

Digital Adoption and Labor Productivity in Thai Enterprises: A Quantile Regression Analysis from the World Bank Enterprise Survey 2025

Wittawat Kadthan*

Received April 21st, 2026
Revised September 7th, 2026
Accepted September 10th, 2026

Abstract

This study examines the relationship between digital technology adoption and labor productivity among Thai enterprises, using the World Bank Enterprise Survey (WBES) Thailand 2025 (813 firms). We estimate log labor-productivity equations using OLS and Quantile Regression (Q10–Q90), decomposing digital adoption into three pillars: Infrastructure (D1), Transaction (D2), and Integration (D3). The aggregate Digital Total Score is positively associated with labor productivity ($\beta = 0.119$, $p < 0.01$), equivalent to a 12.6 percent difference per one-point increase. This association varies across the productivity distribution: lower-to-middle quantile firms (Q10–Q50) associate more strongly with basic infrastructure, while upper-quantile firms (Q75–Q90) associate more strongly with integration — a digital-ladder-type pattern interpreted cautiously given the cross-sectional data. The interaction between the digital score and firm size is negative and significant ($\beta = -0.083$, $p < 0.01$), indicating a comparatively stronger association among smaller firms. As the data are cross-sectional, findings should be read as associations rather than causal effects. Results carry policy relevance for Thailand's digital transition, suggesting differentiated support instruments matched to firms' productivity position may outperform a uniform approach. The paper contributes by decomposing digital adoption into three pillars and documenting heterogeneous digital-productivity associations across the distribution.

Keywords: Digital technology adoption, Labor productivity, Quantile regression, Thai enterprises, World Bank Enterprise Survey

* Lecturer of School of Economics and Investment, Bangkok University E-mail: wittawat.k@bu.ac.th

การนำเทคโนโลยีดิจิทัลมาประยุกต์ใช้และผลผลิตภาพแรงงานในวิสาหกิจไทย:
การวิเคราะห์การถดถอยเชิงควอนไทล์จากการสำรวจวิสาหกิจ
ของธนาคารโลก พ.ศ. 2568

วิทวัส ขัดทาน*

รับวันที่ 21 เมษายน 2569
แก้ไขวันที่ 7 กันยายน 2569
ตอบรับตีพิมพ์วันที่ 10 กันยายน 2569

บทคัดย่อ

การวิจัยนี้ศึกษาความสัมพันธ์ระหว่างการนำเทคโนโลยีดิจิทัลมาใช้ในสามมิติ ได้แก่ โครงสร้างพื้นฐาน ธุรกิจ และการบูรณาการ กับผลผลิตภาพแรงงานของวิสาหกิจไทย โดยใช้ข้อมูลการสำรวจวิสาหกิจของธนาคารโลก (WBES) ประเทศไทย พ.ศ. 2568 จำนวน 813 แห่ง ประเมินค่าด้วย OLS และการถดถอยเชิงควอนไทล์

ผลการวิจัยพบว่าคะแนนรวมการนำดิจิทัลมาใช้สัมพันธ์เชิงบวกกับผลผลิตภาพแรงงาน ($\beta = 0.119$, $p < 0.01$) คิดเป็นส่วนต่างประมาณร้อยละ 12.6 ต่อคะแนนที่เพิ่มขึ้นหนึ่งหน่วย และความสัมพันธ์แตกต่างกันตามควอนไทล์ ระดับล่างถึงกลางสัมพันธ์กับโครงสร้างพื้นฐานดิจิทัลมากกว่า ขณะที่ระดับบนสัมพันธ์กับการบูรณาการดิจิทัลมากกว่า สะท้อนลักษณะคล้ายบันไดดิจิทัล สัมพันธ์กับขนาดวิสาหกิจเป็นลบ ($\beta = -0.083$, $p < 0.01$) โดยเด่นชัดกว่าในวิสาหกิจขนาดเล็ก

ผลการศึกษามีนัยสำคัญเชิงนโยบายต่อการเปลี่ยนผ่านสู่เศรษฐกิจดิจิทัลของไทย มาตรการส่งเสริมที่แตกต่างกันตามควอนไทล์ผลผลิตภาพและขนาดวิสาหกิจอาจเหมาะสมกว่านโยบายเดียวสำหรับทุกกลุ่ม และงานวิจัยนี้ขยายองค์ความรู้ด้านเศรษฐกิจดิจิทัลในบริบทไทย

คำสำคัญ: การนำเทคโนโลยีดิจิทัลมาใช้, ผลผลิตภาพแรงงาน, การถดถอยเชิงควอนไทล์, วิสาหกิจไทย, การสำรวจวิสาหกิจโลกของธนาคารโลก

1. Introduction

The transition to a digital economy has emerged as a key driver of firm-level labor productivity over the past two decades in both advanced and developing countries. Microeconomic evidence consistently shows that investments in information and communication technology (ICT) raise firm productivity in meaningful ways. Brynjolfsson and Hitt (1996) were among the first to document that the gross marginal product of computer capital averaged approximately 81 percent among large U.S. firms, effectively resolving the "IT productivity paradox" at the firm level. Subsequent evidence has reinforced this conclusion for both labor productivity and total factor productivity across measurement approaches and country settings (Cardona, Kretschmer, & Strobel, 2013; Oduro, De Nisco, & Mainolfi, 2023). In the aftermath of the COVID-19 pandemic, digital adoption accelerated sharply across many economies. Jaumotte et al. (2023) document that firms with higher pre-pandemic digitalization levels maintained productivity and hours worked more effectively during the crisis and recovered more strongly afterwards.

Thailand is in the midst of a consequential digital transition under the Thailand 4.0 strategy and its broader path toward high-income status. The World Bank's Thailand Economic Monitor (World Bank, 2025) notes that while mobile internet access is now nearly universal, substantial gaps remain in fixed broadband penetration, advanced digital skills, and data-center infrastructure for enterprises. The most recent Digital Density Survey conducted by the Digital Economy Promotion Agency (depa, 2025) finds that seventy percent of sampled industrial firms sit at Industry 2.0, still distant from the Industry 4.0 target that policy seeks to reach within five years. These trajectories imply that the 2025 data collection window captures Thai enterprises in a transitional phase, where measuring digital adoption carries particular policy salience.

The broader literature on digital adoption in developing countries consistently reports a positive link with firm productivity. Cusolito, Lederman, and Peña (2020) use WBES data from 82 developing economies and estimate median TFP premiums of 1.6 percent for email adoption and 2.2 percent for website adoption. Commander, Harrison, and Menezes-Filho (2011) report similar findings for Brazil and India, emphasizing that institutional context and infrastructure quality moderate the intensity of the effect. At the ASEAN level, Guindo and Harjito (2025) show that the digital-productivity relationship differs structurally between catching-up ASEAN-10 economies and more advanced ASEAN-6 economies that include Thailand, where frontier innovation increasingly drives productivity. For Thai small and medium enterprises specifically, Jongwanich and Kohpaiboon (2025) find that transactional digital uses — e-commerce, online purchasing, and digital payments — deliver significant performance gains, whereas mere internet access without commercial integration yields limited benefits.

