Artificial Intelligence and Intangible Capital in the ASEAN+3 Region

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Abstract

This paper explores the evolution and characteristics of intangible capital among firms in four ASEAN+3 economies with deeper financial markets, benchmarked against the United States. Our findings reveal significant variations in the accumulation paths of intangible capital across these economies, underscoring the pivotal role of knowledge capital in accelerating intangible capital accumulation in the last decade. Employing an interrupted time series design, we present empirical evidence that the advent of widely accessible deep learning in 2016 and generative artificial intelligence in 2021 represent critical milestones that have influenced intangible capital investment in several of the economies under study.

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1. Introduction

Intangible capital, encompassing knowledge capital, such as research and development (R&D) investments, software development; and organizational capital, including human resources, management practices, has increasingly been recognized as a pivotal asset for economic growth and firm competitiveness. Despite its universal significance, standard accounting treatment makes it difficult for firms to recognize intangibles as assets.

This discrepancy is evident in the high price-to-book ratios of the five firms with the largest market capitalizations globally, ranging from 67.8 times (Apple) to 7.47 times (Google) as of 2024, suggesting that physical capital can only account of a small proportion of these giant firms' values. While there is a growing academic literature on firm-level intangible capital, it predominantly focuses on the United States (Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017) and Europe (Bontempi and Mairesse, 2015; Marrocu, et al., 2012). This leave a notable void in understanding the dynamics in other regions.

This study seeks to fill the gap by examining the characteristics and evolution of intangible capital of both public and private firms in Hong Kong, Singapore, South Korea, and Japan. The selection of these four economies, which have more developed equity markets in the region, was guided by cross-economy evidence suggesting that the development of an economy's equity market is positively correlated with the size of its high-tech sector and the intensity of innovation (Hsu et al., 2014; Brown et al., 2017).[1] As these economies transitioned from manufacturing- and service-based to knowledge-intensive structures, the role of intangible capital becomes increasingly critical in driving innovation and economic development (Bloom et al., 2012; Bresnahan, et al., 2002; Brynjolfsson et al., 2002). This shift underscores the need for

[1] In 2022, the market capitalization of listed domestic companies as a percentage of GDP ranked Hong Kong 1st, Japan 11th, Singapore 12th, and South Korea 17th globally, according to the World Bank (https://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS?most_recent_value_desc=true)

a comprehensive analysis of the role of intangible capital in these markets and understanding its boarder economic implications.

Using a comprehensive dataset of firm-level financial statements from Standard and Poor's (S&P) Capital IQ Pro (CIQ) database, this paper examines the accumulation of intangible capital in the four selected ASEAN+3 economies and the United States (US). Our analysis spans the period from 2012 to 2023, with a focus on the impact of technological advancements, particularly the widespread adoption of deep learning in 2016 and the emergence of Generative Artificial Intelligence (GenAI) in 2021.

Marked as one of the most important milestones in AI development since 2010, deep learning is a subset of machine learning that employs algorithms inspired by the brain's structure and function. This technology enables computers to learn from vast amounts of data, enhancing their pattern recognition and decision-making capabilities without human intervention. GenAI, which utilizes deep learning techniques, generates new and realistic content, such as text, images, or music, based on its training data. As the realization of AI's potential heavily relies on knowledge and organizational capital rather than physical assets, we hypothesize that the advent of deep learning and GenAI may stimulate the accumulation of intangible capital.

We apply a perpetual inventory method, which is standard in the literature, to consistently estimate the stocks of knowledge capital and organizational capital, which are then combined to form total intangible capital at the firm-level (Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017; Van Criekingen et al. 2022). Our estimates show significant variations in the accumulation paths of intangible capital across economies, with the US, Hong Kong, and Singapore exhibiting an acceleration of intangible capital formation since the GenAI breakthrough in 2021, primarily driven by the knowledge capital. In contrast, Japan and South Korea display a decline and stability in intangible capital accumulation, respectively, since the early 2010s.

We then utilize an interrupted time series (ITS) design to estimate the impact of deep learning developments since 2016 and GenAI advancements sicne 2021, on the accumulation of intangible capital in the five economies. This method is particularly suited to our analysis as it allows for the assessment of changes in investment trends following specific milestones, without the need for an observable control group, which is unfeasible in this context due to the universal exposure of firms to technology (Bernal et al., 2017, 2021).

Our results suggest that the introduction of GenAI is associated with an acceleration of intangible capital accumulation in the four ASEAN+3 economies and the US. In contrast, the estimated effects of deep learning were smaller in the near term across economies, highlighting the importance of economy-specific factors in shaping firms' investment decisions in response to AI innovations. In the longer-term, the change in the growth path of intangible capital were similar in response to both the widespread availability of GenAI and deep learning. Overall, our findings indicate that the GenAI wave has had a more pronounced impact on intangible capital accumulation in the four ASEAN+3 economies than the preceding AI-related innovation in the mid-2010s.

Several studies have examined the formation of intangible capital in major ASEAN+3 economies, including works by Chun and Nadiri (2016), Fukao et al. (2009), and Hao and Wu (2021). These studies primarily assess the contribution of intangibles to productivity growth at the aggregate level and estimate intangible capital stocks using survey data. Our research extends this body of literature by providing consistent estimates of intangible capital at the firm level across the four ASEAN+3 AEs. By exploring the evolution and determinants of intangible capital investment in these economies, our study offers valuable insights for policymakers in the ASEAN+3 region, enabling them to better tailor their economic strategies to leverage intangible capital for sustainable growth.

The rest of the paper is organized as follows. Section 2 describes our data sources and the methodology used for estimating intangible capital as well as its trends in the four ASEAN+3 economies and the US over time. Section 3 presents the econometric analysis of the impact of AI advancement on intangible capital accumulation in these economies. Section 4 concludes with a discussion on the policy implications of our findings.

2. Data and Trends

Our primary data source is the Standard and Poor's (S&P) Capital IQ Pro (CIQ) database, which is the expanded and updated iteration of the legacy Compustat database. We compile firm-level financial statements information for both public and private firms across the four ASEAN+3 AEs, namely, Hong Kong, Japan, Singapore, and South Korea, as well as the US. Our main analysis centers on the period from 2012 to 2023, although data from 2000 onwards were used to estimate firms' intangible capital. We exclude firms with missing or non-positive book value of assets or sales. Additionally, economy-level real GDP growth, reported by national authorities and extracted via CEIC, were also included later in the econometric analysis to account for background macroeconomic conditions that may also affect the accumulation of intangible capital. Table 1 describes the full list of variables included in the paper.

