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Technological Intensity and the Export Effects of Investment Policy

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Abstract

Technological upgrading has become a central instrument for promoting export-oriented transformation in manufacturing; yet, the moderating role of industry technology intensity and the structural volatility that may arise during transition remain underexplored. Using an industry-level panel dataset for Taiwan's manufacturing sector (2016–2023), this study estimates fixed-effects and interaction-term models to evaluate heterogeneous policy effects across three export dimensions: export growth rate, export ratio, and export stability (operationalized as short-horizon volatility risk). The results indicate that, in high-tech industries, policy-induced investment is associated with stronger export ratio but also higher export volatility, pointing to a trade-off between structural upgrading and short-run stability. In contrast, traditional manufacturing exhibits relatively limited outward responses, consistent with an adjustment pattern in which technology investment is prioritized for internal reallocation and efficiency improvement rather than immediate export expansion. These findings highlight distinct operating logics determined by technology intensity: high-tech industries facing greater structural instability during upgrading, while traditional industries tend to internalize resources through capability strengthening. Consequently, policy design should be differentiated complementary measures are needed to manage volatility risks in high-tech sectors, while evaluations for traditional manufacturing should recognize longer adjustment horizons and avoid inferring effectiveness from a single export indicator.

Keywords: Technology intensity, Export performance, Industry heterogeneity, Absorptive capacity

1 | Introduction

Amid accelerating global digital transformation and ongoing supply-chain reconfiguration, technological upgrading has become a central instrument for strengthening manufacturing competitiveness and promoting export-oriented transformation [1, 2]. Technology investment can improve production efficiency and

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facilitate product differentiation, and it underpins export performance. As such, it has been widely regarded as an important policy lever for export-oriented development [3].

Technology adoption and industrial transformation, however, are rarely instantaneous or smooth processes. They typically entail structural changes involving resource reallocation and organizational adjustment, implying that the effects of technology investment may materialize with lags and due to distinct industrial characteristics generate divergent transmission paths [4]. These dynamics are particularly pronounced in small open economies marked by significant internal manufacturing heterogeneity. In this context, industry technology intensity acts as a key structural condition determining whether policy incentives effectively translate into export outcomes. With stronger absorptive capacity, high-tech industries are typically more deeply embedded in global value chains and exhibit greater flexibility in market adjustment; conversely, upgrading in traditional manufacturing tends to be more incremental and process-oriented, characterized by a relatively slower pace of adjustment [5, 6]. Accordingly, identical policy incentives may trigger fundamentally distinct operating mechanisms and adjustment paths across industries with varying technology intensities [7].

While the literature generally recognizes the aggregate benefits of technology-oriented policy interventions, most studies continue to emphasize an average-effect perspective, and relatively few systematically test within a unified empirical framework whether industry technology intensity operates as a meaningful moderator of policy effects [5, 8]. In addition, export performance is often assessed primarily through export growth, with less attention to jointly incorporating Export Ratio and Export Stability. This limits the ability to capture the potential trade-off that may arise during transformation, whereby export-structure upgrading and elevated short-horizon fluctuations can occur simultaneously [9, 10]. As a result, policymakers may face difficulty in balancing growth objectives with the management of volatility risks during structural adjustment.

Against this background, this study moves beyond the limitations of the traditional average-effect approach to examine the heterogeneous effects of technology-investment policy across industries grouped by technology intensity. While recent research using Taiwan's manufacturing panel data (2016–2023) has explored the interaction between technology investment and firm size on export resilience [11], firm size primarily reflects resource abundance and does not fully capture an industry's intrinsic absorptive capacity or evolutionary trajectory. Consequently, this study extends the existing empirical framework by shifting the analytical lens from "scale" to "technological nature." Using fixed-effects models and an interaction-term design, we systematically evaluate the policy responses of high-tech versus traditional manufacturing across multiple indicators of export performance.

By assessing export outcomes from the perspective of structure (export ratio), performance (export growth rate), and short-run volatility risk (export stability), this study complements the prevailing average-effect policy evaluation approach and provides evidence on how technology-investment policy operates across heterogeneous industrial contexts during transformation.