Much of the existing literature, however, measures digital adoption as a single aggregate or a binary indicator and focuses on average effects. A growing recent strand suggests that the effects of digital technologies are distributed unevenly across the population of firms. Gómez-Bengoechea and Jung (2024) present evidence of a "Matthew Effect" in which more productive firms extract larger gains from digitalization than less productive firms, thereby widening productivity dispersion. Gal et al. (2019) document a parallel pattern across EU economies, showing that effects concentrate among high-productivity firms and weaken in the presence of skill shortages. These findings motivate methodological approaches that explicitly examine the conditional distribution of outcomes — most prominently Quantile Regression (Koenker & Bassett, 1978; Koenker & Hallock, 2001) — to uncover heterogeneity that mean-based OLS regressions obscure.

An important gap in the current literature is the absence of studies that decompose digital adoption into pillars reflecting a developmental ladder of digital maturity and simultaneously test effect heterogeneity across the productivity distribution in a developing-country context. The "technology ladder" framework articulated by Cirera and Maloney (2017) proposes that firm-level technology adoption proceeds through ordered stages — from basic infrastructure, through operational use, to frontier integration — each demanding progressively greater internal capabilities. Bringing this conceptual framework to firm-level data from Thailand and testing it through a quantile-based empirical design represents an opportunity to make both a theoretical and an empirical contribution that carries direct policy relevance.

This paper therefore pursues three objectives. First, to estimate the overall relationship between digital adoption and labor productivity in Thai enterprises. Second, to examine the heterogeneous effects of three digital pillars — Infrastructure, Transaction, and Integration — on productivity. Third, to test effect heterogeneity across the productivity distribution using Quantile Regression. The study draws on the WBES Thailand 2025, covering 813 firms in the first wave capturing the post-pandemic structural shift in Thailand's digital economy. The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 details the data and methodology. Section 4 presents the empirical results. Section 5 discusses the findings in light of the literature. Section 6 concludes with policy implications.

2. Literature Review

2.1 Digital Adoption and Firm Productivity: Theoretical Foundations and Empirical Evidence

Brynjolfsson and Hitt (1996) pioneered the resolution of the IT productivity paradox at the firm level. Using data on 367 large U.S. firms between 1987 and 1991, they estimated that the gross marginal product of computer capital averaged 81 percent, matching or exceeding the marginal product of other forms of capital. Their subsequent work (Brynjolfsson & Hitt, 2000) extended this conclusion by arguing that the full productivity value of IT emerges only when firms co-invest in complementary organizational assets — business process redesign, decentralized decision rights, and worker skill upgrading. This complementarity framework now forms the conceptual foundation of contemporary work on the digital economy and firm productivity.

Cross-study evidence converges on the same direction of effect. Cardona et al. (2013) provide a comprehensive survey of the empirical ICT-productivity literature and conclude that effects are positive on balance, though with considerable variation across measurement methods, sectors, and country contexts. More recently, Oduro et al. (2023) synthesize 109 studies covering over 1.3 million observations between 2006 and 2021 and report that digital technologies — including artificial intelligence, big data analytics, the Internet of Things, and 3D printing — exert a moderate positive effect on firm performance overall. Effects on innovation performance are the largest, followed by operational efficiency, with financial performance showing the smallest effects.

Syverson (2011) provides the methodological rationale for why average effects alone are insufficient. Within narrowly defined industries, the productivity gap between firms at the 90th and 10th percentiles averages roughly a factor of two — an enduring and substantial dispersion driven by technology use, managerial quality, and human capital. Bartelsman and Doms (2000)

reach similar conclusions in their survey of longitudinal micro-data research, emphasizing that technology use and human capital correlate robustly and persistently with productivity growth. Together, these reviews provide both theoretical and empirical justification for moving beyond mean-based analyses of firm productivity.

Recent quasi-experimental work strengthens confidence in the causal interpretation of digital-productivity effects. Cetté, Nevoux, and Py (2022) use an original Banque de France firm survey and an instrumental variable strategy, finding that employing ICT specialists and using digital technologies raise firm labor productivity by approximately 23 percent and total factor productivity by approximately 17 percent. Jaumotte et al. (2023) further show that pre-pandemic digitalization acted as a buffer for firm productivity and hours worked during the COVID-19 shock. These findings suggest that digital adoption is not only a productivity lever in normal times but also a source of structural resilience under stress.

2.2 Digital Adoption in Developing Economies and the ASEAN Context

Commander et al. (2011) are among the earliest to establish the ICT-productivity link in developing countries using firm-level data. Studying Brazilian and Indian manufacturing firms, they find a positive association between ICT capital and productivity in both countries, while demonstrating that infrastructure quality and labor-market institutions modulate both adoption rates and returns. Hjort and Poulsen (2019) provide causal evidence for this link in a lower-income context, using the staggered arrival of submarine internet cables across twelve African countries as a source of identification. They document significant gains in employment and firm productivity, especially in manufacturing, following the arrival of high-speed internet.

Studies using the World Bank Enterprise Survey add breadth to this evidence base. Cusolito et al. (2020) estimate TFP premiums from ICT adoption across 82 developing economies using a control-function approach to address endogeneity and document median log-TFP premiums of 1.6 percent for email adoption and 2.2 percent for website adoption. Their study — which includes Thailand in earlier waves — has become the benchmark reference for evaluating digital-productivity effects in the developing world, both methodologically and substantively.

Cirera and Maloney (2017), in *The Innovation Paradox*, develop the theoretical framework that underpins much of the contemporary research on technology adoption in developing countries. They argue that low rates of technology adoption in these settings are a rational firm response to binding constraints — limited physical and human capital accumulation, weak firm capabilities, and insufficient state capacity. Their core conceptual contribution is a "capability ladder" in which technology adoption proceeds through ordered stages, each requiring greater absorptive capacity than the last. This framing directly motivates the decomposition of digital adoption into distinct pillars used in the present paper.

In the ASEAN region, Guindo and Harjito (2025) use dynamic panel models for ASEAN-6 and ASEAN-10 economies between 2000 and 2023 and identify an important structural divide. In the catching-up ASEAN-10 group, basic internet access and foreign direct investment drive labor productivity. In the more advanced ASEAN-6 economies — which include Thailand — productivity is increasingly driven by frontier innovation, while broad digital expansion yields diminishing returns. The World Bank's regional assessment (World Bank, 2019, 2025) further documents a persistent gap between consumer-side and business-side digital adoption in

Southeast Asia, attributable to regulatory frictions, trust deficits in electronic transactions, and shortages of advanced digital skills.

2.3 Heterogeneous Effects of Digital Adoption and the Digital Ladder

A growing body of work demonstrates that digital-productivity effects are distributed unevenly across firms. Gómez-Bengoechea and Jung (2024) apply unconditional quantile regression to large firm-level datasets and document a "Matthew Effect" in which firms at higher productivity levels extract disproportionately large gains from digitalization, widening the productivity gap with less productive firms. They caution that in the absence of proactive policy support for laggards, broad digital expansion risks deepening structural inequality among firms rather than narrowing it.