Table 1: Variables included

Variable	Source	Explanation
Research and development expenditure (R&D)	S&P CIQ	Input for knowledge capital
Selling, general and administrative expenses (SG&A)	S&P CIQ	Input for organisational capital
Net property, plant and equipment (Net PP&E)	S&P CIQ	Proxy for physical capital
Knowledge capital	Computed	Computed from R&D
Organisational capital	Computed	Computed from SG&A
Intangible capital	Computed	Sum of knowledge and organisational capital
Real gross domestic product (GDP) growth	CEIC	Proxy for overall macroeconomic conditions
Market capitalisation	S&P CIQ	Market valuation

The accounting treatment of intangible capital is governed by International Accounting Standard (IAS) 38, which stipulates that a company may only recognise intangibles an asset if it is identifiable, controlled, measurable, and if it is probable that the company will accrue future economic benefits from the asset. The

International Financial Reporting Standards (IFRS) permit the capitalisation of development costs, but only under stringent conditions. In contrast, under Generally Accepted Accounting Principles (GAAP), internally generated intangibles are typically not capitalised. These accounting regulations render the valuation of intangibles from financial reports challenging, necessitating assumptions in measuring intangibles.

Our measurements of capital are standard in the literature (Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017; Van Criekingen et al. 2022). We measure the replacement cost of physical capital, C^{phy}, as the book value of property, plant, and equipment. We define the replacement cost of intangible capital, denoted C^{int}, to be the firm's internally created intangible capital. To construct a proxy of the replacement cost, we accumulate past intangible investments, as reported on firms' income statements.

A firm develops knowledge capital by spending on R&D. We estimate a firm's knowledge capital by accumulating past R&D spending using the perpetual inventory method:

$$K_{it} = (1 - \delta_{R\&D})K_{i,t-1} + R\&D_{it} \tag{1}$$

where K_{it} is the end-of-period stock of knowledge capital, $\delta_{R\&D}$ is its depreciation rate, and $R\&D_{it}$ is expenditures on R&D during the year. We assume $\delta_{R\&D} = 0.32$.

We assume that a fraction of a firm's SG&A expenditure represents an investment in organization capital through advertising and marketing, employee training, and information technology. We similarly use the perpetual inventory method to measure the stock of organization capital by accumulating a fraction of past SG&A spending:

$$O_{it} = (1 - \delta_{SG\&A})O_{i,t-1} + SG\&A_{it} \times \mu_{SG\&A} \tag{2}$$

where O_{it} is the end-of-period stock of organization capital, $\delta_{SG\&A}$ is its depreciation rate, $SG\&A_{it}$ is the selling, general, and administrative expenses during the year and $\mu_{SG\&A}$ is the fraction of SG&A that is counted as organization capital expenditure. We assume $\delta_{SG\&A} = 0.2$ and $\mu_{SG\&A} = 0.28$.

A firm's intangible capital is then calculated as the sum of its knowledge and organization capital, $C_{it}^{int} = K_{it} + O_{it}$. The starting stock of either form of capital is 0 at start of our dataset in 2000 or the first instance of the firm appearing in our dataset during the period covered. Due to the way the dynamics of knowledge and organisational capital are defined in equations 1 and 2, even if there are disagreements on the initial quantitative values (at t=0), the subsequent paths from 2012 should not vary significantly.[2]

Figure 1 illustrates the trends in annual average R&D and SG&A expenditures, alongside the annual average stocks of knowledge, organizational, and intangible capital across five studied economies. We observe variations in the accumulation paths of intangible capital over time in the ASEAN+3 AEs and the US, as depicted by solid black lines. In the US (Panel A), the accumulation of intangible capital first accelerated around 2016, coinciding with the widespread adoption of deep learning technologies. This acceleration became more pronounced around 2021-22, aligning with the mainstream adoption of GenAI.

In Figure 1, the pattern of intangible capital accumulation observed in the US during the GenAI period is similarly noted in Hong Kong and Singapore (Panels B and C). However, this pattern is not evident in Japan and Korea (Panels D and E), where the average intangible capital has been either declining or remaining flat since the early 2010s. Unlike in the US, the impact of deep learning breakthroughs in 2016 is less apparent in Hong Kong and Singapore, suggesting that the increase in intangible capital formation driven by deep learning may be specific to the United States.

By segregating intangible capital into knowledge capital (blue solid lines) and organizational capital (red solid lines), Figure 1 further demonstrates that the acceleration of intangible capital formation in the US, Hong Kong, and Singapore since the GenAI breakthrough in 2021 is primarily driven by the accumulation of knowledge capital, rather than organizational capital. Notably, the stocks of knowledge capital in the US and Singapore have surpassed those of organizational capital from 2021 onward. The stock of knowledge capital in Hong Kong also increased by 351% (compared to 120% in the US and 104% in Singapore) from 2012 to 2023, which may

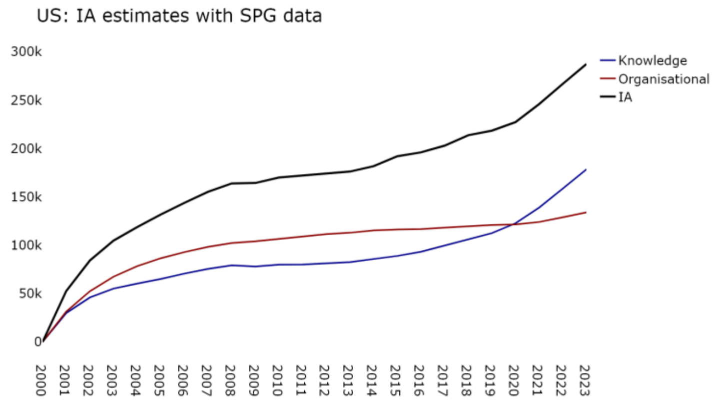
[2] One US dollar worth of knowledge and organization capital in 2000 would be depreciated to US 5.07 cents and 6.87 cents, respectively, by 2012. At a minimum, we can interpret our estimates in terms of trend.

reflect the reconfiguration in the global and regional trade value chain, as well as economy-specific policies to promote innovation and technology. Conversely, the relative proportions of knowledge capital and organizational capital in Japan and South Korea have remained stable since the early 2010s. These cross-economy variations may be attributed to economy-specific factors that influence firms' investments in intangible capital and warrant further research.

