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THE IMPLICATIONS OF DIGITALISATION ADOPTION FOR HONG KONG NON-FINANCIAL CORPORATES – AN ASSESSMENT BASED ON TEXTUAL ANALYSIS

Key points:

- *The last few years have seen the rapid development of digital technology, particularly generative artificial intelligence (GenA.I.). Corporates are increasingly adopting the latest technologies to achieve efficiency gains and generate revenue, and there is significant interest in the impact this may have on corporate performance and employment. While it may be too early to assess the impact of firms' adoption of the latest technologies, digitalisation more generally has been a long-term trend and valuable lessons can be drawn from the impact of firms' digitalisation efforts.*

- *In light of this, this study examines the extent of digitalisation adoption by non-financial corporates in Hong Kong in recent years and its implications for corporates. We measure a firm's level of digitalisation adoption based on textual analysis of annual reports conducted using GenA.I. and classify each firm into one of four categories based on its level of engagement in digitalisation.*

- *The textual analysis reveals that nearly two thirds of the Hong Kong corporates in our sample are engaged in digitalisation, up from around 50% in 2019. Over half of the sample firms are in more advanced stages of digitalisation adoption ('more advanced firms'), up from just over 40% in 2019. Larger firms are likely to be more advanced in adopting digitalisation, and digitalisation adoption is associated with greater investment in intangible assets.*

    - *By sector, the communication services and information technology sectors are the most advanced. Following these, the healthcare, consumer discretionary and transportation sectors are also more advanced than others. Digitalisation adoption grew noticeably in these sectors during and following the COVID-19 pandemic, possibly in response to changes in consumer behaviour.*

- *Regarding corporate performance, this study finds that while digitalisation adoption has a negative impact on profitability initially, the most advanced firms enjoy higher revenue growth and an uplift in price-to-book ratios when they embark on digitalisation, reflecting investors' perception that these firms are more resilient and enjoy stronger business prospects. Digitalisation adoption does not appear to have a notable adverse impact on overall corporate employment in the short term, as we find that more advanced firms see a higher growth (or a smaller decline) in total full-time employees, although granular analysis concerning different types of employees is beyond the scope of this study.*

- *Our analysis underscores the importance for Hong Kong corporates of engaging deeply in digitalisation to remain competitive and resilient. Firms are increasingly adopting digitalisation, and only firms with the most advanced digitalisation adoption are expected to see stronger business prospects. In addition, as larger firms tend to be more advanced in adopting digitalisation, possibly because economies of scale enable them to afford the resources needed for digitalisation, such as increased investment and hiring, smaller firms face a greater risk of losing competitiveness and becoming more vulnerable.*

- *The findings of this study offer several valuable implications for policymakers seeking to encourage and enable firms across the economy to engage deeply in digitalisation. For example, policymakers could launch initiatives to encourage financial products and services that facilitate digitalisation adoption by corporates (especially small and medium-sized enterprises), and education and training programmes can be provided to upskill the labour force to meet the growing demand for digital skills.*

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1. INTRODUCTION

The last few years have seen the rapid development of digital technology, particularly generative artificial intelligence (GenA.I.). Companies around the world are increasingly adopting the latest technologies to generate new value-creation opportunities and achieve efficiency gains. For example, digital sales channels can enhance revenue growth without the need to set up brick-and-mortar shops while also collecting customers' data for sales and marketing purposes. The automation of some tasks may also improve efficiency and lower production costs. Recent breakthroughs in GenA.I. may further enhance the benefits and expand the use cases of digital technology. Failing to embrace digitalisation may negatively affect a firm's competitiveness and performance.

As a result, there is significant interest in the potential impact of digitalisation adoption on corporate performance and employment. While it may be too early to assess the full impact of firms' adoption of the latest technologies, such as GenA.I., digitalisation more broadly has been a long-term trend and valuable lessons can be drawn from how digitalisation efforts in the recent past have impacted corporates.

In light of this, **this study examines the extent, as well as the implications, of digitalisation adoption by non-financial corporates** (hereafter 'corporates') **in Hong Kong** (HK) **in recent years**, including whether digitalisation adoption could improve corporate financial performance, which has not been examined extensively in the literature.[1] Specifically, this study explores the following research questions:

(I) To what extent do Hong Kong corporates adopt digitalisation?
(II) What factors influence the adoption of digitalisation by Hong Kong corporates?
(III) How does digitalisation adoption impact corporate performance and employment?

A major challenge in answering these questions is the measurement of a firm's level of digitalisation adoption, which is not available in conventional financial data. **This study circumvents this challenge by leveraging GenA.I. tools to conduct textual analysis of annual reports** and **classify firms into different digitalisation adoption categories**, based on their level of engagement in digitalisation, i.e. the extent to which they set a clear strategy and mention specific use cases of digitalisation.

The rest of the paper is organised as follows. Section 2 introduces the methodology and data used in this study; Sections 3 to 5 answer the three research questions in turn; and Section 6 concludes the study and discusses its policy implications.

[1] Studies have usually focused on the impact on labour, wages and productivity, e.g. Borowiecki et al. (2021). See also Comunale and Manera (2024).

2. METHODOLOGY AND DATA

2.1 Data sample

Our data sample consists of HK-listed corporates that are headquartered and operating in Hong Kong and have annual reports available for all fiscal years from 2017 to 2024 at the time of analysis.[2] **The sample comprises 734 firms, covering 78% of HK-listed and HK-headquartered firms**. Our final sample consists of firms from a broad range of sectors, the largest of which are the consumer discretionary, capital goods, real estate and information technology (IT) sectors (**Table 1**).

Table 1: Sample firms by sector

Sector	Number of firms	Share of firms
Consumer Discretionary	210	29%
Capital Goods	125	17%
Real Estate	104	14%
Information Technology	86	12%
Communication Services	45	6%
Commercial and Professional Services	35	5%
Consumer Staples	32	4%
Health Care	31	4%
Materials	23	3%
Transportation	22	3%
Energy	16	2%
Utilities	5	1%
Total	***734***	

Sources: S&P Global and HKMA staff calculations.

2.2 Classification of firms' level of digitalisation adoption

We classify firms' level of digitalisation adoption by conducting textual analysis of public disclosures using GenA.I. tools. This approach is motivated by both data gaps in conventional sources and scalability. Conventional financial data do not contain readily available measures related to firms' digitalisation adoption. As a result, studies often rely on bespoke surveys or interviews to infer the level of digitalisation adoption, but these methods are costly, time-consuming, and difficult to scale across many firms and years. In contrast, the use of GenA.I. models to analyse publicly disclosed documents allows for the efficient classification of a large number of firms across several years, while preserving the nuance embedded in narrative disclosures.

[2] Sample firms are identified through S&P Global's database. We focus on firms for which Bloomberg classifies the location of risk as Hong Kong (this takes account of a firm's location of management, primary listing and revenue, as well as reporting currency). We manually remove firms from the energy, materials and utilities sectors that do not include Hong Kong as one of their business segments. Analysis was conducted during Q3 2025. Extending our analysis to the years pre-2017 would have considerably reduced the size of our sample.

Firms' annual reports are used as the source of information. This reflects several advantages that annual reports have over other forms of disclosure in the context of this study.[3] First, annual reports provide a more comprehensive and standardised account of a firm's strategy, business operations, risks, and investments each year. This makes the content of annual reports relatively comparable across firms and time. In contrast, alternative sources such as earnings call transcripts and press releases may be dominated by discussions of specific aspects relevant to an individual firm at a particular point in time. Second, the use of annual reports gives us broader coverage of firms, as earnings calls transcripts may not be available for smaller listed firms.

Based on the information revealed in annual reports, we classify firms into four categories that reflect their level of engagement in digitalisation adoption, i.e. whether they have *clear digitalisation strategies* and whether they mention *specific digitalisation projects or use cases* and *measurable outcomes* of digitalisation. The categories are summarised in **Table 2**. For a full definition of each category, please see **Annex 1**.

Table 2: Categories of the level of digitalisation adoption by firms

Category	Characteristics
Leader (L)	The firm provides detailed information on its engagement in digitalisation, with specific projects, investments, platforms and/or use cases directly related to digitalisation. It demonstrates a strategy for digital transformation. It provides measurable outcomes or quantitative metrics for the impact of these digital initiatives.
Active Adopter (AA)	The firm provides detailed information on its engagement in digitalisation, with specific projects, investments, platforms and/or use cases directly related to digitalisation. However, it does not yet demonstrate a strategy for digital transformation, and it lacks measurable outcomes or quantitative metrics for the impact of these projects.
Elementary Stage (ES)	The firm mentions digitalisation initiatives, but the discussion is generic and lacks detail. There is no mention of specific projects, investments, platforms or use cases.
No Engagement (NE)	The firm does not mention its engagement in digitalisation.

[3] We gather firms' annual reports from Hong Kong Exchanges and Clearing Limited's (HKEX) news website, a centralised platform that provides access to all disclosures and announcements by firms listed on HKEX.