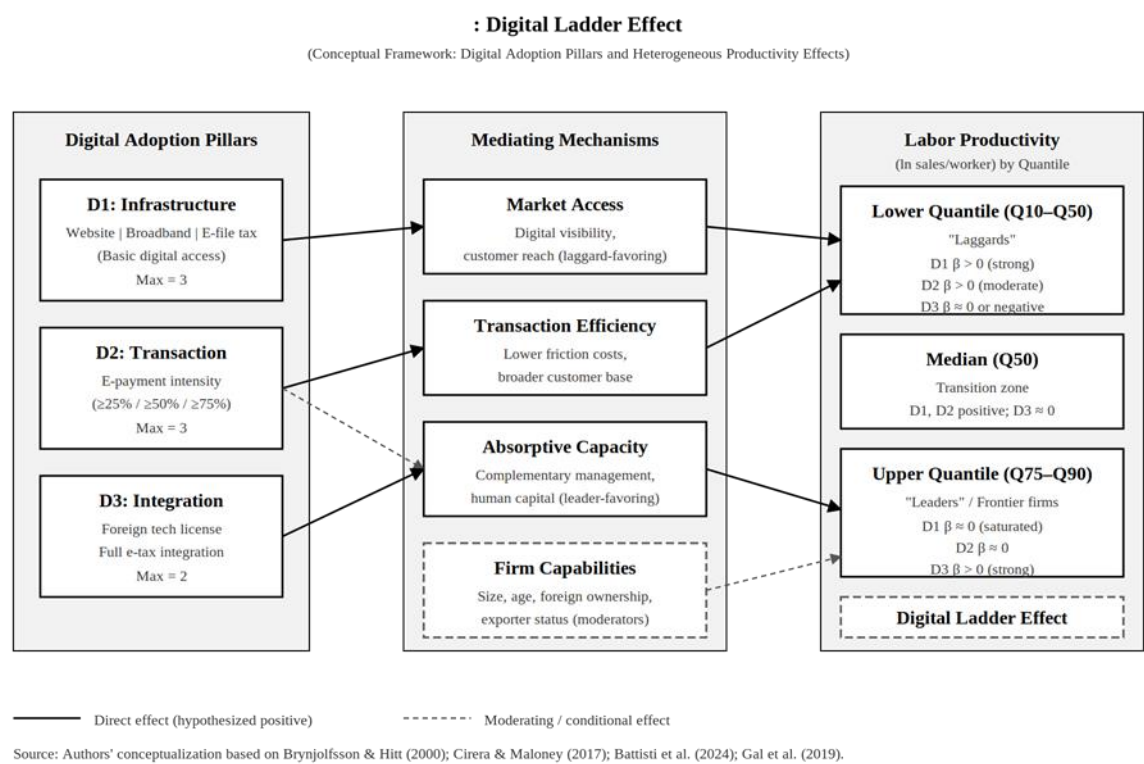
EU-level evidence from Gal et al. (2019) reinforces this pattern. Drawing on firm-level data from 19 EU countries plus Turkey, they find that digital effects on firm productivity are stronger for high-productivity firms and weaker where skill shortages are binding. Brambilla and Tortarolo (2018) apply an instrumental-variable strategy to Argentine manufacturing firms and find that ICT effects on productivity and wages are 12–13 percent larger for firms with above-median shares of skilled workers. Taken together, this evidence suggests that complementarity between digital technology and internal firm capabilities is the central mechanism driving effect heterogeneity.

Bloom and Van Reenen (2007) provide supporting evidence on the role of management quality. Their survey of 732 medium-sized manufacturing firms across four advanced economies shows that IT has substantially larger productivity effects in firms with complementary managerial structures. At the theoretical level, Acemoglu and Restrepo (2019) develop a task-based framework that distinguishes the displacement and reinstatement effects of technology, implying that basic and advanced digital technologies operate through different mechanisms and may therefore produce distinct productivity signatures across the firm distribution.

Thailand-specific evidence offers close parallels. Jongwanich and Kohpaiboon (2025) use panel data on Thai SMEs between 2018 and 2021 and show that e-commerce, online purchasing, and digital payments yield significant performance gains, whereas internet access without commercial use has limited impact. They also find that deeper software adoption benefits medium and large firms more than small firms, suggesting capability-technology complementarity within the Thai context. Survey evidence from DAI Global, LLC (2022) documents that 86 percent of Thai micro, small, and medium enterprises used digital tools during the COVID-19 pandemic — descriptive evidence that the digital transition in Thailand accelerated in the years preceding the data used in the present study.

Building on this literature, Figure 1 sets out the conceptual framework motivating the present study's hypothesis that the three digital pillars are differentially associated with productivity across the distribution — with basic infrastructure (D1) hypothesized to show a stronger association among lower-quantile firms and integration (D3) hypothesized to show a stronger association among upper-quantile firms, a pattern we test empirically in Section 4 and describe, with appropriate caution, as a digital-ladder-type pattern.

Figure 1: Conceptual Framework: The Digital Ladder Effect



Source: Authors' conceptualization based on Brynjolfsson & Hitt (2000); Cirera & Maloney (2017); Gal et al. (2019); Gómez-Bengoechea & Jung (2024).

2.4 Quantile Regression in Firm-Level Productivity Research

Koenker and Bassett (1978) introduced the quantile regression estimator in their seminal paper Regression Quantiles. The method extends ordinary least squares from estimation of the conditional mean to estimation of any conditional quantile of the dependent variable. Koenker and Hallock (2001) summarize the method's wider importance in an accessible review article, arguing that quantile regression enables researchers to characterize the entire conditional distribution rather than collapsing it to a single mean. The method is particularly well-suited to heterogeneous populations in which covariate effects vary systematically with the location of the outcome in its distribution.

Application of quantile regression to firm productivity research was inspired most directly by Coad and Rao (2008), who applied the method to four high-technology sectors and found that innovation mattered little for the average firm but was crucial for a small group of "superstar" fast-growing firms in the upper tail of the growth distribution. Their contribution demonstrated that mean-effect estimates obscure the most important heterogeneity in how productive activities translate into firm outcomes. Coad and Rao (2008) has since become a methodological reference point for firm-level studies seeking to uncover effects that differ systematically between leaders and laggards.

Contemporary applications of quantile regression to the ICT-productivity relationship in developing economies are still relatively sparse but point in a consistent direction. Gómez-

Bengoechea and Jung (2024), referenced above, find that digitalization effects are strongest at higher productivity quantiles in the European context. Regional evidence from Vietnamese provincial data indicates that ICT and human capital have statistically significant effects at lower and intermediate productivity quantiles, with diminishing effects at the upper tail — a pattern consistent with Cirera and Maloney's (2017) capability-ladder prediction that basic technologies yield greater marginal benefit to firms further from the frontier. No existing study, however, applies a quantile regression framework to decomposed digital pillars in the Thai context, which is the gap this paper aims to fill.