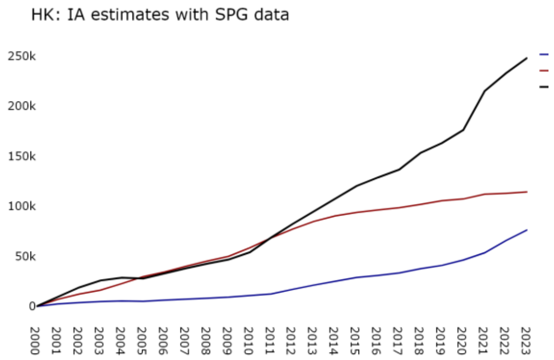
Figure A1 in the Appendix depicts the accumulation path of physical capital over time in the five economies. It is observed that intangible and physical capital are positively correlated over time. This correlation aligns with existing literature and suggests that firms choose optimal intangible and physical investment rates at the margin (Peters and Taylor, 2017). The higher volatility observed in physical capital stocks over time can be attributed to the fact that while the estimation of intangible capital is cost-based, firms are required by IAS 16 to mark the value of physical capital to fair market value.

Figure 1: Average R&D, SG&A, knowledge capital, organisational capital, and intangible capital

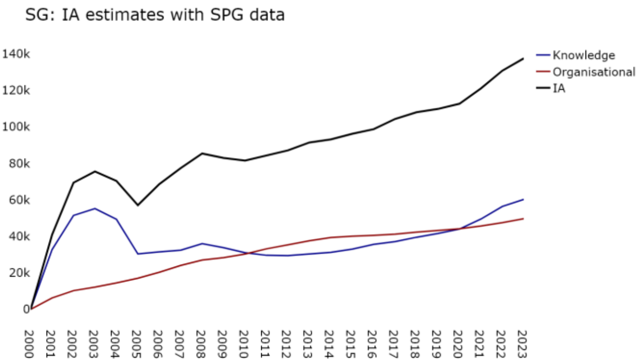
A. United States



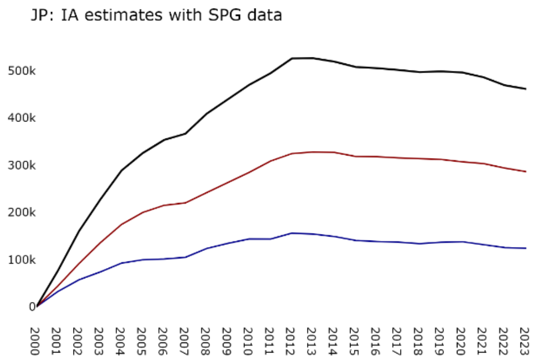
B. Hong Kong



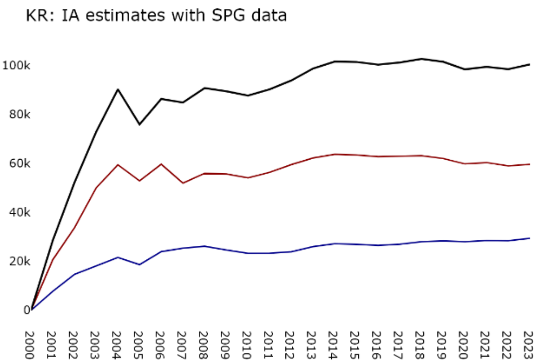
C. Singapore



D. Japan



E. South Korea



In each panel, the blue, red, and black solid lines represent the annual average stocks of knowledge, organizational, and intangible capital, respectively, of public and private firms in an economy. All variables are measured in thousands US Dollars (USD '000s).

Tables A1 to A5 provide the summary statistics of the firm-level variables in Table 1. Guided by our observation that the advancements of deep learning in 2016 and GenAI in 2021 might have stimulated intangible capital formation in some economies, we divided our full sample from 2012 into two overlapping periods. The first spans 2012 to 2019, and is segmented by 2016, the year when deep learning became widespread globally, indicated by a jump in number of academic papers on deep learning (Saputra et al., 2024; Yapıcı et al., 2019) and in the number of searches on Google for "deep learning AI" (Figure A2 in the Appendix). The second period spans 2012 to 2019, and is segmented by 2021, the year when Dall-E was first launched to the public. The first and second panels in each table present the summary statistics in the two periods, respectively.

The time coverage and segmentation of these two panels correspond to our subsequent ITS analysis. As the dataset covers both public and private firms, there is a considerable degree of heterogeneity in terms of both physical and intangible capital accumulation, despite the removal of firms with insufficient data coverage. This variation is also evident in the variation in market capitalization, which later informs our decision to include firm fixed effects in our econometric analysis to account for the non-trivial between-firm heterogeneity.

3. Econometric Analysis

If major AI innovations are introduced concurrently to the global economy, how should one estimate the impact of AI on intangible capital accumulation? Conceptually, any resultant change in a firm's accumulation path comprises two components: (i) a direct effect from the adoption or intent to adopt the technology, and (ii) an indirect effect or spillovers from other parties that have adopted the technology. Consequently, comparing firms with varying degrees of exposure to the technology will likely underestimate the effect of AI, as this approach discounts the indirect effect entirely or partially. In the context of a global technological shock, it is not possible to identify true control groups, which precludes the use of a difference-in-difference research design.

The interrupted time series (ITS) methodology offers a solution to this challenge. As described by Bernal et al. (2017, 2021), the ITS methodology is increasingly being adopted in the adjacent field of epidemiology, which often lacks true control groups, a circumstance also applicable to our situation. This approach involves estimating a segmented linear regression model that captures two key components: (i) a trend shift and (ii) a slope shift associated with the global event or shock. In essence, the ITS methodology assesses the difference between the actual post-event trend and a counterfactual post-event trend derived from the pre-event trend.[3]

Our implementation of the ITS follows Bernal et al. (2017, 2021), extended to a panel data setting with a fixed effects regression model in equation (3). We regress intangible capital y_{it} on economy fixed effects α_i, a trend term t, a dummy indicating when the event of interest has taken place $1\{post_t\}$, an interaction term between the post-event dummy and the time elapsed since the event, as well as both firm- and economy-level controls in $\boldsymbol{X_{it}}$. ε_{it} is the error term. y_{it} is expressed as the percentage difference in intangible capital relative to its level during the event year t_{event}. For example, $y_{i,2023}$=26 means that intangible capital for firm i in year 2023 were 26% higher than in 2021. This allows us to better compare changes in intangible capital in response to both shocks between firms that may differ in scale. Essentially, the ITS model segments the trends in the pre- and post-event periods, and compares them in β_3, which yields the slope difference in the post-event period relative to the pre-event period. β_2, on the other hand, represents the level shift that is associated with the onset of the event at t_{event}.

$$y_{it} = \alpha_i + \beta_1 t + \beta_2 \cdot 1\{post_t\} + \beta_3 (t - t_{event}) \cdot 1\{post_t\} + \boldsymbol{X_{it}\beta_4} + \varepsilon_{it} \qquad (3)$$

To estimate the effects of deep learning and GenAI, we restrict our dataset to the periods 2012-2019 and 2016-2023, respectively. t_{event} is assumed to be 2016 for deep learning and 2021 for Gen AI, the specifics of which are discussed in Section 1. In the deep learning case, the starting year of 2012 is chosen to avoid confounding effects from the immediate aftermath of the global financial crisis, while the ending year of

[3] Botosaru et al. (2024) discussed the evaluation of treatment effects in the absence of control groups. Schaffer et al. (2021) proposed a variant of the ITS methodology that utilizes forecasts from a time series model as counterfactuals.

