.

Sources: The Conference Board Total Economy Database (2022), Output, Labour and Labour Productivity, 1950–2021: CBTED1 and CBTED2 (accessed 29 September 2022); and World Bank (2022).

4. Empirical Findings

4.1. Growth accounting

Table 12.2 presents descriptive statistics for all countries. AMS differ considerably in terms of long-term growth, which tends to be higher (average annual growth rate of 5.37% compared with 3.71%), and ICT capital accumulation (average share of ICT capital of 3.96% compared with 2.75%).

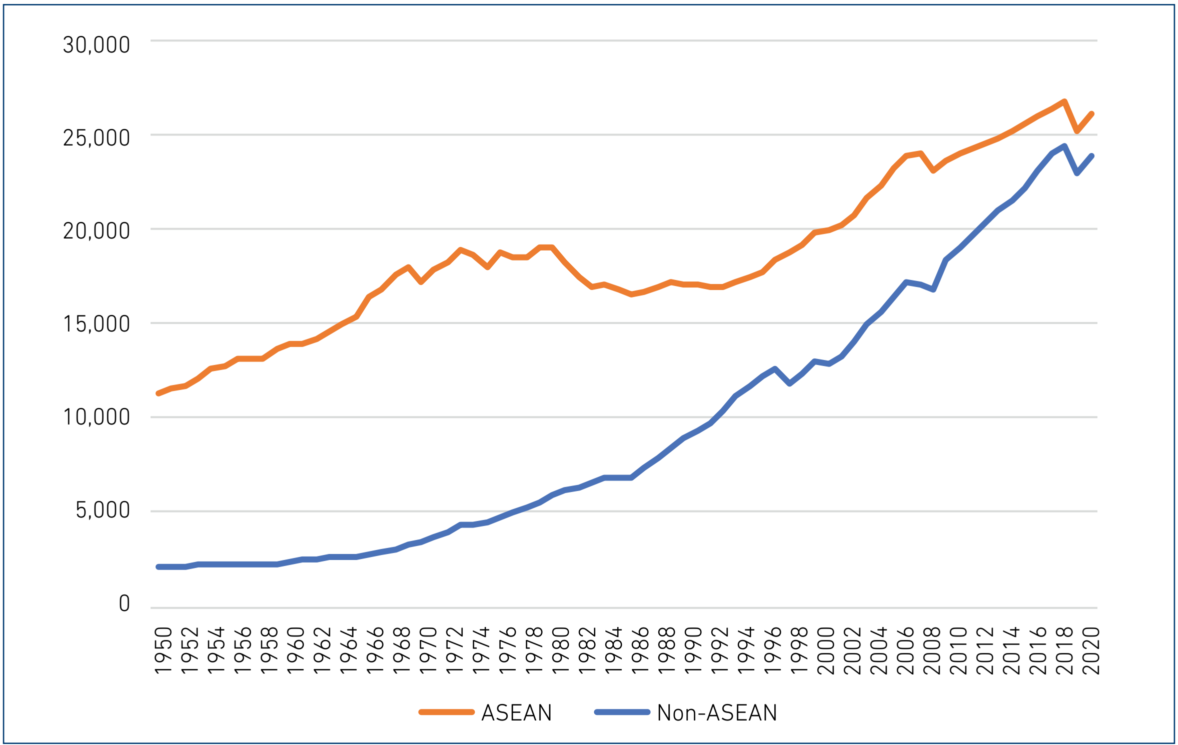
Table 12.2. Descriptive Statistics

Variable	Count	mean	std	25%	50%	75%
r_gdp	9,154	561.633	1928.417	24.542	78.989	311.669
n_gdp	9,154	388.3	1645.766	8.427	34.691	168.575
Emp	9,576	20.239	76.012	1.423	3.589	10.477
Hours	4,949	2,025.826	316.856	1,792.904	2,013.929	2,239.586
t_hours	4,949	7,4188.34	23,7623.4	5,092.157	12,009.7	40,967.44
Pop	9,576	45.585	150.344	3.624	8.97	27.837
out_p	9,154	44,284.56	65,639.52	10,898.84	26,636.42	55,797.31
out_h	4,947	25.775	21.315	8.13	20.356	38.223
inc_pc	9,154	18,152.9	27,789.22	3,665.533	9,683.518	22,195.47
gdp_g	9,021	3.814	6.185	1.629	3.923	6.438
emp_g	9,443	1.94	3.29	0.76	1.861	3.007
t_hours_g	4,816	1.398	3.44	-0.046	1.45	2.972
pop_g	9,443	1.779	1.846	0.754	1.671	2.678
out_p_g	9,021	1.869	5.956	-0.319	2.022	4.437
out_h_g	4,814	2.43	4.926	0.486	2.491	4.653
inc-pc_g	9,021	2.008	5.936	-0.066	2.263	4.606
Gdp	4,256	2.934	6.795	1.407	3.588	5.806
l_quant	4,256	1.394	4.738	0.058	1.664	3.177
l_qual	4,256	0.584	0.972	0.205	0.489	0.925
c_total	4,256	4.25	6.26	2.068	3.753	6.104
c_ict	4,170	16.067	14.317	9.503	15.136	22.539
c_non_ict	4,170	3.65	6.38	1.447	2.933	5.357
l_quant_c	4,256	0.598	2.319	0.033	0.81	1.489
l_qual_c	4,256	0.286	0.463	0.099	0.234	0.434
c_total_c	4,256	2.184	3.173	0.948	1.802	3.177
c_ict_c	4,170	0.408	0.587	0.162	0.354	0.608
c_non_ict_c	4,170	1.807	2.965	0.58	1.319	2.641
Tfp	4,256	-0.134	6.294	-1.78	0.049	2.023
l_share	4,256	49.665	11.562	44.803	50	55.969
c_share	4,256	50.335	11.562	44.031	50	55.197
ict_share	4,170	2.823	2.129	1.461	2.438	3.634
non_ict_share	4,170	47.375	11.717	40.588	46.949	52.515

Source: Data analysis conducted by the authors.

Figure 12.4 plots income per capita for the average AMS compared with the global average, indicating convergence due to catch-up growth after 1950.