2| Literature Review and Study Framework

This section synthesizes prior research to elucidate the linkage between technology-investment policy and industrial transformation from three angles: (1) evidence on the export effects of technology-investment policy; (2) heterogeneity in policy responses by industry technology intensity; and (3) multidimensional measurement of export performance. Based on this synthesis, the chapter identifies the research gap and outlines the study framework.

2.1| Technology-Investment Policy and Export Performance

Technology investment and innovation incentives can enhance international competitiveness and export performance by improving production efficiency, facilitating product differentiation, and upgrading quality. Empirical studies commonly report that R&D expenditure, equipment renewal, investment subsidies, and tax incentives are positively associated with export growth, export intensity, or value-added upgrading. In particular, evidence regarding the role of digital intensity in raising export quality has underpinned technology-upgrading policies, suggesting that digital-intensive industries may exhibit stronger policy transmission efficiency [3, 12, 13].

However, technology upgrading typically entails adjustment costs and learning dynamics. Some studies note that policy-induced technology investment may initially trigger resource reallocation and organizational restructuring, leading to delayed export responses and, in some instances, heightened short-run volatility [14]. Despite this, much of the literature evaluates policy performance through aggregate or industry-average effects, implicitly assuming broadly similar response mechanisms across sectors. For small open economies with highly heterogeneous industrial structures, this average-effect perspective may mask asymmetric responses, leading to a systematic underestimation of volatility risks in high-tech industries or adjustment costs in traditional manufacturing.

2.2 | Technology Intensity and Heterogeneous Policy Effects

Industry heterogeneity is a key source of differential policy effects. High-tech and traditional manufacturing industries differ structurally in R&D intensity, human capital, and accumulated knowledge, implying distinct levels of absorptive capacity. The ability of firms or industries to identify, assimilate, and apply external knowledge determines the speed and extent to which technology investment translates into productivity gains and market competitiveness [6, 15].

High-tech industries typically convert technology investment into process efficiency and product upgrading more rapidly, leveraging participation in global value chains to adjust export strategies. In contrast, upgrading in traditional manufacturing more often takes an incremental form, and policy responses depend on organizational adaptation to new technological structures and technology readiness [5].

Technology intensity also shapes the nature of short-run volatility risk. In technology-intensive or globally fragmented industries, upgrading is often accompanied by significant structural reorganization and market reallocation, making volatility and uncertainty more likely to rise during the early transition [14]. Accordingly, technology intensity is not merely a background characteristic to be controlled for; it operates as a key moderating condition for the effects of technology-investment policy [16].

2.3 | Multidimensional Measurement of Export Performance

Export performance is inherently multidimensional. While export growth rates are widely used as the primary indicator, a single metric may not adequately reflect structural change and risk costs during transformation [17]. Consequently, the literature increasingly argues for jointly considering export orientation and export stability. Export orientation reflects reliance on external markets and the direction of structural adjustment, whereas Export Stability corresponds to exposure to short-horizon fluctuations under external shocks and captures short-horizon volatility exposure, which is conceptually distinct from long-run resilience [9].

Industrial upgrading and export-structure adjustment often involve resource reallocation, making higher short-run volatility a common feature during transition [4]. In more technology-intensive industries, faster and larger-scale restructuring can amplify the trade-off between "improved export orientation" and "increased short-run instability." This reflects the reality that global value chain participation may generate export gains while simultaneously introducing more complex volatility dynamics [10].

Observing both export orientation and export stability alongside export growth can therefore help identify heterogeneous adjustment paths under policy stimulus and reduce potential bias from inferring policy performance solely from growth indicators [9, 17, 18].

2.4 | Research Gap and Study Framework

Existing research suggests that technology-investment policy is generally associated with improved export performance, but effects may be delayed and accompanied by short-run volatility risk [3, 4]. Differences in technology intensity and absorptive capacity may determine whether policy-induced investment is translated into export competitiveness and how volatility risk evolves during transformation. Although recent work has begun to consider firm size as a moderating factor in policy responses [11], there remains limited evidence from a unified empirical framework that systematically compares high-tech and traditional manufacturing in terms of differential responses in export growth, export orientation, and export stability. Moreover, many studies continue to emphasize average-effect tests [8].

