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Machinery Usage and Productivity in Manufacturing: Firm-Level Matter in Developing Countries

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Abstract

This study examines the determinants of machinery usage and its relationship with productivity outcomes among Vietnamese manufacturing firms, using nationally representative panel data from 2010 to 2019. A multinomial logit model and panel regressions with first- and second-differences reveal substantial heterogeneity in machinery choices, reflecting differences in firm size, ownership, and sectoral contexts. Medium and large enterprises tend to use computer-controlled machinery and are more likely to exhibit positive associations with labor productivity, although these effects often diminish over time. In contrast, micro and small firms remain reliant on handheld tools and show mixed or short-lived productivity gains. Foreign-invested enterprises demonstrate more consistent productivity benefits from advanced machinery than state-owned firms. These findings suggest that sustained productivity improvements require more than technological upgrades alone. The study highlights the potential importance of complementary investments – such as workforce development, managerial capacity, and institutional support – for fostering inclusive and effective machinery usage. These insights may inform targeted policy efforts aimed at narrowing technology gaps across heterogeneous firms in developing economies.

Keywords:

Machinery Usage; Labor Productivity; Total Factor Productivity; Vietnam; Manufacturing Sector; Technology Integration; Policy Interventions.

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1- Introduction

Industrial upgrading through machinery usage is widely acknowledged as an essential factor influencing industrial competitiveness [1-3], productivity growth [1], and economic catching-up [1, 2]. Historically, developed and leading developing economies have experienced gradual industrial transformations, moving progressively from basic mechanization toward automation and advanced digital manufacturing [1]. This process has been facilitated by long-standing institutional support [4], sustained investments in research and development (R&D) [2], and a highly skilled workforce, allowing firms to integrate new machinery effectively and achieve continuous productivity improvements [2]. Prominent national strategies - such as Germany's SME digitalization programs, the U.S. "Advanced Manufacturing Program," China's "Made in China 2025," and Japan's "Industrial Value Chain Initiative" – clearly illustrate the strategic importance attributed to sustained industrial upgrading by policymakers [2, 5, 6].

In contrast, developing countries seeking accelerated industrialization frequently encounter considerable obstacles when integrating advanced machinery. Common constraints include limited access to financing [1], shortages of skilled labor, and institutional inefficiencies [1, 7, 8]. Additionally, firms often experience short-term productivity disruptions

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due to higher training expenses [9-11] and operational adjustments when introducing new machinery [11, 12], even though these changes may generate substantial productivity improvements in the long run [13, 14]. Misaligned incentives and fragmented policy environments can further diminish the effective use of advanced machinery, limiting potential productivity gains [4, 9, 10].

Existing research clearly documents that machinery usage and associated productivity outcomes vary considerably across firms of different sizes [11-13] and industry-specific characteristics [11]. Larger firms typically possess distinct advantages such as greater financial capacity [1 , 12, 14], access to skilled labor [1, 15], and managerial capabilities to integrate advanced machinery effectively [1, 12], enabling effective integration and leveraging of new machinery. Consequently, these firms often benefit from significant economies of scale and substantial improvements in production efficiency [9, 11, 16, 17]. In contrast, despite potential flexibility, smaller firms face persistent challenges, including high initial investment requirements [18, 19], limited institutional support [1, 4, 8], and inadequate workforce training [4, 8, 10], thus constraining their ability to fully realize the benefits of advanced machinery [6, 18, 19]. Industry characteristics also play an important role. Firms operating in technology-intensive sectors, such as electronics and automotive industries [1, 17, 20], typically experience pronounced productivity gains from machinery integration, whereas firms in low-tech or labor-intensive industries frequently obtain only marginal productivity improvements [11].

Vietnam provides a particularly relevant context for examining these issues, as the country aims to become a high-income, industrialized economy by 2045, with manufacturing serving as a central component of its economic modernization and global competitiveness strategies [21, 22]. Recent national strategies, such as Resolution 23-NQ/TW on Industrial Policy and Vietnam's Socio-Economic Development Strategy (SEDS) 2021–2030, explicitly emphasize technological upgrading [23], enhanced automation [23], and increased productivity as key pathways for transitioning from labor-intensive production towards higher-value industrial activities [22, 24, 25].

Despite these strategic ambitions, machinery usage across Vietnam's manufacturing sector remains markedly uneven, reflecting broader structural challenges to industrial upgrading [26]. According to authors' calculations using Vietnam's National Enterprise survey data, micro, small, and medium enterprises (SMEs) constitute more than 90% of manufacturing firms, indicating the highly fragmented nature of the sector. Firm ownership also varies significantly: micro-enterprises are predominantly privately owned (99.07%), whereas foreign direct investment (FDI) participation rises notably to 10.3% among medium firms and reaches 28.54% among large enterprises. Persistent productivity disparities accompany this fragmentation. In 2019, micro and small enterprises reported average labor productivity levels of 73.41 and 106.10 million VND per year, respectively – significantly lower compared to 197.10 million VND in large firms. Similarly, total factor productivity (TFP) contributions to value-added are notably different across firm sizes, with micro (31.19%) and small enterprises (37.28%) lagging considerably behind larger firms (26.55%). Machinery usage patterns reflect similar disparities: manually operated machines dominate usage overall (83.96%), especially among medium-sized firms (86.39%), while usage of computer-controlled machinery remains relatively low, varying from just 3.13% in micro-enterprises to 15.34% among large enterprises.

This fragmentation coincides with substantial disparities in productivity and machinery usage patterns, raising critical research questions about how firm-level and industry-specific factors correlate with machinery usage choices across different firm sizes, how machinery usage patterns correlate with labor productivity and TFP across firm-size categories, and how these correlational relationships evolve over time – from short-term adjustments to longer-term productivity outcomes. Unlike previous studies largely based on single-period data, this study leverages panel data spanning 2010 – 2019 and employs first- and second-difference estimators to rigorously examine dynamic correlations between machinery usage and productivity outcomes. Addressing these questions offers empirical insights into the dynamics of industrial upgrading in Vietnam, offering relevant insights for industrial upgrading in other developing economies.

The paper is structured as follows: Section 2 reviews the relevant theoretical frameworks and empirical literature concerning technology usage, productivity, and total factor productivity (TFP). Section 3 presents the data, variables, and econometric methods used in the analysis. Section 4 discusses the empirical findings, focusing particularly on differences related to firm size and industry-specific characteristics. Section 5 concludes with broader implications and suggests avenues for future research.

2- Literature Review

2-1- Associational Patterns of Enterprises' Machinery Usage: A TOE Framework Perspective

A firm's likelihood of machinery usage is influenced by both internal characteristics and external market conditions, which are systematically structured within the Technology-Organization-Environment (TOE) framework [18, 27, 28]. TOE comprises three interconnected dimensions: technological feasibility, organizational readiness, and environmental factors. These three dimensions collectively provide a structured approach to examining firms' usage behaviors [29, 30].

- ***Technological Factors and Machinery Usage***

Technological attributes are central to firms' decisions to integrate new machinery, as machinery usage depends on both perceived benefits and operational feasibility [1]. Rogers [31] identifies relative advantage, compatibility, and complexity as key technological factors associated with firms' tendency to use innovations. Machinery that offers efficiency gains, cost reductions, or improved product quality is more likely to be used in firms' production processes [18, 32]. Conversely, high complexity can be a barrier to machinery usage [18], particularly for SMEs in resource-constrained environments, where firms may lack the necessary technical expertise and capital investments to integrate advanced machinery [15].