3. Methodology

The study uses firm-level data from the World Bank Enterprise Survey (WBES) Thailand 2025 wave, which is drawn using a stratified random sampling design on firm size, industry sector, and subnational region. The final analytical sample covers 813 firms. The sampling frame and weighting procedures follow the World Bank's standard Enterprise Survey methodology, which is designed to produce nationally representative estimates for the formal private sector (World Bank Group, 2021). Productivity estimation from WBES data follows the methodology developed by Francis et al. (2020) and adopted as the institutional standard by the World Bank Group.

The dependent variable is the natural logarithm of labor productivity, computed as annual sales divided by the number of permanent full-time employees at the end of the most recent fiscal year. The main explanatory construct is a Digital Adoption Score decomposed into three pillars. The first pillar, D1 Infrastructure, comprises website ownership, broadband application in the past two years, and electronic tax filing (maximum of 3 points). The second pillar, D2 Transaction, is measured through ordinal thresholds of electronic payment intensity at 25, 50, and 75 percent of transactions (maximum of 3 points). The third pillar, D3 Integration, combines the use of foreign-licensed technology with full electronic tax integration — defined as firms that both file and pay taxes electronically (maximum of 2 points). The aggregate Digital Total Score ranges from 0 to 8.

Control variables follow the conventions of WBES-based productivity research (Commander et al., 2011; Cusolito et al., 2020) and include the log of permanent full-time employment (firm size), log firm age, the share of foreign ownership, an indicator for female top manager, an indicator for direct exporter status, and an indicator for extreme-weather damage to physical assets. Sector and regional fixed effects are included in all specifications to absorb unobserved structural heterogeneity across industries and locations. All estimations report heteroskedasticity-robust standard errors.

The baseline specification is an OLS regression of log labor productivity on the digital score and controls, given in Equation (1):

$$\ln(\text{LabProd})_i = \alpha + \beta \cdot \text{Digital}_i + \gamma \cdot X_i + \delta_s + \delta_r + \varepsilon_i \quad (1)$$

where $\ln(\text{LabProd})_i$ denotes the log labor productivity of firm i , Digital_i denotes either the aggregate Digital Total Score or the three individual pillar scores (D1, D2, D3) depending on the specification, X_i is a vector of firm-level controls, δ_s and δ_r represent sector and region fixed effects respectively, and ε_i is the idiosyncratic error term.

To investigate effect heterogeneity across the productivity distribution, the study estimates Equation (2) at quantiles $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$:

$$Q_{\tau}(\ln(\text{LabProd})_i|X) = \alpha_{\tau} + \beta_{\tau} \cdot \text{Digital}_i + \gamma_{\tau} \cdot X_i + \delta_{s,\tau} + \delta_{r,\tau} \quad (2)$$

To test the hypothesis that digital effects differ by firm size — a reduced-form test of the Digital Divide versus Digital Equalizer narratives — the study estimates an interaction specification given in Equation (3):

$$\ln(\text{LabProd})_i = \alpha + \beta^1 \cdot \text{Digital}_i + \beta^2 \cdot \ln(\text{emp})_i + \beta^3 \cdot (\text{Digital} \times \ln(\text{emp}))_i + \gamma \cdot X_i + \delta_s + \delta_r + \varepsilon_i \quad (3)$$

A negative and statistically significant β_3 implies that digital benefits weaken as firm size increases, consistent with a Digital Equalizer interpretation in which smaller firms gain disproportionately. A positive β_3 would support the Digital Divide interpretation. All estimations were implemented in Stata 17 MP. Robustness is assessed by varying the control set and restricting the sample to firms with non-missing values on all three digital pillars.

Two interpretive caveats apply throughout the empirical analysis that follows. First, because the WBES Thailand 2025 data are cross-sectional, none of the estimated coefficients reported below should be read as causal effects: digital adoption and labor productivity may be jointly determined through reverse causality (more productive firms may be better able to afford digital adoption), omitted-variable bias (unobserved managerial quality may drive both), or simultaneity, and all results are therefore reported and interpreted as associations rather than effects. Second, the quantile regression estimates reported in Section 4.4 characterize conditional quantiles of labor productivity — that is, the quantile position of the outcome given each firm's observed covariates — rather than firms' fixed or unconditional position in the population distribution. For brevity, firms whose estimated conditional position lies in the Q10–Q50 range are referred to below as lower-quantile firms, and those in the Q75–Q90 range as upper-quantile firms; these labels denote estimated statistical positions rather than a fixed categorical grouping of firms.

4. Results

This section presents the empirical findings from the analysis. The presentation proceeds in four steps. Subsection 4.1 reports descriptive statistics on digital adoption across the sample. Subsection 4.2 reports OLS estimates of the average effect of digital adoption on labor productivity. Subsection 4.3 reports the interaction between digital adoption and firm size. Subsection 4.4 reports the quantile regression results, which constitute the central empirical contribution of the paper.

4.1 Descriptive Statistics of Digital Adoption

The pattern of digital adoption among Thai enterprises reveals a firm population in the midst of a digital transition. Table 1 presents adoption rates for the eight component indicators used to construct the digital score, ordered from highest to lowest. Transactional digital uses — particularly the acceptance of electronic payments — are near-universal, while advanced digital integration through foreign-technology licensing remains rare.

Table 1: Digital Component Adoption Rates Among Thai Enterprises

Component	Pillar	Adoption Rate (%)	N
E-payment received ($\geq 25\%$ of transactions)	D2	95.8	770
E-payment received ($\geq 50\%$ of transactions)	D2	92.5	770
Electronic tax filing	D1	78.7	762
Full electronic tax integration (file and pay)	D3	67.2	759
Own website	D1	61.9	811
E-payment received ($\geq 75\%$ of transactions)	D2	50.3	770
Foreign-licensed technology	D3	8.1	799
Broadband application (past 2 years)	D1	6.4	812

Source: Authors' calculations from WBES Thailand 2025.

Descriptive statistics of the pillar-level scores confirm the unevenness of the digital landscape. The D1 Infrastructure pillar has a mean of 1.42 out of 3, reflecting moderate take-up of basic digital access. The D2 Transaction pillar shows the highest saturation with a mean of 2.39 out of 3, consistent with the rapid diffusion of electronic payments in Thailand. The D3 Integration pillar lags substantially, with a mean of 0.71 out of 2. The aggregate Digital Total Score averages 4.39 on the 0–8 scale, with a standard deviation of 1.61 and a pairwise correlation of 0.25 with log labor productivity ($p < 0.01$).

4.2 OLS Estimates of Digital Adoption and Labor Productivity

Table 2 reports the OLS estimates of Equation (1) across five specifications: three single-pillar models (D1, D2, D3 entered separately), a joint model (D1, D2, D3 entered together), and an aggregate model (Digital Total Score). The estimates provide the first view of how digital adoption correlates with productivity at the sample mean.