2.2.1 Classification methodology

Our methodology for classifying firms' digitalisation adoption involves a three-step process that leverages a GenA.I. model for textual analysis, followed by a rule-based overlay.

Step 1: Identification of relevant sections from annual reports via a keyword search

We select sections from each firm's annual report that are relevant to digitalisation. Given that annual reports can be several hundred pages long, processing the full document for each firm with the GenA.I. tool would be computationally inefficient and would often exceed the capacity, or context window, of current models. To address this, we use a Python-based script to scan each annual report. This script uses a predefined dictionary of keywords related to digitalisation (e.g., 'artificial intelligence', 'big data', 'cloud computing') to identify and extract the pages containing these terms, along with the immediately previous and subsequent pages, in cases where the keywords appear in the first or last incomplete sentence on that page.[4]

Step 2: GenA.I.-based classification of digitalisation adoption

We then use a GenA.I. tool to classify each firm's level of digitalisation adoption for each sample period. For this task, we select Google's Gemini 2.5 Pro model which was released in June 2025. This model is appropriate given its advanced capabilities in handling long-context tasks, which are essential for processing the concatenated pages extracted from the reports, as well as its strengths in logic, reasoning, and nuanced instruction-following.[5]

Each firm's extracted text is fed into the model using a detailed, specific and structured prompt that defines the classification categories and provided clear analytical rules (see **Annex 1** for the detailed prompt). The model is tasked with analysing the text and assigning a single category (out of the four categories in **Table 2**) based on the provided framework. As discussed in Section 2.2, key parameters of the classification framework include whether a firm has specific digitalisation projects or use cases and whether measurable outcomes of digitalisation are described.

[4] The full list of keywords is as follows: 'digital', 'digiti', 'artificial intelligence', ' AI ', 'cyber', 'cyber security', 'cloud', 'cloud computing', 'big data', 'internet of things', 'IoT', 'blockchain', 'machine learning', 'automation', 'robot', 'fintech', 'quantum computing', 'virtual reality', ' VR ', 'augmented reality', ' AR ', and '5G'.

[5] See https://deepmind.google/models/gemini/pro/ for Google's evaluation of Gemini 2.5 Pro. We also evaluated multiple GenA.I. models available at the time of analysis and concluded that Gemini 2.5 Pro's evaluation aligns more closely with our own judgment.

To ensure that the classification reflects substantive digital transformation initiatives, we specify several exclusions in our prompt, including management of basic IT infrastructure (e.g. standard hardware or software), provision of generic IT training for staff, and standard online presence (e.g. corporate website).

To ensure that the classification generated by GenA.I. aligns closely with human judgement, we manually test its robustness with a subset of sample firms. We select a random sample of approximately 80 firms (i.e. about 10% of the sample) that are evenly split across sectors. Each classification generated by GenA.I. is then manually checked against the source text and human judgement. After several iterations and modifications, the final prompt exhibits a high degree of alignment with human judgement (nearly 95%), providing confidence in the scalability of the methodology.

Step 3: Application of an overlay

In the final step, we impose an overlay on the raw classification generated by the GenA.I. tool. This overlay takes into consideration that digital initiatives discussed in one year's annual report may not be discussed in subsequent years' reports, even if the initiatives are ongoing. Specifically, if a firm's digitalisation classification drops by one or more categories from one year to the next, we hold it constant at the previous level, but only for the initial year in which the drop occurs. For example, if a firm is classified as a "Leader" in year *t-1* and drops to "Active Adopter" in year *t*, we manually adjust the year *t* classification to "Leader". For *t+1*, we follow the raw classification and do not apply an overlay. In essence, this overlay assumes that a firm with established digital capabilities is unlikely to lose them in a short period of time, while also generating a smoother digitalisation adoption classification over time.

Caveats

Two important caveats in our methodology are worth noting. First, a major challenge to the application of GenA.I. models is related to their "black-box" nature, as they are prone to generating inconsistent content due to their stochastic nature. This means that running the exact same prompt may occasionally yield slightly different responses, although our structured prompt is designed to minimise this variability. Second, our analysis is reliant upon corporate disclosure practices in annual reports. Digitalisation initiatives may be ongoing within a firm but not be discussed in its annual report for a given year, which could lead to an inappropriate classification. Our overlay, discussed in Step 3, provides a partial mitigation for this.

3. TO WHAT EXTENT DO HONG KONG CORPORATES ADOPT DIGITALISATION?

The textual analysis enabled by GenA.I. finds that nearly two thirds (64%) **of Hong Kong corporates in the sample are currently adopting digitalisation, up from nearly half** (49%) **of the sample firms in 2019** (**Chart 1**). **Over half of the sample firms** (53%) **are in more advanced stages of digitalisation adoption**, i.e. classified as Leaders and Active Adopters ('more advanced firms'), up from 42% in 2019. In line with our classification framework, these Leaders and Active Adopters have demonstrated specific use cases (e.g. a mobile app for use by customers, and the use of A.I. for travel disruption management), as opposed to generic discussion of digitalisation by firms in the Elementary Stage (see **Annex 2** for examples of GenA.I. responses).

Firms in the communication services and IT sectors are more advanced in their adoption of digitalisation (**Chart 2**) than those in other sectors, with 78% of communications firms and 76% of IT firms classified as Leaders or Active Adopters. The extent of digitalisation adoption has not changed much over the years for these sectors, which may reflect the fact that these sectors are, in general, more technologically focused by nature and the adoption of the latest technologies is an important part of their activities. In addition, many of these firms are also providers of technology that enables other sectors to adopt digitalisation, e.g. providing data centres and software solutions.

Following communications and IT firms, **companies in the healthcare, consumer discretionary and transportation sectors are more advanced in their digitalisation adoption than the rest of the economy**. Digitalisation adoption grew noticeably in the transportation sector during the COVID-19 pandemic, while adoption grew considerably in the post-pandemic years for the healthcare and consumer discretionary sectors.

Some of the advancement in digitalisation in these sectors is likely to be a response to the changing patterns of consumer behaviour following the pandemic, e.g. a preference for online shopping and consultations. For example, a healthcare firm has been offering video consultations, using A.I. to undertake pre-diagnosis assessment, and using big data to offer personalised solutions. Meanwhile, a consumer discretionary firm has been accelerating its e-commerce business and leveraging data analytics for data-driven merchandising decisions.

Chart 1: Digitalisation adoption classification

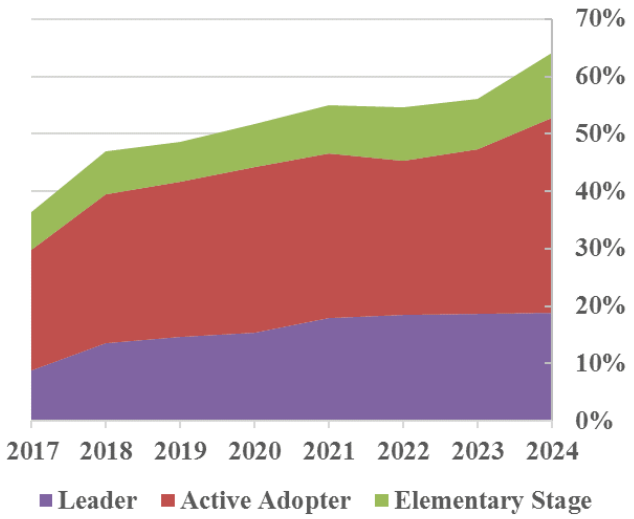
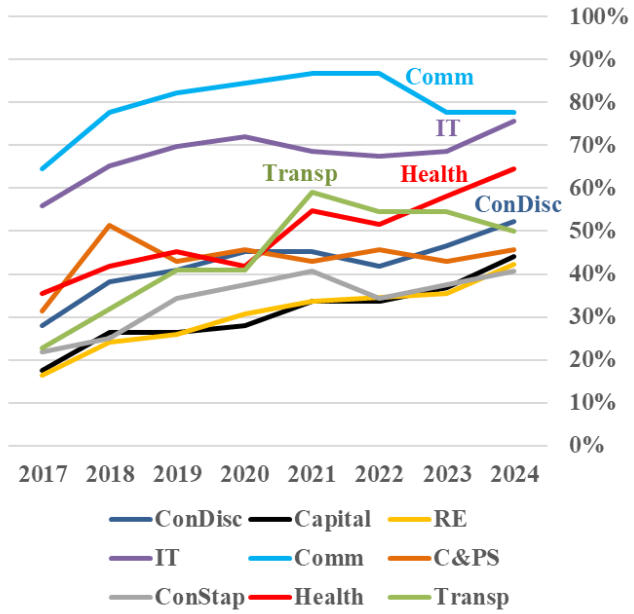


Chart 2: Share of firms classified as Leaders or Active Adopters, by selected sector



Note: IT = information technology, Capital = capital goods, ConDisc = consumer discretionary, RE = real estate, Health = health care, ConStap = consumer staples, Comm = communication services, Transp = transportation, C&PS = commercial and professional services.
Sources: S&P Global and HKMA staff calculations.