2019 is chosen to avoid the COVID-19 pandemic and the subsequent global rollout of GenAI tools. The GenAI case overlaps with the COVID-19 pandemic but we attempt to address this consideration by including economy-level real GDP growth in $\boldsymbol{X_{it}}$ to control for overall macroeconomic conditions.

Tables 2 and 3 present the estimates of Equation 3 for the GenAI (2016-23; shock in 2021) and deep learning (2012-19; shock in 2016) cases, respectively. It is essential to note upfront that there may be some degree of uncertainty in the ITS estimates for some economies due to the relatively short time window at an annual frequency.

Table 2 reports an increase in the level, as well as the slope of intangible capital accumulation, as indicated by the coefficients on the event dummy and the interaction term (*Post-time x Post-event*), respectively that is associated with the introduction of GenAI globally in 2021. The β_2 estimates for the US show a statistically significant 52.25% (95% confidence interval: 46.96% to 57.52%) jump in intangible capital, followed by a 23.83% (95% CI: 21.88% to 25.78%) increase in the slope of intangible accumulation relative to its 2021 levels, as indicated by the β_3 estimates. The estimates for the four ASEAN+3 economies are also similar qualitatively, i.e., a slope shift that follows a larger level shift, with variation in the degree of statistical significance. The generalizability of our ITS estimates suggests that, in response to the recent global GenAI rollout, firms in the four selected ASEAN+3 economies and the US on average have accelerated their accumulation of intangible capital. As indicated in Figure 1, most of this acceleration is in the form of knowledge capital, although some acceleration in organizational capital is also observed.

In contrast, the estimated effects of deep learning are smaller compared to those of GenAI. In table 3, across all five economies, the level shift in intangible capital in response to the widespread availability of deep learning in 2016, as indicated by the estimates for the event dummy β_2 were smaller than in response to the GenAI rollout. However, the slope shifts in intangible capital accumulation, as indicated by the coefficient estimates on the interaction term β_3, in response to both the deep learning and GenAI rollouts were similar. In the US, Hong Kong, Japan and Korea, the slope shift terms were statistically significant, while the trend shift terms were statistically significant only in Japan and Korea. Again, this reflects some degree of uncertainty in some of the estimated parameters owing to the short time window in an annual setting. These estimates underscored that the GenAI wave was, at least from the perspective of its effects on intangible capital, orders of magnitude larger than the preceding AI-related innovation in the mid-2010s in the near-term, although the longer-term effects on intangible capital growth were potentially comparable.

Table 2: ITS estimates for 2016 to 2023 (event: 2021)

	Intercept	GDP	Post-event	Post-time x Post-event	Time
Panel A: United States					
Parameter	227.93	-3.76	52.25	23.83	-43.41
Lower bound	222.47	-4.30	46.96	21.88	-44.68
Upper bound	233.39	-3.23	57.54	25.78	-42.13
Panel B: Hong Kong					
Parameter	85.40	-0.41	15.43	8.22	-16.58
Lower bound	60.55	-1.89	-8.86	-1.44	-23.42
Upper bound	110.24	1.08	39.72	17.87	-9.74
Panel C: Singapore					
Parameter	116.70	-0.69	19.76	9.68	-21.82
Lower bound	47.75	-6.48	-69.07	-10.08	-39.06
Upper bound	185.65	5.10	108.59	29.45	-4.58
Panel D: Japan					
Parameter	101.99	-2.22	24.53	10.26	-20.28
Lower bound	89.96	-4.01	10.08	6.13	-23.89
Upper bound	114.02	-0.44	38.99	14.39	-16.66
Panel E: South Korea					
Parameter	127.63	-4.10	35.51	14.54	-24.12
Lower bound	108.23	-6.65	18.90	9.05	-28.15
Upper bound	147.03	-1.55	52.12	20.03	-20.09

Note: The lower and upper bounds refer to the 95% confidence intervals.

Table 3: ITS estimates for 2012 to 2019 (event: 2016)

	Intercept	GDP	Post-event	Post-time x Post-event	Time
Panel A: United States					
Parameter	143.79	2.61	18.59	26.53	-33.85
Lower bound	104.94	-17.62	-7.39	18.80	-39.78
Upper bound	182.63	22.84	44.57	34.27	-27.92
Panel B: Hong Kong					
Parameter	58.29	-1.26	3.89	12.70	-11.97
Lower bound	34.25	-6.28	-9.83	4.65	-18.11
Upper bound	82.34	3.76	17.62	20.74	-5.84
Panel C: Singapore					
Parameter	52.22	-1.12	7.85	5.47	-11.07
Lower bound	-29.12	-12.37	-23.62	-7.54	-25.72
Upper bound	133.57	10.13	39.31	18.48	3.58
Panel D: Japan					
Parameter	69.43	-0.55	6.81	10.12	-15.30
Lower bound	61.89	-2.18	2.81	7.58	-17.40
Upper bound	76.98	1.09	10.82	12.65	-13.20
Panel E: South Korea					
Parameter	102.66	-7.18	8.61	12.11	-17.67
Lower bound	77.93	-14.32	2.62	9.18	-20.09
Upper bound	127.38	-0.05	14.60	15.03	-15.25

Note: The lower and upper bounds refer to the 95% confidence intervals.

There are several limitations in our econometric analysis. First, there may be other macro-level confounders, as well as country-specific factors that may distort the path of intangible capital. To address this, our analysis controlled for real GDP growth, which directly accounts for the booms and busts experienced throughout our sample period, including the COVID-19 pandemic, as well as various geopolitical and trade events in the late-2010s.

Second, the time coverage of our analysis is relatively short. However, the limitations that may have instead arisen from a longer time series could have been greater in our setting, due to the presence of other major economic shocks, such as the Global Financial Crisis, as well as multiple AI-related shocks may have been greater. Other papers that deployed similar methodology also often utilised annual data with short time coverage specifically to avoid preceding or successive shocks that are irrelevant to the event of interest.

Third, our analysis lacks a control group, which precludes an implementation of DiD due to the global nature of both the deep learning and GenAI shocks. The ITS approach is precisely suitable for such a circumstance. While synthetic controls are technically feasible, they may underestimate the effect of global shocks, such as the deep learning and GenAI shocks, by potentially precluding the indirect effects of AI adoption by other firms.