Within the TOE framework, technological readiness is closely linked to absorptive capacity [5, 33], which refers to a firm's ability to identify, assimilate, and apply external knowledge [5, 33, 34]. Firms embedded in global supply chains or exposed to FDI spillovers tend to exhibit higher engagement with advanced technology [3, 8], as they gain access to foreign expertise [3, 35], technical standards [8, 35], and managerial practices [8, 36, 37]. However, exposure alone does not automatically translate into machinery usage – firms require internal capabilities, such as technological capabilities [15], workforce training [38], process optimization, and R&D investments, to effectively integrate new machinery [1]. The interaction between technological attributes and firm-specific absorptive capacity highlights the variation in machinery usage patterns across different enterprise types [39], making this relationship central to the empirical analysis.

- ***Organizational Factors: Firm-Level Characteristics and Machinery Usage***

The organizational dimension of the TOE framework highlights how firm-specific attributes – such as size, resources, ownership, and management – shape machinery usage decisions [27, 28, 30]. Larger firms typically possess greater financial and human capital, supporting investments in advanced machinery and innovation [27, 40]. Yet, bureaucratic inertia and rigid structures may slow technology uptake [15]. Smaller firms, though resource-constrained, often display agility in adopting new technologies [15, 41]. Organizational complexity, influenced by workforce specialization, can also delay integration due to training and coordination demands [30].

Ownership further differentiates usage patterns. SOEs often lag in adopting advanced machinery due to risk aversion, bureaucratic constraints, and dependence on state support [11, 20]. In contrast, FDI firms are more technologically advanced, with better financial capacity and global integration [3, 35] They leverage parent company networks and supply chains to access high-tech machinery and maintain production quality [3]. Domestic private firms, however, face capital, skills, and institutional barriers [1, 8] with investment uncertainty and information asymmetry exacerbating adoption delays [1, 18, 39].

Ownership and firm size influence machinery usage, shaping firms' perceived usefulness (PU) and ease of use (PEOU) in using machinery [42]. Larger firms, with greater financial and human resources, tend to perceive machinery usage as feasible, while smaller firms, despite their agility, face capital and expertise constraints. Private firms, experiencing higher investment uncertainty and information asymmetry, may use machinery more cautiously. These factors interact with external influences, such as supplier support, industry norms, and policy incentives, affecting firms' machinery usage trajectories [43].

- ***Environmental Factors: External Market Pressures and Institutional Influences***

The external environment significantly influences firms' machinery usage decisions, as industry conditions, trade participation, and institutional factors shape usage incentives [1, 7, 8, 15, 16, 18, 28, 30, 44, 45]. Export participation is often linked to higher rates of advanced machinery usage [18, 28, 30, 44], as firms engaged in global markets must align with international production standards, efficiency benchmarks [1, 3, 18], and machinery-specific requirements [18, 30, 44]. Exporting firms frequently interact with foreign buyers and global value chains, leading to increased technological exposure and industry learning [8]. However, the nature of this relationship remains bidirectional - firms may adopt new technology to enter export markets, while technologically advanced firms may be more likely to export [15, 39].

Beyond export-related pressures, industry competition [1, 15, 18, 28, 30, 35, 46, 47] and sectoral dynamics [1, 6, 8, 11, 48-50] influence firms' likelihood of machinery usage. Advanced technologies, such as robotics and automation, are more prevalent in automotive, chemicals, and electronics, where efficiency and precision are essential [1, 8]. Machinery usage rates evolve as technology becomes more affordable and widely accessible across industries [8]. Digital integration also varies, particularly in agriculture and manufacturing, where automation is embedded in specialized machinery [1]. Additionally, policy frameworks and regulatory requirements create different levels of incentives and compliance pressures across sectors [8, 11, 48-51].

Industry characteristics influence machinery usage through market concentration, demand elasticity, and entry conditions [18, 51]. The Industry Concentration Index (ICI) reflects competitive pressure – higher concentration may enhance financial capacity for investment but also reduce innovation incentives [51]. Competitive markets with elastic demand tend to accelerate machinery adoption as firms strive to remain efficient [51]. Moreover, lower entry barriers support wider technology diffusion, while concentrated markets may delay transitions [12].

2-2- Machinery Usage and Labor Productivity

Machinery usage significantly enhances labor productivity through automation, process optimization, and improved quality. Solow [52] identified technical change as a key driver of productivity, and Jorgenson & Griliches [53] showed that greater capital intensity – such as investing in advanced machinery – boosts worker efficiency. Empirical studies confirm that computer-controlled machinery and robotics increase accuracy and output while reducing costs [8, 11]. For instance, automation has improved manufacturing precision and reduced transaction times in banking via ATMs [20, 54]. However, impacts vary by firm size, sector, and technology context. Larger firms benefit more due to economies of scale, stronger resources, and advanced management [50, 55], and can invest in complementary assets like training and R&D [34, 51]. In contrast, SMEs often face financial and skill constraints that limit machinery effectiveness [56, 57]. As a result, while advanced machinery boosts productivity in medium and large firms, outcomes in micro and small firms remain mixed [8, 58].

The productivity gains from machinery are influenced by sectoral characteristics and technological intensity. High-tech and medium-high-tech industries derive substantial benefits from automation and digitalization, as these technologies complement their innovation-driven production models [49, 59]. In contrast, low-tech sectors experience modest productivity improvements due to limited compatibility with advanced technologies [31, 60]. Technologies such as robotics, AI, and IoT have proven particularly effective in enhancing productivity by enabling precision, real-time decision-making, and production flexibility [20, 54]. These findings align with observations that productivity gains are more pronounced in industries with high absorptive capacities and robust innovation ecosystems [34, 61].

Automation and advanced machinery reshape labor dynamics by complementing skilled labor and automating repetitive tasks. Autor et al. [60] emphasized the complementary relationship between technology and skilled labor, where automation enhances worker productivity by enabling a shift towards higher-value activities. However, machinery usage often requires workforce reskilling, as outdated skills may hinder productivity gains [8, 62]. Firms with higher absorptive capacity - bolstered by investments in education, training, and R&D – are better equipped to leverage new technologies effectively [34, 40]. Empirical findings highlight that skill mismatches may explain negative productivity impacts observed in small enterprises using advanced machinery [56, 63].

The regional and institutional context significantly affects the productivity outcomes of machinery usage. Krugman [61] and Porter [46] underscored the role of industrial clusters and regional infrastructure in fostering technology diffusion and innovation. Regions with better infrastructure, skilled labor pools, and access to global markets are more likely to reap the benefits of machinery usage [8, 20]. Conversely, firms in underdeveloped regions face barriers such as inadequate institutional support and limited market access, which restrict productivity improvements [56, 64]. These disparities are evident in the significant regional effects observed in productivity models, where firms in resource-rich regions achieve higher productivity gains from technology usage [3].

Ownership structure is a crucial determinant of productivity outcomes. Foreign-invested enterprises (FDIs) often lead in productivity improvements due to their access to advanced technologies, managerial expertise, and global networks [57, 58]. These advantages enable FDIs to overcome barriers such as resource constraints and skill gaps, resulting in more efficient machinery usage [55, 56]. By contrast, state-owned enterprises (SOEs) may face inefficiencies and rigidities that limit their ability to leverage advanced machinery effectively [57].

Labor productivity is commonly measured as output per worker, with alternative metrics such as TFP providing additional insights into the interplay of capital, labor, and technology [3, 50]. While advanced machinery contributes to productivity gains, challenges such as high initial costs, skill mismatches, and technological misalignment can hinder outcomes, particularly for SMEs [11, 16]. Complementary investments in education, infrastructure, and R&D are essential to addressing these barriers and maximizing the productivity potential of machinery usage [40, 51].

