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Unveiling the path to the fourth industrial revolution: Exploring technology adoption and firm-level barriers

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ABSTRACT

Technology adoption is an important driving force for economic growth. This study investigates the determinants of technology adoption among firms in Vietnam using nationally representative enterprise survey data focusing on prominent technology in the Fourth Industrial Revolution (4IR). It focuses on three main barriers to adoption – financial constraints, human resource limitations, and perceived practicality – and assesses their empirical relevance towards different measurements of technology adoption levels. Our analysis employs logit, ordered logit, and Poisson regressions, complemented by inverse probability weighting with regression adjustment to represent selection on observables. The findings indicate that financial capacity does not significantly influence firms' adoption decisions. In contrast, human resource factors, especially firms' information technology capability, play a crucial role by underscoring the importance of digital skills in the workforce. Additionally, firms' perceptions of the practical value of technologies, particularly regarding competitiveness and profitability, are strongly associated with higher adoption levels. The findings offer policy-relevant insights for promoting effective 4IR technology adoption in developing economies.

1. Introduction

Technology adoption is crucial for driving development and progress at the macroeconomic level and within individual firms. It facilitates development by enabling nations and firms to harness the benefits of innovation and enhance their productivity and efficiency (United Nations, 2018). It streamlines business operations, enhances productivity, adapts to market demands, and capitalises on emerging opportunities (Comin et al., 2022; Tornatzky and Fleischer, 1990).

Although technology adoption is beneficial and imperative to the development of firms in developing countries, significant lags remain in the adoption rate between developing and developed countries (UNCTAD, 2021). Moreover, documented divides exist in technology adoption across sectors and firms within developing countries (Comin et al., 2022). Uneven adoption potentially widens the productivity gap, perpetuating inequality among firms. Given that more capable and technologically advanced enterprises are also more robust, the technical gap among firms affects how differently they handle competitions and economic fluctuations (Comin et al., 2022).

To address the technological adoption gap, we must understand the barriers that prevent firms from technology adoption. Extensive literature relying on the technology-organisation-environment (TOE) framework has identified various determinants, ranging from financial costs to organisational readiness (Ghobakhloo et al., 2022; Tornatzky and Fleischer, 1990) (Gangwar et al. (2014); Fu et al. (2018) and Stornelli et al. (2021) for systematic reviews). However, a critical analysis of these studies reveals two major limitations. First, most research is concentrated in developed economies, particularly the US and Europe (Raj et al., 2020). This geographical imbalance limits the applicability of findings to developing countries, where firms operate under distinct regulatory environments and face higher resource constraints (Cirera et al., 2021). Second, extant literature is dominated by correlational studies that often aggregate diverse technologies into single measures (Agostini and Nosella, 2020). These studies frequently rely on self-reported barriers, such as high costs, without establishing causality. Consequently, whether reported financial constraints are actual binding

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barriers or merely perceived obstacle remains unclear. This study addresses these gaps using firm survey data from Vietnam.

The central research question is as follows: Do the reported barriers truly represent firms' limited adoption of advanced 4IR technologies in Vietnam?

We consider Vietnam as our research setting to analyse the risks and benefits of technology adoption. Although Vietnam is one of the fastest growing economies in the world, declining productivity growth threatens its long-term economic development and population welfare (Cirera et al., 2021). Sustainable growth requires the ability to adopt sophisticated technologies and build innovation capacity. To manage this problem, the Vietnamese government has embraced a national strategy focusing on 'science, technology, and innovation', in which the concept of the Fourth Industrial Revolution (4IR) plays a central role (Government of Vietnam, 2020). Practically, the 4IR is a recent concept. It refers to a wave of disruptive technologies emerging in the early 21st century, including artificial intelligence, big data analytics, the Internet of Things (IoT), and robotics (Vaidya et al., 2018). These technologies are transforming industries by enabling automation, enhancing productivity, supporting data-driven decision-making, and improving supply chain efficiency (Vaidya et al., 2018; Bousdekis et al., 2019).

The main source of data is the Survey on Technology Adoption in Enterprise (STAE) in Vietnam, conducted by the General Statistics Office (GSO) in 2019–2020. Its focus is aligned with the Vietnamese government's policies on technological innovation and concept of 4IR with multiple technologies. The summary data from the survey indicates that the current rate of 4IR technologies adoption in Vietnam is low. Only approximately 20% of the surveyed firms report adopting at least one 4IR technology, and this number is as low as nearly 3% for certain types of technology. On average, 20.24% of firms report that 4IR technologies are 'too expensive' and that firms lacked the financial capacity to adopt; 39.69% report that these technologies require skilled human resources to adopt, which firms lack. The other 18.47% of firms think that these technologies are impractical; therefore, they are reluctant to adopt. However, as these *barriers* are reported by firms' managers, they are prone to biases. Therefore, this study investigates the three commonly reported obstacles (financial constraints, human resource limitations, and perceived practicality) to assess whether they genuinely impede the adoption of advanced 4IR technologies.

With the sample size of 3898 representative firms obtained from merging STAE with the firms' financial statements, this study adopts multiple quantitative techniques based on the TOE framework. To overcome the limitations of previous correlational studies and address the potential endogeneity of self-reported barriers, it employs rigorous causal estimation methods, including inverse probability weighting with regression adjustment (IPWRA). Our analyses reveal that the financial capacity of firms, as represented by liquidity and quick solvency ratios, does not significantly influence their adoption decisions for 4IR technologies. However, human resource barriers, proxied by skilled information technology (IT) personnel and share of undergraduate employees, emerge as a significant determinant of technology adoption.

Furthermore, firms' perceptions about the practicality of 4IR technologies, including perceptions of profit, competition, and organisational development, play a vital role in adoption decisions.

This study's contributions are threefold. First, theoretically, it challenges the prevailing consensus within the TOE framework that financial constraints are the primary barriers to technology adoption in developing economies. By distinguishing between perceived barriers and actual binding constraints, it demonstrates that financial capacity is not a significant determinant when causal inference is applied. Second, methodologically, it advances the literature by transcending the correlation-based analyses of self-reported barriers that dominate the field. By employing IPWRA, it provides causal evidence that human capital, specifically specialised IT capability rather than general education, is the decisive enabler. Finally, from a practical policy perspective, the findings suggest that, rather than offering financial subsidies, policy interventions in developing economies should prioritise digital upskilling and reshaping managerial perceptions of technological practicality to drive 4IR adoption.

The remainder of the study is organised as follows. Section 2 provides an overview of the literature on firms' technology adoption and firms' resources and external environment as a foundation or barriers to adopt new technologies. Section 3 provides the background of the study, datasets, empirical situation of 4IR technology adoption in Vietnam and key measurements. Next, Section 4 introduces the techniques used to answer the research question. Section 5 reports the estimation results, and Section 6 discusses them in relation to the current literature. Finally, Section 7 concludes the study.

2. Literature review

The literature on technology adoption and its determinants dates back to the 1980s, with the introduction of Wernerfelt's (1984) resource-based view of firms providing the analysis of firms' decisions with a stronger foundation. Then, firms are analysed from their resource side rather than the product side; thus, their decisions, including that to adopt new technology, are made based on firms' resources and capacity to sustain competitive advantage (Barney, 1991). By the end of the 1980s, Tornatzky and Fleischer (1990) publish a seminal work about the process of firms' technological innovation, stressing that this process is complex, multi-dimensional, and involves strategic interactions among departments and stakeholders inside and outside the firm. This book provides a comprehensive review of the then-current understanding of how technological innovations are created, adopted, and diffused within organisations (Drazin, 1991). Furthermore, it effectuated the TOE framework that pioneered the research on technological development and adoption.

This framework comprises three components: technology, organisation, and environment. *Technology* refers to the functionality and compatibility with existing systems of technologies being considered. *Organisation* includes factors such as firms' size, structure, culture, and resources; generally, any internal settings where technologies are adopted or developed. *Environment* refers to the external context surrounding a firm, such as market conditions, legal requirements, or norms. Given the robust and agile structure, the TOE framework is the underlying foundation for many analyses on firms' technological adoption.

Regarding *technology*, several studies investigate the complexity, advantages, and compatibility of technologies. Tornatzky and Fleischer (1990) find that firms consider only those technologies for adoption that provide additional competitive advantage. However, these technologies must be compatible with the technological ability (Corrocher, 2003) and needs and current operations of firms (Cooper and Zmud, 1990). These sub-components significantly contribute to whether firms adopt technologies (Wang et al., 2010; Oliveira et al., 2014; Oettmeier and Hofmann, 2017; Ghobakhloo et al., 2022).

Regarding *organisation*, many firms' characteristics influence their adoption decision, such as firms' size (Wang et al., 2010), firms' age (Haller and Siedschlag, 2011), ownership structure (Bayo-Moriones, and Lera-López, F., 2007), workforce skill (Bartoloni and Baussola, 2001), export proportion (Giunta and Trivieri, 2007), and research and development (R&D) activities (Gómez and Vargas, 2012). Several studies examine the role of top managers in estimating the costs and benefits of adoption and then making decisions about firms' technology adoption (Wang et al., 2010; Oliveira et al., 2014; Ghobakhloo et al., 2022).

Lastly, the market or business *environment* facilitates or even forces firms to adopt technologies. Hannan and McDowell (1984) find that banks in more concentrated local banking markets are more likely to adopt ATMs. These positive spillovers are observed among Irish manufacturing firms (Haller and Siedschlag, 2011). Wan et al. (2005) show that an extra-firm environment that is decentralised and intra-firm environment that promotes the exchange of ideas and willingness to take risks are beneficial for innovation and technology adoption. Additionally, the pressure from competitors or partners is important (Wang et al., 2010; Oettmeier and Hofmann, 2017; Ghobakhloo et al., 2022). On a global scale, Comin and Hobijn (2004) document a trickle-down diffusion of technologies from advanced economies to less advanced ones represented by factors such as human capital endowment, type of government, openness to trade, and adoption of predecessor technologies.

In the context of 4IR, the last 5 years have witnessed a boom in the literature on the enablers and barriers to adopting 4IR technologies. Moreover, these studies, influenced by the TOE framework, generally categorise these factors into three types: technological, organisational, and environmental determinants; each type contains multiple sub-factors (Ghobakhloo et al., 2022). Technological determinants consist of characteristics of the technologies being considered for adoption, such as perceived strategic benefits, compatibility, complexity, and cost. Perceived strategic benefits are the most common driver for 4IR technologies adoption (Chatterjee et al., 2021; Ghobakhloo and Ching, 2019; Horvath and Szabo, 2019; Stentoft et al., 2021), while cost is the most common barrier (Ghobakhloo and Ching, 2019; Masood and Sonntag, 2020; Prause, 2019). Other barriers are compatibility (Ghobakhloo and Ching, 2019; Prause, 2019), complexity, and cybersecurity risk (Prause, 2019; Rauch et al., 2019).