As a further validation, we assess whether digitalisation adoption is associated with greater investment in intangible assets, as a firm that is adopting digitalisation is expected to invest more in intangible assets such as human capital and software. Our regression analysis confirms that digitalisation adoption is indeed associated with greater intangible investment, suggesting that our methodology produces a satisfactory proxy for the extent of firms' digitalisation adoption. Please see **Annex 4** for details.

4. WHAT FACTORS INFLUENCE THE ADOPTION OF DIGITALISATION BY HONG KONG CORPORATES?

In this section, we examine the factors commonly discussed in the literature as having a potential influence on the level of digitalisation adoption by corporates. We focus on the factors listed below.

- **Firm size**: *larger* firms may be *more advanced* in digitalisation adoption, as they are more likely to have the resources to make the necessary investments and hiring, and to benefit from economies of scale (see EIB 2023 and Acemoglu et al. 2022).

- **Firm age**: *younger* firms may be *more advanced* in digitalisation adoption, as they face fewer organisational barriers to digital transformation and are less likely to have to adapt existing systems, which can be costly (see Acemoglu et al. 2022).

- **Labour cost**: *higher labour cost* may *increase firms' incentives* to engage in digitalisation to reap the potential benefits of greater automation and productivity (Hémous et al. 2025).

- **Market concentration**: theoretical arguments suggest that market concentration (or competition) has mixed effects on innovation (see EIB 2023 and Griffith and Van Reenen 2021). On the one hand, lower market concentration (more intense competition) incentivises firms to innovate to stay ahead of competitors. On the other hand, lower market concentration (more intense competition) could reduce the expected returns from innovation, as profitability gains from digital innovation may be eroded quickly. This discourages innovation.

We estimate the following panel regression model to assess the extent to which the above factors influence the level of firms' digitalisation adoption:

$$digit_{i,t} = \alpha + \boldsymbol{\beta_1 size_{i,t-1}} + \boldsymbol{\beta_2 age_{i,t-1}} + \boldsymbol{\beta_3 staffcti_{i,t-1}} + \boldsymbol{\beta_4 conc_{i,t-1}} + \beta_5 controls_{i,t-1} + FE_i + FE_{s*t} + \varepsilon_{i,t} \quad (1)$$

where $digit_{i,t}$ is our measure of the level of digitalisation adoption of firm i in year t, defined as the score we give each firm based on their digitalisation adoption classification, i.e. 0 for No Engagement, 20 for Elementary Stage, 50 for Active Adopter and 100 for Leader. Our scoring approach references the way in which some data providers set quantitative scores (e.g. environmental, social and governance (ESG) scores) based on qualitative data.[6]

[6] For example, S&P's ESG scores are evaluated based on firms' responses to a questionnaire, many of which are qualitative. Our scoring scheme is similar to those of some of the S&P's ESG questions, based on our observation.

Our independent variables comprise firm size measured by logarithm of total assets ($size$); firm age in logarithmic form (age); staff cost-to-income ratio ($staffcti$) in percentage; and sectoral concentration ratio ($conc$), which ranges from 0 to 1 in increasing market concentration. Data on all firm-level financial variables are sourced from S&P Global. Market concentration is measured by the different sectoral concentration ratios calculated by the HK Census and Statistics Department (C&SD). These include two concentration ratios, defined as the industry share of business receipts of the top 10 and 20 establishments, respectively, in the industry, and the Herfindahl Hirschman Index (HHI).[7] We include firm-level control variables.[8]

For this and subsequent regression models, we use firm fixed effects (FE_i) and sector*year (FE_{s*t}) fixed effects,[9] as well as robust standard errors clustered at the firm level. To prevent the problem of reverse causality, control variables are generally lagged by one year.[10] See **Annex 3** for summary statistics and further details of the regression variables.

The estimation results show that larger firms are indeed more advanced in their digitalisation adoption (**Table 3**)**.** Larger firms appear to enjoy the economies of scale that enable them to make the necessary investments (e.g. in intangible assets; see Section 3 and **Annex 4**) and hiring (see Section 5) for digitalisation adoption. Indeed, a recent survey by the Hong Kong Productivity Council (HKPC) noted that high implementation costs are particularly significant for SMEs with limited resources, which impacts their willingness to adopt A.I. technology.[11]

Meanwhile, firms with higher labour costs are less advanced in their digitalisation. This seems to imply that cutting staff costs is not a major motive for undertaking digitalisation. Engaging in depth in digitalisation may itself be costly, as it involves greater investments as well as hiring.

We do not find strong evidence that firm age or market concentration affects the level of digitalisation adoption. Some coefficient estimates for market concentration are statistically significant, while others are insignificant; this finding is in line with the mixed theoretical arguments regarding the impact of competition on innovation.

[7] The HHI is defined as the sum of squares of the output share of every establishment in an industry.

[8] The control variables are profitability (return on assets); leverage (ratio of debt to assets); fixed assets (ratio of property, plant and equipment assets to total assets); free cash flow (relative to assets); and equity concentration ('eqconc'), defined as the percentage of outstanding shares held by a firm's largest shareholder.

[9] Firm fixed effects capture unobserved time-invariant firm-level characteristics that may affect the dependent and explanatory variables. Sector*year fixed effects capture unobserved firm-invariant sectoral time-varying characteristics that may affect the dependent and explanatory variables.

[10] We only include firms for whom we have data for all requisite variables from 2017 to 2024. Continuous variables are winsorised at the 1% and 99% levels to mitigate the effect of outliers, with the exception of firm age, market concentration and intangible investment.

[11] See https://www.hkpc.org/en/about-us/media-centre/press-releases/2025/ai-readiness-in-workplace-survey-2025.

Robustness testing show that our findings remain valid for alternative forms of the dependent variable measuring the level of digitalisation adoption. We conduct robustness testing using (i) alternative scoring approaches for the different levels of digitalisation adoption; and (ii) an ordered logistic regression model that allows us to model the order of the different levels of digitalisation adoption without having to specify the quantitative distance between the levels. Both analyses yield similar results to our baseline model (see **Annex 6** for details).

Table 3: The influence of factors on the level of digitalisation adoption (estimation results of regression model (1))

Dependent variable	$\boldsymbol{digit_{i.t}}$		
Measure of market concentration used ($conc_{i,t-1}$)	Concentration ratio (Top 10)	Concentration ratio (Top 20)	HHI
$size_{i,t-1}$	**4.66****	**4.59****	**4.73****
$age_{i,t-1}$	**4.54**	**4.52**	**4.50**
$staffcti_{i,t-1}$	**-0.082****	**-0.084****	**-0.080***
$conc_{i,t-1}$	**9.05**	**18.24***	**-7.44**
$profitability_{i,t-1}$	-0.21**	-0.22**	-0.21**
$leverage_{i,t-1}$	-0.034	-0.033	-0.035
$fixed_{i,t-1}$	0.041	0.041	0.042
$cashflow_{i,t-1}$	-0.019	-0.020	-0.019
$eqconc_{i.t-1}$	0.083	0.086	0.080
Firm fixed effects	Yes	Yes	Yes
Sector # Year fixed effects	Yes	Yes	Yes
No. of firms	552	552	552
No. of observations	3,864	3,864	3,864

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels.
Source: HKMA staff estimates.

5. HOW DOES DIGITALISATION ADOPTION IMPACT CORPORATE PERFORMANCE AND EMPLOYMENT?

In this section, we explore the impact of digitalisation adoption on corporate performance and employment.

5.1 The impact of digitalisation adoption on corporate performance

First, we explore the impact of digitalisation adoption on *profitability*, as measured by return on assets. This is the most intuitive measure of whether digitalisation benefits corporates. However, the benefits of adopting digitalisation for profitability may take time to materialise. Investment and hiring are likely to increase in the initial years of adoption, which may incur high costs.

Therefore, **we explore whether digitalisation adoption has a positive impact on firm *revenue***, which may lead to higher profitability in the longer term, once a firm has made the initial investments necessary for digital transformation.

In addition, **we explore whether digitalisation adoption has a positive impact on a firm's *market valuation***, as measured by the price-to-book ratio.[12] As digitalisation and A.I. development continue to advance, they have the potential to significantly enhance corporate productivity and profitability. As a result, digitalisation adoption could lead to higher market valuations now, as market participants perceive better business prospects for such firms than for their peers, e.g. higher profitability, greater resilience and more sustainable business models.