Table 2: OLS Estimates of Digital Adoption on Log Labor Productivity

Variable	(1) D1	(2) D2	(3) D3	(4) Joint	(5) Total
D1: Infrastructure	0.220***			0.091	
	(0.063)			(0.075)	
D2: Transaction		0.199***		0.169**	
		(0.065)		(0.067)	
D3: Integration			0.302***	0.176*	
			(0.086)	(0.100)	
Digital Total Score					0.119***
					(0.030)
ln(employment)	0.321***	0.333***	0.327***	0.310***	0.322***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)

Variable	(1) D1	(2) D2	(3) D3	(4) Joint	(5) Total
ln(firm age)	0.268***	0.241***	0.260***	0.230***	0.261***
	(0.076)	(0.077)	(0.076)	(0.077)	(0.076)
Foreign ownership	0.412***	0.350**	0.334**	0.347**	0.386**
	(0.148)	(0.153)	(0.155)	(0.159)	(0.152)
Female manager	−0.064	−0.121	−0.050	−0.095	−0.041
	(0.093)	(0.094)	(0.094)	(0.095)	(0.094)
Exporter	−0.058	−0.050	−0.044	−0.063	−0.080
	(0.133)	(0.136)	(0.133)	(0.137)	(0.134)
Sector & Region FE	Yes	Yes	Yes	Yes	Yes
N	796	755	794	754	796
R ²	0.277	0.285	0.278	0.293	0.281

Notes: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Weather damage control included but suppressed. Source: Authors' calculations from WBES Thailand 2025.

Each pillar is positively associated with productivity when entered alone. In the single-pillar specifications, D3 Integration shows the largest point estimate ($\beta = 0.302$, $p < 0.01$, equivalent to an estimated 35.3 percent difference in labor productivity when converted via the exact log-linear formula $[\exp(\beta) - 1] \times 100$ rather than the linear approximation of the coefficient), followed by D1 Infrastructure ($\beta = 0.220$, $p < 0.01$, an estimated 24.6 percent difference) and D2 Transaction ($\beta = 0.199$, $p < 0.01$, an estimated 22.0 percent difference). In the joint specification, D2 and D3 retain significance while D1 loses statistical significance, reflecting the high pairwise correlation among the pillars. The aggregate score (column 5) is positive and highly significant ($\beta = 0.119$, $p < 0.01$), corresponding via $[\exp(\beta) - 1] \times 100$ to an estimated 12.6 percent difference in labor productivity per one-point increase in the Digital Total Score (rather than the 11.9 percent implied by a linear reading of the coefficient). The models explain 27.7 to 29.3 percent of the variation in log labor productivity.

The results so far establish that digital adoption is positively associated with labor productivity on average. However, they do not address whether the effects differ systematically across firms of different sizes or across the productivity distribution. The next subsection turns to the size-interaction test

4.3 Heterogeneity by Firm Size

Table 3 reports the results of Equation (3), which tests whether the productivity returns to digital adoption vary with firm size. Column (1) interacts the aggregate Digital Total Score with log employment; column (2) interacts each pillar with log employment simultaneously.

Table 3: Heterogeneity of Digital Effects by Firm Size

Variable	(1) Aggregate × Size	(2) Pillar × Size
Digital Total Score	0.393***	
	(0.074)	
D_total × ln(emp)	−0.083***	
	(0.020)	
D1: Infrastructure		0.025
		(0.224)
D2: Transaction		0.278
		(0.177)
D3: Integration		0.877***
		(0.299)
D1 × ln(emp)		−0.001
		(0.064)
D2 × ln(emp)		−0.039
		(0.047)
D3 × ln(emp)		−0.176***
		(0.067)
ln(employment)	0.708***	0.551***
	(0.099)	(0.140)
Controls + Sector & Region FE	Yes	Yes
N	796	754
R ²	0.295	0.303

Notes: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Controls include log firm age, foreign ownership, female manager, exporter, and weather damage. Source: Authors' calculations from WBES Thailand 2025.

The interaction term on the aggregate score is negative and highly significant ($\beta = -0.083$, $p < 0.01$), indicating that the marginal productivity gain from digital adoption declines as firm size rises. The pillar-level decomposition in column (2) attributes the interaction entirely to D3 Integration ($\beta = -0.176$, $p < 0.01$), while the D1 and D2 interactions are small and statistically indistinguishable from zero. This pattern implies that the aggregate Digital Equalizer result is driven by the differential relationship between advanced integration technologies and firm scale, rather than by a uniform size-gradient across all digital activities. This D3-driven size

pattern is examined further, alongside the seemingly contrasting quantile-based pattern reported in Section 4.4, in Section 5.4.

These size-based results, while informative, average across firms at different productivity levels. Because productivity and size are correlated but not identical, the size interaction may mask richer heterogeneity along the productivity distribution itself. The quantile regression results presented next uncover this heterogeneity directly.

4.4 Quantile Regression: The Digital Ladder Effect

Table 4 reports the joint-pillar quantile regression estimates at Q10, Q25, Q50, Q75, and Q90 of the conditional distribution of log labor productivity. The specification corresponds to Equation (2) and controls for firm size, age, foreign ownership, female manager, exporter status, weather damage, and sector and region fixed effects.

Table 4: Quantile Regression of Digital Pillars on Log Labor Productivity

Pillar	Q10	Q25	Q50	Q75	Q90
D1: Infrastructure	0.277***	0.334***	0.183*	−0.047	−0.179
	(0.103)	(0.098)	(0.100)	(0.117)	(0.151)
D2: Transaction	0.070	0.176**	0.180**	0.071	0.149
	(0.084)	(0.080)	(0.082)	(0.096)	(0.123)
D3: Integration	−0.179	−0.039	−0.011	0.300**	0.442**
	(0.129)	(0.123)	(0.125)	(0.147)	(0.189)
Controls + FE	Yes	Yes	Yes	Yes	Yes
N	754	754	754	754	754

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Controls: $\ln(\text{employment})$, $\ln(\text{firm age})$, foreign ownership, female manager, exporter, weather damage. Source: Authors' calculations from WBES Thailand 2025.

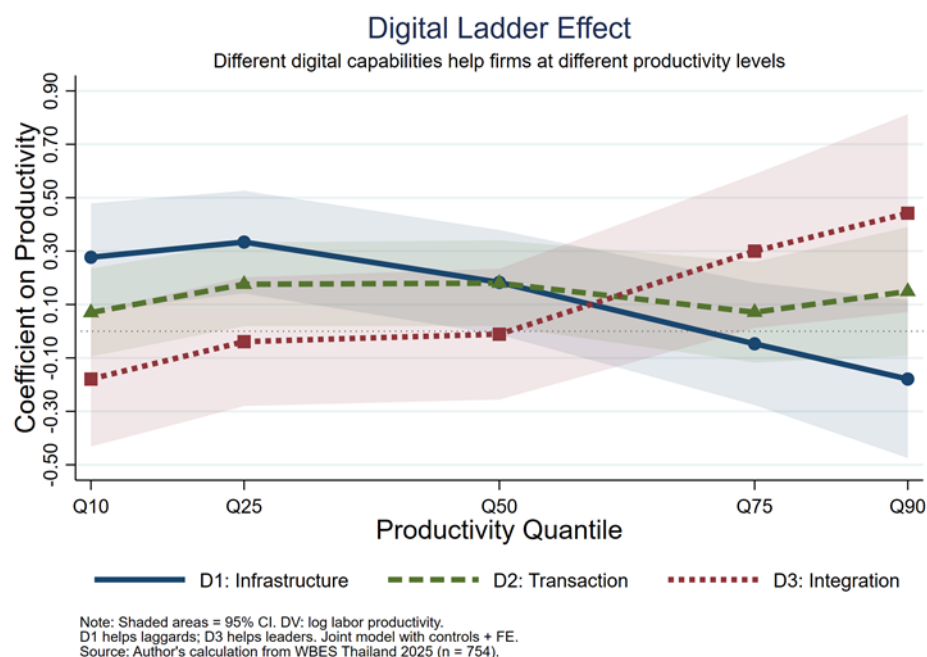
The pattern in Table 4 is the central empirical finding of the paper. D1 Infrastructure has positive and statistically significant effects at the lower and middle quantiles — $\beta = 0.277$ at Q10 ($p < 0.01$), $\beta = 0.334$ at Q25 ($p < 0.01$), and $\beta = 0.183$ at Q50 ($p < 0.10$) — but turns statistically indistinguishable from zero, and eventually negative, at the upper quantiles. D2 Transaction is most effective in the middle of the distribution, with significant coefficients at Q25 ($\beta = 0.176$, $p < 0.05$) and Q50 ($\beta = 0.180$, $p < 0.05$). D3 Integration follows the opposite pattern: the coefficient is negative at Q10 and indistinguishable from zero through the median, before turning positive and significant at Q75 ($\beta = 0.300$, $p < 0.05$) and Q90 ($\beta = 0.442$, $p < 0.05$).