Figure 12.4. Convergence of ASEAN Member States After 1950

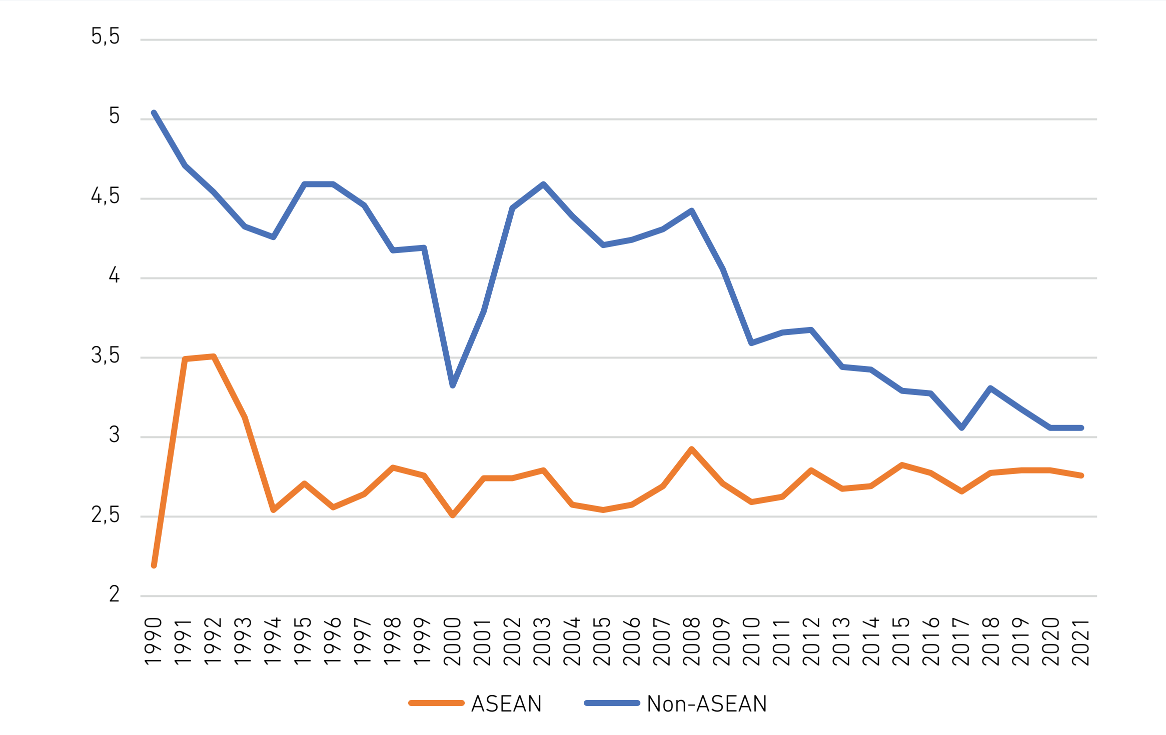


ASEAN = Association of Southeast Asian Nations.

Source: Data analysis conducted by the authors.

Compared with other countries, AMS exhibited high shares of ICT investment throughout the investigation period, as shown in Figure 12.5. Significant improvements can be observed in all AMS in terms of fixed broadband subscriptions (per 100 people). Access to the internet and mobile phone coverage are prerequisites for e-health, benefiting from data sharing.

Figure 12.5. **Share of ICT Capital in ASEAN Member States**



ASEAN = Association of Southeast Asian Nations, ICT = information and communication technology.

Note: ASEAN refers to a dummy variable, which uses the label 1 for ASEAN Member States and 0 otherwise.

Source: Data analysis conducted by the authors.

Next, we assess whether AMS benefit more from ICT investment than other countries. Hence, we estimate Equation (3) using pooled ordinary least squares (POLS) [A], fixed effects [B], a constrained regression [C], and POLS with interaction effects related to AMS. The constrained regression imposes constant returns to scale. These models try to explain GDP per capita growth rates using growth in ICT investment (c), in non-ICT capital (k), and labour market participation (l). We add an intercept dummy (*ASEAN*) and three interaction terms with capital and labour growth to test whether AMS differ from their peers.

Table 12.3. Growth Regressions

Variable	A	B	C	D
ICT investment (c)	0.007*** 0.000	0.006*** 0.000	0.007*** 0.000	0.004** 0.002
Non-ICT capital (k)	0.020*** 0.000	0.020*** 0.000	0.016*** 0.000	0.016*** 0.000
Labour market participation (l)	0.402*** 0.000	0.436*** 0.000	0.978*** 0.000	0.260*** 0.000
*ASEAN * c*				0.019*** 0.000
*ASEAN * k*				0.01 0.131