2-3- Machinery and Equipment Usage and TFP

The relationship between machinery usage and TFP involves both short-term adjustment costs and long-term gains. Initial TFP declines may occur as firms integrate new machinery, facing disruptions and learning curves [13, 47]. Evidence from Colombian manufacturing shows TFP growth drops by 3–9% post-investment due to temporary inefficiencies, underscoring the need for early complementary investments such as workforce training [15].

Over time, machinery usage can enhance TFP through technological upgrading, cost savings, and process innovation [3, 18]. Automated systems reduce energy intensity and waste, supporting sustainable production [8]. Firms also benefit from learning-by-doing, gradually improving operations with repeated usage [13]. FDI can amplify these effects by transferring advanced technologies and managerial practices to domestic firms [1].

Firm size remains an important moderator. Larger firms typically achieve greater TFP gains due to superior resources and standardized systems [8, 14] though they may face internal inertia [15]. In contrast, smaller firms often lack the capacity to integrate and exploit advanced machinery fully [1].

TFP outcomes also depend on technology characteristics and institutional conditions. Standardized production environments better utilize advanced manufacturing technologies, while differentiated production demands more flexible systems [15, 51]. Supportive policies, training, and trade incentives enhance the machinery-productivity link [3, 22]. General-purpose technologies like electricity, AI, and blockchain serve as enablers of broader TFP growth by supporting complementary innovations [1, 8, 18, 39]. Challenges persist, particularly for SMEs. High capital costs, skill shortages, and integration difficulties limit their ability to capture TFP gains [1, 15, 47, 65].

Finally, TFP impacts vary across sectors and regions. High-tech industries benefit most [51], while low-tech sectors gain modestly [8]. Industrial clusters with strong infrastructure foster better TFP outcomes, reinforcing the spatial dimension of technology diffusion [1, 61].

Existing studies have predominantly analyzed machinery adoption as a one-time, binary decision, offering limited insights into how firms actually utilize machinery over time and how these usage choices vary by firm size, ownership, and sectoral contexts. Moreover, few studies have systematically examined how specific types of machinery usage relate to labor productivity and TFP within a dynamic framework. This study seeks to contribute to these gaps by applying a multinomial logit model to capture heterogeneous usage choices, and by using first- and second-difference estimators to explore how these usage patterns correlate with productivity outcomes across different firm sizes and over time.

3- Research Methodology

To investigate how firm- and industry-level factors relate to machinery usage and productivity outcomes, the study applies a three-part empirical strategy (Figure 1). (1) Labor productivity and TFP are measured using value-added-based indicators and semi-parametric estimation. (2) A multinomial logit model identifies determinants of machinery usage across three technology categories. (3) Finally, panel regressions with first- and second-difference estimators assess the dynamic association between machinery usage and productivity, capturing both short-term adjustment costs and longer-term gains. This design controls for unobserved heterogeneity and endogeneity arising from selection into technology use and contemporaneous productivity shocks.

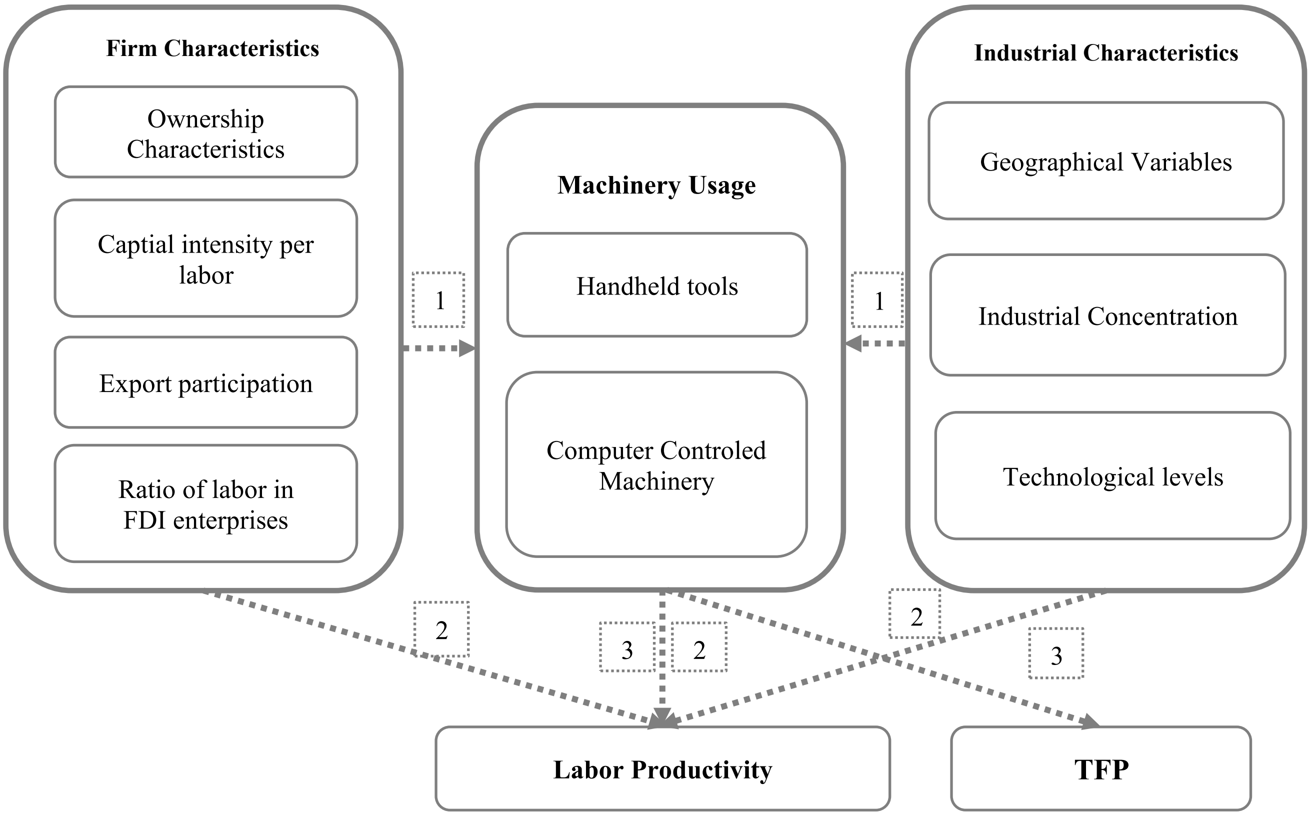


Figure 1. Empirical strategy

3-1- The Concept and Measurement of Labor Productivity and TFP

Labor productivity, a fundamental measure of economic efficiency, is defined as the output generated per unit of labor input [64]. To ensure cross-sector comparability, output is quantified in monetary terms as value-added, calculated as total revenue minus the cost of intermediate inputs [13]. This definition isolates the net contribution of the production process and provides an accurate measure of productivity while accounting for differences in production technology and input-output structures. The reliance on value-added ensures that labor productivity reflects not only labor efficiency but also the effective utilization of capital and machinery [15].

Mathematically, labor productivity (LP) is expressed as:

$$LP = \frac{VA}{L} \tag{1}$$

where:

- Value Added (VA) = Total income of different stakeholders (labor income, depreciation and profit, interest paid, and direct taxes).
- Labor Input (L) = Number of Workers.