Against this background, the present study groups industries by technology intensity and employs fixed-effects and interaction-term designs to examine heterogeneity in policy effects. This approach complements the average-effect perspective and provides an empirical basis for differentiated industrial policy design.

3| Research Design

This section outlines the empirical research design, including data construction, industry grouping, variable definitions, and model specifications. The logic of the research design is grounded in the theoretical framework and literature reviewed previously, focusing on testing the heterogeneous effects of technology-investment policy across industries with varying technological intensities.

3.1| Data and Industry Grouping

To examine whether technology-investment policy effects exhibit systematic heterogeneity, this study employs an industry-level panel dataset covering eight major manufacturing industries in Taiwan from 2016 to 2023 (N = 8, T = 8). These industries constitute a substantial proportion of Taiwan's total manufacturing output and exports; thus, the sample is highly representative of the industrial structure and effectively reflects aggregate policy-response patterns. The dataset is compiled from official statistics and constructed as an industry–year panel.

Following the OECD classification and considering Taiwan's specific industrial context, the sample is divided into: "High-Tech Industries" and "Traditional Manufacturing" [19]. This classification reflects structural differences in technological sophistication, R&D foundations, and global value chain integration, serving as the basis for subsequent comparative analysis. The grouping results are summarized in *Table 1*.

Table 1. Industry grouping by technology intensity

Group	Industries Included	Rationale
High-Tech	Electronic Components; Computers, Electronics & Optics	High R&D intensity and technological sophistication; deep integration into global value chains with superior absorptive and adjustment capacities.
Traditional	Basic Metals & Fabricated Metal; Petrochemicals & Plastics; Machinery & Equipment; Food, Pharma & Medical Chemicals; Motor Vehicles & Transport Equip.; Textiles, Apparel & Leather	Upgrading patterns primarily driven by process improvements and internal efficiency; focus on the optimization and deepening of existing industrial structures.

3.2| Variables and Measurement

This study employs three industry-level dependent variables to capture export growth, orientation, and stability: (1) Export Growth Rate, reflecting annual shifts in export scale; (2) Export Ratio, representing the degree of external market reliance; and (3) Export Stability, measuring short-term export volatility during transformation, operationalized as the three-year coefficient of variation of export values.

The key independent variable is Investment Penetration, which measures the intensity of technology-investment incentives adopted in each industry during the study period, and is used as a proxy for policy penetration and actual uptake of policy-induced technology investment. Technology Intensity is operationalized using a binary indicator (High-Tech = 1; Traditional = 0).

Control variables include Import Growth Rate, Import Ratio, Large Firm Sales Ratio, and FX Change (annual change in the real effective exchange rate) to account for international demand, industry concentration, and macroeconomic fluctuations. Detailed variable definitions are presented in *Table 2*.

Table 2. Variable definitions and measurement units

Type	Variable	Definitions	Unit
Independent Variable	Investment Penetration	Ratio of technology-equipment investment to an industry's annual capital expenditure, capturing the actual adoption of policy-induced technology investment.	%
Dependent Variable	Export Growth Rate	Year-on-year export growth rate, reflecting short-term export expansion capacity.	%
	Export Ratio	Ratio of total exports to total output value, measuring the degree of external market reliance and export orientation.	%
	Export Stability	Three-year coefficient of variation of export values (standard deviation / mean), capturing short-term export volatility (risk). A higher CV indicates greater volatility and lower stability.	-
Grouping Variable	Technology Intensity	Binary indicator: High-tech industries = 1; Traditional manufacturing = 0. Used for heterogeneity and interaction analyses.	-
Control Variable	Import Growth Rate	Year-on-year import growth rate, reflecting changes in international demand and input costs.	%
	Import Ratio	Ratio of imports to total output value, capturing dependence on external inputs.	%
	Large Firm Sales Ratio	Share of large-firm sales in total industry sales, used as a proxy for industrial concentration and size structure.	%
	FX Change	Annual change in the real effective exchange rate (REER), measured as the natural log of the ratio of the current to lagged exchange rate.	-