We use a panel regression model to estimate the impact of digitalisation adoption on the above corporate performance measures:

$$y_{i,t} = \alpha + \boldsymbol{\beta_1 ES_{i,t-j}} + \boldsymbol{\beta_2 AA_{i,t-j}} + \boldsymbol{\beta_3 L_{i,t-j}} + \beta_4 controls_{i,t/t-1} + FE_i + FE_{s*t} + \varepsilon_{i,t} \quad (2)$$

where the dependent variable y refers to return on assets (roa), the year-on-year percentage growth of revenue ($revg$) or the price-to-book ratio (ptb).[13] Digitalisation adoption is measured by $ES_{i,t-j}$, $AA_{i,t-j}$ and $L_{i,t-j}$, which are dummy variables that take the value of 1 if firm i is classified as in the Elementary Stage, as an Active Adopter, or as a Leader in year $t-j$ respectively, and 0 otherwise. We explore the impact of digitalisation on corporate performance in the same year, in the year after and in two years' time (i.e. with j

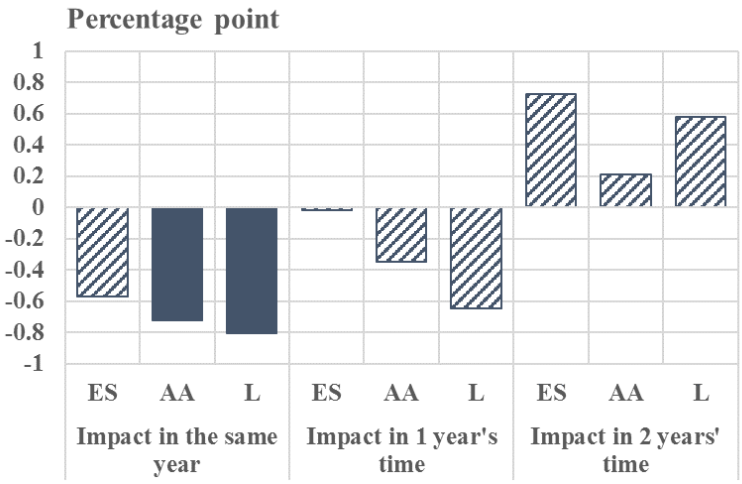
[12] The price-to-book ratio is the ratio of the market value of a firm's equity to its accounting value. It captures investors' expectation of how much shareholder value the firm will create from a given stock of assets and liabilities.

[13] The price-to-book ratio is measured as the average daily price-to-book value during the last month of the current fiscal year and the first month of the next fiscal year. This allows the digitalisation adoption efforts of a firm in a particular year to be factored into the price-to-book ratio measure for that year.

= 0, 1 and 2 in model (2)).[14] Following the literature, we include a range of firm-level control variables.[15]

The estimation results show that digitalisation adoption initially has a negative impact on profitability (Chart 3, and Annex 5 Table A5). We find that digitalisation adoption has a negative contemporaneous impact on return on assets, with a statistically significant negative impact of 0.7 percentage points (pp) and 0.8pp for Active Adopters and Leaders, respectively. This could in part reflect the upfront costs of investment in intangible assets and increased hiring for digitalisation adoption (see Sections 3 and 5.2). The estimated impact on return on assets turns positive after two years, but it is not statistically significant (**Chart 3, Annex 5 Table A5**).

Chart 3: The estimated impact of digitalisation adoption on return on assets (%)



Note: solid bars denote a statistically significant impact (at the 1%, 5%, or 10% level). These are estimates for β_1, β_2 and β_3 in equation (2), which are estimated relative to No Engagement (NE) firms. Please see Annex 5 Table A5 for full regression results. ES = Elementary Stage; AA = Active Adopter; L = Leader.
Source: HKMA staff estimates.

These findings appear consistent with other studies and real-world cases. **First, it is likely to take time for firms to reap the profitability benefits of digitalisation**. For instance, digitalisation may necessitate higher operational costs and spending on cyber resilience, system upgrades and compliance-related technologies, especially in the short term (Bullock 2025, Guo et al. 2023). **Second, many digital transformation projects are experimental in nature, with uncertain outcomes.** Thus, it is possible that, at this stage,

[14] Guo and Xu (2021) cited evidence from the literature that information technology has a strong impact on performance in the two to three years after its introduction. Due to our relatively short panel dataset, we limit our exploration to at most a two-year lag to ensure sufficient observations for regression analyses and the coverage of the period prior to COVID-19.
[15] The common control variables are size, leverage, fixed assets, age, free cash flow, sectoral concentration ratio (top 20 establishments) and equity concentration. An additional control for the profitability (RoA) regression is revenue growth. Additional controls for the revenue growth regression are cost-to-income ratio, intangible investment (research and development expenses plus 30% of sales, general and administrative expense, relative to total assets), capital expenditure (relative to assets) and profitability. Additional controls for the price-to-book regression are revenue growth, intangible investment, capital expenditure, profitability, earnings volatility, 12-month total stock return, 1-year stock beta and 12-month stock return volatility. See, for example, Alzyod et al. (2025), Kuang et al. (2023), Guo and Xu (2021) and Wong et al. (2024).

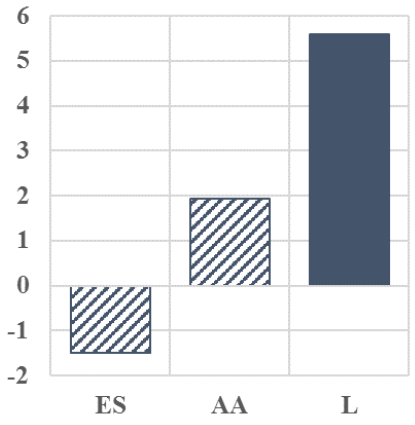
only a modest proportion of digitalisation initiatives lead to a significant impact on profitability. For instance, Challapally et al. (2025) found that for the vast majority of organisations, investing in GenA.I. yielded no measurable impact on profitability, even though such investment enhanced individual productivity.

Although digitalisation adoption does not appear to enhance profitability in the near term, we do find that firms that are more advanced in their digitalisation adoption enjoy higher revenue growth when they embark on digitalisation (**Chart 4A** and **Annex 5 Table A6**). Leaders in digitalisation enjoy higher growth in their revenue (by nearly 6pp) when they embark on digitalisation.[16] This points to positive growth prospects for digitalisation adoption.

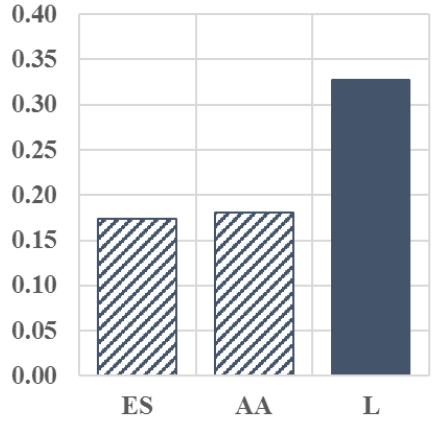
Market participants also perceive the impact of digitalisation favourably, as advanced digitalisation adoption leads to a higher market valuation. We find that Leaders in digitalisation enjoy an uplift in their price-to-book ratios in the same period (by 0.3 units) when they embark on digitalisation **(Chart 4B and Annex 5 Table A7)**. Higher price-to-book ratios are also observed for Leaders and Active Adopters in the following year (**Annex 5 Table A7**). These show that investors perceive better prospects for these firms, such as higher profitability and a more resilient and sustainable business model in the longer term.

Chart 4: The estimated impact of digitalisation adoption on revenue growth and price-to-book ratio

Panel A: Estimated impact on revenue growth in the same year (in percentage point)



Panel B: Estimated impact on price-to-book ratio, in the same year



Note: solid bars denote a statistically significant impact (at the 1%, 5%, or 10% level). These are estimates for β_1, β_2 and β_3 in equation (2), which are estimated relative to No Engagement (NE) firms. Please see Annex 5 Tables A6 & A7 for full regression results. ES = Elementary Stage; AA = Active Adopter; L = Leader.
Source: HKMA staff estimates.

[16] Meanwhile, the impacts of digitalisation adoption on revenue growth in the next one to two years are statistically insignificant (Annex 5 Table A6).

5.2 The impact of digitalisation adoption on corporate employment

Finally, we look at the impact of digitalisation adoption on corporate employment, for which the literature has reported inconclusive findings. Comunale and Manera's (2024) literature review found inconsistent empirical findings regarding the employment effects of A.I. Acemoglu et al.'s (2022) analysis of US survey data showed that the adoption of advanced technologies exerted limited or ambiguous effects on firms' employment levels. While Aum and Shin (2025), using regional data from South Korea, found that the adoption of digital technologies had a negative effect on employment, Bignandi et al.'s (2024) firm-level study on Belgium found that digitalised firms experienced higher employment growth than non-digitalised firms.

Corporate employment decreased for most of our sample firms during the sample period, **which is broadly in line with the evolution of Hong Kong's labour force**.[17] From 2019 to 2024, the average (median) number of full-time employees of the firms in our sample fell from 320 to 223. With this broad picture, we examine the changes in employment across firms with different digitalisation levels.