4. Conclusion

Intangible capital has been the subject of extensive and intensive study in the field of economics, shedding light on persistent macroeconomic trends such as the deceleration of total productivity growth, the diminishing share of labor income, weak physical capital investment, and the escalation of firm valuations (Crouzet et al., 2022). Utilizing the US as a benchmark, this paper has provided two consistent points on the evolution and characteristics of intangible capital in four ASEAN+3 economies. First, the near-term effects of the advent of GenAI in 2021 on the level of intangible capital were larger than that of deep learning in 2016. Second, the longer-term effects on the growth of intangible capital were similar in both cases of AI innovation. Our findings suggest that these economies may follow distinct paths in the accumulation of intangible capital, which merits further investigation.

Recent advancements in GenAI, marked by the introduction of technologies such as Dall-E and ChatGPT in 2021/2022, are widely recognized as a significant technological breakthrough. Early adoptions and macroeconomic projections suggest that GenAI could substantially enhance productivity, potentially contributing up to a 7% increase in global GDP over the next decade (Brynjolfsson et al., 2023; Briggs and Kodnani, 2023). Over a brief period, our analysis provides suggestive evidence that the advent of GenAI has catalyzed an acceleration in the accumulation of intangible capital in the US, Hong Kong, Japan, Singapore, and South Korea since 2021, primarily driven by the accumulation of knowledge capital.

Over the past century, experiences with transformative technologies such as the steam engine, electricity, the internal combustion engine, and computers indicate that the diffusion of new technologies typically begins with a period of relatively slow productivity growth, followed by significant accelerations (Brynjolfsson et al., 2009). A similar trajectory is likely with the diffusion of GenAI. To capitalize on the potential benefits of AI transformation, policymakers in the ASEAN+3 economies are encouraged to assess their current standing in terms of intangible capital and to develop strategies that support investments in intangible capital, thereby facilitating the AI transformation within their respective economies.

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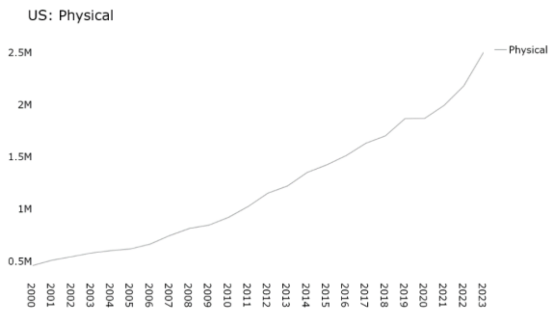
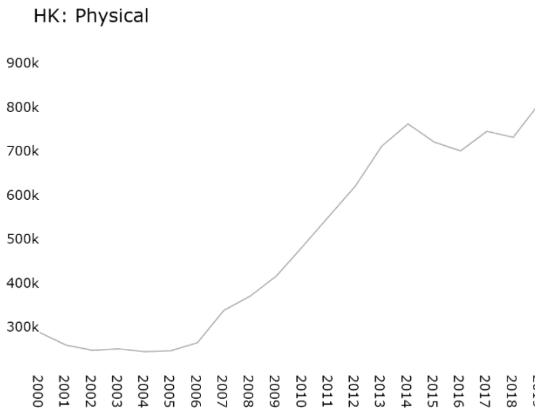
Appendix

Figure A1: Physical capital accumulation

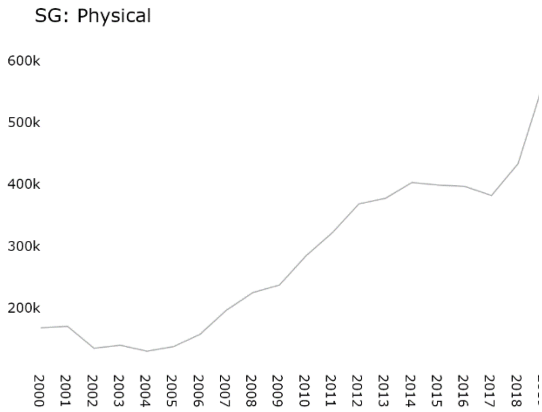
A. United States



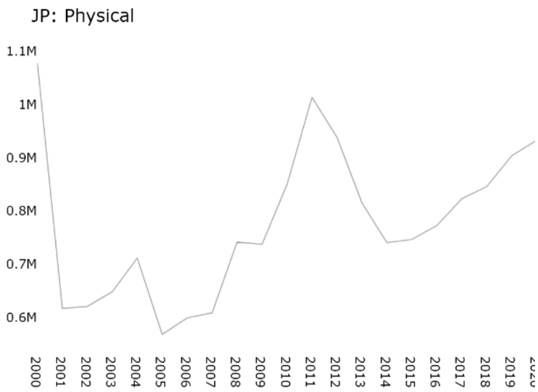
B. Hong Kong



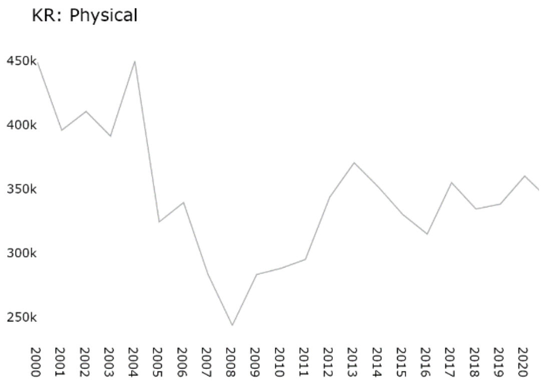
C. Singapore



D. Japan



E. South Korea



In each panel, the vertical axis represents the annual average stock of physical capital of public and private firms in an economy, measured in US Dollars.