Regarding the organisational determinants, a factor can be the driver of one firm but a barrier to another owing to firms' properties (Ghobakhloo et al., 2022). Among the findings, top management, digital knowledge and expertise, and 4IR management competency are the most mentioned (Horvath and Szabo, 2019; Stentoft et al., 2021; Maisiri et al., 2021; Masood and Sonntag, 2020; Mittal et al., 2020). While top management can boost or reduce the process of adopting new technologies, given the current level of development, lack of digital knowledge and expertise and 4IR management competency act as deterrents to technology adoption (Oke and Arowoiya, 2022; Rauch et al., 2019; Stentoft et al., 2021). Additionally, firms' culture and structure discourage them from adopting 4IR technologies (Horvath and Szabo, 2019; Maisiri et al., 2021; Prause, 2019). Unlike organisational determinants, environmental determinants consistently promote technology adoption. The two most common drivers, namely competitive environment and stakeholder pressure, encourage firms to adopt 4IR technologies (Ghobakhloo and Ching, 2019; Horvath and Szabo, 2019; Stentoft et al., 2021; Won and Park, 2020).

Despite the extensive extant literature on technology adoption, several critical gaps persist, particularly concerning the measurement, interpretation, and contextual un- derstanding of adoption. First, most studies are concentrated in developed countries, especially the US and Europe, leaving firms in developing countries significantly understudied (Raj et al., 2020). This geographical imbalance is problematic, as firms in these regions often face distinct barriers and operate within unique regulatory and competitive environments, and data limitations frequently hinder the process to capture complex adoption metrics such as the intensity or simultaneous adoption of multiple technologies. Second, extant literature lacks a robust causal understanding of technological adoption. Although correlations between firms' characteristics (e.g., higher capacities) and technology uptake are frequently reported, the direction of causality remains ambiguous, potentially engendering misinformed decision-making by businesses and policymakers. Finally, the measurement of technology adoption itself presents significant limitations. Many studies either aggregate diverse technologies into a single measure (Agostini and Nosella, 2020; Chatterjee et al., 2021) or rely on binary (adopted/not adopted) or intention-based measures (Prause, 2019; Won and Park, 2020), disregarding the crucial intensity of adoption and heterogeneous nature of individual technologies. Furthermore, the focus on single technologies and/or sectors in most literature limits the generalisability and comparative insights into adoption behaviours across diverse technological landscapes and industries.

3. Background, data, and key measurements

3.1. Data

This study used the data from two datasets designed and collected by the GSO of Vietnam: the Vietnam Enterprise Survey (VES) and STAE. Both surveys were conducted in 2020 and collected data for the financial year 2019[1]. The VES is an annual survey conducted by the GSO to gather information available in firms' financial statements. For the 2020 wave, the VES covered approximately 500,000 enterprises, with samples representative at the industry and provincial levels.

In contrast, the STAE, was a one-year customised survey conducted in 2019, comprising 8624 firms across Vietnam, and commissioned by the Ministry of Science and Technology. While the sample was nationally representative, the questionnaire focused on technologies emblematic of the 4IR, including cloud computing, 3D printing, augmented reality, the IoT, and big data. Firms were asked to report their level of adoption for each of nine designated 4IR technologies. For each technology, respondents could select an 'irrelevant' category if the technology was deemed inapplicable to their sector or operations. Given the sector-specific nature of many 4IR technologies, this information was later used to filter adoption indicators by sub-sector. In addition to adoption metrics, the survey collected data on firms' labour composition by educational attainment, IT capacity, and perceptions of the potential impact of these technologies (Table 3).

We merged the two datasets using firms' tax identification numbers as the unique identifier, resulting in 4971 matched observations. To ensure the validity of our analysis, we restricted the sample in several ways. First, we excluded firms that reported all surveyed technologies as irrelevant, constituting approximately 15% of the original sample. Removing these firms prevented downward bias in adoption measures, as they are structurally unable or unwilling to adopt any of the considered technologies. Second, we excluded firms operating in the financial and real estate sectors owing to their distinct financial structures, which are not comparable to firms in other sectors. This step reduced the sample by only 2%, as most firms adopting 4IR technologies are concentrated in manufacturing and related industries. Finally, we excluded industry sub-sectors with fewer than 10 firms, reducing the sample by approximately 1%.

These two rounds of data cleaning effected a dataset comprising 3898 firm-level observations, covering 78 sectors and 9 4IR technologies. However, not all firms are equally capable of adopting every technology, largely owing to sector-specific relevance (for example, it is reasonable that an agricultural firm might not consider 3D printing applicable). Ignoring this issue could inflate the share of non-adopters for technologies that are non-applicable in some sectors, lowering the observed average adoption rate. Responses from the STAE survey reveal that some firms explicitly reported non-adoption for 'practicality' reasons, including the lack of relevance to their operations.

To address this, we constructed a refined sub-sample by removing firms that reported a technology as 'irrelevant to the business' in sectors where that technology was not considered universally relevant. Although the survey provides clear responses on firm-level irrelevance, it does not determine whether a technology is irrelevant at the sector level. We addressed this by applying a general rule: if fewer than a specified percentage of firms in a sector were deemed technology-relevant, we treated it as irrelevant for the entire sector. To identify the optimal threshold for sectoral relevance, we tested thresholds ranging from 50% to 100%, based on the share of firms in each sector reporting the technology as relevant. For each threshold, we estimated a baseline linear regression and evaluated model fit using the Akaike information criterion and Bayesian information criterion (Fig. A1 and Table A1). Although 90% marked the elbow point in model

[1] In Vietnam, the financial year is the calendar year.

performance, we adopted the stricter 100% threshold to prioritise estimation precision, given the minimal loss of observations. This means that a technology was treated as irrelevant to a sector only if *all* firms in that sector, 100%, reported it as such, ensuring that excluded firms genuinely could not adopt the technology rather than choosing not to.

The final sample includes 2653 observations across 70 sectors, where firms' adoption decisions are based on their actual capabilities rather than on the technological relevance to their operations.

3.2. Technology adoption in Vietnam

To provide an overview of 4IR technology adoption in Vietnam, Table 1 summarises the adoption status of the nine technologies covered in the STAE survey. These technolo- gies, defined by the STAE and detailed in the corresponding footnotes, include *cloud computing* [2], *advanced robotics* [3], *3D printing* [4], *augmented reality* [5], *modelling* [6], *the IoT* [7], *cybersecurity* [8], *big data* [9], and *integrated systems* [10].

The relevance of these technologies varies substantially across sectors (Table 1). On average, *cybersecurity* is reported as the most relevant, while *3D printing* is the least relevant. Among firms that considered the technologies relevant, including those in a trial phase, approximately 23.5% adopt cybersecurity and 22.2% adopt the IoT. In contrast, adoption rates for *augmented reality*, *advanced robotics*, *3D printing*, and *modelling* remain low, ranging from 3% to 5%. Adoption of *big data* and *integrated systems* is moderately higher at approximately 12%, while *cloud computing* is adopted by approximately 16% of firms.

This pattern is consistent with the adoption levels reported by firms (Table 2). Among the nine technologies, the *IoT* and *cybersecurity* exhibit the highest levels of adoption, with approximately 18–20% of firms reaching level 4. Moreover, these are the only two technologies where more than 1% of firms report active upscaling efforts. *Cloud computing* follows, with over 12% of firms adopting it at level 4, while *big data* and *integrated systems* reach level 4 adoption in more than 8% of firms.

In contrast, *advanced robotics*, *3D printing*, *augmented reality*, and *modelling* show minimal uptake, with over 90% of firms reporting no adoption. While these technologies are adopted in specific sectors, such as advanced robotics in electronics manufacturing; 3D printing in oil and gas extraction and furniture manufacturing; augmented reality in wholesale trade; and modelling in the production of rubber, plastic, and electrical equipment, the number of firms operating in these sectors is small, effectuating low average adoption rates overall.

Some sectors report high perceived relevance of these technologies despite low adoption. For example, robotics and modelling are considered relevant in drainage and wastewater treatment, 3D printing in printing and media reproduction, and augmented reality in sports, entertainment, and recreational activities. Nevertheless, even within these sectors, actual adoption remains negligible.

Table 1
Summary of technologies.

Variable	Obs.	Relevance (%)	Ordered categories		Adopted dummy	
			Mean	Std. dev.	Mean	Std. dev.
Cloud computing	3353	86.04	1.499	1.069	0.159	0.366
Robot	3108	79.76	1.142	0.598	0.044	0.205
3D printing	2979	76.42	1.158	0.624	0.048	0.215
Augmented reality	3037	77.91	1.111	0.513	0.033	0.179
Modelling	3101	79.58	1.169	0.629	0.050	0.219
Internet of Things	3454	88.64	1.702	1.228	0.222	0.416
Cybersecurity	3580	91.84	1.746	1.247	0.235	0.424
Big data	3353	86.02	1.388	0.959	0.121	0.326
Integrated system	3361	86.22	1.393	0.953	0.120	0.325

3.3. Key measurements

From the nine technologies covered in the STAE, we construct three

Table 2
Summary of technologies adoption level.

		Level 1: Not adopted	Level 2: R&D for trial	Level 3: In trial	Level 4: Adopted	Level 5: Up-scaling
Cloud computing	No.	2680	138	96	412	28
	Freq. (%)	79.90	4.11	2.86	12.28	0.83
Robot	No.	2910	61	40	85	12
	Freq. (%)	93.63	1.96	1.29	2.73	0.39
3D printing	No.	2764	71	44	89	12
	Freq. (%)	92.75	2.38	1.48	2.99	0.40
Augmented reality	No.	2868	68	46	44	12
	Freq. (%)	94.40	2.24	1.51	1.45	0.39
Modelling	No.	2846	100	58	85	14
	Freq. (%)	91.72	3.22	1.87	2.74	0.45
Internet of Things	No.	2512	175	96	628	44
	Freq. (%)	72.71	5.07	2.78	18.18	1.27
Cyber security	No.	2532	205	96	711	36
	Freq. (%)	70.73	5.73	2.68	19.86	1.01
Big data	No.	2809	138	84	290	32
	Freq. (%)	83.78	4.12	2.51	8.65	0.95
Integrated system	No.	2785	172	86	288	30
	Freq. (%)	82.86	5.12	2.56	8.57	0.89

[2] Cloud computing: Employing third-party data storage services and software, such as Google Apps and Microsoft Office 365, to manage substantial volumes of data within an open-source operating system, facilitating online connectivity to production and management systems.

[3] Advanced robotics: Industrial robots that are autonomously self-managing, utilising multiple sensor devices and standardised interfaces.

[4] 3D printing: Also known as additive manufacturing technology, with applications in prototyping, component manufacturing, and sample production, helping to reduce transportation and inventory costs.

[5] Augmented reality: Used to support maintenance, logistics, and standard operating procedures by displaying information or images through virtual prisms.

[6] Modelling: Network modelling of value chains using real-time feedback to optimise processes, identify bottlenecks, and improve efficiency.

[7] IoT: A system connecting computing devices, mechanical machines, digital tools, and people over the Internet, each with a unique identifier, enabling data exchange without human interaction.

[8] Cybersecurity: Technologies designed to secure information systems in environments with high connectivity, such as the IoT and cloud computing, as systems shift from closed to open architectures.

[9] Big data: Comprehensive analysis of all available firm-level data (e.g., personnel, value chain, CRM, and device data) to support real-time decision-making and generate optimal solutions.