We assess the impact of digitalisation adoption on corporate employment by estimating the following panel regression model:

$$fteg_{i,t} = \alpha + \boldsymbol{\beta_1 ES_{i,t}} + \boldsymbol{\beta_2 AA_{i,t}} + \boldsymbol{\beta_3 L_{i,t}} + \beta_4 controls_{i,t/t-1} + FE_i + FE_{s*t} + \varepsilon_{i,t} \quad (3)$$

where the dependent variable ($fteg$) is the year-on-year percentage change in the number of full-time employees. Following the literature, we include a range of firm-level control variables.[18]

The estimation results suggest that digitalisation adoption does not have a notable adverse impact on the growth of overall employment in the short term. **In fact, more advanced firms see a stronger growth, or smaller reduction, in employment (Chart 5** and **Annex 5 Table A8).** For Active Adopters and Leaders, relative to No Engagement firms, digitalisation adoption is estimated to have a positive impact of 3.5pp and 10pp on employment growth in the same year, while the lagged impacts in one to two years are statistically insignificant.[19] The positive impact on overall employment growth is applicable to firms that are *expanding* their workforce as well as to those that are *shrinking* theirs. Sub-sample analysis shows that among firms expanding their workforce, Leaders in

[17] Cheung (2024) showed that Hong Kong's labour force reached a peak in 2018 and declined in the following years, before showing some bounce-back in 2023.

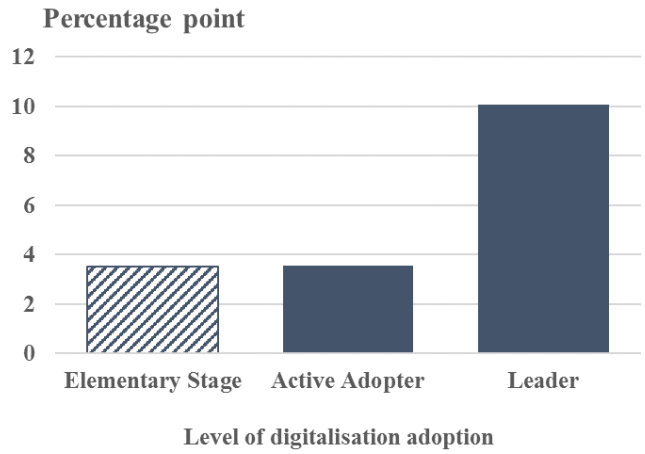
[18] The control variables are size, profitability, leverage, fixed assets, age, free cash flow, staff cost-to-income ratio, a "merger" dummy (a dummy variable that equals 1 if the firm incurred merger or re-structuring related costs in a year), sectoral concentration ratio (top 20 establishments), intangible investment, and capital expenditure. See, for example, Acemoglu (2022) and Bignandi (2024).

[19] We run additional regression analyses exploring the lagged impact of digitalisation adoption on the change in full-time employees by replacing the contemporaneous explanatory variables in (3) with lagged ones (by one and two periods). We do not find a statistically significant lagged impact of digitalisation adoption on the change in full-time employees.

digitalisation adoption see a 9 pp higher employment growth. Among firms shrinking their workforce, Leaders have a 12 pp smaller decline in employment (**Annex 5 Table A8**).[20]

The higher growth in employment resulting from digitalisation adoption may be due to increased demand for the skilled labour that firms require to undertake digital transformation (e.g. Acemoglu et al. 2022, Bullock 2025). However, digitalisation may have a heterogeneous impact across occupations, e.g. lower-skilled roles may be displaced by higher skilled ones, which is not captured by the dataset used in this study.[21] Finally, while we do not find that digitalisation adoption in the recent past had an adverse impact on employment, the impact of the fast-evolving digital technology on employment patterns warrants close monitoring, as new use cases of GenA.I. may emerge.

Chart 5: The estimated impact of digitalisation adoption on the year-on-year percentage change in the number of full-time employees



Note: solid bars denote a statistically significant impact (at the 1%, 5%, or 10% level). These are estimates for β_1, β_2 and β_3 in equation (3), which are estimated relative to No Engagement (NE) firms. Please see Annex 5 Table A8 for full regression results.
Source: HKMA staff estimates.

[20] We define firms expanding (or shrinking) their workforce as those that increased (or decreased) their number of full-time employees from 2017 to 2024.
[21] Our dataset does not allow for a breakdown of firm-level full-time employees by skillset. A thorough analysis of the impact on employees with different skillsets, using alternative data sources, is beyond the scope of this study.

6. CONCLUSION AND POLICY IMPLICATIONS

This study examines the extent of digitalisation adoption by Hong Kong corporates in recent years and its implications for firms. With the help of GenA.I. tools, we analyse annual reports and classify firms according to their levels of digitalisation adoption.

Our textual analysis reveals that nearly two thirds of the sample firms are engaged in digitalisation, and over half of the sample firms are in more advanced stages of digitalisation adoption. By sector, the communications and IT sectors are the most advanced in terms of digitalisation. They are followed by the healthcare, consumer discretionary and transportation sectors, whose digitalisation adoption grew noticeably during and following the COVID-19 pandemic, possibly in response to changes in consumer behaviour. We also find that the adoption of digitalisation is associated with greater investment in intangible assets. This validates our classification as a proxy for assessing digitalisation adoption.

In terms of the factors that influence the level of digitalisation adoption, larger firms are likely to be more advanced in adopting digitalisation, but higher initial labour costs do not appear to incentivise digitalisation. We do not find strong evidence that the degree of market concentration affects the level of digitalisation adoption, in line with the mixed theoretical arguments on this topic.

Regarding corporate performance, while digitalisation adoption initially has a negative impact on profitability, the most advanced firms enjoy higher revenue growth and an uplift in price-to-book ratios when they embark on digitalisation, as investors perceive these firms to be more resilient and to have stronger business prospects. Furthermore, **digitalisation adoption does not appear to have a notable adverse impact on overall corporate employment in the short term**. In fact, we find that more advanced firms see higher growth (or a smaller decline) in full-time employees.

Our analysis underscores the importance for Hong Kong corporates of engaging deeply in digitalisation to remain competitive and resilient. The majority of firms are already engaged in digitalisation, and only firms with the most advanced digitalisation adoption are expected to see stronger business prospects. In addition, as larger firms tend to be more advanced in adopting digitalisation, possibly because economies of scale enable them to afford the resources needed for digitalisation, smaller firms face a greater risk of losing competitiveness and becoming more vulnerable.

The findings of this study offer valuable policy implications to incentivise and support firms across the economy to engage deeply in digitalisation, **given the need for more hiring and greater investment in intangible assets.** In particular, targeted support can be given to SMEs to adopt and invest in digital solutions. To this end, the Hong Kong Monetary Authority (HKMA) has been collaborating with the banking sector to provide credit products and services to help SMEs in their digital transformation

journeys. These include e-commerce financing and electronic payment services to enable SMEs to better utilise data and adopt innovative business solutions,[22] and fast-approval loan products for SMEs that have applied to funding schemes launched by the HKSAR Government to support SMEs in applying digital solutions.[23]

In addition, education and training programmes can be offered to strengthen capacity building by upskilling the labour force to meet the growing demand for digital skills. A lack of A.I. expertise and training represents a core obstacle to firms' adoption of advanced technology such as A.I..[24] Authorities in Hong Kong and the industry have been working to address the digital skill gap, such as through A.I.-related training activities organised by the HKPC[25] and the capacity-building activities organised by the HKMA and the banking and technology sectors.[26]

[22] See https://www.hkma.gov.hk/eng/news-and-media/press-releases/2024/10/20241018-4/.

[23] See https://www.hkma.gov.hk/eng/news-and-media/press-releases/2024/11/20241111-4/.

[24] See, for example, https://www.hkpc.org/en/about-us/media-centre/press-releases/2025/ai-readiness-in-workplace-survey-2025 and World Economic Forum (2025).

[25] The HKPC Academy has delivered over 500 AI-related training activities in the last two years, and it now offers over 20 A.I. courses. It will collaborate with leading technology companies to invite instructors with practical experience to teach and launch free A.I. activities to help corporate employees master A.I. skills.

[26] An example is the "SME Digital Technology Solution Day" in November 2024, co-organised by the HKMA, Hong Kong Cyberport Management Company Limited, the Hong Kong Association of Banks and the Chinese Banking Association of Hong Kong.

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Annex 1: Excerpt from the prompt provided to the GenA.I. model for the classification of firms' level of digitalisation adoption

You are a helpful, respectful, and expert financial analyst responsible for analysing financial disclosure documents. You follow instructions extremely well. You work on an extractive summarisation task and your task is to find whether the firm is engaging in digitalisation and then advise clients. Review the attached annual report of each firm and analyse the extent of its engagement in digitalisation solely based on the report's content.