To analyze the relationship between machinery usage and productivity, the Cobb-Douglas production function is employed. This framework, widely used for its simplicity and interpretability, captures the relationship between inputs and output.

$$VA_{it} = A(Z_{it})K_{it}^{\alpha}L_{it}^{\beta}e^{\varepsilon_{it}} \tag{2}$$

Taking the natural logarithm transforms the equation into a linear form:

$$lnVA_{it} = lnA(Z_{it}) + \alpha lnK_{it} + \beta lnL_{it} + \varepsilon_{it} \tag{3}$$

This equation can be transformed to make labor productivity the dependent variable:

$$lnVA_{it} - lnL_{it} = lnA(Z_{it}) + \alpha lnK_{it} + \beta lnL_{it} - lnL_{it} + \varepsilon_{it} \tag{4}$$

$$ln\left(\frac{VA_{it}}{L_{it}}\right) = lnA(Z_{it}) + \alpha ln\left(\frac{K_{it}}{L_{it}}\right) + (\alpha + \beta - 1)lnL_{it} + \varepsilon_{it}\ (1) \tag{5}$$

In the Equation 5, Z_{it} represents enterprise-specific characteristics, including technology type, origin, and duration of use, alongside other firm attributes affecting productivity.

TFP reflects how efficiently firms convert inputs (capital, labor) into outputs [47]. Normally, TFP is define as:

$$TFP_{it} = \ln(VA_{it}) - \alpha\ln(K_{it}) - \beta\ln(L_{it}) \tag{6}$$

Estimated via semi-parametric methods, e.g., [65, 66]. These approaches are designed to control for endogeneity arising from unobserved productivity shocks that influence both input decisions and output levels [67].

3-2- Modeling Machinery Usage

Machinery and equipment choices are central to understanding technological usage and productivity outcomes. Following the Diffusion of Innovation (DOI) theory [31], technologies are classified based on complexity, relative advantage, and compatibility [3, 8]. Firms' technology structures are categorized into three groups: (1) handheld tools; (2) electrically powered tools and manually operated machines; (3) computer-controlled machines.

To examine the determinants of machinery usage, we employ a Multinomial Logit (MNL) model. Let TEC_{ijt} represent the discrete choice of machinery type for firm i in sector j at time t. Suppose there are K mutually exclusive machinery categories {1,2,3}. The probability that firm i selects category k is given by:

$$P(TEC_{ijt} = k) = \frac{exp(Z_{ijt}\beta_k)}{\sum_{m=1}^{k} exp\ (Z_{ijt}\beta_m)} \qquad k = 1,2,\ldots,K \tag{7}$$

where:

- TEC_{ijt} denotes the machinery category selected by firm i in sector j at time t.
- K is the total number of machinery categories (i.e., 3 categories: (1) handheld tools; (2) electrically powered tools and manually operated machines; (3) computer-controlled machines).

- m is the index iterating through all possible machinery categories.
- Z_{ijt} is a vector of firm-level explanatory variables (e.g., firm size, ownership structure, technological intensity, export/import status).
- β_k is the parameter vector corresponding to machinery category k, indicating how each variable in Z_{ijt} influences the probability of selecting type k.
- Baseline category: Typically, the group 2 (i.e., electrically powered tools and manually operated machines) is chosen as the reference (i.e., its parameter vector is normalized to zero for identification). Consequently, estimated coefficients β_k reflect the log-odds of choosing category k relative to the baseline.

To investigate how different machinery choices relate to productivity, we estimate a series of panel data regressions, complemented by first-difference and second-difference estimators: (i) First-Difference Regression: Subtracts each firm's observations across consecutive years to remove time-invariant unobserved heterogeneity [68, 69]; (ii) Second-Difference Regression: Applies differencing twice, capturing medium-run or lagged effects that may arise from learning curves or adjustment costs [70, 71].

By combining these difference estimations with semi-parametric TFP measurement [66], we address endogeneity due to self-selection into technology usage or concurrent shocks [72, 73]. This methodological design helps distinguish short-term disruptions - such as initial usage costs - and long-term gains - such as enhanced productivity after learning-by-doing [74, 75].

3-3- Description of Sample and Variables

3-3-1- Description of Sample

The enterprises in this study are classified according to the criteria set out in Vietnam's 2017 Law on Support for Small and Medium Enterprises. The classification divides firms into four categories based on size. Micro-enterprises are those with fewer than 10 employees, annual revenue under 10 billion VND, or capital under 3 billion VND. Small enterprises are those with fewer than 100 employees, annual revenue under 50 billion VND, or capital under 20 billion VND. Medium enterprises are those with fewer than 200 employees, annual revenue under 200 billion VND, or capital under 100 billion VND. Large enterprises exceed the thresholds set for micro, small, and medium enterprises.

The dataset used in this study combines two key data sources to offer both longitudinal and industry-specific data. The first is the General Statistics Office (GSO)'s annual enterprise surveys conducted between 2010 and 2019, which provide detailed information on ownership, revenue, workforce, assets, and profits. The second is specialized surveys on manufacturing enterprises conducted from 2012 to 2019, which capture technology usage patterns at the 2-digit industry level (Figure 2).

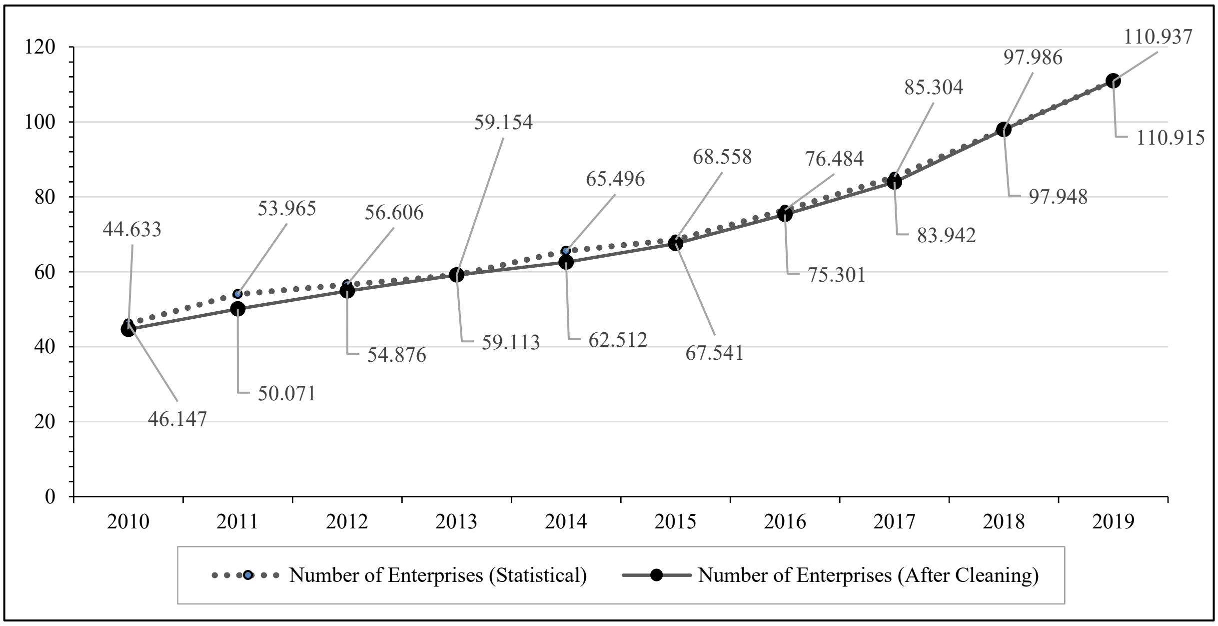


Figure 2. Data Scale and Cleaned Data

To ensure the reliability and accuracy of the data, a rigorous data cleaning process was conducted in two steps. First, duplicate enterprise codes within provinces were merged to create unique entries for each year. Second, observations missing key variables, such as end-of-year labor, average capital, or net revenue, were excluded from the dataset. This cleaning process resulted in a refined and robust dataset, which is well-suited for analyzing enterprise classifications and examining technology usage trends over the period from 2010 to 2019.

