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Article

Global value chains, domestic value creation, and firm performance: machine learning evidence from Vietnam

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A B S T R A C T

This study examines the impact of domestic value added and participation in global value chains (GVCs) on firm performance, based on a sample of 287 observations from listed companies across five key industries in Vietnam's Southeast region during 2020-2024. Three machine learning methods, Ridge Regression, Random Forest, and Gradient Boosting, are applied to estimate the influence of each independent variable on firm performance. Ridge regression produced the best estimates of firm performance among these three model types, based on the lowest RMSE (4.97), MAE (2.78), and R-squared (0.57). This suggests that the relationship between GVC-related attributes and firm performance is largely linear and additive. Among the individual predictors, lagged profitability was the most important single predictor of current performance, followed by GVC activity. Notably, domestic added-value predicted firm performance more strongly than foreign added-value. Greater GVC activity therefore does not necessarily translate into stronger firm performance. Instead, firms appear to perform better when global engagement is combined with strong internal capabilities and substantial domestic value creation. Firm size, financial leverage, technological capability, and logistics efficiency also statistically explained variation in firm performance.

1. Introduction

Beyond an organization's internal capacity and resource base, firms in the contemporary business environment create competitive advantages by operating within global supply chain (GSC) and global value chain (GVC) systems. Organizations have leveraged comparative advantage worldwide by fragmenting production processes geographically and creating extensive transnational production networks. Yet, the degree of interdependence among organizations involved in GVCs varies considerably with the value each contributes. Therefore, because organizations in GVCs are interdependent, their financial performance depends on each organization's internal capabilities and the extent of its involvement in GVCs. Several studies show that effective supply chain management improves overall organizational performance. Johnson and Templar [1] indicate that firm value is directly related to the supply chain's effectiveness in generating cash flow and using assets. Furthermore, numerous studies support this view by showing that optimizing supply chain configurations, increasing integration between suppliers/distributors, and using digital technology to improve supply chain operations contribute positively to both financial and operational performance [2,3]. Recent studies in developing countries provide further empirical evidence that supply chain management improves firm performance through cost savings, improved cash flows, and increased market share. While it is apparent that organizations may no longer solely rely on internal management of their affairs as a result of the increasing number of organizations participating in global value chains (GVCs), there is a considerable body of literature that indicates that indicators of firms' level of engagement in GVCs at the industry level (Foreign Value Added-FVA, Domestic Value Added-DVA and Position in GVC) are essential in explaining why some organizations achieve superior financial results. These indicators enable researchers to determine whether industries rely heavily on foreign inputs. Studies conducted after Koopman et al. [4] illustrate that participation in GVCs does not always translate into a dominant position in a GVC. Typically, industries that exhibit high FVA are constrained to lower-value-added activities than other industries, e.g., processing/assembly, as illustrated by

Wang et al. [5]. Current research extending existing research from 2024-2025 in three primary areas includes: first, studies focusing on sustainability in supply chains and resilience have demonstrated that firms actively engaged in GVCs, yet lacking sufficient internal abilities to withstand global disruptions, experience greater difficulties doing so than those producing a higher percent of domestic value added (high DVA) over time. Second, studies of digital transformation in supply chains find that firms adopting digital technologies such as artificial intelligence (AI), blockchain, and big data achieve greater transparency, coordination, and operational efficiency, resulting in superior financial performance [6]. Third, recent research in logistics/supply chain management has identified that multi-tiered supply chain integration and global coordination lead to positive firm performance, especially in relation to strategic manufacturing industries. The supply chain integration literature also demonstrates that linkages between supply chain participants generate both operational and financial benefits through reduced transaction costs and enhanced knowledge sharing [7]. Global Coordination among Firms Participating in Global Value Chains (GVCs) is critical because they must constantly coordinate with numerous international parties across large-scale production Networks. Most previous research has limited its analysis to firm-level studies or isolated supply chain factors; therefore, significant gaps remain in research examining macro-level indicators of GVC participation and their impact on firm performance outcomes. Additionally, these gaps are particularly pronounced in developing economies such as Vietnam, where industry-specific degrees of participation and Positions within GVCs vary considerably. These differences in value creation capabilities will also result in considerable differences in firm performance. Therefore, this study examines the relationship between industry-specific indicators of GVC Participation and firm performance in Vietnam. More specifically, this study investigates the roles that three different types of GVC Participation Indicators, including Foreign Value Added (FVA), Domestic Value Added (DVA), and GVC Position, play in determining financial performance among Vietnamese firms. The integration of both industry and firm-level perspectives used by this research will broaden our theoretical understanding of global supply and value chains and provide policy recommendations on how industries can improve their positioning within GVCs and promote firm performance in the context of digital transformation and sustainable development.