You must use the following framework for your classification. We define digitalisation or digital transformation as the integration of digital technologies to fundamentally change a company's business models, operational processes, and/or customer experiences. Evaluate the document's content against these definitions:

Category 1: Leader
Initiatives: The company has detailed engagement in digitalisation. The report details specific projects, investments, platforms or use cases directly related to digitalisation (e.g., a global digital centre, new digital tools, data analytics platforms, digital products and services). Meanwhile, the company has also demonstrated a fully integrated, top-down strategy for digital transformation.
Impact: The firm provides measurable outcomes or quantitative metrics on the impact of these digital initiatives (e.g., revenue enhancement, efficiency gains, cost savings, improved risk identification).

Category 2: Active Adopter
Initiatives: The company has detailed engagement in digitalisation. The report details specific projects, investments, platforms or use cases directly related to digitalisation (e.g., a global digital centre, new digital tools, data analytics platforms, digital products and services). However, the company may not yet demonstrate a fully integrated, top-down strategy for digital transformation.
Impact: The report lacks measurable outcomes or quantitative metrics on the impact of these digital initiatives.

Category 3: Elementary Stage
Initiatives: The company mentions digitalisation initiatives, but the discussion remains generic and lacks detail. There is no mention of specific projects, investments, platforms or use cases.
Impact: Not applicable.

Category 4: No Engagement
Initiatives: The company has no mention of its own engagement in digitalisation. Where digitalisation is mentioned, it is only referring to market or industry trends, rather than the company's own initiatives.
Impact: Not applicable.

To ensure accuracy, you must exclude the following from being considered as digitalisation engagement:
1) Basic IT Infrastructure: Standard IT infrastructure, cybersecurity, data privacy policies, or management of existing software/hardware.
2) Employee Training: Only mentioning that staff are being trained on AI, big data, or related aspects.
3.) A company manufacturing a physical product used in the digital sector. However, a company that provides digital solutions to customers or digitalising its own core functions should not be excluded.
4.) Standard Web Presence: a corporate website, e-commerce store, or social media accounts.

Annex 2: GenA.I. model responses to prompts by digitalisation adoption category

Table A1: Examples of GenA.I. model responses to prompts, by digitalisation adoption category (fiscal year 2024)

Note: the responses have been redrafted slightly to preserve the anonymity of each firm.

1.) Leader	
Sector	**Prompt response**
Consumer Discretionary	The company is executing a clear strategy of using digitalisation to enhance efficiency and customer experience. It has implemented specific technologies like self-ordering kiosks in the vast majority of its stores, robotic servers, and an integrated mobile app. The report provides strong quantitative operational metrics, such as the number of registered users and that digital channels now account for the majority of orders, and directly links these initiatives to profit margin improvement.
Communication Services	The company demonstrates a clear, top-down strategy for digital transformation, evidenced by its stated transformation into a technology solutions provider and the creation of a dedicated A.I. taskforce. The report details numerous specific digital initiatives, including a media streaming platform using audience analytics and A.I.-driven enterprise solutions, and provides quantifiable metrics on their impact, such as a double-digit percentage increase in subscription revenue.
2.) Active Adopter	
Sector	**Prompt response**
Transportation	The company has a clear strategic goal of transforming into a digital leader and has deployed numerous A.I. machine learning models to optimise core operations, e.g. travel disruption management. It also pursues network and systems modernisation and runs internal innovation programs. Despite the specificity of these initiatives, the report does not provide measurable outcomes or quantitative metrics on their business impact.
Real Estate	The company details specific digital initiatives aimed at enhancing customer experience and its business model, including the exploration of virtual/augmented reality, intelligent marketing engines, and innovative digital platforms. The report also mentions specific projects to enhance data analytics. However, the report lacks measurable outcomes or quantitative metrics to demonstrate the impact of these initiatives.
3.) Elementary Stage	
Sector	**Prompt response**
Consumer Staples	The company mentions its intention to use "digitalisation and intelligence" to optimise processes and reduce costs as a future strategy. This indicates an awareness of digitalisation's importance but lacks any detail on concrete projects or platforms that have been implemented.

Materials	The company states its intention to strengthen the level of automation and digital transformation within its manufacturing division. However, its discussion remains generic and lacks specific details on projects, platforms, or investments.
4.) No Engagement	
Sector	**Prompt response**
Health Care	The annual report is focused entirely on the company's portfolio of pharmaceutical products, clinical trial progress, and medical R&D pipeline. There is no mention of the company engaging in digital transformation. The report does not describe any initiatives related to integrating digital technologies like AI, big data, or digital platforms to fundamentally change its business models, operational processes, or R&D methods.
Capital Goods	The report exclusively details the company's traditional engineering services, financial performance, and treasury policies. There is no mention of any engagement in digitalisation, digital transformation, data analytics, or specific technological initiatives within the company's own operations or strategy.

Annex 3: Data description

Table A2 Summary statistics of the variables used in the regression

Variables	Obs	Mean	Median	St. Dev.
ES (0/1)	5,872	0.08	0.00	0.28
AA (0/1)	5,872	0.28	0.00	0.45
L (0/1)	5,872	0.16	0.00	0.36
$digit$	5,872	31.23	20.00	36.39
$intgb$ (%)	5,756	5.76	3.45	10.19
$fteg$ (%)	5,038	-0.22	-2.28	31.45
$profitability$ (RoA, %)	5,846	-0.95	0.22	7.61
$revg$ (%)	5,708	3.70	-0.56	42.11
ptb	5,590	1.77	0.71	3.76
$size$ (US$m)	5,871	1,310	133	4,140
$leverage$ (%)	5,866	24.09	17.16	30.05
$fixed$ (%)	5,857	24.25	16.32	24.38
$capex$ (%)	5,868	2.11	0.80	3.32
age (years)	5,792	32	28	22
$cashflow$ (%)	5,815	2.80	2.47	14.63
$merger$ (0/1)	5,872	0.04	0.00	0.20
cti (%)	5,859	112.60	99.04	75.06
$staffcti$ (%)	5,466	23.27	17.53	22.23
$conc$ (top 10 establishments)	5,408	0.41	0.40	0.23
$conc$ (top 20 establishments)	5,408	0.51	0.53	0.23
$conc$ (HHI)	5,408	0.051	0.024	0.073
$eqconc$ (%)	5,871	46.49	50.05	20.34
$roavol$	5,870	4.06	2.53	4.57
ret	5,718	-3.83	-13.21	58.33
$beta$	5,847	0.30	0.28	0.75
$retvol$	5,706	14.94	11.57	12.07

Table A3: Details of data items and sources

Variable	Description	Source
Firm-level variables		
ES	A dummy variable that equals 1 if a firm is classified as Elementary Stage in our digitalisation adoption classification framework, or 0 otherwise.	HKMA staff analysis
AA	A dummy variable that equals 1 if a firm is classified as an Active Adopter in our digitalisation adoption classification framework, or 0 otherwise.	HKMA staff analysis
L	A dummy variable that equals 1 if a firm is classified as a Leader in our digitalisation adoption classification framework, or 0 otherwise.	HKMA staff analysis
$digit$	A score measure for the level of digitalisation adoption of a firm, defined as 0 for No Engagement, 20 for Elementary Stage, 50 for Active Adopter, and 100 for Leader.	HKMA staff analysis
$intgb$	Investment in intangible assets, relative to total assets, in percentage. Investment in intangible assets is measured as the sum of R&D expense and 30% of sales, general and administrative expense.	S&P Global and HKMA staff calculations
$fteg$	Year-on-year percentage change in the number of full-time employees, winsorised	S&P Global
$profitability$	Return on assets, in percentage, winsorised.	S&P Global
$revg$	Year-on-year change in total revenue, in percentage, winsorised.	S&P Global

ptb	Average price-to-book ratio during the last month of the fiscal year and the following month (i.e. the first month of the next fiscal year), in multiple, winsorised.	S&P Global
$size$	Natural logarithm of total assets (in US dollars), winsorised.	S&P Global
$leverage$	The ratio of total debt to total assets, in percentage, winsorised.	S&P Global
$fixed$	The ratio of property, plant and equipment assets to total assets, in percentage, winsorised	S&P Global
$capex$	The ratio of capital expenditure to total assets, in percentage, winsorised.	S&P Global
age	Natural logarithm of firm age (in years), winsorised.	S&P Global
$cashflow$	Free cash flow available following the servicing of interest payments but before capital expenditure, relative to total assets, in percentage, winsorised.	S&P Global
$merger$	A dummy variable that equals 1 if the firm incurred costs related to mergers and acquisitions and/or re-structuring in a given year.	S&P Global
cti	The ratio of total operating cost to total revenue, in percentage, winsorised	S&P Global
$staffcti$	The ratio of staff costs to total revenue, in percentage, winsorised.	S&P Global
$conc$	The sectoral concentration ratios calculated by the HK C&SD. 1.) The industrial concentration ratio for the top 10 establishments. This is defined as the share of business receipts of the top 10 establishments in the industry (in decimals), ranging from 0 to 1. Higher values indicate greater market concentration. 2.) The industrial concentration ratio for the top 20 establishments. 3.) The Herfindahl-Hirschman Index (HHI) is obtained by taking the sum of squares of the output share of every establishment in an industry. The value lies between 1/N and 1. Higher values indicate greater sectoral concentration. Please see HK C&SD (2016) for further details of these measures. The industrial classification for the C&SD's data on industrial concentration ratio is the Hong Kong Standard Industrial Classification (HSIC), which is different from that of S&P Global. In order to match the relevant industrial concentration ratio to each of our sample firms, we assign each firm their sector under the HSIC by matching each firm's NACE code (available from S&P Global) to the HSIC. As the C&SD publishes the relevant data on sectoral concentration every two years, data for 2023 were missing at the time of analysis, and we assumed that the ratios in 2023 are the same as those in 2022.	HK C&SD
$eqconc$	Equity concentration, defined as the percentage share of outstanding shares held by a firm's largest shareholder, winsorised.	S&P Global
$roavol$	Earnings volatility, defined as the standard deviation of annual return on assets over the past 5 years, winsorised.	S&P Global
ret	12-month total stock return, defined as the total return of the firm's share over a 12-month period, including price appreciation and the reinvestment of dividends, winsorised.	S&P Global
$beta$	1-year stock beta, winsorised.	S&P Global
$retvol$	12-month return volatility, defined as the standard deviation of the monthly return on share price over the past 12 months, winsorised.	S&P Global