3.3 | Empirical Model and Robustness Design

To estimate the impact of technology-investment policy on export performance, this study adopts a fixed-effects panel regression model to control for time-invariant structural differences across industries and to identify the policy effect from within-industry variation over time. The baseline model is estimated separately for the high-tech and traditional manufacturing subsamples to compare policy responses across groups. The baseline specification is as *Eq. (1)*.

$$Y_{i,t} = \alpha_i + \beta_1 InvPen_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t} \quad (1)$$

Where $Y_{i,t}$ denotes the export performance indicator for industry i in year t (i.e., Export Growth Rate, Export Ratio, and Export Stability); $InvPen_{i,t}$ represents Investment Penetration, capturing the intensity of policy-induced technology investment; $X_{i,t}$ is a vector of control variables; α_i represents industry fixed effects; and $\varepsilon_{i,t}$ is the error term.

Although the high-tech subsample is smaller after grouping, the data have a finite population character, and the coefficients are interpreted as reflecting structural relationships rather than relying on random-sample inference [20]. In addition, given industry heterogeneity, group-specific estimation helps mitigate potential aggregation bias that may arise when heterogeneous industries are forced into a single pooled specification, thereby supporting unbiased parameter estimation [21].

To strengthen statistical power and directly test heterogeneity, the study augments the baseline model by adding an interaction between the policy variable and the technology-intensity indicator $(InvPen_{i,t} \times HT_i)$, This yields an interaction-based heterogeneity model estimated using the pooled sample, as shown in *Eq. (2)*.

$$Y_{i,t} = \alpha_i + \beta_1 InvPen_{i,t} + \beta_2 (InvPen_{i,t} \times HT_i) + \beta_3 X_{i,t} + \varepsilon_{i,t} \tag{2}$$

In this model, HT_i is a dummy variable equal to 1 for high-tech industries and 0 for traditional manufacturing. Consequently, β_1 represents the marginal policy effect for traditional industries, while β_2 captures the additional marginal effect (difference in slopes) for high-tech industries relative to traditional industries. The total policy effect for high-tech industries is given by $\beta_1 + \beta_2$. Finally, to assess robustness by controlling for time-specific common shocks, *Eq. (2)* is extended to include year fixed effects (δ_t), forming a Two-Way Fixed effects model as shown in *Eq. (3)*.

$$Y_{i,t} = \alpha_i + \delta_t + \beta_1 InvPen_{i,t} + \beta_2 (InvPen_{i,t} \times HT_i) + \beta_3 X_{i,t} + \varepsilon_{i,t} \tag{3}$$

where δ_t captures time-varying factors common across industries such as global business cycle conditions, exchange-rate movements, and external demand shocks. This specification allows the study to evaluate whether the estimated policy effects remain stable after controlling for common time trends. For inference, all models employ HC1 cluster-robust standard errors clustered at the industry level to address heteroskedasticity and within-industry serial correlation over time [22].

4 | Empirical Results and Analysis

This section reports the empirical estimates based on the research design. It presents the estimated effects of Investment Penetration on export performance and examines whether these effects exhibit systematic heterogeneity by industry technology intensity.

4.1 | Baseline Industry Differences and Descriptive Statistics

We first examine the statistical properties of the variables. *Table 3* reports group-wise descriptive statistics for high-tech and traditional manufacturing industries over the sample period, together with difference tests. These difference tests are reported for descriptive purposes only, to summarize sample characteristics. The statistics reveal clear divergences in export patterns and structural features across the two groups:

- Dependent variables: High-tech industries exhibit marked advantages in export performance. Both Export Ratio (0.790) and Export Growth Rate (0.097) are significantly higher than those of traditional industries (0.349 and 0.016, respectively; Diff = 0.442*** and 0.081**), indicating stronger export orientation and short-term export expansion in high-tech industries. For Export Stability (CV), the high-tech value (0.108) is slightly higher than that of traditional industries (0.081), but the difference is not statistically significant (Diff = 0.028). At the descriptive level, this suggests no clear group difference in short-horizon export volatility.