*ASEAN *l*				-0.188 0.117
ASEAN				0.018*** 0.000
N	3298	3298	3298	3298
Ll	6,405.986	6,793.862	6,181.443	6,678.837
Aic	-12,804	-13,579.7	-12,356.9	-13,281.7
Bic	-12,779.6	-13,555.3	-12,338.6	-13,049.8

ASEAN = Association of Southeast Asian Nations, ICT = information and communication technology.

Source: Data analysis conducted by the authors.

Table 12.3 shows that AMS, on average, outperform their peers as the coefficient for the *ASEAN* dummy is positive and significant. Moreover, the interaction term with ICT capital growth denoted *ASEAN * c* exhibits a positive and significant shift. Hence, a marginal increase in ICT investment is likely to generate about four times more growth than in other countries.

In summary, our findings stress that AMS exhibit a high level of ICT investment. This investment, in turn, contributes more to economic growth than in other countries. Accordingly, AMS are in a unique position to benefit from their lead in ICT investment, which will underpin the digital transformation of healthcare.

4.2. Linking data sharing to e-health and ICT investment

The main challenge is the lack of time series data on e-health. Consulting firms and commercial data providers such as Statista use a bottom–up approach. They identify companies that operate in e-health and use their company reports to assess the market size. We followed this approach – but noticed significant limitations due to the nascent nature of the industry. The main issue is the reliability of the data, as most companies in e-health are private limited companies. Hence, they are only required to report simplified income statements (if at all) and balance sheets. Furthermore, the data displayed by Statista are projections. They are not actually observed at each point in time. We use similar projections in our report based on several consulting firms.