3-3-2- Description of Variables

This study employs a range of variables to analyze the determinants of machinery usage and its impact on productivity. The variables are based on the TOE framework, covering firm characteristics (such as size, ownership, and export participation), industry dynamics (including technological intensity and concentration), and regional influences. Handheld tools and computer-controlled machinery are used as the dependent variables in usage models, while labor productivity and TFP serve as outcome measures in the productivity analysis.

Table 1 provides a detailed description of the variables used in the study, including their data sources and expected correlations based on prior research. This comprehensive approach ensures theoretical alignment and empirical robustness, enabling a thorough evaluation of technology usage and productivity outcomes.

Table 1. Variable description

Variable Name	Description	Data Source	Expected correlation					
			Machinery and Equipment usage		Labor productivity		TFP	
			Sign	Studies	Sign	Studies	Sign	Studies
Export participation	Binary indicator (1 = firm participates in export activities, 0 = otherwise).	Enterprise Surveys	(+)	[1, 3]	Positive (+)	[1, 76]		
State-owned Enterprise	Binary indicator (1 = firm is state-owned, 0 = otherwise).	Enterprise Surveys	Mixed	[11, 57]	Mixed	[55]		
Foreign-invested Enterprise	Binary indicator (1 = firm has foreign investment, 0 = otherwise).	Enterprise Surveys	(+)	[8, 58]	Positive (+)	[3, 8]		
High-Tech Sector	Binary indicator (1 = firm operates in high-tech industries, 0 = otherwise).	Categorization from Industry Statistics	(+)	[8, 31]	Positive (+)	[51]		
Medium-High-Tech Sector	Binary indicator (1 = firm operates in medium-high-tech industries, 0 = otherwise).	Categorization from Industry Statistics	(+)	[8, 51]	Positive (+)	[30]		
Medium-Low-Tech Sector	Binary indicator (1 = firm operates in medium-low-tech industries, 0 = otherwise).	Categorization from Industry Statistics	Mixed	[1]	Mixed	[41]		
Low-tech Sector	Binary indicator (1 = firm operates in low-tech industries, 0 = otherwise).				Negative (-)	[51]		
Industry Concentration Index	Index measuring market concentration within an industry (e.g., Herfindahl-Hirschman Index).	Industry Statistical Data	Mixed	[3, 46]	Mixed	[1]		
Ratio of Labor in FDI Enterprises	Proportion of employees working in foreign-invested firms within the industry.	Industry Statistical Data	(+)	[58]	Positive (+)	[77]		
Capital Intensity per Labor	Ratio of capital to labor, representing investment intensity per worker.	Enterprise Surveys			Positive (+)	[55]		
Geographical Variables	Location-based dummy variables to capture regional effects (e.g., Red River Delta, Mekong Delta).	Regional Economic Statistics			Mixed	[8]		
Handheld Tools	Binary indicator (1 = firm primarily uses handheld tools, 0 = otherwise).	Enterprise Surveys					(-)	[1]
Computer-controlled Machinery	Binary indicator (1 = firm primarily uses computer-controlled machinery, 0 = otherwise).	Enterprise Surveys					(+)	[51]

4- Empirical Analysis

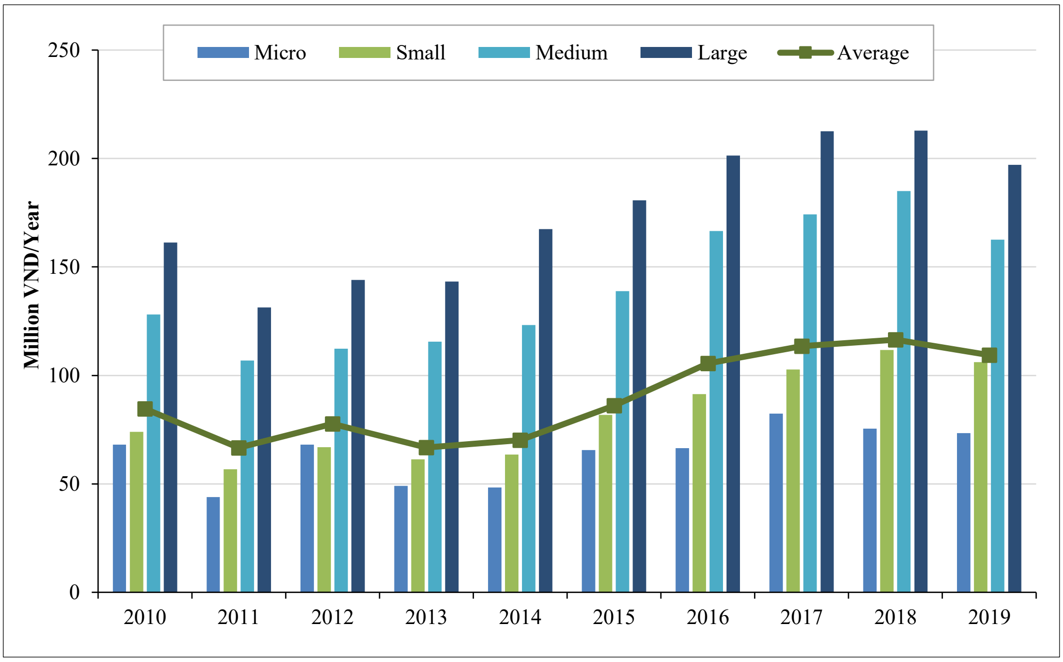
4-1-Empirical Context and Initial Observations

From 2010 to 2019, Vietnam's manufacturing sector was dominated by manually operated and semi-automated machines, especially among micro, small, and medium-sized enterprises (Table 2). Usage of computer-controlled machinery increased with firm size—rising from 3.13% in micro firms to 15.34% in large ones—indicating scale-related advantages in technology upgrading. Foreign-invested enterprises (FDIs) consistently reported higher usage of advanced machinery (13.64%) than domestic private firms (6.86%), reflecting better access to capital and global networks. In contrast, private micro firms showed continued reliance on basic tools. These patterns highlight deep structural disparities in technological adoption across ownership types and firm sizes within Vietnam's manufacturing landscape.

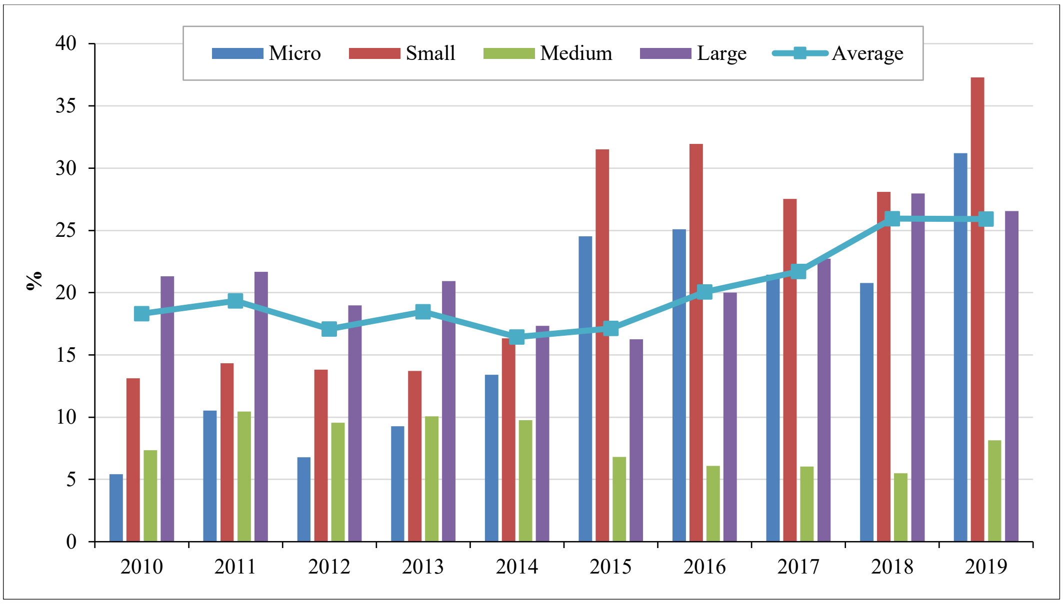
Table 2. **Machinery and equipment usage rates (%)**