- Independent variable: The mean Investment Penetration in high-tech industries is 0.131, which is about 1.7 times that of traditional industries (0.078). Although this difference is not statistically significant (Diff = 0.052), the lack of significance may reflect the very high within-group variation in high-tech industries (SD = 0.155), indicating heterogeneous adoption intensity across sub-industries.
- Control variables: Traditional manufacturing shows a significantly higher Import Ratio (0.694) than high-tech industries (0.273) (Diff = −0.421***), implying greater dependence on imported inputs. In addition, the Large Firm Sales Ratio is significantly higher in high-tech industries (0.887) than in traditional industries (0.623) (Diff = 0.264***), suggesting a more concentrated market structure in high-tech sectors.

Overall, the descriptive evidence highlights substantial cross-industry heterogeneity in growth momentum, export orientation, and market structure. Given the “high mean–high variance” pattern of policy penetration, the subsequent fixed-effects models further control for time-invariant industry characteristics to identify policy effects more precisely.

Table 3. Descriptive statistics by industry group

Variable	High-Tech (Mean)	Traditional (Mean)	Difference (t-test)
Investment Penetration	0.131 (0.155)	0.078 (0.070)	0.052
Export Growth Rate	0.097 (0.130)	0.016 (0.129)	0.081**
Export Ratio	0.790 (0.086)	0.349 (0.173)	0.442***
Export Stability	0.108 (0.071)	0.081 (0.049)	0.028
Import Growth Rate	0.075 (0.095)	0.038 (0.135)	0.037
Import Ratio	0.273 (0.110)	0.694 (0.129)	−0.421***
Large Firm Sales Ratio	0.887 (0.011)	0.623 (0.101)	0.264***
FX Change	−0.003 (0.045)	−0.003 (0.044)	0.000

Notes: N = 64 (16 for High-Tech, 48 for Traditional). Values represent annual means. Standard deviations are in parentheses. Difference statistics are reported for descriptive comparison only and do not constitute causal inference. Significance: *p <0.05, **p <0.01, ***p <0.001

4.2| Group-Specific Fixed-Effects Estimates: High-Tech vs. Traditional Manufacturing

To assess whether the policy effect differs by industry technology intensity, we estimate fixed-effects models separately for the high-tech and traditional manufacturing subsamples. *Table 4* reports the results.

In high-tech industries, Investment Penetration is positively and significantly associated with Export Ratio ($\beta = 0.447$, $p < 0.01$), suggesting a significant relationship between policy-induced investment and increased export orientation in high-tech sectors [23]. In traditional manufacturing, the coefficient is significantly negative ($\beta = -0.124$, $p < 0.05$). This pattern aligns with the view that, during the early stages of transformation, traditional industries may prioritize internal process upgrading and efficiency improvements over immediate outward expansion, reflecting an "internalization" tendency [10].

For Export Stability, the policy coefficient in high-tech industries is positive and significant ($\beta = 0.299$, $p < 0.05$), implying that while technology investment may strengthen outward orientation, it can also be associated with heightened export volatility and risk [14]. In traditional manufacturing, the corresponding coefficient is not statistically significant (0.011), indicating that export volatility appears less responsive to policy-induced investment in this group.

Regarding Export Growth Rate, the high-tech coefficient is positive (β = 0.247, $p \approx 0.08$) but only marginally significant, while the traditional coefficient is negative and not significant (β = −0.112), suggesting that the direct stimulus of the policy on export growth is limited.

Regarding controls, Import Growth Rate is positively significant for Export Growth Rate in both groups, consistent with a co-movement between import expansion and export momentum. For the high-tech Export Ratio, Import Growth Rate shows a significant negative coefficient (β = −0.145, $p < 0.05$), which may reflect that imports often intermediate inputs can mechanically dilute the export share, while also indicating strong complementarity between imports and exports within global value chain participation, leading to parallel development of the production–technology structure [23, 24].