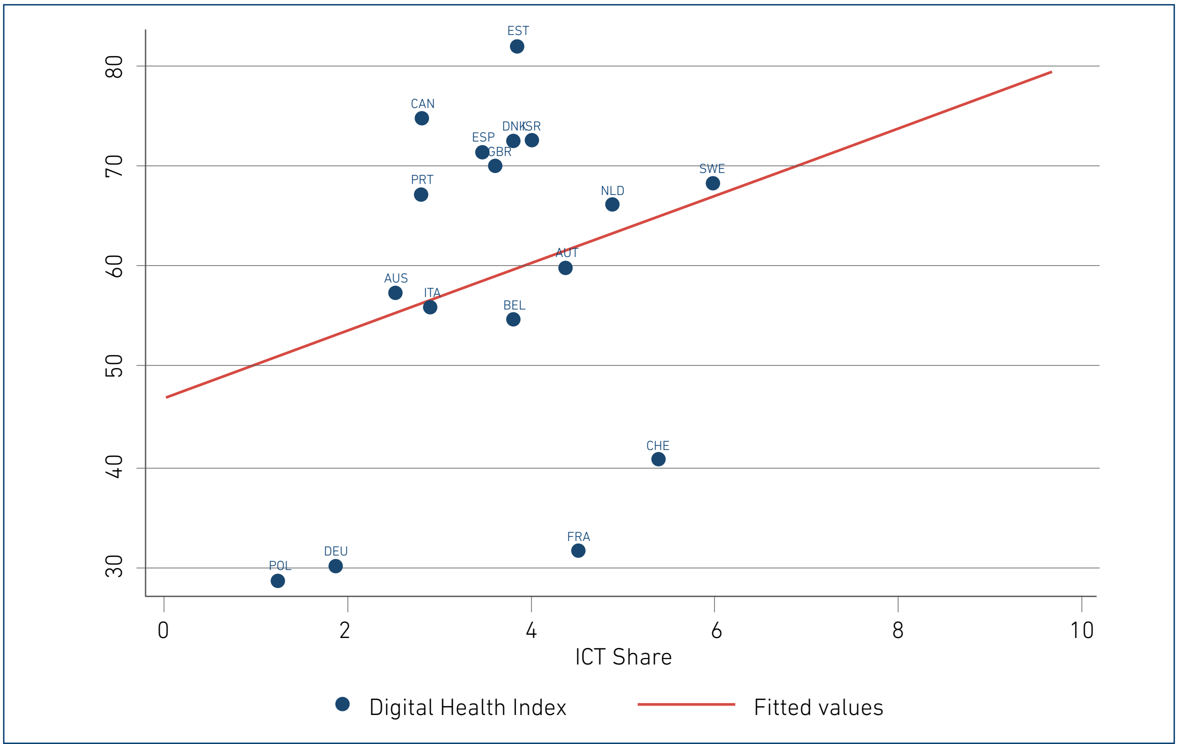
Table 12.4 summarises our data collection effort to uncover the size and growth of e-health in AMS. In 2021, McKinsey published 'The Future of Healthcare in Asia: Digital Health Ecosystems', which estimated the current size of the e-health market in Asia at $37.4 billion (Baur, Yew, and Xin, 2021). Global Market Insights (2023) estimated the size of the global e-health market at $114.8 billion, which seems to be consistent with the McKinsey report. By 2025, both reports project a trebling of the e-health market, implying annual growth rates from 21.7% to 22.5%.

Using World Bank data on health spending, which are only available for 2018 for most countries, we estimate that e-health constitutes 1.4% of the global healthcare market and 2.2% of the market in the Asia-Pacific region. Due to the high growth expectations in e-health, the market share is likely to more than double by 2025 compared to 2018. As outlined in various reports, including Baur, Yew, and Xin (2021) and HKTDC (2021), telemedicine and online pharmacies account for two-thirds of the e-health market. These segments will experience the highest growth rates. Based on current industry trends, medical devices powered by IoT are in a nascent stage and less likely to contribute significantly to short-term growth.