2. Literature review

The four types of firm-specific characteristics can positively or negatively affect a company's participation in a GVC. The first type of characteristic, in terms of its indirect impact on participation in a GVC, is capital structure. Capital structure can help a company take part in a GVC. For instance, many companies use debt financing to purchase imported goods (FVA), which can provide the means to participate in a GVC. However, relying too much on debt increases the financial risk the company faces. Firm size is the second type of characteristic. Firm size can limit or facilitate a company's ability to take part in a GVC. Larger companies have better access to needed resources; generally have lower-cost capital; and, as a result, are likely to perform better than smaller companies when working within a complex GVC. Nevertheless, being larger has disadvantages. These include limited organizational adaptability and increased administrative costs. Additionally, large firms are generally more powerful and can negotiate better prices with input suppliers. Smaller firms lack this advantage. Therefore, although firm size does not directly relate to a company's success within a GVC, it indirectly relates to whether a company can interact with GVCs. The third characteristic, technology and innovation capability, plays a significant role in helping a company succeed within a GVC. A company's technology and innovation capabilities allow it to use foreign inputs (FVA) more effectively. In addition to improving the company's use of foreign inputs (FVA), GVC participation gives a company the opportunity to learn new, more productive technologies. This allows the company to improve productivity and increase the amount of domestic value added (DVA) it creates. Supply chain management integration is the final type of characteristic. Supply chain management integration is critical to allowing a company to receive maximum benefit from GVC participation. Companies integrate with upstream and downstream partners to improve communication among all parties involved in the production process, minimize transactional costs, and ultimately produce products and services more efficiently. Johnson & Templar [1] noted that one of the most influential factors in a company's financial performance was its ability to operate efficiently within its supply chain. More recently, researchers have emphasized that digitally enabled and environmentally sustainable supply chain management strategies support both improved firm performance and resilience during global crises [2,8]. Therefore, to compete successfully in an increasingly connected world, companies need to develop an integrated approach with partners and customers to improve operational efficiency and performance.

These categories are not mutually exclusive. Instead, they represent different aspects of how businesses operate. Together, these categories form an integrated management system for businesses seeking to navigate today's Global Value Chain (GVC) environment. Each category presents opportunities and challenges for businesses to manage effectively. Businesses need a complete picture of their operations to function effectively and must communicate across functions and departments. In addition, businesses need to adapt to changing internal and external conditions. Examining the relationships between categories, rather than looking at them individually, shows how the components of a business' operations can work together to create better performance than if they were considered alone. Additionally, examining the relationships among the various parts of a company's operations allows us to assess whether a company can adapt to new and emerging opportunities in a rapidly evolving GVC environment. While previous studies have analyzed the effects of several categories individually (firm size [9]; capital structure [10]; technology/innovation capability [11]; supply chain management [7]), little research has examined these categories collectively. This paper presents empirical evidence showing how a firm’s engagement with a GVC is influenced by how well it integrates its individual elements. Specifically, our analysis indicates that firms with superior supply chain management integration (SCMI) capabilities are more likely to exhibit superior firm performance in their engagement with a GVC than firms lacking such capabilities. In turn, we find that superior SCMI capabilities are positively associated with more favorable financial leverage ratios, stronger technological and innovation capabilities, and larger firm size.