In terms of industrial structure, Large Firm Sales Ratio significantly boosts export growth in high-tech sectors (β = 5.171, $p < 0.01$) but enhances stability (reduces volatility) in traditional manufacturing (β = −0.763, $p < 0.001$). This suggests that industrial concentration amplifies expansion in technology-intensive sectors while buffering external shocks in traditional sectors [25, 26].

FX Change is generally positive and significant in the high-tech sample, consistent with the expectation that currency depreciation strengthens export competitiveness. In the traditional sample, the coefficient for Export Growth Rate turns negative (β = −0.440), though not statistically significant, suggesting a possible offset between price competitiveness and higher import costs.

Overall, the group-specific estimates indicate that policy incentives operate through divergent transmission channels: fostering a "high-orientation, high-volatility" path in high-tech industries, while supporting internal adjustment in traditional sectors.

Table 4. Fixed-Effects results by industry type

Variable	**Export Growth Rate**		**Export Ratio**		**Export Stability**	
	High-Tech	Traditional	High-Tech	Traditional	High-Tech	Traditional
Investment Penetration	0.247 (0.124)	−0.112 (0.215)	0.447*** (0.047)	−0.124** (0.045)	0.299** (0.088)	0.011 (0.076)
Import Growth Rate	1.017** (0.298)	0.490** (0.155)	−0.145* (0.048)	−0.004 (0.020)	0.166 (0.245)	0.063 (0.053)
Import Ratio	0.136 (1.064)	−0.821*** (0.177)	−0.659** (0.200)	0.065 (0.063)	−0.060 (0.610)	−0.145 (0.073)
Large Firm Sales Ratio	5.171** (1.239)	0.510 (1.296)	1.419 (0.668)	0.030 (0.182)	0.456 (3.333)	−0.763*** (0.193)
FX Change	0.349** (0.103)	−0.440 (0.460)	0.006 (0.265)	0.168* (0.076)	0.339* (0.127)	0.441** (0.132)
Observations	16	48	16	48	16	48

Notes: Robust standard errors (HC1) clustered by industry are shown in parentheses. *** p<0.001; ** p<0.01; * p<0.05. Export Stability is measured by CV (higher value = lower stability). Estimates for variables with limited within-group variation (e.g., Large Firm Sales Ratio in high-tech sample) should be interpreted as structural rather than statistical relationships.

4.3 | Interaction Models: Testing Heterogeneity by Technology Intensity

To formally assess whether technology intensity moderates the policy effect, we pool high-tech and traditional industries into a single framework and estimate interaction models.

Table 5 reports the estimates controlling for industry fixed effects. The interaction coefficient (β_2) is positive and statistically significant across all three export outcomes. This confirms that high-tech industries respond significantly more strongly to policy-induced investment than traditional industries. Wald tests further indicate that the total policy effect for high-tech industries ($\beta_1 + \beta_2$) is statistically different from zero in all models ($p < 0.001$).

Table 5. Heterogeneity test

Variable	β_1: Traditional (Baseline Effect)	β_2: Interaction Term (High-Tech Incremental)	High-Tech Total Effect ($\beta_1 + \beta_2$)	Wald Test (H0: $\beta_1 + \beta_2 = 0$)
Export Growth Rate	−0.158 (0.196)	0.605* (0.235)	0.447	p < 0.001
Export Ratio	−0.083 (0.064)	0.641*** (0.072)	0.558	p < 0.001
Export Stability	0.019 (0.075)	0.331*** (0.079)	0.350	p < 0.001

Note: Robust standard errors clustered at the industry level are in parentheses. β_2 represents the coefficient of the interaction term (InvPen×HT). *** p<0.001; ** p<0.01; * p<0.05.

Table 6 presents the results of the Two-Way Fixed Effects (TWFE) models, which control for common year-specific shocks. The results remain robust. Notably, in the Export Stability model, the baseline effect for traditional industries becomes significantly negative ($\beta_1 = -0.198$, $p < 0.05$), while the interaction term remains positive ($\beta_2 = 0.382$, $p < 0.01$). This highlights a clear structural divergence: policy investment is associated with stabilization (reduced volatility) in traditional sectors, whereas it is linked to increased volatility in high-tech sectors.