[10] Integrated systems: Highly automated systems that communicate across firms using open standards and protocols (e.g., JDF for job data and CxF for colour information) to enable seamless information flow.

main dependent variables: *maximum adoption*, *adopted in use*, and *number of technologies adopted* (Table 3).

M*aximum adoption* captures the highest adoption level a firm reports across all nine technologies. It ranges from 1 to 5, where 1 denotes 'not adopted', 2 is 'R&D for trial', 3 is 'in trial', 4 is 'adopted', and 5 is 'upscaling'. This measure is most meaningful under two key assumptions. First, a firm's technological capability is represented by the highest level of adoption it reaches in any of the technologies, regardless of how many it adopts. That is, a firm adopting one technology at level 5 is considered more technologically intensive than a firm adopting multiple technologies at level 3. Second, the adoption levels are comparable across technologies despite their differences. While we acknowledge that technologies such as advanced robotics, the IoT, and big data require distinct skills and investments, these differences are difficult to quantify, as they depend on firm-specific sectoral and operational characteristics. Therefore, after controlling for sectoral heterogeneity, it is reasonable to treat adoption levels as comparable across technologies. For example, a firm adopting augmented reality at level 4 is considered to have similar technological capacity as a firm adopting cloud computing at level 4. However, this approach overlooks variation in the breadth of adoption, that is, between firms adopting a single technology versus multiple technologies at the same level. To address this limitation, we introduce a third dependent variable.

Adopted in use is a binary indicator equal to 1 if the firm has adopted at least one technology (including those in trial phases) and 0 otherwise. Unlike *maximum adoption*, which reflects adoption intensity, this variable captures the basic adoption decision. Although it is less granular, it reduces classification ambiguity between adjacent categories (e.g., between 'not adopted' and 'R&D for trial').

N*umber of technologies adopted* counts how many of the nine technologies each firm adopts, ranging from 0 to 9. It is based on the same assumptions as *maximum adoption* but focuses on the scope rather than intensity. This variable helps distinguish between firms adopting one technology and those adopting several, even if the adoption level is the same.

In summary, we employ three dependent variables: (i) the highest level of adoption across technologies, (ii) a binary indicator of whether any technology is adopted, and (iii) the number of technologies adopted. Table 3 reports the summary statistics for these measures.

Furthermore, we selected the variables of interest to align with the main barriers reported by firms: financial, human resource, and practicality barriers. According to the STAE, 20.24% of firms stated that 4IR technologies were 'too expensive' and that they lacked the financial capacity to adopt them. Another 39.69% reported that these technologies required skilled (non-financial) resources to adopt and that firms were short of capable personnel. Additionally, 18.47% of firms did not see the practicality of these technologies and were therefore reluctant to adopt them.

Based on these three main reasons, we chose liquidity and the quick solvency ratio to reflect firms' financial capacity; the percentage of undergraduate employees and firms' IT capacity to assess their human resources; and firms' outlook on the current and near-future market, including changes in competitiveness, profit, and organisation, to reflect their perception of practicality. Within the TOE framework, the liquidity and human resource variables fall under the category of *organisation*, such as 'absorptive capacity' (Agostini and Nosella, 2020; Mittal et al., 2020), 'resource availability' (Arifin et al., 2015; Oliveira et al., 2014), or 'knowledge and expertise' (Won and Park, 2020; Stentoft et al., 2021).

The liquidity is obtained from firms' tax reports via the VES, and the quick solvency ratio is calculated as the ratio of the difference between current assets and inventories to current liabilities. The remaining variables are from the STAE. While the percentage of undergraduates is a single variable from a question in the survey, IT capacity and other perception variables result from the principal component analysis (PCA) of multiple questions. IT capacity is the PCA of 7 questions about IT skills on the scale of 1–3, where one is 'weak' and 3 is 'good'. This includes IT platform, automation technology, data analysis, information security, data security, development or implementation of support systems, collaboration software, and non-technical skills such as systematic thinking and process understanding.

The 'competitiveness effect' variable is calculated from the question 'How do you think the impact of technological breakthroughs of 4IR affects the competitive pressure of your business'? The STAE asked this question three times for three time points: present, next 1–2 years, and after the next 3 years. For each question, firms select from a scale of 1–3, in which 1 means 'reduce', 2 means 'keep unchanged', and 3 means 'increase'. Correspondingly, the 'profit effect' and 'organisation effect' are also calculated using similar practices.

Moreover, we included other variables to control for firms' characteristics, for example, profitability, debt structure, size, R&D investment, intangible asset value, education costs for employees, and total international trade value. Table 3 shows the distributions of these variables.

4. Estimation method

To check the robustness of the research question, we discuss three main parts of the content resulting from three estimation methods. Despite the different approaches, the main target of all these estimation methods is to observe if the three barriers – financial constraints, human resource limitations, and perceived practicality – act as deterrents for firms to adopt technologies and if the lower barriers cause firms to adopt more 4IR technologies.

The first part includes regression with the three presented dependent variables. As these variables have different distributions, we use three estimations: ordered logistic regression for 'maximum adoption', logistic regression for 'adopted in use', and Poisson regression for 'number of technologies adopted'.

The ordered logistic regression is specified as follows:

$$\begin{aligned} \textit{Maximum adoption}^{*} = {} & \beta_{1,2}\textit{Financial}_i + \beta_{3,4}\textit{HR}_i + \beta_{5,6,7}\textit{Practicality}_i \\ & + \beta_k X_i + \delta_i + \gamma_i + \lambda_i + \epsilon_i, \end{aligned} \tag{1}$$

where.

$$\textit{Maximum adoption}_i = \begin{cases} 1 \text{ if } & \textit{Maximum} - \textit{adoption}^{*} \leqslant \mu_1 \\ 2 \text{ if } \mu_1 < & \textit{Maximum} - \textit{adoption}^{*} \leqslant \mu_2 \\ 3 \text{ if } \mu_2 < & \textit{Maximum} - \textit{adoption}^{*} \leqslant \mu_3 \\ 4 \text{ if } \mu_3 < & \textit{Maximum} - \textit{adoption}^{*} \leqslant \mu_4 \\ 5 \text{ if } \mu_4 < & \textit{Maximum} - \textit{adoption}^{*} \end{cases} \tag{2}$$

with μ_j, ($j = 1, 4$) are 4 latent thresholds corresponding to 5 levels of *Maximum adoption.*

Financial, *human resource*, and *Practicality* are the three groups of variables of interest (Section 3.3). δ_i, γ_i, and λ_i are the type, province, and sector fixed effects, respectively. These variables control for firms' types of ownership, province of location, and sector of operation. X_i is a $k \times i$ matrix of control variables, and ϵ_i is the robust error term.

The binary logistics regression is specified as follows:

$$\begin{aligned} log\frac{P\,[\textit{Adopted in use} = 1|Z = z]}{1 - P\,[\textit{Adopted in use} = 1|Z = z]} = {} & \beta 0 + \beta 1,2\textit{Financiali} + \beta 3,4\textit{HRi} \\ & + \beta 5,6,7\textit{Practicalityi} + \beta kXi \\ & + \delta i + \gamma i + \lambda i + \epsilon i. \end{aligned} \tag{3}$$

With P (.) is the probability of the variable *adopted in use* equal 1 on the condition of all independent variables included, denoted by Z.

For the *number of techs adopted* variable, we use Poisson regression with the same model specification. We use the three perceived barriers, financial, 'human resource, and 'practicality, as the predictors for the *zero* observations in the sample.

The second part includes the analyses for the dependent variables

Table 3
Summary of all variables.

Variable	Mean	Std. dev.	Min	5%	Median	95%	Max
Dependent variables							
Maximum adoption	2.133	1.413	1	1	1	4	5
Adopted in use	0.355	0.478	0	0	0	1	1
Number of techs adopted	0.895	1.658	0	0	0	4	9
Variables of interest							
Liquidity (mil. VND)	19,440.13	145,814	0	69.8	2031.15	58,113.7	5,829,842
Quick ratio (%)	9.344	88.697	0.001	0.187	1.111	27.838	4445.918
Finance barriers (PCA)	3.722	1.117	1.000	2.495	3.698	4.920	39.968
% Undergrads (%)	33.368	27.819	0	0	25	100	100
IT capacity (PCA)	4.523	2.173	1.000	1.000	4.532	7.672	9.190
Human barriers (PCA)	2.977	1.085	1.000	1.254	2.938	4.937	6.207
Competitiveness effect (PCA)	6.073	1.470	1.000	4.258	6.501	7.515	7.515
Profit effect (PCA)	4.520	1.478	1.000	1.851	4.531	6.327	6.327
Organisation effect (PCA)	4.714	1.492	1.000	1.970	4.703	6.668	6.668
Practicality barriers (PCA)	5.672	1.412	1.000	3.612	5.423	7.698	7.698
Control variables							
ROE (%)	−0.081	2.165	−83.519	−0.409	0.011	0.346	11.576
Debt-to-Equity (%)	4.102	60.828	−228.851	0.004	1.097	10.919	3624.607
Asset (mil. VND)	316,459.6	4,040,749	57.65	1091.7	25,224.38	888,426.4	211,000,000
Labour (people)	178.347	625.222	1	2	30	714	14,666
Firm age (year)	11.981	6.426	2	4	11	23	64
R&D investment (mil. VND)	51.877	1531.501	0	0	0	0	68,512
Intangible asset (mil. VND)	3347.549	57,147.49	−3349	0	0	6643.2	3,215,591
Education costs (mil. VND)	7.230	277.509	0	0	0	0	15,000
Int'l trade (mil. VND)	133,746.3	6,192,131	0	0	0	24,964	384,000,000

(maximum adoption and adopted in use[11]) on the nine technologies. These regressions show if any special pattern exists in the reasons why firms do (not) adopt a specific technology after controlling for the irrelevance cause and differences among sectors.

In the last part, we test the robustness of our aggregated models using the IPWRA models. This allows us to compare the variables of interest between different groups of *treatments*[12] with the *treatment* and outcome models specified, making it 'doubly robust'. To define the *treatment* variables, we must calculate the composite variables for each group of reported barriers using PCA to reduce the dimension from two or three to one. For each composite variable of the reported barriers, we classify all firms into two groups of barriers: high and low. The former groups have the barriers higher than the median of all firms, while the latter group has barriers lower than the median.

This method shows the actual causal effect of lowering firms' barriers to technology adoption after controlling for all the firms' characteristics that engender the differences in barriers (*treatment* model) and factors driving the adoption behaviour other than the barriers (outcome model). This means, after reweighing the firms, that the group of firms with higher barriers is comparable to those with lower barriers in the observable characteristics. Taking the simple difference of outcomes between these two groups allows us to observe the effect of having lower barriers on adoption outcomes.