Figure A2: Google trends index for searches of “deep learning AI” worldwide

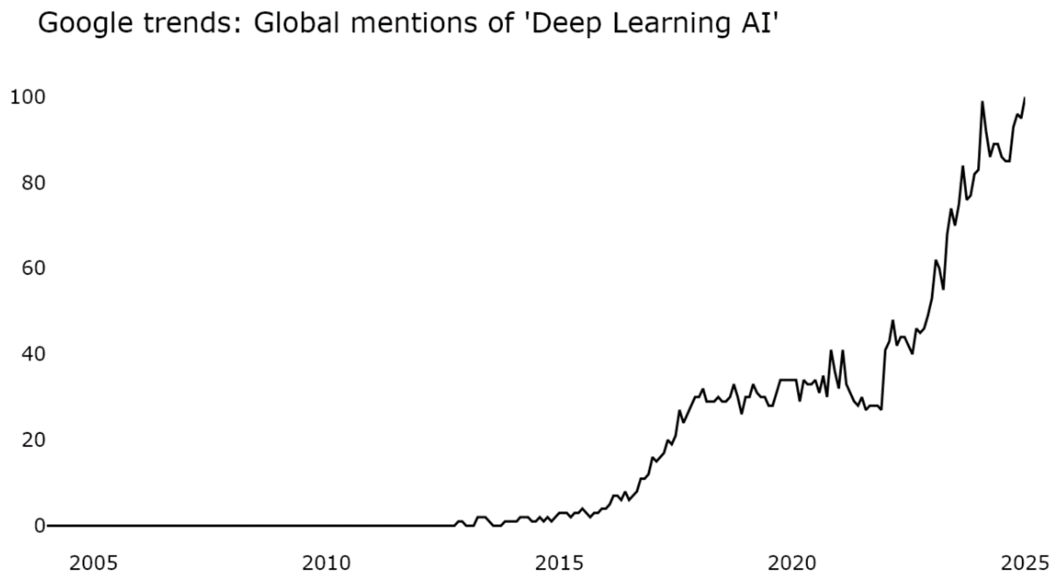


Table A1: Summary statistics for the United States

A. 2012 to 2019 (breakpoint: 2016)

	US: 2012 to 2019													
	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016
mean	345297.33	320847.35	192470.18	159860.42	202779.06	191817.24	68933.2	54413.5	152934.73	148668.82	3918610.49	3286169.64	4419.25	4421.17
std	2451166.24	2235728.57	1893869.2	1257125.86	2021738.88	1819916.36	795046.8	450305.98	1627373.99	1513058.37	12573629.8	11147817.36	57126.02	57128.4
min	0.0	0.0	-13.35	-62.43	-10279.37	-6331.8	-355.0	-2456.18	-22000.0	-1485000.0	-3671981.0	0.0	0.0	0.0
10%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6069.84	4068.0	8.96	8.96
25%	68.57	175.5	0.95	4.23	20.9	49.83	0.0	0.0	0.0	0.0	34096.75	25651.06	32.63	32.68
50%	1189.17	3056.02	84.56	363.36	646.05	1447.83	0.0	0.0	0.0	0.0	310204.5	228589.0	132.7	132.7
75%	19497.4	32000.58	3089.87	8492.09	13945.2	20781.84	0.0	0.0	0.0	1474.49	2354750.0	1907237.35	752.3	745.93
90%	288561.79	299751.69	86873.57	101051.01	165799.85	173547.32	16580.7	27663.2	87647.0	113046.5	9520716.0	8499000.0	4141.86	4135.65
max	61203276.33	53488602.68	76287326.94	25700688.56	135041237.47	115312967.26	35931000.0	12540000.0	107891000.0	97041000.0	259651000.0	252668000.0	2033984.4	2033984.4
N(firms)	1737.0	1737.0	1776.0	1776.0	11854.0	11854.0	1776.0	1776.0	11854.0	11854.0	1914.0	1914.0	4367.0	4367.0

B. 2016 to 2023 (breakpoint: 2021)

	US: 2016 to 2023													
	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021
mean	388101.03	348722.4	281006.58	199437.89	222371.44	204365.13	109186.84	72020.84	176524.05	154156.01	5034709.78	4042109.16	4422.35	4418.11
std	2913048.87	2490037.24	4158680.22	2084211.71	2361562.51	2054838.83	1849693.35	880851.63	1969886.25	1660659.93	15529338.0	12868239.88	57128.57	57125.27
min	0.0	0.0	-1.94	-13.35	-432468.09	-13005.44	-3.0	-1118.11	-2195315.0	-26000.0	-5223000.0	-3671981.0	0.0	0.0
10%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8757.5	6552.5	8.97	8.96
25%	24.3	60.12	0.18	0.76	7.8	18.71	0.0	0.0	0.0	0.0	54311.5	36131.75	32.68	32.63
50%	411.24	1066.9	15.1	68.9	244.15	578.73	0.0	0.0	0.0	0.0	447120.5	326750.0	132.7	132.7
75%	10793.14	18397.18	748.78	2672.35	7258.05	13140.53	0.0	0.0	0.0	0.0	3065747.0	2426504.75	751.64	751.64
90%	242640.26	290048.9	51081.83	80877.94	139124.86	163869.8	5655.9	15087.2	64610.5	84453.4	11465321.6	9679400.0	4141.86	4141.86
max	70465805.68	63372219.68	191075388.69	94615382.32	157328688.95	140593629.98	85622000.0	42740000.0	130971000.0	116288000.0	276690000.0	259651000.0	2033984.4	2033984.4
N(firms)	1737.0	1737.0	1776.0	1776.0	11854.0	11854.0	1776.0	1776.0	11854.0	11854.0	1914.0	1914.0	4367.0	4367.0

Table A2: Summary statistics for Hong Kong

A. 2012 to 2019 (breakpoint: 2016)

	HK: 2012 to 2019													
	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016
mean	354367.56	249695.16	107743.83	72380.96	162312.57	127310.52	38679.17	30471.99	137870.07	121998.04	1722277.13	1565116.04	2407.4	2145.66
std	1164056.58	734863.42	457749.38	270218.58	720653.65	591714.27	165982.23	133330.09	650529.39	549012.15	7793686.84	7595673.36	11270.52	11571.27
min	0.0	0.0	-0.68	-3.17	0.0	0.0	0.0	0.0	-2194.31	-4016.69	0.46	2.71	0.0	0.0
10%	121.71	297.15	0.0	0.0	406.37	803.49	0.0	0.0	0.0	0.0	1786.62	1388.73	35.08	28.44
25%	2473.21	3778.68	2.93	13.68	4628.55	4709.21	0.0	0.0	1236.16	1985.95	18904.79	16253.87	75.95	62.98
50%	8898.25	11102.58	328.58	724.32	17563.4	15363.16	0.0	0.0	11585.25	11079.18	96007.69	78932.39	210.35	163.21
75%	94823.25	106802.35	17271.05	15468.78	65402.63	52868.03	5320.63	4358.07	53562.59	49713.43	551721.77	414925.16	787.8	606.22
90%	963465.95	629246.68	189153.07	173939.49	258719.66	187841.59	62095.1	55257.07	203470.43	188328.8	2763851.84	2094458.72	3776.45	3268.0
max	9495413.99	6883068.19	3844854.67	2934331.99	13402291.83	11042738.06	1374745.0	1563997.0	11620431.87	9724289.35	117353114.36	112750096.62	236037.78	259814.61
N(firms)	67.0	67.0	68.0	68.0	693.0	693.0	68.0	68.0	693.0	693.0	384.0	384.0	524.0	524.0