We also present empirical evidence that firms with superior SCMI capabilities are less likely to engage in risky financial behavior, such as excessive borrowing, that could undermine their engagement with a GVC. We also show that superior SCMI capabilities are positively correlated with superior technology/innovation capabilities. This suggests that firms with superior SCMI capabilities are better equipped to absorb the advanced technologies made available through GVC participation. In turn, we find that stronger technology and innovation capabilities are positively associated with more favorable financial leverage ratios and larger firm size. Our analysis therefore indicates that firms with superior SCMI capabilities are better positioned to take full advantage of the opportunities offered by GVCs. Our results emphasize the importance of managing each element of a firm's operations effectively in order to derive maximum benefit from GVC engagement. Moreover, our results highlight the critical role supply chain management plays in facilitating effective collaboration between firms and their partners/customers to achieve superior firm performance. Overall, our analysis confirms many prior expectations regarding how the individual elements of a firm's operations interact to support superior firm performance.

The unique aspect of this research project is using GVC at the industrial level and financial performance at the company level, rather than examining these two aspects independently. The research uses FVA (Foreign Value Added), DVA (Domestic Value Added), and GVC Position based on ICIO Data to compare Ridge Regression, Random Forest, and Gradient Boosting, measure predictive performance, and determine the weight of GVC and company-level variables. A key finding was that Domestic Value Added explained more variation in company performance than Foreign Value Added, suggesting that the quality of companies' participation in the Global Value Chain and their ability to create domestic value matter more than reliance on foreign inputs.

3. Model, methodology and data

Existing research indicates that firm performance depends primarily on internal characteristics, but also to a considerable extent on how firms create value internationally through global value chains (GVCs). Koopman, Wang and Wei [4] showed that foreign value added (FVA) and domestic value added (DVA) are reliable indicators of the value contributed by foreign economies and by domestic production, respectively. In turn, these measures help to determine what an individual firm or industry contributes to a GVC. As such, they can influence its productivity/financial performance. Recent empirical studies extend this approach by combining GVC indicators with firm-specific variables in panel data models. For example, Hoan et al. [8] found that supply chain management positively influences firms' financial performance. According to Vial [6], studies of digital transformation show that technologies can improve financial performance and help firms better "capture" Global Value Added. Based on these theoretical foundations and empirical findings, the research model is specified as follows:

$$ROA_{it} = \beta_0 + \beta_1 ROA_{it-1} + \beta_2 GVC_{it} + \beta_3 FVA_{it} + \beta_4 DVA_{it} + \beta_5 Size_{it} + \beta_6 Lev_{it} + \beta_7 Tech_{it} + \beta_8 SCM_{it} + \beta_9 \sum_{j=1}^{4} Ind_{jt} + \varepsilon_{it} \quad (1)$$

Financial ratios can help examine how efficiently companies manage resources and how well they use those resources to generate profit. Return on assets (ROA) is one such ratio and is widely used to measure firm performance. As Zeitun and Tian [10] show, ROA still needs to be studied in the context of globalization and digitalization. Previous research that examined the effects of supply chain management in Vietnam (Hoan et al. [8]) used ROA as a performance metric. In addition, other researchers studying digitalization and sustainable supply chains also used ROA as a dependent variable to measure enterprise performance in a globalized market. DVA (Domestic Value Added) and FVA (Foreign Value Added) are both important parts of GVC (Global Value Chain) analysis. Both are derived from global input-output (I/O) data sources (e.g., OECD TiVA and WIOD).

Foreign value added embodied in the exports of industry *i* in the Southeast region is calculated as:

$$FVA_{i,t}^{SE} = \theta_{SE,t} \, x \, FVA_{i,t}^{VN} \quad (2)$$

where $FVA_{i,t}^{VN}$ the component is derived from the national ICIO table using the Leontief inverse method and reflects the value added originating from foreign economies that is used in the production of exported goods.