The binary treatment effect model is as follows:

$$Effect = \frac{1}{N_T}\sum_{i=1}^{N_T}\left(E[Adoption_1|Lower\ barries = 1] - E[Adoption_0|Lower\ barries = 1]\right) \tag{4}$$

where $Adoption_1$ and $Adoption_0$ are the potential outcomes if a firm belongs to the treatment or control group; $Lower\ barriers = 1$ denotes when a firm has lower barriers; N_T is the number of adopted firms. However, as $E[Adoption_0|Lower\ barriers = 1]$ is unobservable, we must calculate the probability of having lower barriers via propensity score by estimating a probit or logit model with *Lower barriers* as a dependent variable and firms' characteristics as independent variables. Then, the propensity score $P\ (Lower\ barriers|Z_i)$, with Z_i is the matrix of observable covariates, is used as the weight for the outcome models.

$$\text{Inverse propability} = \begin{cases} \dfrac{1}{P(Lower\ barriers|Z_i)} & \text{if } Lower\ barries = 1 \\ \dfrac{1}{1-P(Lower\ barriers|Z_i)} & \text{if } Lower\ barries = 0 \end{cases} \tag{5}$$

Given that, we calculate the effect of having lower barriers on firms' adoption as

$$Effect = \frac{1}{N_T}\sum_{i=1}^{N_T}\left(\left[\frac{\overline{\widehat{Adoption}_{Lower\ barries=1}}}{\widehat{P}(Lower\ barries|Z_i)}\right] - \left[\frac{\overline{\widehat{Adoption}_{Lower\ barries=0}}}{1-\widehat{P}(Lower\ barries|Z_i)}\right]\right). \tag{6}$$

With

$$\begin{cases} \widehat{Adoption}_{Lower\ barries=1} = (\widehat{\beta}_0 + \widehat{\beta}Z_1)_{Lower\ barries=1} \\ \widehat{Adoption}_{Lower\ barries=0} = (\widehat{\beta}_0 + \widehat{\beta}Z_1)_{Lower\ barries=0} \end{cases} \tag{7}$$

are the adjusted regression outcome models.

5. Empirical results

This section discusses the results in four parts. The first part, including Tables 4–6, explores the determinants of adoption at the aggregated level. Table 4 analyses each barrier separately, and Table 6 includes all barriers one regression to observe if the effects get cancelled out. The second part examines each technology and its determinants (Tables 7 and A2). The third part discusses some additional analyses to test the robustness of the results, including the relevance of technologies to each sub-sector and composite barriers. The last part examines the causal effects of lowering the reported 'barriers' that firms claimed to

[11] The variable 'Number of techs adopted' cannot be analysed for this disaggregated level since we only examine one technology at a time.

[12] The word 'treatment' is in italic since it bears a modified meaning in this study. As we do not work in an experimental setting, no actual treatment variable exists that is (randomly) assigned to firms.

Table 4
Determinants of technological adoption by different measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquidity	−0.007			−0.035			−0.036*		
	(0.005)			(0.024)			(0.020)		
Quick ratio	−0.000			−0.000			0.000		
	(0.000)	0.001*		(0.000)	0.003**		(0.000)	0.002*	
% Undergrads.									
		(0.000)			(0.002)			(0.001)	
IT capacity		0.047***			0.268***			0.267***	
		(0.003)	0.023***		(0.018)	0.145***		(0.013)	0.060**
Competitiveness effect									
			(0.006)			(0.027)			(0.025)
Profit effect			0.038***			0.184***			0.219***
			(0.007)			(0.033)			(0.029)
Organisation effect			−0.001			0.021			−0.015
			(0.007)			(0.031)			(0.023)
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3897	3897	3897	3897	3897	3897	3897	3897	3897
Mean outcome	1.000	1.000	1.000	2.135	2.135	2.135	0.898	0.898	0.898
Chi-2	459.12	597.90	539.16	589.719	806.732	720.341	1049.625	1765.978	1282.610
Pseudo R2	0.110	0.145	0.129	0.071	0.100	0.087	0.139	0.207	0.166

Note: This table reports the results from regressing the adoption measures on each group of reasons. The dependent variables in models are *adopted in use* (models (1)–(3)), *maximum adoption* (models (4)–(6)), and *number of techs adopted* (models (7)–(9)). Models (1)–(3), (4)–(6), and (7)–(9) are estimated from logit, ologit, and Poisson (STATA), respectively. The coefficients reported for logit and ologit are the marginal effects and log odd-ratios, respectively. Robust standard errors are in parentheses.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Marginal effects for each level of adoption.

	Not adopted	R&D for trial	In trial	Adopted	Up-scaling
Liquidity	0.004	0.000	0.000	−0.003	−0.001
	(0.005)	(0.000)	(0.000)	(0.004)	(0.001)
Quick ratio	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Undergrads.	−0.001 (0.000)*	0.000 (0.000)*	0.000 (0.000)*	0.000 (0.000)*	0.000 (0.000)*
IT capacity	−0.047 (0.003)***	0.003 (0.000)***	0.002 (0.000)***	0.036 (0.003)***	0.006 (0.001)***
Competitiveness effect	−0.022 (0.005)***	0.001 (0.000)***	0.001 (0.000)***	0.017 (0.004)***	0.003 (0.001)***
Profit effect	−0.029 (0.007)***	0.002 (0.000)***	0.001 (0.000)***	0.023 (0.005)***	0.004 (0.001)***
Organisation effect	0.000	0.000	0.000	0.000	0.000
	(0.006)	(0.000)	(0.000)	(0.005)	(0.001)

Note: This table reports the marginal effects from regressing *maximum adoption* on all three groups of reasons as presented in model (2) (Table 6). Robust standard errors are in parentheses.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

prevent them from adopting new 4IR technologies on their actual behaviours.

5.1. Determinants of adoption: Aggregated

Table 4 shows the results of estimations using three variables – *adopted in use*, *maximum adoption*, and *number of techs adopted*. The set of control variables is excluded, and we add three groups of 'barrier' variables (finance, human resources, and practicality) sequentially into the model. Specifically, columns (1), (4), and (7) show the estimated correlation between firms' technology adoption measurements and financial barriers; columns (2), (5), and (8) estimate the relationship with human resource barriers, and columns (3), (6), and (9) show practicality barriers. In Table 4, the coefficients from the logistics regression model and ordered logistics regression are the average marginal effects and log odds ratios, respectively.

The results from models (1), (4), and (7) indicate that firms' financial capacity – measured by liquidity (cash holdings) and the quick ratio (a proxy for short-term solvency) – is not significantly associated with technology adoption across any of the three key outcome measures. This suggests that a firm's financial position neither influences whether it adopts 4IR technologies nor the extent to which it adopts them. This lack of statis- tical significance remains consistent across various model specifications and robustness checks.

Regarding human resources, the undergraduate percentage and firms' IT capacity are positively associated with firms' technology adoption in all measurements. From model (2), a 1% increase in the share of undergraduate employees correlates with a 0.1% increase in the probability of typical firms adopting at least one technology.[13] The effect remains significant and positive when we consider the ordinal dependent variable *maximum adoption*. From model (5), the share of tertiary-educated employees and level of IT capacity significantly and positively contribute to the likelihood that firms adopt new technologies at higher levels (than their current level), although the effect of having a higher share of college-educated employees is less pronounced. Table 5 presents the average marginal effects of indicators on each level of

[13] In interpreting the average marginal effect of a certain indicator on technology adoption tendency, we examine typical FIrms with the indicator equal to the sample average. For example, typical firms, in this case, are firms in which 33.36% of staff has undergraduate degrees. Additionally, the magnitude of the IT capacity driver is prominent. A one-unit increase in IT capacity correlates to approximately a 4.7% increase in the probability of adoption for typical firms.

Table 6
Determinants of technological adoption by different measures.

	(1)	(2)	(3)
Liquidity	−0.003	−0.022	−0.018
	(0.005)	(0.024)	(0.019)
Quick ratio	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)
% Undergrads.	0.000	0.003*	0.002
IT capacity	(0.000)	(0.002)	(0.001)
	0.041***	0.237***	0.241***
Competitiveness	(0.003)	(0.018)	(0.014) 0.037*
effect	0.016***	0.112***	
Profit effect	(0.005)	(0.027)	(0.022)
	0.031***	0.148***	0.158***
	(0.007)	(0.033)	(0.027)
Organisation effect	−0.004	0.001	−0.034
	(0.006)	(0.031)	(0.022)
Control	Yes	Yes	Yes
Type FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Observations	3897	3897	3897
Mean outcome	1.000	2.135	0.898
Chi-2	637.65	875.505	1944.125
Pseudo R2	0.157	0.109	0.217

Note: This table reports the results from regressing the adoption measures on all three groups of reasons. The dependent variables in models are a*doption dummy*, *maximum adoption*, and *number of adoption*. Models (1)–(3) are estimated from logit, ologit, and Poisson (STATA), respectively. Coefficients reported for logit are marginal effects, for ologit are log odd-ratios. Robust standard errors are in parentheses.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

technological adoption. Among the significant indicators, increases in the number of employees with undergraduate degrees and firms' IT capacity effect decreases in the probability of typical firms being in the ‘Not adopted’ phase. This can be interpreted as a higher tendency to leave the ‘Not adopted’ stage. However, these indicators have the strongest effect on inducing firms to adopt new technology as shown in the increase in the probability of firms being in the ‘Adopted’ phase.

Regarding the practicality barrier, columns (3), (6), and (9) show that firms' perceptions of the positive effects of 4IR technologies on profit impels them to adopts new technologies and/or moving to a higher level of technology adoption process. Moreover, firms that believe 4IR technologies drive more competition are more likely to adopt these technologies. However, the perception of organisational effect – meaning the perceived effects of technologies on the organisation's operations – does not induce any intention or action. The coefficients of profit and competitiveness effects show statistically significant magnitude and positive signs across all three key measurements of technology adoption. The average marginal effects on *maximum adoption* (Table 5) show the positive effect of an increase in firms' perception of market profit and competitiveness on their maximum technology adoption level. For a typical firm, a one-unit increase in competitiveness effect prompts a 2.2% decrease in the probability of being in the ‘Not adopted’ phase and a 1.7% increase in the probability of being in the ‘Adopted’ phase. Moreover, similar effects are observed with the profit effect: a one-unit increase in profit effect leads to a 2.9% decrease and 2.3% increase in the probability of being in ‘Not adopted’ phase and ‘Adopted’ phase, respectively.

Table 4 shows that the human resource barrier is the most important factor among the three. Regardless of the outcome variable, the estimations using human resource variables yield the highest R^2 value. Among the three reasons for not adopting 4IR technologies, the lack of human resources is the reason that best explains the adoption behaviours in our statistical models.