Annex 4: Validation of the classification framework for digitalisation adoption

Due to the novelty of using GenA.I. tools to classify firms' level of digitalisation adoption, we assess whether our methodology produces a satisfactory proxy for the extent of firms' digitalisation adoption. As a firm that is engaged in digitalisation is expected to invest more in intangible assets such as human capital and software, we assess whether digitalisation adoption is associated with greater investment in intangible assets by estimating the following panel regression model:

$$intgb_{i,t} = \alpha + \boldsymbol{\beta_1 ES_{i,t}} + \boldsymbol{\beta_2 AA_{i,t}} + \boldsymbol{\beta_3 L_{i,t}} + \beta_4 controls_{i,t-1} + FE_i + FE_{s*t} + \varepsilon_{i,t} \quad (4)$$

where $intgb_{i,t}$ is the intangible investment made by firm i in year t. In line with the literature,[27] intangible investment is measured as the sum of research and development (R&D) expenses and 30% of sales, general and administrative (SG&A) expenses, relative to total assets. R&D expenses are a proxy for investment in knowledge capital, while a fraction of SG&A expenses is a proxy for investment in organisation capital, e.g. human capital and software. Following the literature, we include a range of firm-level control variables.[28]

We find that digitalisation adoption is associated with greater investment in intangible assets. Elementary Stage firms and Active Adopters have on average a 0.5 and 0.3 percentage point (pp) higher intangible investment relative to assets, respectively, than firms not engaging in digitalisation (although the latter impact is not statistically significant). Leaders of digitalisation adoption have on average an even higher intangible investment relative to total assets (0.8pp) than firms not engaging in digitalisation (**Table A4**).[29] This confirms that our classification framework is a satisfactory proxy for a firm's level of digitalisation adoption.[30]

[27] See ECB (2018) and Peters and Taylor (2017).

[28] The control variables are size, profitability, leverage, fixed assets, age, price-to-book ratio, free cash flow and capital expenditure. See, for example, García-Posada et al. (2020), Yang and Zhou (2017), Dancaková (2024) and Nunes et al. (2017).

[29] For a firm whose R&D expense data are 'missing' (i.e. R&D expense is not explicitly reported), we assume that R&D expense takes the value 0, except if the firm's SG&A expense is also 'missing' (in which case we do not replace 'missing' R&D data with 0). For robustness testing, we run the same regression again but only for firms whose R&D expense is not 'missing'; although the sample is significantly smaller, the results are qualitatively similar to those presented.

[30] We also find that digitalisation adoption is associated with higher capital expenditure, although the impact is not estimated to be statistically significant.

Table A4: The impact of digitalisation adoption on investment in intangible assets (estimation results of regression model (4))

Dependent variable	$\boldsymbol{intgb_{i.t}}$
$\boldsymbol{ES_{i,t}}$	**0.47***
$\boldsymbol{AA_{i,t}}$	**0.28**
$\boldsymbol{L_{i,t}}$	**0.78****
$size_{i,t-1}$	-1.78
$profitability_{i,t-1}$	-0.085***
$leverage_{i,t-1}$	-0.0016
$fixed_{i,t-1}$	-0.0065
$age_{i,t-1}$	0.63
$ptb_{i,t-1}$	-0.016
$cashflow_{i,t-1}$	-0.0035
$capex_{i.t-1}$	0.054**
Firm fixed effects	Yes
Sector # Year fixed effects	Yes
No. of firms	561
No. of observations	3,927

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels.
Source: HKMA staff estimates.

Annex 5: Regression results

Table A5: The impact of digitalisation adoption on return on assets (estimation results of regression model (2) in Section 5.1)

Dependent variable	$\boldsymbol{profitability\ (roa)_{i.t}}$		
Number of time period lags for digitalisation adoption level (j)	***j = 0***	***j = 1***	***j = 2***
$\boldsymbol{ES_{i,t-j}}$	**-0.57**	**-0.017**	**0.72**
$\boldsymbol{AA_{i,t-j}}$	**-0.72***	**-0.34**	**0.21**
$\boldsymbol{L_{i,t-j}}$	**-0.81***	**-0.64**	**0.58**
$size_{i,t-1}$	0.78*	0.78*	0.68
$leverage_{i,t-1}$	0.018	0.018	0.023
$fixed_{i,t-1}$	-0.010	-0.011	-0.0056
$age_{i,t-1}$	0.28	0.17	0.58
$cashflow_{i,t-1}$	0.019**	0.019**	0.013
$conc_{i,t-1}$	0.78	0.87	1.47
$eqconc_{i,t-1}$	0.014	0.014	0.00066
$revg_{i,t-1}$	0.016***	0.016***	0.017***
Firm fixed effects	Yes	Yes	Yes
Sector # Year fixed effects	Yes	Yes	Yes
No. of firms	546	546	546
No. of observations	3,822	3,822	3,276

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels. Market concentration is measured by the industrial concentration ratio (top 20 establishments).
Source: HKMA staff estimates.

Table A6: The impact of digitalisation adoption on revenue growth (estimation results of regression model (2) in Section 5.1)

Dependent variable	$revg_{i.t}$		
Number of time period lags for digitalisation adoption level (*j*)	***j = 0***	***j = 1***	***j = 2***
$ES_{i,t-j}$	**-1.49**	**-1.16**	**3.20**
$AA_{i,t-j}$	**1.92**	**-2.80**	**-1.17**
$L_{i,t-j}$	**5.59***	**-2.41**	**1.55**
$size_{i,t-1}$	-14.87***	-14.66***	-20.37***
$leverage_{i,t-1}$	0.11*	0.11*	0.085
$fixed_{i,t-1}$	0.087	0.083	0.11
$age_{i,t-1}$	-6.82	-6.54	-11.85
$cashflow_{i,t-1}$	-0.14**	-0.14**	-0.16**
$conc_{i,t-1}$	1.94	2.92	3.06
$eqconc_{i,t-1}$	0.037	0.050	0.11
$roa_{i,t-1}$	-0.18	-0.20	-0.28
$cti_{i,t-1}$	0.24***	0.24***	0.24***
$intgb_{i,t-1}$	-0.36	-0.35	-0.38
$capex_{i,t-1}$	0.42	0.43	-0.0060
Firm fixed effects	Yes	Yes	Yes
Sector # Year fixed effects	Yes	Yes	Yes
No. of firms	526	526	526
No. of observations	3,682	3,682	3,156

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels. Market concentration is measured by the industrial concentration ratio (top 20 establishments).
Source: HKMA staff estimates.

Table A7: The impact of digitalisation adoption on price-to-book ratio (estimation results of regression model (2) in Section 5.1)

Dependent variable	$ptb_{i.t}$		
Number of time period lags for digitalisation adoption level (*j*)	***j = 0***	***j = 1***	***j = 2***
$ES_{i,t-j}$	**0.17**	**0.13**	**-0.064**
$AA_{i,t-j}$	**0.18**	**0.30****	**0.052**
$L_{i,t-j}$	**0.33***	**0.36****	**0.026**
$size_{i,t-1}$	-0.98***	-1.00***	-1.06***
$leverage_{i,t-1}$	0.030***	0.030***	0.035***
$fixed_{i,t-1}$	0.0011	0.0016	0.0043
$age_{i,t-1}$	0.34	0.37	1.23
$cashflow_{i,t-1}$	0.0065*	0.0067*	0.0053
$roa_{i,t-1}$	0.0026	0.0027	0.0057
$roavol_{i,t-1}$	0.031	0.032	0.025
$capex_{i,t-1}$	0.042**	0.041**	0.029**
$intgb_{i,t-1}$	0.044***	0.043***	0.048***
$revg_{i,t-1}$	0.0030*	0.0030*	0.0036*
$conc_{i,t-1}$	-0.20	-0.18	-0.16
$eqconc_{i,t-1}$	0.0087	0.0083	-0.00065
$ret_{i,t}$	0.0086***	0.0087***	0.0072***
$beta_{i,t}$	0.20**	0.20**	0.18*
$retvol_{i,t}$	-0.00073	-0.00072	-0.0015
Firm fixed effects	Yes	Yes	Yes
Sector # Year fixed effects	Yes	Yes	Yes
No. of firms	445	445	445
No. of observations	3,115	3,115	2,670

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels. Market concentration is measured by the industrial concentration ratio (top 20 establishments).
Source: HKMA staff estimates.