B. 2016 to 2023 (breakpoint: 2021)

	HK: 2016 to 2023													
	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021
mean	477499.22	366481.91	161468.23	112614.75	186508.21	165282.18	60936.03	41670.16	144311.99	137763.67	2002914.14	1764245.78	2051.74	2342.9
std	1670080.23	1209266.35	677171.1	471006.53	855874.12	736845.27	266414.31	173065.78	714963.52	654567.07	9002831.59	7993222.71	9065.84	10823.0
min	0.0	0.0	-0.1	-0.68	0.0	0.0	0.0	-158.46	-133.74	-2194.31	0.0	0.46	0.0	0.0
10%	42.43	113.94	0.0	0.0	169.67	376.87	0.0	0.0	0.0	0.0	2558.72	1932.98	13.31	28.35
25%	838.96	2222.3	0.6	2.65	3723.37	4568.32	0.0	0.0	0.0	709.25	21463.21	21079.11	34.29	66.18
50%	7983.47	8921.67	109.27	253.91	16311.14	17447.53	0.0	0.0	6790.92	11090.9	105339.72	99428.9	111.51	189.0
75%	175250.19	111896.17	35440.63	18785.25	73649.95	66562.28	4362.04	5717.33	44108.79	52381.32	631179.74	567216.76	445.23	738.73
90%	752507.62	877442.52	252304.16	190850.88	273080.61	262549.79	85325.0	75501.22	182842.02	201013.96	3613417.61	2862300.8	3119.6	3591.38
max	12922213.56	10120983.07	5698622.55	3998873.17	16056883.33	14039196.97	2221522.0	1384372.0	13132044.83	11847726.81	129985989.99	129015255.95	175198.39	236037.78
N(firms)	67.0	67.0	68.0	68.0	693.0	693.0	68.0	68.0	693.0	693.0	384.0	384.0	524.0	524.0

Table A3: Summary statistics for Singapore

A. 2012 to 2019 (breakpoint: 2016)

SG: 2016 to 2023	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021
mean	576483.0	536881.41	390032.9	357911.53	94173.82	86113.62	129567.59	128823.41	74119.56	67645.07	578288.02	551135.96	1739.22	1539.09
std	1410433.54	1253157.72	1042471.42	959429.09	410397.31	329824.54	355053.85	349434.86	367641.39	293737.81	1196555.2	1250553.77	6764.77	5614.08
min	0.0	0.0	0.0	0.0	0.0	0.0	-1.45	0.0	-6537.0	-326.54	0.0	2.0	1.05	0.52
10%	492.68	1084.41	1.07	3.52	31.0	83.96	0.0	0.0	0.0	0.0	2282.63	2251.7	11.85	12.12
25%	5133.41	6020.14	51.6	170.62	557.69	1234.95	0.0	0.0	0.0	0.0	10597.62	11402.32	21.99	24.48
50%	24123.22	38849.91	2027.67	4385.1	4753.43	8213.23	0.0	68.19	0.0	1067.61	54317.22	40805.89	74.91	73.53
75%	274046.62	404971.29	49259.23	88260.02	23096.52	26726.26	13250.58	26179.61	9554.96	15524.43	447328.09	407768.34	420.38	420.77
90%	1178380.45	968231.8	754314.19	602902.59	98533.2	119081.51	267941.01	219910.67	61161.57	73376.96	2153851.56	1899257.89	2627.69	3039.71
max	6116308.71	5247978.33	4335777.63	3754885.75	4010093.79	3167662.42	1712744.7	1544979.64	3931981.35	2757960.36	6298400.0	9072929.91	63287.35	51013.4
N(firms)	21.0	21.0	21.0	21.0	332.0	332.0	21.0	21.0	332.0	332.0	113.0	113.0	173.0	173.0

B. 2016 to 2023 (breakpoint: 2021)

SG: 2012 to 2019	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016
mean	529704.21	360701.66	353305.19	232045.66	85084.91	73126.79	132779.72	89199.38	67595.01	66049.66	539917.51	513452.98	1585.92	1657.56
std	1230284.21	876954.93	950054.25	717653.42	320057.19	247111.2	361335.57	270067.49	289672.91	242159.33	1258440.61	1291829.14	5761.34	5441.07
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-326.54	-5186.36	2.0	46.79	0.52	1.56
10%	1360.42	2648.99	5.1	23.87	88.26	198.25	0.0	0.0	0.0	0.0	2159.43	3315.73	13.03	17.93
25%	6420.29	8111.73	246.12	404.67	1353.49	2678.18	0.0	0.0	0.0	0.0	11321.14	10588.53	26.12	34.47
50%	40177.91	58404.24	6230.39	11754.15	8644.89	9792.07	491.05	792.18	1412.34	5820.64	39873.9	33515.83	76.69	106.5
75%	413891.6	326830.81	90433.51	129829.64	27376.4	28988.23	27708.84	33339.28	16656.48	23954.62	392643.08	338140.21	425.05	474.15
90%	920342.83	547219.21	570677.21	336694.13	123310.45	127075.9	218801.28	147895.1	75701.21	108466.32	1815832.78	1223241.83	3150.02	3639.28
max	5247978.33	4569394.92	3754885.75	3720420.23	2994772.17	2176111.09	1544979.64	1353000.0	2757960.36	2104521.37	9072929.91	10453769.0	51013.4	47399.98
N(firms)	21.0	21.0	21.0	21.0	332.0	332.0	21.0	21.0	332.0	332.0	113.0	113.0	173.0	173.0

Table A4: Summary statistics for Japan

A. 2012 to 2019 (breakpoint: 2016)

	JP: 2012 to 2019													
	Intangible assets		**Knowledge capital**		**Organisational capital**		**R&D**		**SG&A**		**Physical capital**		**Market capitalisation**	
	Post-2016	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**	**Post-2016**	**Pre-2016**
mean	1698247.53	1761951.93	627516.52	689970.38	851989.26	840001.84	197835.14	218934.23	624545.89	632177.86	1501116.76	1434403.16	2255.46	1776.69
std	6023285.52	6258826.77	2486714.63	2725538.72	2920431.61	2785510.73	821747.77	904575.61	2254873.86	2199215.13	5865964.28	6064648.48	7742.0	6711.68
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-7196938.25	0.0	128.82	91.44	0.29	0.27
10%	291.24	747.29	2.82	12.99	346.75	844.59	0.0	0.0	0.0	0.0	11928.83	12634.49	32.07	27.1
25%	4805.09	8642.66	53.61	235.64	6087.72	9922.87	0.0	0.0	0.0	0.0	49945.88	50998.75	78.38	62.83
50%	37322.04	51534.22	3835.91	5231.41	52725.31	71717.44	597.8	909.19	17045.68	25410.16	192650.46	189762.86	276.6	215.2
75%	314484.33	334598.27	67145.43	69061.02	407301.32	459735.98	19345.38	20174.62	255655.29	300354.69	629016.36	603018.48	1174.0	883.42
90%	3761689.9	3165670.37	1036899.02	1029998.27	1645299.19	1629689.03	330376.49	348289.0	1192572.79	1208201.9	3186053.04	2989800.08	4696.21	3622.73
max	61802359.38	58013304.44	28073278.01	26672701.41	35290824.84	31629612.86	9734255.1	9818121.85	27929951.0	26070825.8	87158984.88	112144975.29	185366.98	204217.98
N(firms)	370.0	370.0	371.0	371.0	910.0	910.0	371.0	371.0	910.0	910.0	356.0	356.0	1711.0	1711.0