Table 6 presents the results from models including all variables of interest. The magni- tude and significance of the coefficients are consistent with previous models. In summary, there are three main takeaways. First, firms' financial strength, specifically cash and current solvency ability, does not relate to their decisions to adopt 4IR technologies, as indicated by the level of adoption, dummy of adopted in use, or number of adopted technologies. Second, the role of IT capacity among employees outweighs that of the tertiary-educated share in inducing adoption, as represented by all three independent variables. Additionally, this barrier holds the highest explanatory power of the models, indicating that human resources are the most critical aspect

Table 7
Determinants of each technology adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquidity	−0.005	0.002	−0.002	−0.004	−0.002	−0.004	−0.001	−0.003	−0.001
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Quick ratio	−0.000	−0.000	0.000	0.000	0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Undergrads.	0.001**	−0.000	0.000	−0.000	−0.000	0.000	0.001**	0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IT capacity	0.029***	0.021***	0.019***	0.023***	0.026***	0.030***	0.040***	0.036***	0.039***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Competitiveness effect	0.007	−0.015***	−0.016***	−0.009***	−0.002	0.011**	0.014***	0.014***	0.008*
	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Profit effect	0.014**	0.030***	0.023***	0.020***	0.024***	0.021***	0.032***	0.019***	0.018***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
Organisation effect	−0.002	−0.003	−0.003	−0.003	−0.008**	0.001	−0.014**	−0.004	−0.004
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3255	2015	2213	1919	2333	3441	3521	3129	3145
Mean outcome	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chi-2	597.99	615.02	322.72	328.68	317.33	361.34	558.40	488.76	524.28
Pseudo R2	0.221	0.344	0.267	0.316	0.278	0.109	0.183	0.267	0.272

Note: This table reports the results from regressing *adopted in use* for each technology on all three groups of reasons. The technologies in columns (1)–(9) are cloud computing, robot, 3D printing, augmented reality, modelling, the Internet of Things, cyber security, big data, and integrated system, respectively. The models are estimated from logit, and the reported coefficients are the marginal effects. Robust standard errors are in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

during firms' decision-making. Finally, the practicality of technologies is associated with firms' adoption. The effect is observed in firms' perception of increasing competitiveness and profit resulting from the movement towards 4IR technologies.

5.2. Determinants of adoption: Individual technologies

This section examines the drivers of adopting individual technologies. Table 7 shows that the essence of the results remains. Across all nine technologies, financial capacity, captured by liquidity and the quick ratio, does not affect firms' adoption decisions, similar to aggregated measurements. However, human resources and practicality perception show positive associations with the adoption of all technologies. Regarding human resources, IT capacity is more important than the share of tertiary-educated employees. Regarding the perceptions, firms' perceived competitiveness and profit effect show positive relationships to adoption decisions, while the organisational effect perception does not.

Besides the similarities to our previous aggregated analyses, some differences exist among different types of technology. The first difference arises from the share of college-educated employees. While, for most technologies (6 of 9), this variable does not significantly contribute to firms' adoption, it does positively affect firms' decisions on cloud computing, cybersecurity, and big data. The second difference is in the perceived competitiveness effect. In our aggregated model, the more market competition a firm perceives, the more it adopts technologies. However, this relationship is reversed for advanced robots and 3D printing. After controlling for firm-level characteristics and sector-level heterogeneity, a higher perception of market competition demotivates firms to adopt these technologies. In addition, the competitiveness effect does not significantly affects the adoption probability of augmented reality and modelling.

5.3. Robustness check

5.3.1. Irrelevant technologies

One major concern when analysing the adoption of technologies is their relevance: firms may not adopt some technologies since they are not relevant to their operations. This argument holds in the context of 4IR, where technologies focus on a high level of customisation and are specific to each sub-sector.

To address this concern, we provide a more granular examination of our data sample. Tables 8 and 9 replicate the same analyses in Sections 5.1 and 5.2 but focus only on firms that responded that the surveyed technologies are relevant to their business activities.

Tables 8 and A3 show that, when considering only firms reporting surveyed technologies as relevant, all statistically significant variables still hold, except for the proportion of college-educated employees. In addition, the magnitude of the coefficients of IT capacity, competitiveness effect, and profit effects slightly increases across all three key measurements. This difference provides the following insight: when we zoom in on the adoption intensity of only technologies that firms believe are relevant to their business (e.g., a real estate agency may find robotics technology less appealing than augmented reality), the need for employees with higher education degrees is alleviated. Instead, high firms' IT capacity and high perception of competitiveness and profit effect are more important to technology adoption.

Tables 9 and A4 indicate the effect of the three groups of barriers on each type of technology. The results show certain differences among the sample of all firms (Tables 7 and A2) and sample of firms indicating the survey technology's relevance. Regarding the human resources barriers, employees with college degrees still significantly contribute to the feasibility of adopting cloud computing (1), cybersecurity (2), and big data (3) technologies. However, the magnitude of the coefficients is lower than that of the same analysis with the whole sample, denoting a weaker effect of this variable. In contrast, firms' IT capacity remains

Table 8
Determinants of relevant technological adoption by different measures.

	(1)	(2)	(3)
Liquidity	−0.004	−0.029	−0.022
	(0.006)	(0.030)	(0.025)
Quick ratio	−0.000*	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
% Undergrads.	0.000	0.003	0.002
IT capacity	(0.000)	(0.002)	(0.002)
	0.046***	0.280***	0.281***
	(0.004)	(0.023)	(0.018)
Competitiveness effect	0.018***	0.143***	0.022
Profit effect	(0.006)	(0.035)	(0.027)
	0.029***	0.122***	0.168***
	(0.008)	(0.041)	(0.035)
Organisation effect	−0.012	−0.032	−0.051*
	(0.008)	(0.039)	(0.030)
Control	Yes	Yes	Yes
Type FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Observations	2635	2652	2652
Mean outcome	1.000	2.001	0.833
Chi-2	501.79	2060.719	5047.556
Pseudo R2	0.191	0.128	0.259

Note: This table reports the results from regressing the adoption measures on all three groups of reasons. This sample has all the firms reporting a technology as relevant, while other firms in the same sub-sector report dropped. The dependent variables in models are a*doption dummy*, *maximum adoption*, and *number of adoption*. Models (1–(3) are estimated from logit, ologit, and Poisson (STATA), respectively. The coefficients reported for logit and ologit are the marginal effects and log odd-ratios, respectively. Robust standard errors are in parentheses. *Note:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

significant towards the adoption of all types of technology with prominent effects. For the group of practicality barriers, while the significance of the profit effect still remains pronounced across 7 of 9 technologies, the competitiveness effect is only relevant among 5 technologies.

By focusing on the group of firms reporting which surveyed technologies are significant to their business functions, we extend the pragmatic motivations and perceptions of firms towards technology adoption. Hence, when making decision regarding adopting technologies relevant to the firm's domain, the quality of IT infrastructure and firm's perception of the technology's disruptive impact on profitability and market competition are the key factors. Meanwhile, contrary to popular belief, having college-educated employees only has a minor effect on the likelihood of technology adoption.

5.3.2. Composite barriers

This section examines the effects of the interactions among the barriers besides their individual effects. Financial barriers have significant effects on adoption because *lower* financial and *lower* human or practicality barriers are not complementary but substitutive in adopting. This shows the strong negative interactive effects of the *lower* financial and *lower* human or practicality barriers, which offsets the positive effect of lower barriers. To examine the interactive effects, we use the composite indices of *lower* barriers as the principal components of the variables representing the barriers of each type.

Table 10 shows that, in samples of all firms and of firms indicating the survey technologies relevance, lower human barriers and practicality barriers facilitate the tendency of technology adoption in terms of all three key measurements *adoption dummy, maximum adoption,* and *number of adoption*; most components in these composite variables are statistically significant to technology adoption (Section 5.2).

We analyse the behaviour of the interaction terms. Having lower financial barriers negatively associates with the relationship between practicality barriers and the number of adopted technologies. Moreover, it negatively associates with the relationship between practicality

Table 9
Determinants of each relevant technology adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquidity	−0.003	−0.004	−0.000	−0.005	−0.005	−0.003	−0.003	−0.003	0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
Quick ratio	0.000	0.000	0.000	0.000	0.000	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Undergrads.	0.001*	−0.000	−0.000	0.000	−0.000	−0.000	0.000	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IT capacity	0.030***	0.027***	0.022***	0.027***	0.029***	0.034***	0.045***	0.036***	0.042***
	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Competitiveness effect	0.005	−0.016***	−0.018***	−0.008**	−0.003	0.015***	0.006	0.012**	0.007
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Profit effect	0.010	0.027***	0.026***	0.022***	0.021***	0.022***	0.034***	0.017***	0.010
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Organisation effect	−0.000	−0.005	−0.001	−0.006	−0.009*	−0.003	−0.022***	−0.006	−0.002
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2456	1265	1452	1317	1457	2538	2538	2251	2176
Mean outcome	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chi-2	457.49	235.13	190.64	241.39	206.39	320.97	461.68	1878.88	376.13
Pseudo R2	0.253	0.358	0.277	0.323	0.310	0.142	0.217	0.299	0.296

Note: This table reports the results from regressing *adopted in use* for each technology on all three groups of reasons. This sample has all the firms reporting a technology as relevant, while other firms in the same sub-sector report dropped. The technologies in columns (1)–(9) are cloud computing, robot, 3D printing, augmented reality, modelling, the Internet of Things, cyber security, big data, and integrated system, respectively. The models are estimated from logit, and the coefficients reported are the marginal effects. Robust standard errors are in parentheses.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 10
Composite determinants of technological adoption by different measures.

	(1)	(2)	(3)	(4)	(5)	(6)
Finance barriers	−0.017	−0.040	−0.015	−0.015	−0.034	−0.023
	(0.011)	(0.039)	(0.040)	(0.010)	(0.045)	(0.042)
Human barriers	0.078***	0.443***	0.423***	0.088***	0.526***	0.498***
	(0.007)	(0.039)	(0.029)	(0.009)	(0.050)	(0.037)
Practicality barriers	0.041***	0.238***	0.178***	0.034***	0.206***	0.168***
	(0.005)	(0.027)	(0.023)	(0.006)	(0.034)	(0.030)
Finance × Human barriers	0.005	0.031	−0.001	0.010	0.056	−0.008
	(0.009)	(0.039)	(0.030)	(0.010)	(0.050)	(0.043)
Finance × Practicality barriers	−0.006	−0.013	−0.048**	−0.012**	−0.030	−0.059***
	(0.006)	(0.022)	(0.023)	(0.005)	(0.020)	(0.021)
Human × Practicality barriers	−0.011**	−0.048*	−0.030*	−0.011*	−0.039	−0.043*
	(0.005)	(0.025)	(0.017)	(0.006)	(0.032)	(0.024)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3897	3897	3897	2635	2652	2652
Mean outcome	1.000	2.135	0.898	1.000	2.001	0.833
Chi-2	592.18	811.655	1658.264	474.56	1728.951	4606.539
Pseudo R2	0.148	0.102	0.197	0.178	0.117	0.235

Note: This table reports the results from regressing the adoption measures on the composite indices of the three groups of reasons. The three first models are on the full sample, while the last three models are on the *relevant* sample. The dependent variables in models are a*doption dummy*, *maximum adoption*, and *number of adoption*. The models are estimated from logit, ologit, and Poisson (STATA), respectively,. The coefficients reported for logit and ologit are the marginal effects and log odd-ratios, respectively. The variables of interest are the *lower* barriers. Robust standard errors are in parentheses.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

barriers and the probability of adopting any technology overall but just for the sample of firms indicating relevant technologies. This implies that, while financial barriers alone do not affect technology adoption intention, firms with lower practicality barriers are more conservative about adopting new technology if they are in better financial positions. A similar phenomenon is observed from the interaction between human and practicality barriers: better human resources weaken the effect of having lower practicality barriers on firms' technology adoption. Additionally, the reversed statement holds: lower practicality barriers reduce the benefit of better human resources for adopting new technology.