Machinery Type	Micro	Small	Medium	Large	Average
All Enterprises					
Handheld Tools	3.3	1.5	0.58	0.47	1.15
Electrically Powered Tools and Manually Operated Machines	93.58	93.12	90.82	84.19	90.13
Computer-Controlled Machines	3.13	5.38	8.6	15.34	8.73
Private Enterprises					
Handheld Tools	3.36	1.55	0.63	0.48	1.35
Electrically Powered Tools and Manually Operated Machines	93.58	93.66	91.84	85.92	91.8
Computer-Controlled Machines	3.05	4.78	7.54	13.6	6.86
FDI Enterprises					
Handheld Tools	2.01	1.2	0.47	0.44	0.64
Electrically Powered Tools and Manually Operated Machines	93.29	89.73	88.46	82.62	85.71
Computer-Controlled Machines	4.7	9.07	11.07	16.93	13.64

Productivity differences further illustrate disparities in technological capabilities. Large firms consistently outperformed smaller ones: labor productivity rose from 161.25 to 197.10 million VND, while TFP contribution increased from 21.31% to 26.55% (Figure 3). Small firms also improved, with productivity rising from 73.98 to 106.10 million VND and TFP contribution from 13.12% to 37.28%. Micro-enterprises showed modest labor productivity gains (from 68.03 to 73.41 million VND), but TFP peaked later at 31.19% in 2019. Medium firms stagnated in TFP (6 - 10% post-2015) despite some productivity growth.



(a) Firm's labor productivity by size (Million VND/Year)



(b) Firm's contribution of TFP to VA by size (%)

Figure 3. Firms' labor productivity and TFP by size

These patterns set the stage for a deeper analysis of the firm- and industry-level characteristics associated with machinery usage and productivity outcomes in the following sections.

4-2- Factors Associated with Machinery and Equipment Usage

Among micro-enterprises, the results reveal significant barriers in adopting even basic equipment. State ownership is strongly negatively correlated with both handheld tools and computer-controlled machinery, highlighting the bureaucratic inertia typical of SOEs [11]. This finding aligns with the TOE framework, where risk aversion and limited managerial autonomy impede even modest upgrades. However, micro firms in high-tech sectors show a positive correlation with handheld tool use, suggesting that basic equipment remains necessary in resource-constrained firms - even in advanced industries. This echoes [15], who emphasize how complexity and resource intensity prevent adoption of advanced machinery despite sectoral pressure.

In small firms, machinery usage patterns become more nuanced. Foreign-invested enterprises are less reliant on handheld tools, consistent with the AC framework's emphasis on knowledge transfer and superior resources [3, 8]. In contrast, medium-tech firms still use handheld tools due to persistent financial and skills constraints, consistent with [41]. Notably, export-oriented and high-tech small firms use more computer-controlled machinery, showing that external market exposure and competition promote upgrading, as theorized in the TOE and DOI frameworks [1, 31].

Among medium-sized enterprises, sectoral technological intensity is a key determinant of machinery choice. Firms operating in more technologically advanced sectors exhibit a distinct trend toward using computer-controlled systems while reducing their reliance on manual tools. This transition reflects a strategic move to enhance competitiveness by adopting more complex production processes, a finding consistent with theories on sectoral patterns of technical change [49]. Furthermore, foreign ownership is a critical driver, as foreign-invested enterprises (FDI) demonstrate a superior capacity for investing in and integrating modern production technologies, leveraging their advantages in capital and managerial expertise [51].

Large enterprises show a clear shift toward advanced machinery. Computer-controlled systems are more common in foreign-owned and high-tech firms, suggesting both internal capacity and external linkages are key. Surprisingly, export participation negatively correlates with computer-controlled machinery at this scale, possibly reflecting Vietnam's reliance on low value-added, labor-intensive exports [25, 78]. Interestingly, this negative correlation with exporting also holds for basic handheld tools (Table 3), suggesting that large exporting firms concentrate heavily on a middle ground of technology – electrically powered and manually operated machines – rather than specializing at either the high-tech or low-tech ends of the spectrum. This suggests a "hollowing out" effect, wherein FDI and export activity do not always translate into deep technological upgrading, particularly when local absorptive capacity remains weak [79]. Nonetheless, Notably, unlike for smaller firms where market structure plays a role, domestic market concentration no longer shows a statistically significant association with machinery choice for large enterprises, implying that at this scale, factors like global integration and sectoral characteristics may outweigh domestic competitive pressures in driving technology decisions [1, 35].

Across all sizes, sectoral technological intensity consistently shapes machinery use. High-tech sectors favor computer-controlled systems, while medium-tech firms show more variation by size. Smaller firms rely on handheld tools, whereas larger firms transition toward more advanced systems (Table 3). This heterogeneity supports the DOI theory's emphasis on relative advantage and observability and highlights the importance of firm-level readiness [31].

Table 3. Multinomial Logit Regression Results on Machinery and Equipment Usage (%)

Variable	Micro-enterprises	Small Enterprises	Medium Enterprises	Large Enterprises
Dependent Variable: Type of most important machinery and equipment				
Handheld Tools				
Export Participation	0.221	0.0564	0.0276	-0.302**
	(0.71)	(0.69)	(0.23)	(-2.24)
State-owned Enterprise	-13.21***	-0.402	0.0683	-0.334
	(-12.83)	(-0.55)	(0.13)	(-0.46)
Foreign-invested Enterprise	-1.231***	-0.465***	-0.152	0.184
	(-2.64)	(-4.36)	(-1.11)	(1.53)
High-tech Sector	(-2.64)	(-4.36)	(-1.11)	(1.53)
	0.936***	-0.240	-1.507**	-0.548
Medium-high-tech Sector	(2.69)	(-0.97)	(-2.10)	(-1.58)
	0.276*	0.467***	-0.218	-0.362**
Medium-low-tech Sector	(1.68)	(5.73)	(-1.26)	(-2.01)
	0.423***	0.215***	-0.216*	-0.470***
Low-tech Sector (Reference)	(3.52)	(3.57)	(-1.85)	(-2.96)
Industry Concentration Index	-0.0465	-0.0360	-0.0419	0.218***
	(-1.11)	(-1.34)	(-0.71)	(3.36)
Ratio of Employees in FDI	-0.0257	-0.0172	-0.00331	-0.0140
	(-1.14)	(-1.46)	(-0.60)	(-0.41)
Constant	-1.885***	-2.417***	-2.840***	-2.973***
	(-7.02)	(-18.73)	(-14.07)	(-13.26)
Computer-controlled Machinery				
Export Participation	0.488	0.520***	-0.0841	-0.203***
	(0.88)	(5.51)	(-0.88)	(-2.92)
State-owned Enterprise	-12.89***	-0.134	-0.410	0.367
	(-11.19)	(-0.13)	(-0.79)	(1.58)
Foreign-invested Enterprise	-0.255	0.196*	0.274***	0.259***
	(-0.35)	(1.80)	(2.67)	(4.07)
High-tech Sector	0.633	0.572***	0.666***	0.757***
	(0.94)	(2.86)	(2.83)	(6.59)
Medium-high-tech Sector	-0.769*	0.266**	0.407***	0.395***
	(-1.83)	(2.54)	(3.49)	(4.86)
Medium-low-tech Sector	-0.0804	0.149*	0.382***	0.564***
	(-0.30)	(1.90)	(4.12)	(8.66)
Industry Concentration Index	-0.132	-0.156***	0.0187	-0.0139
	(-1.55)	(-4.85)	(0.39)	(-0.44)
Ratio of Employees in FDI	-0.556	0.00351**	-0.0284	0.00165
	(-0.86)	(2.06)	(-1.46)	(0.34)
Constant	-3.152***	-2.747***	-2.269***	-1.826***
	(-5.07)	(-18.29)	(-14.15)	(-16.69)
Number of observations	2,557	16,847	7,984	11,411
Adjusted R^2	0.0254	0.0200	0.0188	0.0197
F-statistic	NA	377.62	149.18	9401.83
Prob > F	.	0.000	0.000	0.000