Firm-level data are scarce, as most companies can be classified as microbusinesses or small and medium-sized enterprises with limited financial history. Based on our data collection effort, we can obtain estimates for the current and future size of the e-health market and its growth from 2020 to 2025. These estimates are used in our growth simulation to understand the likely impact on short- and medium-term economic growth in AMS, driven by the expansion of the e-health market. As the e-health market relies extensively on sharing health-related data, this simulation will provide a lower bound to assess the economic impact of enhanced data sharing.

We argue that ICT investments are a prerequisite for a thriving e-health market, as infrastructure such as mobile networks and high-speed internet facilitates the development of digital products. Apart from this qualitative argument, can we provide any quantitative evidence? As outlined above, there is a lack of reliable time series data on digital health. However, Bertelsmann Stiftung (2019) published a Digital Health Index for selected European countries, Canada, Australia, and Israel. We used this cross-sectional study to explore the relationship between e-health and ICT investment. Figure 12.6 shows a scatter plot and a fitted line based on a linear regression model. The share of ICT investment has a positive and significant (p-value: 0.000) impact on the Digital Health Index.

Figure 12.6. Relationship Between ICT and e-Health



AUS = Australia, AUT = Austria, BEL = Belgium, CAN = Canada, CHE = Switzerland, DEU = Germany, DNK = Denmark, ESP = Spain, EST = Estonia, FRA = France, GBR = United Kingdom, ICT = information and communication technology, ISR = Israel, ITA = Italy, NLD = Netherlands, POL = Poland, PRT = Portugal, SWE = Sweden.

Note: This figure plots the Digital Health Index for selected European countries, Canada, Australia, and Israel, published by Bertelsmann Stiftung (2019) against the share of ICT investment. The fitted line refers to an ordinary least squares regression that explains the Digital Health Index using the share of ICT investment as an independent variable.

Source: Data analysis conducted by the authors.

Table 12.4. **Combining Macro-Level, Industry, and Firm-Level Data Sources**

Panel A: Market reports			2020	2025
Organisation	**Report**	**Variables**	**Values in USD billion**	**Values in USD billion**
McKinsey & Company (2021)	The future of healthcare in Asia: Digital health ecosystems	Size of digital health market in Asia	37,4	100
		Telemedicine, remote monitoring	16,8	37,1
		Digital pharmacies	7,1	33,8
		Digital therapies (CDM and CDS)(*)	6,1	7,6
Global Market Insights (MGI) (2023)	GMI833	Size of digital health market in Asia (global)	114,8	316,2
Panel B: Health spending				
Organisation	**Database**	**Variables**	**Asia-Pacific**	**World**
World Bank (2022)	World Development Indicators	Current health expenditure USD billion	1685,6	8440,8
		Current health expenditure per capita (current USD)	720,91	1110,27
		Population	2.338.223.462	7.602.454.161
		Estimated share of e-health	2,22%	1,36%
Panel C: Companies in e-health operating in telemedicine				
Name	**Country**	**Website**	**Revenue ($ million)**	**Employees**
Doctor Anywhere	30A Kallang Place, #11-06, Singapore	https://doctoranywhere.com/	14	80
MyDoc	43A HongKong St, Singapore	https://my-doc.com/		<25
Speedoc	60, Jalan Sri Hartamas 1, Kuala Lumpur, 50480, Malaysia	https://speedoc.com/sg	18	97
Alodokter	No.7, RT.7/RW.2, Kuningan, Jakarta, Indonesia	https://www.alodokter.com/	19	461
Halodoc	Jl. HR Rasuna Said Kav. B32-33, Jakarta, Indonesia	https://www.halodoc.com/	5	<25

Sources: Arizton Advisory and Intelligence, BCC Research, MarketsandMarkets, Mind Commerce, TechNavio 1MG, AliHealth, Alodokter, Halodoc, JD Health, Ping An Good Doctor, Practo, WeDoctor, Zoominfo, RocketReach, PitchBook. Data analysis conducted by the authors.