Table 11 assays the result from Table 10 (column (1)) into different types of technology. The coefficients of the interaction term between finance and practicality barriers show that lower finance barriers decrease the effect of practicality barriers on the probability of adopting advanced robots, the IoT, and integrated systems. Specifically, for typical firms, a one-unit decrease in finance and practicality barriers decreases the probability of adopting advanced robots by 0.3%, the IoT by 1.3%, and integrated system by 0.7%, compared with the scenario of a one-unit decrease in practicality barriers alone. The interaction term between human resources and practicality barriers only shows statistical significance for cybersecurity. It implies that, for a typical firm, a one-unit decrease in human resources and practicality barriers effectuates a 0.8% decrease in the probability of adopting cybersecurity, compared with the scenario of a one-unit decrease in human barriers or practicality barriers alone.

The results obtained from exploring the interaction between the three barriers show that the effect of one barrier changes negatively if the other barriers are considered. A better perception of the practicality of new technology increases the number of new technologies adopted; however, the effect is reduced if firms have better financial positions. A similar effect is observed when interacting with human resources and practicality barriers. This result implies two things: either a lack of synergy remains between the surveyed barriers or firms with better financial positions in the market are more selective about the types of technology they want to adopt.

5.4. *Effects of lowering barriers*

This section examines whether the reported barriers are the de facto barriers that prevent firms from adopting 4IR technologies by adding weights to firms so that the groups of firms with lower and higher barriers are comparable in observable characteristics (Section 4).

We investigate whether lower barriers engender higher adoption probability (first row, Table 12). We observe that lower financial barriers do not lead to significantly higher adoption probability (columns (1) and (4)). Regarding the human barriers, columns (2) and (5)) show that firms with lower barriers have more than 15% probability of adopting any of the 4IR technologies. The effects of having lower practicality barriers are even higher, almost 17% (columns (3) and (6)). These results indicate that financial barriers do not prevent firms from adopting technologies.

Similar to the above sections, we also analyse the effect of lower barriers on *maximum adoption* and *number of techs adopted* (Tables A9 and A10). The structure of Tables A9 and A10 is strictly similar to that of Table 12 discussed above. The results are also consistent: across all analyses with different outcomes, financial barrier is not a significant barrier preventing firms from adopting 4IR technologies, while the human and practicality barriers are the *real* barriers. Across outcomes, the magnitude of the effects of these two barriers differs. Therefore, to precisely examine which one is more important, further research is required.

6. Discussion

Our empirical findings offer a nuanced understanding of technology adoption determi- nants and barriers, particularly within a developing country context, extending and sometimes challenging existing literature, and reinforce the consistent statistical non-significance of financial capacity as a barrier to 4IR technology adoption, observed across various aggregated measures and even in causal analyses. This result, although contrasting with the common emphasis on cost as a major barrier in the literature (Ghobakhloo and Ching, 2019; Masood and Sonntag, 2020; Prause, 2019), suggests a critical distinction: firms may perceive these technologies as expensive; however, financial constraints may not be the actual binding obstacle to adoption. This indicates that, on average, affordability is not the primary factor preventing firms from adopting these technologies.

In contrast, human resource factors emerge as consistently significant and strong de- terminants of technology adoption. The strong positive association between firms' IT capacity and adoption across all aggregated and individual technologies underscores the critical role of specialised digital skills. This aligns well with the literature emphasising absorptive capacity and digital knowledge as key enablers (Agostini and Nosella, 2020; Mittal et al., 2020; Masood and Sonntag, 2020; Stentoft et al., 2021). Furthermore, our analysis refines this understanding: while general undergraduate education contributes to the

Table 11
Composite determinants of each technology adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Finance barriers	−0.009	−0.000	−0.001	−0.008	−0.003	−0.012	−0.002	−0.007	−0.001
	(0.010)	(0.006)	(0.005)	(0.006)	(0.007)	(0.010)	(0.009)	(0.009)	(0.007)
Human barriers	0.059***	0.032***	0.036***	0.031***	0.039***	0.052***	0.079***	0.067***	0.062***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Practicality barriers	0.019***	0.012***	0.007*	0.006	0.015***	0.030***	0.031***	0.026***	0.021***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Finance × Human barriers	0.004	0.006	0.003	0.006	0.002	0.006	0.000	0.006	−0.002
	(0.008)	(0.007)	(0.007)	(0.005)	(0.006)	(0.008)	(0.008)	(0.007)	(0.007)
Finance × Practicality barriers	−0.006	−0.003*	−0.004	−0.004	−0.005	−0.013**	−0.004	−0.005	−0.007*
	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)
Human × Practicality barriers	−0.001	0.001	−0.005	0.005	−0.003	−0.000	−0.008*	0.000	0.004
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3255	2015	2213	1919	2333	3441	3521	3129	3145
Mean outcome	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chi-2	582.50	283.41	291.60	303.11	331.02	342.56	525.40	496.54	507.95
Pseudo R2	0.213	0.287	0.227	0.258	0.225	0.102	0.169	0.247	0.245

Note: This table reports the results from regressing *adoption in use* for each technology on the composite indices of the three groups of reasons. The technologies in columns (1)–(9) are cloud computing, robot, 3D printing, augmented reality, modelling, the Internet of Things, cyber security, big data, and integrated system, respectively. The models are estimated from logit, and the coefficients reported are the marginal effects. The variables of interest are the *lower* barriers. Robust standard errors are in parentheses.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 12
Difference of adoption in use between high and low barrier firms.

	(1)	(2)	(3)	(4)	(5)	(6)
Lower barriers	0.002	0.151***	0.168***	−0.003	0.154***	0.166***
	(0.025)	(0.016)	(0.015)	(0.029)	(0.018)	(0.018)
POmean High barriers	0.404***	0.293***	0.281***	0.361***	0.242***	0.234***
	(0.022)	(0.012)	(0.011)	(0.026)	(0.013)	(0.012)
Outcome model	Yes	Yes	Yes	Yes	Yes	Yes
Treatment model	Yes	Yes	Yes	Yes	Yes	Yes
Obs. level-0	1949	1949	1991	1330	1325	1339
Outcome mean level-0	0.305	0.267	0.265	0.261	0.223	0.220
Obs. level-1	1948	1948	1906	1322	1327	1313
Outcome mean level-1	0.406	0.444	0.450	0.358	0.396	0.400

Note: This table reports the results from IPWRA with the outcome being *adoption in use*. The treatment variables are the composite barriers reported by the firms, including financial (models (1) and (4)), human capacity (models (2) and (5)), and practicality barriers (models (3) and (6)). The first three models use full sample, while the last three use sample. Robust standard errors are in parentheses.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

adoption of ubiquitous technologies such as cloud computing and cybersecurity, its impact is less pronounced for more specialised 4IR technologies. This suggests that, for advanced, industry-specific applications, targeted IT expertise is more crucial than a broad base of highly educated employees, highlighting the heterogeneous skill requirements across different technologies. Moreover, while this may seem straightforward, our results empirically support the finding of Rauch et al. (2019) that more user-friendly and less complex technologies are more likely to be adopted.

Moreover, the perceived practicality of 4IR technologies, particularly their anticipated positive effects on competitiveness and profit, play a vital role in driving adoption, confirming findings from previous studies on strategic benefits (Chatterjee et al., 2021; Ghobakhloo and Ching, 2019; Horvath and Szabo, 2019; Prause, 2019). However, an intriguing nuance arises for advanced robots and 3D printing, where a higher perception of market competition is associated with lower adoption. This is similar to the results of Oke and Arowoiya (2022) for augmented reality in Nigeria. The au- thors argue that various factors – from lack of technological awareness to difficulty in system set-up and unwillingness to invest in research – discourage firms from adopting. Additionally, they find that the opinions of respondents on this technology varied greatly, which may also contribute to the uncertainty around it. This finding reflects the highly disruptive nature of these specific technologies, where perceived competitive pressure effectuates caution owing to high investment costs, complexity, or radical organisational changes rather than immediate adoption. This suggests that, for certain transformative technologies, the perceived risks or challenges temporarily outweigh the perceived benefits.

Our study's methodological approach, including the techniques to estimate causal ef- fects, directly addresses a significant gap in the existing literature concerning the lack of causal understanding of technology adoption. By demonstrating that lowering human resource and practicality barriers causally leads to higher adoption rates, we provide in- sights for policymakers. By constructing composite barrier variables, we examine the interactions among barriers affecting firms' behaviours. The observed negative interaction effects among certain barriers, where addressing one barrier may reduce the positive impact of lowering another, suggest a complex interplay, indicating that firms with higher overall readiness become more selective in their technology choices. Furthermore, our in-depth analysis of adoption intensity across multiple technologies and sectors, rather than relying solely on aggregated or binary measures, offers a comprehensive and nuanced picture of firms' adoption behaviours. This multi-dimensional measurement, coupled with our focus on a developing country such as Vietnam, provides valuable comparative evidence and extends the generalisability of findings beyond the current developed-country-centric literature (Raj et al., 2020).

7. Conclusion

This study examines the determinants of 4IR technology adoption among firms in Vietnam, focusing on three commonly reported barriers: financial constraints, human resource limitations, and perceived practicality. By combining disaggregated measures of adoption, firm-level survey data, and rigorous econometric techniques, including causal estimation, we provide a more nuanced understanding of technology uptake in a developing country context.

Contrary to common assumptions in the literature, our findings show that financial ca- pacity does not significantly influence adoption decisions. In contrast, human resource factors, particularly IT capacity, emerge as robust predictors of adoption across aggregated and individual technologies. Moreover, firms' perceptions of practical benefits, especially with respect to competitiveness and profitability, play a vital role. However, this relationship weakens or reverses for highly disruptive technologies such as advanced robotics and 3D printing, where perceived competition is associated with lower adoption. Additionally, our causal analysis confirms that reducing human resource and practicality barriers significantly increases adoption, whereas lowering financial barriers does not.

These findings make several contributions to the literature. First, they shift the focus away from affordability as the primary constraint and towards internal capability and perceived strategic value. Second, they provide empirical insights into how firms respond differently to distinct types of 4IR technologies. Third, they highlight the need for targeted policy interventions that strengthen digital skills and reshape firms' perceptions about technological utility. Finally, this study offers a methodological contribution by measuring adoption intensity and identifying causal effects in a developing economy setting, expanding the generalisability of prior research.

Future research should explore the role of managerial decision-making, particularly in small and medium enterprises, and identify effective ways to improve firms' perceptions of technological relevance. Additionally, cross-country comparisons can explicate how local context shapes adoption practices.

In sum, understanding the true barriers to 4IR adoption is crucial for designing effective interventions. Our findings underscore that addressing skill gaps and enhancing the perceived value of technologies, not simply providing financial subsidies, will be the key to accelerate digital transformation and foster inclusive economic growth in the 4IR era.

CRediT authorship contribution statement

Chinh Hoang-Duc: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Kien Hoang-Le:** Writing – review &

editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Tuan Nguyen-Anh:** Supervision, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Linh Nguyen-Thi-Thuy**: Data curation, Methodology, Formal analysis, Writing – final draft. **Uyen Nguyen-Dinh:** Formal analysis, Data curation, Conceptualization. **Huong Nguyen-Thi-Lan:** Resources, Investigation, Conceptualization. **Nguyen To-The:** Validation, Supervision, Investigation, Data curation, Conceptualization.

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Declaration of competing interest

The authors declare no conflict of interest.