This constitutes a clear sign reversal across the conditional productivity distribution, consistent with the conceptual framework presented earlier in Figure 1 (Section 2.3), which set out the hypothesized heterogeneous associations between the three pillars and firms' relative position in the productivity distribution. We refer to this empirical pattern descriptively as a digital-ladder-type pattern: lower-quantile firms show a stronger association with basic infrastructure, and upper-quantile firms show a stronger association with integration, though — as noted in

Section 3 — this labeling reflects estimated conditional-quantile positions rather than fixed firm categories, and the cross-sectional design means the pattern should not be read as evidence of a firm-level developmental sequence over time.

Figure 2 visualizes the quantile coefficients with 95 percent confidence bands. The three coefficient lines cross at different points along the distribution, giving visual expression to the ladder pattern. The aggregate Digital Total Score shows a generally positive but flatter quantile profile, reflecting the offsetting dynamics of D1 and D3. Taken together, the OLS and quantile results support three descriptive conclusions, each interpreted as an association rather than a causal claim: digital adoption is positively associated with labor productivity on average; the digital-productivity association is comparatively stronger among smaller firms (Table 3); and, conditional on firm size and other controls, upper-quantile firms show stronger productivity associations with advanced integration while lower-quantile firms show stronger associations with basic infrastructure (Table 4). Because firm size and productivity quantile are correlated but not identical, these two forms of heterogeneity are not necessarily in conflict; Section 5.4 reports an additional test of this distinction. These findings form the basis for the discussion that follows.

Figure 2: Quantile Coefficients of Digital Pillars on Log Labor Productivity



Notes: Line with circle markers represents D1 (Infrastructure); line with triangle markers represents D2 (Transaction); line with square markers represents D3 (Integration). Shaded areas represent 95% confidence bands. Source: Authors' calculations from WBES Thailand 2025.

5. Discussion

5.1 The Aggregate Digital-Productivity Link in Thai Enterprises

The first objective of this study was to estimate the overall relationship between digital adoption and labor productivity among Thai enterprises. The OLS results confirm a positive and statistically significant association, with a one-point increase in the Digital Total Score corresponding to an estimated 12.6 percent difference in labor productivity, calculated as $[\exp(\beta) - 1] \times 100$ ($\beta = 0.119$, $p < 0.01$). In substantive terms, this implies that a two-point increase in the Digital Total Score (approximating a move from the 25th to the 75th percentile of the digital-score distribution) is associated with an estimated 26.9 percent difference in productivity at the sample mean, calculated as $[\exp(2 \times 0.119) - 1] \times 100$. The mechanism most consistent with this finding is the complementarity channel articulated by Brynjolfsson and Hitt (2000), in which digital technology is associated with higher productivity when combined with supporting organizational and human capital. The magnitude of the Thai association is broadly consistent with firm-level evidence from other developing economies (Commander et al., 2011; Cusolito et al., 2020), though smaller than the IV-identified effects reported for France (Cette et al., 2022), which likely reflects both measurement differences and the earlier stage of Thailand's digital transition.

5.2 Heterogeneous Effects Across Digital Pillars

The second objective was to examine whether the three digital pillars have distinct productivity effects. The OLS joint model indicates that all three pillars contribute meaningfully on average, with D3 Integration showing the largest single-pillar point estimate ($\beta = 0.302$, $p < 0.01$, equivalent to an estimated 35.3 percent difference in labor productivity, calculated as $[\exp(\beta) - 1] \times 100$). In substantive terms, this means that firms with both foreign-licensed technology and full electronic tax integration are associated with productivity premiums above and beyond those observed among firms with only basic digital infrastructure or transactional adoption. The underlying mechanism is consistent with the absorptive capacity argument developed by Cirera and Maloney (2017), in which the returns to advanced technology depend on firms' complementary capabilities. This finding is consistent with Jongwanich and Kohpaiboon (2025), who report that deeper digital uses are associated with substantially better performance among Thai SMEs than mere internet access, and suggests that the Thai case aligns with the ASEAN-6 pattern identified by Guindo and Harjito (2025) in which frontier innovation is an increasingly important correlate of productivity.

5.3 The Digital Ladder Effect Across the Productivity Distribution

The third objective was to investigate effect heterogeneity across the productivity distribution. The quantile regression results document a clear sign-reversal pattern that we describe, with the caveats set out in Section 3, as a digital-ladder-type pattern. Lower-quantile firms show a stronger positive association with basic infrastructure ($\beta = 0.277$ at Q10, an estimated 31.9 percent difference; $\beta = 0.334$ at Q25, an estimated 39.7 percent difference; both calculated as $[\exp(\beta) - 1] \times 100$), while upper-quantile firms show a stronger positive association with integration ($\beta = 0.300$ at Q75, an estimated 35.0 percent difference; $\beta = 0.442$ at Q90, an estimated 55.6 percent difference). In substantive terms, the association between basic digital

access — websites, broadband, and electronic tax filing — and productivity is strongest among lower-quantile firms, whereas the association between advanced integration with foreign technology and fully digitized government interaction and productivity is strongest among upper-quantile firms. A plausible mechanism, consistent with the absorptive-capacity literature, is differential absorptive capacity: basic infrastructure lowers entry-level transaction costs accessible to most firms, while advanced integration requires complementary managerial and human capital that is disproportionately concentrated among upper-quantile firms; we treat this as a plausible interpretation rather than a directly tested mechanism in the present cross-sectional design. This pattern is broadly consistent with Gómez-Bengoechea and Jung (2024) and Gal et al. (2019), who document that digital effects concentrate among high-productivity firms using unconditional quantile approaches, though the present study's use of conditional quantile regression means the comparison should be read as directional rather than exact; the present analysis extends this literature by showing that the specific digital activity appears to determine which part of the conditional distribution shows the stronger association.