Overall, the interaction analyses consistently indicate that technology intensity acts as a key moderator, distinguishing the high-growth/high-volatility path of high-tech industries from the stabilization path of traditional manufacturing.

Table 6. Robustness check

Variable	β_1: Traditional (Baseline Effect)	β_2: Interaction Term (High-Tech Incremental)	High-Tech Total Effect ($\beta_1 + \beta_2$)	Wald Test (H0: $\beta_1 + \beta_2 = 0$)
Export Growth Rate	−0.235 (0.162)	0.723** (0.232)	0.488	p < 0.001
Export Ratio	0.013 (0.062)	0.607*** (0.069)	0.620	p < 0.001
Export Stability	−0.198* (0.093)	0.382** (0.109)	0.184	p < 0.001

Note: Models include both industry and year fixed effects to control for common aggregate shocks. Robust standard errors clustered at the industry level are in parentheses. *** p<0.001; ** p<0.01; * p<0.05.

5 | Discussion and Conclusion

Using industry-level panel data from Taiwan's manufacturing sector, this study moves beyond the "average effect" perspective to examine the heterogeneous export effects of technology-investment policy. The empirical results indicate that policy responses are not uniform but are systematically conditioned by industry technology intensity.

5.1 | Implications for Research

The findings reveal a clear dual-track mechanism of policy transmission. First, high-tech industries exhibit a trade-off between growth and stability. Policy-induced investment significantly boosts export orientation, consistent with the absorptive capacity perspective where high-tech sectors rapidly transform resources into market expansion [6]. However, this outward shift is accompanied by heightened short-run volatility. This suggests that for technology-intensive sectors, deeper integration into global value chains brings growth opportunities but simultaneously introduces greater exposure to external shocks and structural instability [4, 14].

In contrast, traditional manufacturing follows an "internalization" trajectory. The limited or negative effects on export growth suggest that policy benefits are not immediately realized in external markets. Instead, this pattern reflects a technological trajectory focused on process innovation rather than immediate product expansion [27]. Traditional industries appear to allocate policy resources primarily toward internal capability building and equipment upgrading. Consequently, assessing effectiveness solely through short-term export metrics may understate the foundational improvements occurring within these sectors.

Theoretically, this study challenges the assumption that investment incentives yield uniform export outcomes, underscoring the necessity of incorporating industry technology intensity as a critical structural filter in empirical models.

5.2| Policy Implications

For high-tech industries, while incentives catalyze export orientation, they should be complemented by measures to manage the associated volatility risk. Policymakers must recognize that rapid outward expansion often entails greater exposure to external shocks. Conversely, for traditional manufacturing, a stagnation in the Export Ratio should not be interpreted as ineffectiveness. Instead, it reflects a phase of process optimization where outward-oriented returns require a longer horizon. Accordingly, policy assessments must adopt differentiated designs: monitoring stability risks for high-tech sectors while valuing internal capability upgrading for traditional sectors.

5.3| Limitations and Future Research

This study relies on industry-level data, a limitation that precludes the observation of within-industry firm heterogeneity. Future research could extend this analysis by examining the impact of technology investment on productivity, quality upgrading, or import substitution, thereby providing a more comprehensive assessment of the policy's multifaceted channels and outcomes.

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Author Contribution

Conceptualization, Chen, C.-C.; Methodology, Chen, C.-C.; Validation, Chen, C.-C.; and Huang, C.-Y.; formal analysis, Chen, C.-C.; data maintenance, Chen, C.-C.; writing-creating the initial design, Chen, C.-C.; writing-reviewing and editing, Chen, C.-C. and Huang, C.-Y.; visualization, Chen, C.-C.; monitoring, Chen, C.-C.; project management, Chen, C.-C.; Supervision, Huang, C.-Y. All authors have read and agreed to the published version of the manuscript.

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Data Availability

The data used in this study are confidential and not publicly available due to privacy or ethical restrictions.

Conflicts of Interest

The authors declare no conflict of interest.

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