Appendix A

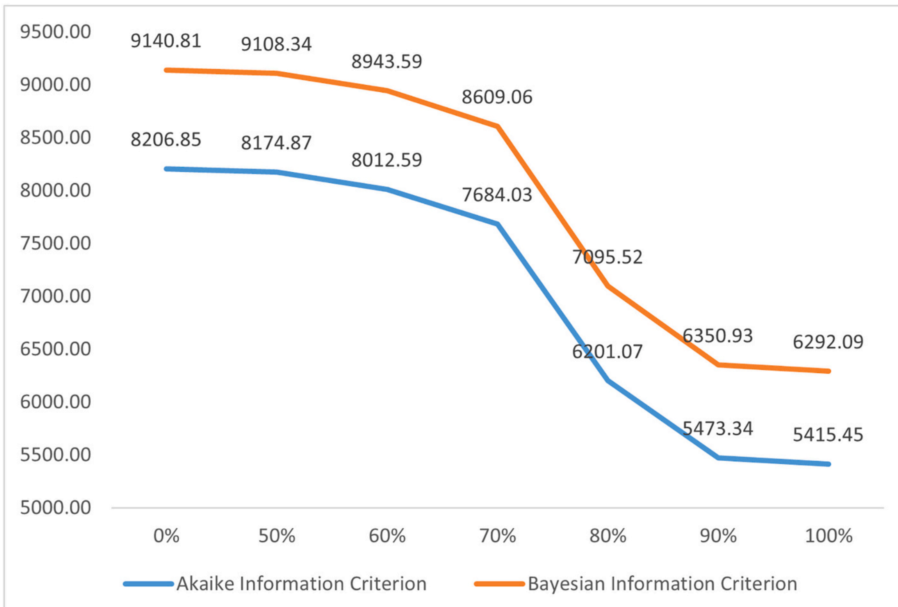

Fig. A1. Reported log-likelihood for each threshold of relevance.

Table A1
Baseline models for different measures of adoption.

	(1)		(2)		(3)	
ROE	0.005*	(0.003)	0.012	(0.010)	0.015*	(0.009)
Debt-to-Equity	0.001*	(0.000)	0.001***	(0.000)	0.000**	(0.000)
Asset	−0.111***	(0.035)	−0.532***	(0.152)	−0.063	(0.119)
Asset-sqr	0.007***	(0.002)	0.031***	(0.007)	0.010*	(0.005)
Labour	0.057***	(0.022)	0.261***	(0.097)	0.147*	(0.085)
Labour-sqr	−0.005*	(0.002)	−0.023**	(0.011)	−0.010	(0.009)
Firm age	−0.002	(0.001)	−0.008	(0.006)	−0.008*	(0.005)
R&D investment	−0.005	(0.012)	0.031	(0.049)	−0.028	(0.036)
Intangible asset	0.017	(0.014)	0.147**	(0.069)	0.049	(0.039)
Education costs	0.041**	(0.018)	0.161**	(0.071)	0.109***	(0.040)
Int'l trade	0.004	(0.003)	0.028**	(0.012)	0.005	(0.011)
Type FE	No		Yes		Yes	
Province FE	No		Yes		Yes	
Sector FE	No		Yes		Yes	
Observations	3897		3897		3897	
Mean outcome	1.000		2.135		0.898	
Chi-2	458.66		587.530		1044.345	
Pseudo R2	0.109		0.070		0.139	

Note: This table reports the results from regressing the adoption measures on the control variables. The dependent variables in models are *adopted in use*, *maximum adoption*, and *number of techs adopted*. The models are estimated from logit, ologit, and Poisson (STATA), respectively. The coefficients reported for logit and ologit are the marginal effects and log odd-ratios, respectively. Robust standard errors are in parentheses.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A2
Determinants of each technology level of adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquidity	−0.046	−0.063	−0.029	−0.019	−0.050	−0.017	−0.000	−0.044	−0.014
	(0.035)	(0.059)	(0.056)	(0.060)	(0.051)	(0.029)	(0.029)	(0.038)	(0.039)
Quick ratio	−0.000	−0.000	0.000	0.000	0.001***	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Undergrads.	0.007***	−0.005	−0.001	−0.002	−0.001	0.000	0.003	0.004*	0.001
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
IT capacity	0.264***	0.438***	0.391***	0.501***	0.439***	0.205***	0.279***	0.385***	0.400***
	(0.027)	(0.057)	(0.048)	(0.059)	(0.045)	(0.022)	(0.022)	(0.031)	(0.031)
Competitiveness effect	0.093**	−0.149**	−0.110*	−0.012	0.036	0.103***	0.121***	0.166***	0.138***
	(0.039)	(0.075)	(0.062)	(0.072)	(0.060)	(0.032)	(0.033)	(0.048)	(0.047)
Profit effect	0.119**	0.477***	0.336***	0.363***	0.436***	0.143***	0.200***	0.229***	0.213***
	(0.049)	(0.102)	(0.080)	(0.096)	(0.079)	(0.038)	(0.041)	(0.056)	(0.057)
Organisation effect	−0.004	−0.030	−0.046	−0.030	−0.141**	0.006	−0.056	−0.041	−0.071
	(0.044)	(0.069)	(0.067)	(0.069)	(0.061)	(0.037)	(0.037)	(0.047)	(0.047)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3353	3108	2979	3037	3102	3454	3579	3352	3360
Mean outcome	1.501	1.143	1.159	1.112	1.170	1.702	1.747	1.390	1.396
Chi-2	5543.911	.	25,157.210	24,568.928	23,318.266	462.449	708.844	9496.544	4775.507
Pseudo R2	0.161	0.282	0.199	0.232	0.197	0.078	0.133	0.185	0.184

Note: This table reports the results from regressing *maximum adoption* for each technology on all three groups of reasons. The technologies in columns (1)–(9) are cloud computing, robot, 3D printing, augmented reality, modelling, the Internet of Things, cyber security, big data, and integrated system, respectively. The models are estimated from ologit, and the coefficients reported are log odd-ratios. Robust standard errors are in parentheses.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A3
Determinants of relevant technological adoption by different measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquidity	−0.006			−0.037			−0.032		
	(0.006)			(0.030)			(0.028)		
Quick ratio	−0.000			−0.000			0.000		
	(0.000)			(0.000)			(0.000)		
% Undergrads.		0.000			0.003			0.002	
		(0.000)			(0.002)			(0.002)	
IT capacity		0.050***			0.306***			0.304***	
		(0.004)	0.025***		(0.022)	0.177***		(0.018)	
Competitiveness effect									0.039
			(0.007)			(0.035)			(0.031)
Profit effect			0.038***			0.167***			0.246***
			(0.008)			(0.041)			(0.038)
Organisation effect			−0.008			−0.007			−0.038
			(0.008)			(0.039)			(0.031)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2635	2635	2635	2652	2652	2652	2652	2652	2652
Mean outcome	1.000	1.000	1.000	2.001	2.001	2.001	0.833	0.833	0.833
Chi-2	354.49	474.06	405.70	2151.755	2096.123	2079.551	3870.230	4886.594	4064.079
Pseudo R2	0.132	0.180	0.150	0.083	0.120	0.098	0.172	0.250	0.196

Note: This table reports the results from regressing the adoption measures on each group of reasons. This sample has all the firms reporting a technology as relevant, while other firms in the same sub-sector reports are excluded. The dependent variables in models are *adopted in use* (models (1)–(3)), *maximum adoption* (models (4)–(6)), and *number of techs adopted* (models (7)–(9)), with models being estimated from logit, ologit, and Poisson (STATA), respectively. The coefficients reported for logit and ologit are the marginal effects and log odd-ratios, respectively. Robust standard errors are in parentheses.
Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4
Determinants of each relevant technology level of adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquidity	−0.021	−0.123*	−0.024	−0.048	−0.113*	−0.019	−0.025	−0.051	−0.017
	(0.043)	(0.069)	(0.063)	(0.063)	(0.059)	(0.035)	(0.036)	(0.047)	(0.049)
Quick ratio	−0.000	−0.000	−0.000	0.000	0.000*	−0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

(*continued on next page*)

Table A4 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Undergrads.	0.005*	−0.007	−0.007	−0.006	−0.006	−0.001	0.003	0.009***	0.003
	(0.003)	(0.006)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.003)
IT capacity	0.328***	0.515***	0.449***	0.525***	0.488***	0.272***	0.340***	0.397***	0.424***
	(0.035)	(0.074)	(0.061)	(0.068)	(0.055)	(0.028)	(0.028)	(0.039)	(0.039)
Competitiveness effect	0.100**	−0.123	−0.102	0.012	0.060	0.164***	0.091**	0.173***	0.164***
	(0.050)	(0.086)	(0.071)	(0.082)	(0.074)	(0.041)	(0.040)	(0.056)	(0.058)
Profit effect	0.083	0.400***	0.343***	0.305***	0.378***	0.154***	0.199***	0.221***	0.154**
	(0.062)	(0.115)	(0.098)	(0.108)	(0.091)	(0.047)	(0.052)	(0.069)	(0.072)
Organisation effect	0.009	−0.038	−0.066	−0.062	−0.162**	−0.015	−0.102**	−0.036	−0.057
	(0.057)	(0.087)	(0.083)	(0.080)	(0.073)	(0.045)	(0.048)	(0.059)	(0.059)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2652.000	2652.000	2652.000	2652.000	2652.000	2652.000	2652.000	2652.000	2652.000
Mean outcome	1.399	1.111	1.126	1.100	1.133	1.558	1.639	1.324	1.316
Chi-2	14,393.634	33,077.391	23,673.091	24,711.033	29,306.440	8295.588	5858.282	15,050.469	15,765.730
Pseudo R2	0.188	0.302	0.229	0.251	0.226	0.110	0.156	0.208	0.199

Note: This table reports the results from regressing *maximum adoption* for each technology on all three groups of reasons. This sample has all the firms reporting a technology as relevant, while other firms in the same sub-sector report dropped. The technologies in columns (1)–(9) are cloud computing, robot, 3D printing, augmented reality, modelling, the Internet of Things, cyber security, big data, and integrated system, respectively. The models are estimated from ologit, and the coefficients reported are log odd-ratios. Robust standard errors are in parentheses.