5.4 Robustness and Structural Stability of the Findings

The final subsection addresses the stability of the main findings. Three observations are relevant. First, the sign and significance of the Digital Total Score are stable across all five OLS specifications reported in Table 2, suggesting that the aggregate positive relationship is not an artifact of one pillar or one control set. Second, the size-interaction result in Table 3 is driven entirely by the D3 Integration $\times$ Size interaction, which is precisely the channel that the theory predicts should be most sensitive to firm capabilities. Third, the quantile coefficients exhibit a monotonic pattern for D1 (declining across quantiles) and D3 (rising across quantiles) rather than isolated outliers, supporting a structural interpretation of the ladder effect rather than a sampling artifact. While the cross-sectional design precludes fully causal identification, the consistency of results across specifications and the alignment with prior quasi-experimental evidence (Cette et al., 2022; Hjort & Poulsen, 2019) suggests that the descriptive patterns documented here reflect genuine economic heterogeneity rather than measurement noise.

A further observation concerns the apparent tension between the negative D3 $\times$ size interaction reported in Table 3 and the positive D3 coefficients at the upper conditional quantiles reported in Table 4. To examine whether these two patterns are compatible, we estimated an additional specification that adds an explicit D3 $\times$ $\ln(\text{employment})$ interaction term within each conditional quantile regression. Across all five quantiles, this size interaction remains negative (β ranging from approximately -0.11 at Q10 to -0.20 at Q75, reaching conventional significance at Q25, Q50, and Q75), while the D3 main-effect coefficient in this specification still rises from the lower to the upper quantiles. This indicates that firm size and productivity-quantile position capture two distinct, coexisting dimensions of heterogeneity in the D3 association rather than a single contradictory result: within a given quantile, smaller firms show a stronger D3 association, and independently of size, firms in higher conditional productivity quantiles also show a stronger D3 association. Consistent with this, firms in the top quartile of the productivity distribution are on average considerably larger than firms in the bottom quartile (mean log-employment of 3.81, equivalent to roughly 45 employees, versus 2.58, equivalent to roughly 13 employees; correlation between log-employment and log labor productivity of approximately 0.35), confirming that size and productivity quantile are related but far from interchangeable in this sample. Firms that are both smaller and located in the upper conditional quantiles of productivity therefore show the strongest estimated D3 association in the data,

consistent with a pattern in which a subset of smaller, unusually productive firms drives much of the observed integration association. We emphasize that the cross-sectional design cannot establish the direction of any underlying mechanism, and we treat this as an informative feature of firm heterogeneity in the Thai data rather than a fully resolved finding. Any policy application of these results (Section 6) should account for firm size and productivity position jointly rather than either dimension considered in isolation.

6. Conclusion and Policy Implications

This paper has examined the association between digital adoption and labor productivity in Thai enterprises, drawing on the World Bank Enterprise Survey Thailand 2025. The analysis decomposed digital adoption into three pillars — Infrastructure, Transaction, and Integration — and estimated associations using both OLS and Quantile Regression. Three findings stand out. The aggregate Digital Total Score is positively associated with labor productivity ($\beta = 0.119$, $p < 0.01$), with a one-point increase corresponding to an estimated 12.6 percent productivity difference. The three pillars contribute differently: Infrastructure and Transaction are positively associated with productivity broadly, while Integration shows the largest single-pillar point estimate ($\beta = 0.302$, $p < 0.01$, an estimated 35.3 percent difference). A digital-ladder-type pattern also emerges from the quantile analysis: D1 shows a stronger association among lower-quantile firms (Q10–Q50) while D3 shows a stronger association among upper-quantile firms (Q75–Q90), with a sign reversal across the conditional distribution; as discussed in Sections 3 and 5.4, this pattern should be read as a descriptive association rather than a confirmed causal or developmental sequence, and it sits alongside a partly distinct finding on firm size. The digital score $\times$ firm-size interaction is negative and significant ($\beta = -0.083$, $p < 0.01$), indicating that the digital-productivity association is comparatively stronger among smaller firms; Section 5.4 reports an additional test of how this size-based result relates to the quantile-based results above.

These findings suggest that a differentiated approach to digital policy in Thailand may be warranted, subject to the qualifications noted in Section 5.4 regarding the cross-sectional and associational nature of the evidence. One implication is that prioritizing basic digital infrastructure for smaller and lower-quantile firms could be worth considering: because D1 shows its largest estimated association at the lower conditional quantiles, expanded support for website development, broadband access, and electronic tax filing may offer a comparatively large aggregate benefit per unit of public investment if targeted toward firms in the lower half of the productivity distribution, subject to the caveat that such targeting assumes policymakers can identify firms by productivity quantile in practice. This possibility is broadly consistent with Hjort and Poulsen's (2019) finding that fast internet access is associated with substantial productivity gains in lower-income settings and with Cirera and Maloney's (2017) recommendation that basic-technology diffusion serve as a starting point for technology-upgrading programs.

A second implication concerns support for advanced digital integration among upper-quantile firms through technology-transfer and absorption programs. Because D3 Integration shows its strongest estimated association among firms already at higher conditional productivity levels (subject to the size-related qualification discussed in Section 5.4), policies such as expanded technology licensing, R&D tax incentives, and fully digitized government-business interfaces could plausibly support continued productivity growth among Thailand's higher-productivity

firms, though this remains an associational rather than a demonstrated causal claim. This possibility is broadly consistent with Guindo and Harjito's (2025) evidence that frontier innovation is an increasingly important correlate of productivity in ASEAN-6 economies and with the World Bank's (2025) assessment that Thailand's next growth stage is linked to closing the advanced-digital gap.

A third implication concerns the middle segment of the distribution. Because D2 Transaction shows its strongest estimated association at the 25th and 50th conditional quantiles, policy instruments that support transactional digitalization — payment interoperability standards, digital financial services for SMEs, and electronic invoicing mandates — may be comparatively well suited to firms in the middle of the productivity distribution. Taken together, a differentiated digital policy package for Thailand could pair infrastructure support aimed at lower-quantile firms with integration support aimed at upper-quantile firms and transactional standards aimed at the middle, rather than treating all firms as homogeneous adopters; we emphasize, however, that this sequencing is a hypothesis suggested by cross-sectional association patterns and would benefit from further validation, including the additional analysis reported in Section 5.4, before being operationalized as targeting criteria.