Source: Authors' estimation based on Vietnamese Enterprise survey 2011-2018 data.

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

4-3- Machinery and Equipment Usage and Labor Productivity

OLS regression results (Table 4) reveal significant correlations between machinery usage and labor productivity, with variations by firm size, ownership, and sector. These estimates reflect associations rather than causal effects due to potential omitted variable bias.

Table 4. Regression Results on Machinery and Equipment Use and Labor Productivity

Variable	Micro	Small	Medium	Large
Dependent Variable: log(labor productivity)				
Handheld Tools	0.0473 (0.58)	-0.0286 (-0.95)	-0.174*** (-3.31)	-0.137*** (-3.32)
Computer-controlled Machinery	0.246** (2.05)	0.0546 (1.37)	0.160*** (3.93)	0.270*** (9.96)
Capital Intensity per Labor	0.0810*** (5.53)	0.140*** (29.17)	0.226*** (32.86)	0.308*** (55.27)
State-owned Enterprise	-3.176*** (-31.02)	0.117 (0.78)	0.326*** (4.01)	0.341*** (4.72)
Foreign-invested Enterprise	0.259* (1.74)	0.336*** (14.57)	0.326*** (13.38)	0.149*** (7.59)
High-tech Sector	-0.162 (-0.64)	0.273*** (4.74)	0.354*** (5.67)	0.617*** (16.27)
Medium-high-tech Sector	0.303*** (4.46)	0.366*** (17.71)	0.562*** (18.58)	0.695*** (28.32)
Medium-low-tech Sector	0.159*** (2.82)	0.0897*** (6.39)	0.211*** (10.35)	0.286*** (15.79)
Handheld Tools * High-tech Sector	0.0441 (0.11)	0.468*** (3.41)	0.910* (1.69)	0.251 (1.49)
Handheld Tools * Medium-high-tech Sector	-0.102 (-0.63)	0.00668 (0.11)	0.110 (1.14)	0.644*** (2.95)
Handheld Tools * Medium-low-tech Sector	-0.222* (-1.79)	0.0988** (2.22)	0.120 (1.38)	0.238** (2.19)
Computer-controlled Machinery * High-tech Sector	0.709* (1.87)	0.149 (0.88)	0.0342 (0.23)	-0.371*** (-4.85)
Computer-controlled Machinery * Medium-high-tech Sector	-0.0742 (-0.23)	-0.196** (-2.37)	0.0620 (0.84)	-0.228*** (-3.92)
Computer-controlled Machinery * Medium-low-tech Sector	-0.222 (-0.65)	0.150** (2.39)	-0.0172 (-0.29)	-0.184*** (-4.51)
The concentration index at the 3-digit industry level	0.00535 (0.37)	-0.0316*** (-7.09)	-0.0175** (-2.38)	-0.0259*** (-4.46)
Ratio of Employees in FDI	-0.122 (-1.18)	0.0239 (0.90)	-0.0848*** (-2.72)	-0.0775*** (-2.96)
Northern Mountainous Area	-0.442*** (-6.64)	-0.313*** (-19.06)	-0.295*** (-13.96)	-0.110*** (-6.91)
Red River Delta	-0.453*** (-4.75)	-0.269*** (-10.24)	-0.216*** (-5.82)	-0.312*** (-10.40)
Central Coast	-0.370*** (-4.71)	-0.376*** (-18.60)	-0.229*** (-7.55)	-0.231*** (-8.77)
Central Highlands	-0.419*** (-3.25)	-0.202*** (-4.79)	-0.356*** (-4.95)	-0.277*** (-3.19)
Mekong Delta	-0.281*** (-3.44)	-0.312*** (-12.83)	-0.149*** (-4.15)	-0.0301 (-1.30)
Intercept	3.701*** (30.68)	3.741*** (114.13)	3.544*** (80.41)	2.982*** (87.91)
Number of observations	2275	16054	7878	11400
Adjusted R^2	0.094	0.236	0.327	0.478
F-statistic	-	170	142	353
Prob > F	-	0.000	0.000	0.000

Source: Authors' estimation based on Vietnamese Enterprise survey 2011-2018 data.

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Firm size moderates the productivity effects of computer-controlled machinery. Large and medium-sized enterprises exhibit strong positive correlations, consistent with their resource advantages and higher absorptive capacities [1, 34]. In contrast, micro and small enterprises show weaker or insignificant effects – likely due to financing and skill constraints [15, 18, 19]. Interestingly, micro-enterprises report a higher coefficient (0.246) than small ones (0.0546), possibly reflecting the leaner structures and agility of very small firms. These results highlight the need for differentiated policy support tailored to SME subgroups.

Ownership structure also shapes productivity outcomes. Foreign-invested enterprises (FDIs) show positive associations with labor productivity ($p < 0.05$), reflecting their access to capital, global networks, and management expertise [35, 38]. In contrast, state-owned enterprises (SOEs) display weaker and more variable productivity correlations. Notably, while medium and large SOEs show modest positive effects, micro SOEs exhibit a significantly negative relationship, suggesting that smaller state-owned units may be particularly hampered by bureaucratic inefficiencies, risk aversion, and limited innovation incentives [11, 13, 57].

Sectoral heterogeneity plays a pivotal role in the machinery–productivity nexus. Our regression results indicate that in high-tech sectors (e.g., electronics and precision manufacturing), the positive impact of computer-controlled machinery on labor productivity grows with firm size – shifting from a negative association in micro-enterprises to a strong positive effect in large firms ($p < 0.05$). This finding is consistent with the TOE and DOI frameworks, which argue that industries with higher value-added processes benefit from advanced technologies due to greater absorptive capacity and capital intensity [20, 34, 49, 60, 80]. In contrast, labor-intensive sectors such as textiles and furniture show weaker or insignificant correlations, reflecting their persistent reliance on low-cost labor and limited automation incentives. Moreover, interaction analyses reveal that even basic equipment – such as handheld tools – can enhance productivity in high-tech environments for small and medium enterprises. This supports evidence that agile SMEs may leverage basic equipment effectively through rapid learning and focused operations [6, 19, 81]. Conversely, large firms may face integration challenges and diminishing returns from advanced machinery because of organizational complexity and the "productivity paradox" [9, 20, 80, 82].