4.3. Panel VAR and growth simulation

We determine the optimal lag structure of a reduced form panel VAR, which suggests one lag. The reduced form panel VAR is estimated using either GMM (dynamic panel data estimation) or OLS. Fixed effects are not relevant in these specifications as first-differencing all dependent variables eliminates country-specific effects to a sufficient degree. As shown in Table 12.3, growth accounting establishes instantaneous relationships between economic growth (y), ICT capital growth (c), non-ICT capital growth (k), and changes to the labour force (l). The panel VAR explores an alleged feedback effect, i.e. past realisations might drive current values of growth rates. Moreover, we added growth rates in health expenses (h_growth) to explore the relationship with economic growth. This is in line with Devlin and Hansen (2001).

Table 12.5 presents Granger causality tests, demonstrating that all dependent variables exhibit a degree of autocorrelation, i.e. their past realisations explain current values significantly. Furthermore, past economic growth (second column) affects all other variables – except ICT capital growth. It is important to note that expanding healthcare (i.e. increasing health expenditure) in the previous year has a significant and positive impact on current economic growth. Hence, we confirm the empirical findings shown in Devlin and Hansen (2001).

Table 12.5. Granger Causality Tests

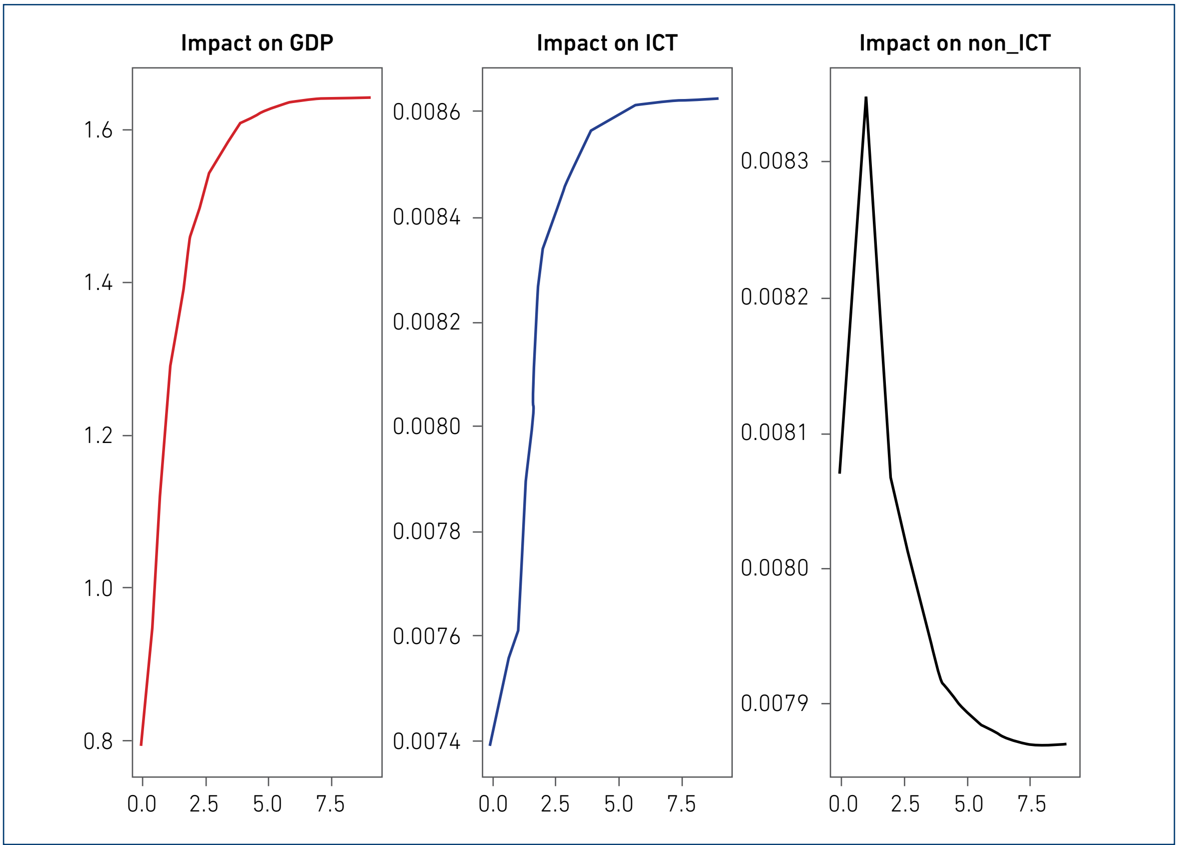
Variable	*y*	*c*	*k*	*l*	h_growth	All
y	0.000***	0.507	0.773	0.327	0.049*	0.000***
c	0.205	0.000***	0.001***	0.070	0.570	0.000***
k	0.000***	0.132	0.000***	0.916	0.130	0.000***
l	0.000***	0.712	0.021*	0.000***	0.156	0.000***
h_growth	0.000***	0.166	0.223	0.334	0.000***	0.000***