Table A8: The impact of digitalisation adoption on the year-on-year percentage change in the number of full-time employees (estimation results of regression model (3) in Section 5.2).

Dependent variable	$\boldsymbol{fteg_{i.t}}$		
Sample of firms	**All**	**Firms that *grew* their number of full-time employees during 2017-24**	**Firms that *shrank* their number of full-time employees during 2017-24**
$\boldsymbol{ES_{i,t}}$	**3.52**	**3.71**	**3.44**
$\boldsymbol{AA_{i,t}}$	**3.55***	**3.84**	**3.21**
$\boldsymbol{L_{i,t}}$	**10.09*****	**9.22***	**11.85*****
$size_{i,t-1}$	-14.20***	-21.82***	-12.03***
$profitability_{i,t-1}$	0.13	0.33	0.00032
$leverage_{i,t-1}$	0.025	0.25	-0.018
$fixed_{i,t-1}$	-0.27**	-0.83***	-0.041
$age_{i,t-1}$	-10.14*	-13.58	-5.21
$cashflow_{i,t-1}$	-0.043	-0.13	-0.021
$staffcti_{i,t-1}$	-0.15***	-0.16	-0.15**
$merger_{i,t}$	10.37**	30.82***	-4.02
$merger_{i,t-1}$	3.10	1.68	3.81
$conc_{i,t-1}$	7.45	29.92	1.66
$intgb_{i,t-1}$	-0.32*	-1.16**	-0.23
$capex_{i.t-1}$	0.20	0.78	-0.046
Firm fixed effects	Yes	Yes	Yes
Sector # Year fixed effects	Yes	Yes	Yes
No. of firms	510	174	336
No. of observations	3,570	1,218	2,352

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels. Market concentration is measured by the industrial concentration ratio (top 20 establishments).
Source: HKMA staff estimates.

Annex 6: Robustness tests – additional regression analysis of the factors influencing the level of digitalisation adoption

We examine whether our findings in Section 4 are robust to alternative forms of the dependent variable that measures firms' level of digitalisation adoption.

Part 1: Alternative scoring approaches

First, we re-run regression model (1) in Section 4 using alternative scoring approaches for the different levels of digitalisation adoption ($digit_{i,t}$). In the baseline model, the score increases in *larger* increments as digitalisation adoption becomes more advanced. For robustness testing, we use two alternative approaches: (i) the score increases in *smaller* increments as digitalisation adoption becomes more advanced; and (ii) the score increases by *equal* increments. These are defined in the second row of **Table A9**.

Our estimation results reveal findings similar to those of the baseline model: larger firms are more advanced in their digitalisation adoption; firms with higher labour costs are less advanced in their digitalisation; and neither firm age nor market concentration has a statistically significant an impact on the level of digitalisation adoption.

Table A9: Estimation results of regression model (1) in Section 4 using alternative scoring approaches

Dependent variable	$\boldsymbol{digit_{i.t}}$	
Scoring definition: {NE, ES, AA, L}	**{0, 50, 80, 100}**	**{0, 33, 67, 100}**
$size_{i,t-1}$	**5.72*** **	**5.14** **
$age_{i,t-1}$	**7.86**	**6.37**
$staffcti_{i,t-1}$	**-0.13*** **	**-0.11*** **
$conc_{i,t-1}$	**14.90**	**16.27**
$profitability_{i,t-1}$	-0.26**	-0.24**
$leverage_{i,t-1}$	-0.036	-0.037
$fixed_{i,t-1}$	0.045	0.042
$cashflow_{i,t-1}$	-0.024	-0.021
$eqconc_{i.t-1}$	0.094	0.092
Firm fixed effects	Yes	Yes
Sector # Year fixed effects	Yes	Yes
No. of firms	552	552
No. of observations	3,864	3,864

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels. NE = No Engagement; ES = Elementary Stage; AA = Active Adopter; L = Leader. Market concentration is measured by the industrial concentration ratio (top 20 establishments).
Source: HKMA staff estimates.

Part 2: Fixed-effects ordered logistic regression model

In addition, we now run an ordered logistic (ologit) regression model that **allows us to specify the *order* of the different levels of digitalisation adoption** ($digit\_level$) **without having to specify the size of the gap between them**. An ologit model is similar to a standard logistic model, but it allows for a dependent variable that has more than two possible categories, and these categories are ordered.

Specifically, we estimate a *fixed-effects* ordered logit (feologit) **model** using the 'feologit' Stata package, as we wish to control for firm-level fixed effects. The Stata package allows us to readily estimate the **'marginal effect at the average'**, i.e. the marginal effect of the regressors on the sample average of the dependent variable. In our case, an example is the impact of firm size on the probability of being classified as No Engagement, Elementary Stage, Active Adopter, or Leader. For details of the ologit and feologit models, please see StataCorp (2025) and Baetschmann et al (2020).

Our model set-up is as follows.

- The observable ordered dependent variable, $digit\_level_{i,t}$, is a function of the unmeasured latent variable, $digit\_level*_{i,t}$, which has various threshold points, κ:
  $digit\_level_{i,t}$ = NE if $digit\_level*_{i,t} \leq \kappa_1$,
  $digit\_level_{i,t}$ = ES if $\kappa_1 \leq digit\_level*_{i,t} \leq \kappa_2$,
  $digit\_level_{i,t}$ = AA if $\kappa_2 \leq digit\_level*_{i,t} \leq \kappa_3$,
  $digit\_level_{i,t}$ = L if $digit\_level*_{i,t} \geq \kappa_3$.
- In our model:

$$digit\_level*_{i,t} = \beta_1 size\_d_{i,t-1} + \beta_2 age_{i,t-1} + \beta_3 staffcti_{i,t-1} + \beta_4 conc_{i,t-1} + \beta_5 controls_{i,t-1} + FE_i + FE_{s*t} + \varepsilon_{i,t} \quad (5)$$

where $\varepsilon_{i,t}$ are independent and identically distributed with a standard logistic cumulative density function. For ease of interpreting the estimated marginal effects, we capture firm size through a dummy variable that equals 1 if a firm's total assets in a year are *above the median* of the sample in that year ($size\_d$), and 0 otherwise.

The estimation yields findings similar to those of the baseline model: larger firms are more advanced in their digitalisation adoption; firms with higher labour costs are less advanced in their digitalisation; and neither firm age nor market concentration has a statistically significant impact on the level of digitalisation adoption (**Table A10**). To illustrate the impact of firm size on digitalisation adoption, the estimated marginal effects show that a larger-than-average firm is 9.2pp and 5.6pp more likely to be a Leader and an Active Adopter respectively (**Table A11**).

Table A10: Estimation results of regression model (5) – the influence of factors on the level of digitalisation adoption.

Dependent variable	$\boldsymbol{digit\_level_{i.t}}$
$size\_d_{i,t-1}$	**0.60***
$age_{i,t-1}$	**1.19**
$staffcti_{i,t-1}$	**-0.012*** **
$conc_{i,t-1}$	**1.89**
$profitability_{i,t-1}$	-0.022*
$leverage_{i,t-1}$	-0.0067*
$fixed_{i,t-1}$	0.0051
$cashflow_{i,t-1}$	-0.0014
$eqconc_{i.t-1}$	0.0097
Firm fixed effects	Yes
Sector # Year fixed effects	Yes
No. of firms	361
No. of observations	2,527

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels. Market concentration is measured by the industrial concentration ratio (top 20 establishments).
Source: HKMA staff estimates.

Table A11: Marginal effect at the average for selected explanatory variables in regression model (5)

Dependent variable	$\boldsymbol{digit\_level_{i.t}}$	**Marginal effect at the average**
$size\_d_{i,t-1}$	No Engagement (NE)	-0.13
	Elementary Stage (ES)	-0.015
	Active Adopter (AA)	0.056
	Leader (L)	0.092
$staffcti_{i,t-1}$	No Engagement (NE)	0.0027
	Elementary Stage (ES)	0.00031
	Active Adopter (AA)	-0.0011
	Leader (L)	-0.0019

Note: the estimated marginal effects are statistically significant at the 1% level for $staffcti_{i,t-1}$ and at the 10% level for $size\_d_{i,t-1}$.
Source: HKMA staff estimates.