* $p < 0.10$

** $p < 0.05$.

*** $p < 0.01$.

Table A5

Composite determinants of each technology level of adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Finance barriers	−0.090	−0.089	−0.030	−0.053	0.007	−0.002	0.010	−0.007	0.033
	(0.080)	(0.106)	(0.088)	(0.096)	(0.067)	(0.040)	(0.041)	(0.062)	(0.052)
Human barriers	0.548***	0.596***	0.641***	0.684***	0.650***	0.343***	0.514***	0.655***	0.603***
	(0.054)	(0.111)	(0.089)	(0.112)	(0.083)	(0.045)	(0.047)	(0.062)	(0.061)
Practicality barriers	0.194***	0.310***	0.221***	0.295***	0.302***	0.230***	0.237***	0.308***	0.240***
	(0.041)	(0.074)	(0.062)	(0.084)	(0.066)	(0.032)	(0.033)	(0.048)	(0.043)
Finance × Human barriers	−0.019	0.096	−0.048	0.013	0.085	0.044	0.026	0.052	0.030
	(0.060)	(0.128)	(0.102)	(0.108)	(0.075)	(0.043)	(0.044)	(0.060)	(0.054)
Finance × Practicality barriers	−0.058	−0.076*	−0.097**	−0.072	−0.030	−0.030*	−0.012	−0.032	−0.039*
	(0.044)	(0.045)	(0.042)	(0.048)	(0.021)	(0.016)	(0.021)	(0.029)	(0.023)
Human × Practicality barriers	−0.012	−0.021	−0.059	0.030	−0.023	−0.026	−0.036	0.012	0.042
	(0.034)	(0.068)	(0.048)	(0.066)	(0.052)	(0.028)	(0.030)	(0.041)	(0.038)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3353.000	3108.000	2979.000	3037.000	3102.000	3454.000	3579.000	3352.000	3360.000
Mean outcome	1.501	1.143	1.159	1.112	1.170	1.702	1.747	1.390	1.396
Chi-2	5327.623	46,481.752	31,892.583	27,964.388	25,428.871	417.727	655.666	9929.782	5550.679
Pseudo R2	0.156	0.250	0.177	0.202	0.166	0.071	0.122	0.169	0.164

Note: This table reports the results from regressing *maximum adoption* for each technology on the composite indices of three groups of reasons. The technologies in columns (1)–(9) are cloud computing, robot, 3D printing, augmented reality, modelling, the Internet of Things, cyber security, big data, and integrated system, respectively. The models are estimated from ologit, and the coefficients reported are log odd-ratios. The variables of interest are the *lower* barriers. Robust standard errors are in parentheses.

* $p < 0.10$.

** $p < 0.05$

*** $p < 0.01$.

Table A6

Composite determinants of each relevant technology adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Finance barriers	−0.003	−0.008	0.001	−0.006	−0.005	−0.008	−0.005	−0.005	0.007
	(0.009)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)	(0.007)
Human barriers	0.060***	0.039***	0.042***	0.042***	0.043***	0.056***	0.086***	0.071***	0.072***
	(0.007)	(0.009)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
Practicality barriers	0.016***	0.008	0.011**	0.006	0.014**	0.032***	0.021***	0.023***	0.016***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Finance × Human barriers	0.002	0.012	0.003	0.004	0.003	0.004	0.006	0.006	−0.008
	(0.009)	(0.010)	(0.009)	(0.006)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)

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Table A6 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Finance × Practicality barriers	−0.007	−0.003*	−0.008*	−0.004	−0.004	−0.012**	−0.007	−0.007*	−0.007*
	(0.005)	(0.002)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Human × Practicality barriers	−0.001	−0.000	−0.009**	0.003	−0.008*	−0.003	−0.008	−0.002	0.005
	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2456	1265	1452	1317	1457	2538	2538	2251	2176
Mean outcome	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chi-2	465.75	191.52	213.96	238.02	219.12	297.97	432.64	1484.86	375.53
Pseudo R2	0.244	0.293	0.228	0.256	0.240	0.128	0.194	0.283	0.269

Note: This table reports the results from regressing *adopted in use* for each technology on the composite indices of three groups of reasons. This sample has all the firms reporting a technology as relevant, while other firms in the same sub-sector report dropped. The technologies in columns (1)–(9) are cloud computing, robot, 3D printing, augmented reality, modelling, the Internet of Things, cyber security, big data, and integrated system, respectively. The models are estimated from logit, and the coefficients reported are the marginal effects. The variables of interest are the *lower* barriers. Robust standard errors are in parentheses.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A7
Composite determinants of each relevant technology level of adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Finance barriers	−0.057	−0.159	−0.066	−0.085	−0.072	0.005	−0.013	−0.011	0.040
	(0.082)	(0.121)	(0.100)	(0.098)	(0.084)	(0.048)	(0.053)	(0.070)	(0.060)
Human barriers	0.613***	0.625***	0.653***	0.681***	0.646***	0.447***	0.611***	0.769***	0.682***
	(0.071)	(0.130)	(0.103)	(0.120)	(0.098)	(0.056)	(0.058)	(0.078)	(0.075)
Practicality barriers	0.179***	0.276***	0.236***	0.276***	0.298***	0.269***	0.174***	0.314***	0.216***
	(0.051)	(0.094)	(0.070)	(0.082)	(0.080)	(0.041)	(0.041)	(0.060)	(0.052)
Finance × Human barriers	−0.002	0.181	−0.040	0.038	0.133	0.035	0.065	0.075	0.046
	(0.079)	(0.159)	(0.129)	(0.123)	(0.093)	(0.053)	(0.060)	(0.083)	(0.070)
Finance × Practicality barriers	−0.061	−0.078*	−0.126**	−0.070	−0.023	−0.044***	−0.020	−0.038*	−0.038*
	(0.040)	(0.043)	(0.053)	(0.052)	(0.029)	(0.016)	(0.021)	(0.023)	(0.022)
Human × Practicality barriers	0.013	−0.013	−0.089	−0.034	−0.093	−0.026	−0.022	0.002	0.055
	(0.043)	(0.084)	(0.054)	(0.062)	(0.062)	(0.036)	(0.037)	(0.051)	(0.047)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2652.000	2652.000	2652.000	2652.000	2652.000	2652.000	2652.000	2652.000	2652.000
Mean outcome	1.399	1.111	1.126	1.100	1.133	1.558	1.639	1.324	1.316
Chi-2	15,409.870	43,487.065	26,358.152	28,195.822	31,089.268	8456.873	6615.857	14,832.536	15,833.650
Pseudo R2	0.180	0.267	0.200	0.216	0.187	0.097	0.141	0.196	0.181

Note: This table reports the results from regressing *maximum adoption* for each technology on the composite indices of three groups of reasons. This sample has all the firms reporting a technology as relevant, while other firms in the same sub-sector report dropped. The technologies in columns (1)–(9) are cloud computing, robot, 3D printing, augmented reality, modelling, the Internet of Things, cyber security, big data, and integrated system, respectively. The models are estimated from ologit, and the coefficients reported are the log odd-ratios. The variables of interest are the *lower* barriers. Robust standard errors in parentheses.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A8
Marginal effects of composite barriers for each level of adoption.

	Not adopted	R&D for trial	In trial	Adopted	Up-scaling
Panel A: Full sample					
Finance barriers	0.008	0.000	0.000	−0.006	−0.001
	(0.008)	(0.000)	(0.000)	(0.006)	(0.001)
Human barriers	−0.089	0.005	0.004	0.069	0.011
	(0.007)***	(0.001)***	(0.000)***	(0.006)***	(0.001)***
Practicality barriers	−0.048	0.003	0.002	0.037	0.006
	(0.005)***	(0.000)***	(0.000)***	(0.004)***	(0.001)***
Finance × Human barriers	−0.006	0.000	0.000	0.005	0.001
	(0.008)	(0.000)	(0.000)	(0.006)	(0.001)
Finance × Practicality barriers	0.003	0.000	0.000	−0.002	0.000
	(0.004)	(0.000)	(0.000)	(0.003)	(0.001)
Human × Practicality barriers	0.010	−0.001	0.000	−0.008	−0.001
	(0.005)*	(0.000)**	(0.000)*	(0.004)*	(0.001)*

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Table A8 (*continued*)

	Not adopted	R&D for trial	In trial	Adopted	Up-scaling
Panel B: Relevant sample					
Finance barriers	0.006	−0.001	0.000	−0.005	−0.001
	(0.008)	(0.001)	(0.000)	(0.006)	(0.001)
Human barriers	−0.100	0.009	0.005	0.074	0.012
	(0.009)***	(0.001)***	(0.001)***	(0.007)***	(0.002)***
Practicality barriers	−0.039	0.003	0.002	0.029	0.005
	(0.006)***	(0.001)***	(0.000)***	(0.005)***	(0.001)***
Finance × Human barriers	−0.011	0.001	0.001	0.008	0.001
	(0.010)	(0.001)	(0.000)	(0.007)	(0.001)
Finance × Practicality barriers	0.006	−0.001	0.000	−0.004	−0.001
	(0.004)	(0.000)	(0.000)	(0.003)	(0.000)
Human × Practicality barriers	0.007	−0.001	0.000	−0.006	−0.001
	(0.006)	(0.001)	(0.000)	(0.004)	(0.001)

Note: This table reports the marginal effects from regressing *maximum adoption* on all three groups of composite barriers and their interactive terms as presented in models (2) and (5) (Table 10). Panel A uses the full sample, while panel B uses the *relevant* sample. Robust standard errors are in parentheses.

[*] $p < 0.10$.

[**] $p < 0.05$.

[***] $p < 0.01$.

Table A9

Difference of level of adoption between high and low barrier firms.

	(1)	(2)	(3)	(4)	(5)	(6)
Lower barriers	−0.011	0.505***	0.552***	0.001	0.500***	0.534***
	(0.081)	(0.047)	(0.044)	(0.083)	(0.054)	(0.052)
POmean	2.299***	1.922***	1.894***	2.152***	1.782***	1.762***
High barriers						
	(0.075)	(0.035)	(0.031)	(0.074)	(0.040)	(0.036)
Outcome model	Yes	Yes	Yes	Yes	Yes	Yes
Treatment model	Yes	Yes	Yes	Yes	Yes	Yes
Obs. level-0	1949	1949	1991	1330	1325	1339
Outcome mean level-0	1.983	1.844	1.838	1.850	1.720	1.712
Obs. level-1	1948	1948	1906	1322	1327	1313
Outcome mean level-1	2.287	2.427	2.446	2.154	2.282	2.296

Note: This table reports the results from IPWRA with the outcome being *maximum adoption*. The treatment variables are the composite barriers reported by the firms, including financial (models (1) and (4)), human capacity (models (2) and (5)), and practicality barriers (models (3) and (6)). The first three models use full sample, while the last three use sample. Robust standard errors are in parentheses.

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10

Difference of number of adopted technologies between high and low barrier firms.

	(1)	(2)	(3)	(4)	(5)	(6)
Lower barriers	−0.017	0.745***	0.608***	0.102	0.757***	0.569***
	(0.160)	(0.053)	(0.053)	(0.108)	(0.066)	(0.066)
POmean	1.121***	0.560***	0.631***	0.930***	0.487***	0.574***
High barriers						
	(0.156)	(0.030)	(0.033)	(0.096)	(0.036)	(0.041)
Outcome model	Yes	Yes	Yes	Yes	Yes	Yes
Treatment model	Yes	Yes	Yes	Yes	Yes	Yes
Obs. level-0	1949	1949	1991	1330	1325	1339
Outcome mean level-0	0.694	0.492	0.573	0.635	0.422	0.529
Obs. level-1	1948	1948	1906	1322	1327	1313
Outcome mean level-1	1.103	1.305	1.238	1.033	1.244	1.143

Note: This table reports the results from IPWRA with the outcome being *number of techs adopted*. The treatment variables are the composite barriers reported by the firms, including financial (models (1) and (4)), human capacity (models (2) and (5)), and practicality barriers (models (3) and (6)). The first three models use full sample, while the last three use sample. Robust standard errors are in parentheses.

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Data availability

Data will be made available on request.

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