The Industry Concentration Index has a significant negative effect on labor productivity for small, medium, and large enterprises (-0.0316, -0.0175, -0.0259, respectively). This result reinforces the view that reduced competitive pressure in highly concentrated markets dampens firms' incentives to innovate and improve efficiency – a notion well supported by Syverson [47] and Arvanitis & Hollenstein [51]. As Hall & Khan [9] and Porter [46] have argued, intense domestic rivalry is crucial for spurring innovation; in its absence, firms may rely on established market positions rather than actively pursuing new technologies.

Geographic factors show a consistent negative correlation with labor productivity across all firm sizes. Firms in peripheral regions—such as the Northern Mountains, Red River Delta, Central Coast, and Central Highlands—exhibit lower productivity due to infrastructure gaps, limited technology access, and reduced human capital [78, 83]. Despite urban centers like Hanoi, the Red River Delta still shows an overall negative effect, reflecting offsetting underdevelopment. In contrast, the Mekong Delta's negative impact is smaller for large firms (-0.0301), suggesting that economies of scale help mitigate regional disadvantages [3, 48]. These correlations underscore the role of geographic disparities in shaping productivity and highlight the need for region-specific policies in emerging economies [1, 3, 84].

The regression results across OLS, first-difference, and second-difference specifications reveal that the observed associations between machinery usage and productivity outcomes tend to diminish over time. For labor productivity, OLS estimates indicate that computer-controlled machinery is positively associated with performance in micro (0.246), medium (0.160), and large firms (0.270), while handheld tools are negatively correlated in medium and large firms. However, these patterns largely dissipate in the first- and second-difference regressions, suggesting that the initial gains may not be sustained. For instance, in the differenced models, the previously significant positive effects of computer-controlled machinery either become statistically insignificant or weaker. Notably, a significant negative short-term effect emerges for small firms in the first-difference model, while only marginal positive effects remain for medium-sized firms (Table 5).

In the case of TFP, OLS results show significant negative correlations with computer-controlled machinery in micro, small, and medium firms. Yet, these effects disappear in the differenced models, indicating that the initial productivity losses – likely stemming from adjustment costs – may be transitory. Notably, micro firms exhibit large negative coefficients for both types of machinery in the second-difference regressions, possibly reflecting their limited absorptive capacity and lack of complementary capabilities.

Table 5. Difference Regression Results on Machinery and Equipment Use and Labor Productivity and TFP

Variable	Micro	Small	Medium	Large
Dependent Variable: log(labor productivity)				
OLS Regression				
Handheld Tools	0.0473	-0.0286	-0.174***	-0.137***
	(0.58)	(-0.95)	(-3.31)	(-3.32)
Computer-controlled Machinery	0.246**	0.0546	0.160***	0.270***
	(5.84)	(16.13)	(9.81)	(7.21)
First Difference Regression				
Handheld Tools	0.303*	0.0542	-0.0512	0.0253
	(1.77)	(1.00)	(-0.72)	(0.34)
Computer-controlled Machinery	0.00684	-0.155*	0.138*	-0.00515
	(0.02)	(-1.92)	(1.65)	(-0.13)
Second Difference Regression				
Handheld Tools	0.122	-0.0327	0.0244	0.0395
	(0.72)	(-0.64)	(0.32)	(0.63)
Computer-controlled Machinery	0.525	-0.0174	0.107*	-0.0385
	(1.62)	(-0.04)	(0.08)	(-0.66)
Dependent Variable: log(TFP)				
OLS Regression				
Handheld Tools	0.0678	0.0586***	-0.0219	0.0854
	(1.55)	(4.74)	(-0.31)	(1.40)
Computer-controlled Machinery	-0.171*	-0.0804***	-0.154**	-0.0114
	(-1.85)	(-5.29)	(-2.51)	(-0.32)
First Difference Regression				
Handheld Tools	-0.224*	0.0247	-0.0102	-0.000190
	(-1.68)	(0.64)	(-0.07)	(-0.00)
Computer-controlled Machinery	-0.355	0.0261	0.103	-0.0183
	(-1.62)	(0.45)	(0.85)	(-0.20)
Second Difference Regression				
Handheld Tools	-1.041**	0.141	-0.0950	-0.135
	(-1.99)	(1.22)	(-0.25)	(-1.02)
Computer-controlled Machinery	-2.636**	-0.00594	0.0185	-0.127
	(-1.99)	(-0.04)	(0.08)	(-0.66)

Source: Authors' estimation based on Vietnamese Enterprise survey 2011-2018 data.

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

These findings imply that the initial productivity changes from machinery adoption are eroded over time by recurring adjustment costs – such as training expenses, process reorganization, and operational disruptions. This pattern is consistent with earlier studies documenting the transient nature of productivity improvements [11-13, 75]. Moreover, in line with the Absorptive Capacity framework [34] and diffusion theory [15, 31], these results suggest that sustained gains in both labor productivity and TFP require continuous complementary investments in workforce upskilling, managerial enhancements, and process optimization. Additional insights from [80] further reinforce the notion that without ongoing organizational improvements, the initial benefits of advanced technology cannot be maintained over time.

5- Conclusions and Implications

This study investigates how firm- and industry-level factors relate to the use of machinery and its association with labor productivity and TFP in Vietnamese manufacturing. Three key insights emerge:

- First, machinery usage patterns are strongly differentiated by firm size, ownership structure, and sectoral context. Larger and foreign-invested enterprises are significantly more likely to use computer-controlled machinery, while micro and small firms remain reliant on handheld tools. These patterns reflect persistent disparities in technological readiness, capital access, and organizational capabilities.
- Second, the correlation between machinery usage and productivity is largely short-lived. OLS models reveal positive associations between computer-controlled machinery and labor productivity, especially among medium and large firms. However, these effects dissipate in first- and second-difference regressions, suggesting that short-term gains may erode over time without sustained complementary investments. For TFP, computer-controlled machinery shows negative or insignificant associations, particularly among micro, small, and medium firms, highlighting the challenges of realizing deeper efficiency gains in resource-constrained settings.
- Third, the productivity effects of machinery usage are shaped by sectoral and market characteristics. Firms in high-tech and export-oriented industries are more likely to experience positive productivity correlations – particularly in the short term – while firms in labor-intensive sectors or peripheral regions tend to exhibit weaker or even negative associations. These differences point to the moderating role of sectoral dynamics, competition intensity, and geographic factors.

Together, these findings underscore that productivity benefits from machinery usage are not guaranteed and depend on specific firm-level capabilities and the type of machinery used, particularly in developing contexts where adoption does not always translate into effective usage. For policymakers, these results highlight the importance of tailored support strategies that go beyond capital investment – emphasizing the role of workforce development, managerial upgrading, and technology diffusion infrastructures. Introducing region-specific and firm-size-targeted programs may help address persistent disparities in absorptive capacity and support more inclusive industrial upgrading. Future research could further explore which public-private mechanisms best sustain productivity gains from machinery, particularly among smaller or disadvantaged firms.

6- Declarations

6-1- Author Contributions

Conceptualization, T.M.T.T., M.H.N., H.D.V., and S.A.P.; methodology, H.D.V. and S.A.P.; software, H.D.V. and S.A.P.; validation, H.D.V. and S.A.P.; formal analysis, T.M.T.T. and M.H.N.; investigation, M.H.N.; resources, T.M.T.T., and H.D.V.; data curation, H.D.V. and T.M.T.T.; writing–original draft preparation, T.M.T.T., M.H.N., H.D.V., and S.A.P.; writing–review and editing, T.M.T.T., M.H.N., H.D.V., and S.A.P.; visualization, T.M.T.T.; supervision, M.H.N. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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