Note: * indicates significance at the 5% level, ** refers to the 1% level, and *** shows the 0.1% level.

Source: Data analysis conducted by the authors.

To explore the dynamics of the system of equations captured by the panel VAR, we estimate the coefficient matrix and derive impulse-response functions. Hence, we can simulate a marginal increase in the healthcare sector on economic growth, capital accumulation, and labour market participation. To derive growth scenarios, we use the sources summarised in Table 12.4. The reports by Baur, Yew, and Xin (2021) and HKTDC (2021) suggested annual growth rates in digital health in the region of 21%–22% per year until 2025. Telemedicine and online pharmacies account for two-thirds of the market. Telemedicine's business model relies on data sharing by default. Service delivery is remote, requiring access to medical data, including medical imaging. However, online pharmacies require only limited access to data (prescriptions, allergies, and underlying medical conditions). Traditional healthcare providers have enhanced their data-sharing capabilities.

Figure 12.7. Cumulative Impulse-Response Function



GDP = gross domestic product, ICT = information and communication technology.

Note: We simulate a 1% increase in healthcare provision and its subsequent impact on GDP, ICT, and non-ICT capital accumulation.

Source: Data analysis conducted by the authors.

Figure 12.7 plots cumulative impulse-response functions for GDP growth rates and ICT and non-ICT capital growth rates. The impulse refers to a 1% increase in healthcare provision. Based on our simulation, the 10-year cumulated effect suggested a GDP increase of 1.64%, whereas the impact on capital accumulation is negligible.

5. Policy Recommendations

5.1. The need for data: Addressing data gaps

Our efforts to obtain data on the extent of data sharing in healthcare demonstrate that a data gap exists. To monitor the progress in data sharing and to mitigate risks, countries should collect more information on current practices of data sharing in healthcare settings. Now, this information is only available in a disaggregated form using industry and firm-level reports.

Apart from information on data sharing, it is crucial to have information on the prevalence of non-communicable diseases by age. While the pandemic on its own does not discriminate between people, our societal and economic structures allow the pandemic to impact certain groups disproportionately. Moreover, the risk of mortality is concentrated amongst older people with and without other risk factors and younger people with non-communicable diseases. As males have a higher mortality risk, it is crucial to have sex-specific data.

Finally, pandemic-related data sources need to be strengthened. These investments will be beneficial for long-term prevention and resiliency building. While the track-and-trace mechanism helps identify areas with higher cases, localised lockdowns can be planned to mitigate the impact. But this might be difficult in smaller counties like Singapore, where the risk of infection continues to be higher due to population density. Another crucial data set is vaccination coverage. While it is important to have vaccination coverage data, the most value from it comes from the age-specific vaccination rates, which require a detailed age¬–sex profile of the population. Where the census data are old, robust projection techniques must be used for pre-COVID-19 data. Furthermore, we need data on vaccines, available hospital beds, and medication. Such data will give the public confidence to carry out their economic activities. In addition, more countries are using apps to report symptoms and ping citizens when they are close to a COVID-19-positive person. All these measures play a significant role. During various stages of the pandemic, these data will also help decide the capacity of various buildings depending on the economic activity and risk involved. Better planning will enable countries to allow tourism, which plays an important role in the Thai economy, to continue. Due to the pandemic, dwindling tourism impacted the Thai baht, one of the best-performing currencies, to join the worst-performing currencies globally such as the Turkish lira and Peruvian sol.