B. 2016 to 2023 (breakpoint: 2021)

	JP: 2016 to 2023													
	Intangible assets		**Knowledge capital**		**Organisational capital**		**R&D**		**SG&A**		**Physical capital**		**Market capitalisation**	
	Post-2021	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**	**Post-2021**	**Pre-2021**
mean	1661457.47	1699601.4	601808.84	630863.85	854823.97	853767.64	183733.12	201320.39	595427.2	622186.37	1489273.75	1542118.64	2508.07	2272.5
std	5782354.11	6021241.03	2408025.21	2504742.99	2984576.24	2930907.66	784334.67	838285.18	2164842.03	2242050.35	5394062.97	5960030.37	9932.97	7919.06
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-7196938.25	173.7	128.82	6.23	0.28
10%	107.83	262.84	0.53	2.29	131.92	301.05	0.0	0.0	0.0	0.0	10730.21	12191.88	29.06	31.99
25%	1775.43	4276.67	11.13	47.81	2589.46	5502.54	0.0	0.0	0.0	0.0	45861.66	50999.82	70.19	78.14
50%	28475.49	36074.12	3014.29	3828.71	42196.9	52080.72	306.66	561.92	8576.08	16486.98	175699.44	195122.21	240.81	270.21
75%	285993.88	314309.54	61677.4	67168.37	357718.73	399430.72	11574.63	18469.77	211933.61	254552.81	612891.5	636623.05	1075.66	1152.48
90%	3835637.39	3855320.83	1005078.32	1060336.85	1676396.84	1650004.71	306324.1	329810.23	1143245.75	1191808.54	3277566.29	3231771.9	4536.35	4661.13
max	61653509.8	62111299.01	25201376.06	28073278.01	36452133.74	35293035.86	10027974.27	10403428.03	27213205.21	27929951.0	86944075.8	94257463.16	230466.84	185366.98
N(firms)	370.0	370.0	371.0	371.0	910.0	910.0	371.0	371.0	910.0	910.0	356.0	356.0	1711.0	1711.0

Table A5: Summary statistics for South Korea

A. 2012 to 2019 (breakpoint: 2016)

KR: 2012 to 2019	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016	Post-2016	Pre-2016
mean	555598.89	481374.12	216655.53	171951.67	280497.73	251234.21	77295.52	64283.41	214677.24	214741.23	2055842.98	1788070.34	1856.35	1594.92
std	5007679.51	4036528.24	2497752.48	1877316.76	1784941.05	1533392.75	911015.53	733793.19	1390980.13	1423489.17	9827772.22	8214690.91	13772.74	9918.02
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-171.26	0.0	0.02	0.02	15.42	8.57
10%	63.21	163.32	0.31	1.28	84.44	191.9	0.0	0.0	0.0	0.0	12846.76	11805.45	41.98	26.7
25%	485.39	1215.46	5.41	20.17	791.0	1717.0	0.0	0.0	0.0	0.0	39544.19	38877.07	75.27	51.02
50%	8994.07	10260.94	173.94	483.84	11526.17	13343.24	0.0	0.0	5555.54	6222.01	187211.61	174684.92	158.15	126.78
75%	78821.57	71526.27	2918.11	4345.01	81551.43	73930.03	667.15	820.12	54503.24	55780.66	824933.72	733379.17	521.11	391.94
90%	372973.5	360156.8	37637.41	37973.86	419515.52	357857.51	11860.61	10532.99	285722.3	307292.57	2837872.51	2763826.61	2398.71	2209.27
max	88979587.22	74489951.06	47905113.9	36421582.47	41292106.04	38068368.59	17333369.44	14095791.57	34475482.51	35573420.95	136274285.62	119472022.2	289998.58	189479.91
N(firms)	317.0	317.0	319.0	319.0	724.0	724.0	319.0	319.0	724.0	724.0	327.0	327.0	359.0	359.0

B. 2016 to 2023 (breakpoint: 2021)

KR: 2016 to 2023	Intangible assets		Knowledge capital		Organisational capital		R&D		SG&A		Physical capital		Market capitalisation	
	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021	Post-2021	Pre-2021
mean	616819.39	561998.71	262241.1	222662.4	297663.61	281466.5	89561.59	78900.9	228971.16	212041.17	2342199.02	2119627.04	2358.99	1860.36
std	5860325.89	5097338.59	3251397.55	2588553.88	1884168.76	1789103.07	1155069.53	939295.07	1452525.39	1370287.74	11512593.82	10155440.37	20923.74	14431.6
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-402.82	0.02	0.02	20.86	12.24
10%	25.08	58.84	0.07	0.26	32.84	76.46	0.0	0.0	0.0	0.0	13504.46	12943.45	51.47	41.8
25%	182.57	424.08	1.0	4.53	320.53	735.62	0.0	0.0	0.0	0.0	39142.23	39590.3	83.82	74.08
50%	9299.91	8931.0	52.67	148.25	11269.51	11423.99	0.0	0.0	6088.5	5513.04	195779.14	192162.71	173.62	152.84
75%	83778.48	78822.42	2891.7	2813.92	84821.03	81518.32	862.35	677.24	60873.84	54503.24	922006.03	845584.7	557.97	500.47
90%	416035.92	368236.97	45764.1	37967.25	442776.19	423068.22	16398.08	12631.84	318966.37	285891.47	3228896.08	2964726.98	2446.85	2296.53
max	102950904.02	91625667.14	60187065.82	50889565.87	42763838.2	41292106.04	21772187.43	18314088.42	32401190.7	34475482.51	145349607.11	148213417.63	465470.65	312381.16
N(firms)	317.0	317.0	319.0	319.0	724.0	724.0	319.0	319.0	724.0	724.0	327.0	327.0	359.0	359.0