Two limitations of the study should be acknowledged. First, the WBES Thailand 2025 is a single cross-section, which precludes the identification of causal effects through firm-level fixed effects or long-difference designs; in particular, the sequential, developmental interpretation implied by the term digital-ladder-type pattern cannot be directly tested with these data and should be regarded as a speculative reading of a cross-sectional association pattern rather than as demonstrated firm-level dynamics over time. Second, the peer-based instrument tested in early specifications did not pass weak-instrument diagnostics once sector and region fixed effects were included, reflecting a structural limitation of cross-sectional IV strategies in this context. Four directions for future research follow. The first is to replicate the quantile analysis using longitudinal WBES data once the 2025 wave can be linked to prior waves, enabling within-firm identification and a direct test of the developmental interpretation. The second is to extend the decomposition framework to other ASEAN economies to test whether the observed pattern generalizes across the region rather than being specific to the Thai case. The third is to investigate the organizational and human-capital mediators that generate the size dependence of the D3 channel, including by extending the control set to measures of internal digital skills and human capital. The fourth is to jointly model firm size and productivity quantile position, building on the additional test reported in Section 5.4, to clarify more precisely how these two dimensions of heterogeneity relate to one another. By documenting a pattern consistent with digital adoption in Thailand operating through a ladder rather than a uniform channel, this paper offers a descriptive framework, grounded in verified empirical associations, that can guide both further academic inquiry and more cautious, evidence-based policy design.

References

- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3–30. <https://doi.org/10.1257/jep.33.2.3>
- Bartelsman, E. J., & Doms, M. (2000). Understanding productivity: Lessons from longitudinal microdata. *Journal of Economic Literature*, 38(3), 569–594. <https://doi.org/10.1257/jel.38.3.569>
- Bloom, N., & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *The Quarterly Journal of Economics*, 122(4), 1351–1408. <https://doi.org/10.1162/qjec.2007.122.4.1351>
- Brambilla, I., & Tortarolo, D. (2018). *Investment in ICT, productivity, and labor demand: The case of Argentina* (Policy Research Working Paper No. 8325). World Bank. <https://doi.org/10.1596/1813-9450-8325>
- Brynjolfsson, E., & Hitt, L. (1996). Paradox lost? Firm-level evidence on the returns to information systems spending. *Management Science*, 42(4), 541–558. <https://doi.org/10.1287/mnsc.42.4.541>
- Brynjolfsson, E., & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic Perspectives*, 14(4), 23–48. <https://doi.org/10.1257/jep.14.4.23>
- Cardona, M., Kretschmer, T., & Strobel, T. (2013). ICT and productivity: Conclusions from the empirical literature. *Information Economics and Policy*, 25(3), 109–125. <https://doi.org/10.1016/j.infoecopol.2012.12.002>
- Cette, G., Nevoux, S., & Py, L. (2022). The impact of ICTs and digitalization on productivity and labor share: Evidence from French firms. *Economics of Innovation and New Technology*, 31(8), 669–692. <https://doi.org/10.1080/10438599.2020.1849967>
- Cirera, X., & Maloney, W. F. (2017). *The innovation paradox: Developing-country capabilities and the unrealized promise of technological catch-up*. World Bank. <https://doi.org/10.1596/978-1-4648-1160-9>
- Coad, A., & Rao, R. (2008). Innovation and firm growth in high-tech sectors: A quantile regression approach. *Research Policy*, 37(4), 633–648. <https://doi.org/10.1016/j.respol.2008.01.003>
- Commander, S., Harrison, R., & Menezes-Filho, N. (2011). ICT and productivity in developing countries: New firm-level evidence from Brazil and India. *The Review of Economics and Statistics*, 93(2), 528–541. https://doi.org/10.1162/REST_a_00080
- Cusolito, A. P., Lederman, D., & Peña, J. (2020). *The effects of digital-technology adoption on productivity and factor demand: Firm-level evidence from developing countries* (Policy Research Working Paper No. 9333). World Bank. <https://doi.org/10.1596/1813-9450-9333>
- DAI Global, LLC. (2022). *MSMEs and digital tool use amidst the COVID-19 pandemic: Thailand country brief*. <https://www.dai.com/uploads/final-msme-reports/thailand-country-brief.pdf>
- Digital Economy Promotion Agency. (2025, April 23). *depa reveals 2024 Digital Density Survey in Thai industry: Moving toward Level 2.0*. https://www.depa.or.th/en/article-view/20250423_01

- Francis, D. C., Karalashvili, N., Maemir, H. B., & Rodriguez Meza, J. L. (2020). *Measuring total factor productivity using the Enterprise Surveys: A methodological note* (Policy Research Working Paper No. 9491). World Bank. <https://doi.org/10.1596/34913>
- Gal, P., Nicoletti, G., Renault, T., Sorbe, S., & Timiliotis, C. (2019). *Digitalisation and productivity: In search of the holy grail—Firm-level empirical evidence from EU countries* (OECD Economics Department Working Papers No. 1533). OECD Publishing. <https://doi.org/10.1787/5080f4b6-en>
- Gómez-Bengoechea, G., & Jung, J. (2024). The Matthew effect: Evidence on firms' digitalization distributional effects. *Technology in Society*, 76, 102423. <https://doi.org/10.1016/j.techsoc.2023.102423>
- Guindo, T., & Harjito. (2025). ICT adoption, innovation, and labor productivity in ASEAN: Evidence from panel data analysis. *Wah Academia Journal of Social Sciences*, 4(2), 28–54. <https://doi.org/10.63954/WAJSS.4.2.2.2025>
- Hjort, J., & Poulsen, J. (2019). The arrival of fast internet and employment in Africa. *American Economic Review*, 109(3), 1032–1079. <https://doi.org/10.1257/aer.20161385>
- Jaumotte, F., Li, L., Medici, A., Oikonomou, M., Pizzinelli, C., Shibata, I., Soh, J., & Tavares, M. M. (2023). *Digitalization during the COVID-19 crisis: Implications for productivity and labor markets in advanced economies* (IMF Staff Discussion Note No. 2023/003). International Monetary Fund. <https://doi.org/10.5089/9798400232596.006>
- Jongwanich, J., & Kohpaiboon, A. (2025). Digital technology adoption and the financial performance of SMEs: Evidence from Thailand. *Asian Economic Papers*, 24(1), 31–64. https://doi.org/10.1162/asep_a_00922
- Koenker, R., & Bassett, G., Jr. (1978). Regression quantiles. *Econometrica*, 46(1), 33–50. <https://doi.org/10.2307/1913643>
- Koenker, R., & Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives*, 15(4), 143–156. <https://doi.org/10.1257/jep.15.4.143>
- Oduro, S., De Nisco, A., & Mainolfi, G. (2023). Do digital technologies pay off? A meta-analytic review of the digital technologies/firm performance nexus. *Technovation*, 128, 102836. <https://doi.org/10.1016/j.technovation.2023.102836>
- Syversen, C. (2011). What determines productivity? *Journal of Economic Literature*, 49(2), 326–365. <https://doi.org/10.1257/jel.49.2.326>
- World Bank. (2019). *The digital economy in Southeast Asia: Strengthening the foundations for future growth*. <https://documents1.worldbank.org/curated/en/328941558708267736/pdf/the-digital-economy-in-southeast-asia-strengthening-the-foundations-for-future-growth.pdf>
- World Bank Group. (2025). *Thailand economic monitor: Digital pathways for growth*. World Bank. <https://openknowledge.worldbank.org/entities/publication/982e03f5-79ab-4b81-857a-4820f3c4eef7>
- World Bank Group. (2021). *Enterprise surveys manual and guide*. <https://www.enterprisesurveys.org/content/dam/enterprisesurveys/documents/methodology/Enterprise-Surveys-Manual-and-Guide.pdf>