5.2. Mitigating risks

Estimating the economic and health benefits of data sharing is essential to inform policymakers. Our analysis suggests that ICT capital plays a more prominent role in AMS than in other countries (Figure 12.5). Our growth accounting approach uncovers that ICT capital contributes more to economic growth in AMS than in its peers (Table 12.3). We extend the growth accounting model by exploring the dual causality between growth, various forms of capital accumulation, and healthcare expenditures. Granger causality tests (Table 12.5) suggest that expanding healthcare will increase future economic growth.

The inherent dual causalities are modelled using panel VAR, and the dynamics of the system are captured in a coefficient matrix. Our simulation reveals that increasing healthcare provision enhances economic growth 1.64-fold over a 10-year period. In summary, there is a clear economic justification to foster growth in healthcare provision (apart from ageing populations, morbidities, etc.). Our firm-level and industry-level analyses identify that digital healthcare will make a considerable contribution to this expansion. Baur, Yew, and Xin (2021) and HKTDC (2021) predicted annual growth rates in digital health in excess of 20% per year until 2025. Not all areas of digital and traditional healthcare rely in a similar way on data sharing – but the most promising areas, such as telemedicine, depend on enhanced data sharing.

Furthermore, we outline mitigation strategies that are likely to affect the willingness to share data (e.g. building trust). The main challenge in healthcare settings is to ensure that data remain private. There has been a considerable expansion of privacy-enhancing technologies (PETs). PETs promise to separate learning from private data and data transmission. Ideally, medical data do not need to be transmitted – only learned parameters are transferred to the service provider. However, now, there are very few providers of PETs, such as a team at Microsoft (CrypTFlow), and practical challenges remain.

Encryption algorithms have witnessed several advances in the context of health data. First, user-centric designs have become more common in healthcare settings, enabling end-users to remain in control of their data (Qiu et al., 2020). Second, wearable medical devices require additional advances in encryption (Chen et al., 2020).

Imaging data have inherent data storage and management challenges. Moreover, wearable medical devices and IoT technology generate increasing data (Zheng et al., 2019). Hence, cloud-assisted wireless body area networks have entered hospital settings to manage these data requirements (Hassan et al., 2017). Finally, distributed ledger technologies (e.g. blockchain) provide solutions for a decentralised system of data sharing (Zheng et al., 2019).

As outlined in our analysis, ICT capital is a prerequisite for data sharing and developing business models in digital health care. Significant progress has been achieved in AMS, as illustrated in Figures 12.2 and 12.3; however, continued investment in ICT infrastructure is needed to sustain and support the expected expansion of digital health care.

6. Conclusion

The ASEAN Digital Master Plan 2025 (ASEAN, 2020) outlined ambitious goals, transforming AMS into digital societies and economies. This policy agenda stresses the importance of digital health care, which accounts for only around 2% of healthcare provision based on our analysis (Table 12.4). Yet, various industry and firm-level reports suggest annual growth rates above 20% in the coming years. Our analysis shows that data sharing is at the heart of some business models, such as providers of telemedicine. However, not all business segments rely on data sharing to the same extent.

This report develops a methodology to quantify the economic impact of data sharing through its role in digital health care. Growth accounting reveals that AMS benefit more from ICT capital, which is a prerequisite of data sharing in healthcare settings. Our panel VAR model permits feedback effects, i.e. changes in health expenditure can cause changes in capital accumulation and economic activity. Causality tests demonstrate that health expenditure in the past drives current economic growth. After estimating the dynamics of the system, we simulate the impact of a 1% increase in health spending over a 10-year period. We find that economic growth increased by 1.64%, suggesting a sustained positive contribution to growth.

The likely upside of enhanced data sharing in health care, however, needs to address security concerns that can undermine trust. This, in turn, can limit the willingness to engage in data sharing. The deliverable (DO3) in the ASEAN Digital Masterplan 2025 (ASEAN, 2020) highlights the importance of consumer protection. Hence, we suggest exploring the use of PETs. These technologies are not yet mature – but developments such as fully homomorphic encryption are suitable in healthcare settings. In this case, data do not have to be transmitted (split deep learning) without compromising the benefits of learning from data (Onoufriou, Mayfield, and Leontidis, 2021; Onoufriou et al., 2021).

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