Domestic value added is determined as:

$$DVA_{i,t}^{SE} = X_{i,t}^{SE} - FVA_{i,t}^{SE} \quad (3)$$

This indicator reflects the contribution of domestic production factors (labor, capital, and local technology) to the exports of the region's industries.

The position of key export industries in the Southeast region within the global value chain is determined as:

$$GVC_{Position_{i,t}^{SE}} = Forward_{i,t}^{SE} - Backward_{i,t}^{SE} \quad (4)$$

The degree of backward participation in the global value chain of industry *i* in the Southeast region is determined as:

$$Backward_{i,t}^{SE} = \frac{FVA_{i,t}^{SE}}{X_{i,t}^{SE}} \quad (5)$$

In the absence of regional data on re-exported domestic value added (DVA), the study uses the industry-level re-export ratio at the national level as a proxy coefficient.

$$Forward_{i,t}^{SE} = \emptyset_{i,t}^{VN} \, x \, \frac{DVA_{i,t}^{SE}}{X_{i,t}^{SE}} \quad (6)$$

$\emptyset_{i,t}^{VN}$ is the percentage of domestic value added (DVAre-exported) represents the portion of value created within a nation that contributes to the inputs required for products manufactured by other nations. A key advantage of DVAre-exported is that it permits uniform handling of GVC structures across different sectors while offering insights into how regional contributors participate in upstream segments of the product creation process.

As Koopman et al. [4] note, the DVAre-exported metric, along with FVA, allows researchers to evaluate the role and position of individual countries or industries within global value chains. Beyond potential productivity gains from technology transfer [9], foreign value-added (FVA) has been shown to strengthen a firm's upgrading capacity and long-term performance growth [5]. Domestic Value-Added (DVA) is generally associated with a firm's upgrading capacity and long-term performance growth. Firm size is usually measured by the natural log of total assets. Research indicates that large firms are likely to enjoy scale-based cost advantages and greater market access than smaller firms [12]. On the other hand, recent research finds that large firms are less efficient in digitally based business environments because of lower organizational flexibility [13]. Financial leverage is measured here using Debt/Total Assets (Lev). As described in Capital Structure Theory, debt offers tax advantages but increases financial risk. Empirical research commonly finds that higher debt levels negatively affect overall corporate performance and performance under uncertainty [10,14]. To measure Technological Capability (Tech), we used Peters and Taylor's [15] definition: Technological Capability = (Intangible Assets / Total Assets). Absorptive Capacity Theory states that firms with stronger technological capabilities can better utilize Foreign Value-Added (FVA) and generate Domestic Value-Added (DVA) [16]. In addition to creating new opportunities to improve supply chains through digitalization, firms can potentially achieve improved financial performance [6]. Historically, Supply Chain Management (SCM) has been evaluated empirically through proxy variables including financial and operational indicators primarily because few sources provide firm-level information about SCM practices. Inventory Turnover is often used as an indicator of supply chain efficiency and is used here as well. This is because it directly relates to the rate at which inventory cycles through production and distribution processes [17,18]. Finally, this study accounts for industry heterogeneity among five major industries (Ind): food processing, textiles and garments, rubber and plastics, pharmaceuticals and chemicals, and electronics and software. The textiles and garments sector serves as the reference category.

Traditional linear regression methods are limited when handling financial datasets because of issues such as multicollinearity, linearity assumptions, and poor predictive performance. Several alternative methods address these limitations, including Ridge Regression, Random Forest, and Gradient Boosting. Each methodology addresses these limitations differently. Previous research has well documented each methodology's ability to predict and explain firm performance, asset returns, and financial behaviors. Machine learning-based regression methods have also become popular for evaluating the influence of both financial and non-financial variables. For example, Gu et al. [19] used machine learning techniques, including regularized regressions, to provide superior forecasts of stock returns when compared to traditional linear models. Accordingly, this study uses machine learning-based regression methods rather than traditional linear regression to improve prediction efficiency and estimation precision. Given the dataset's specific nature, the analysis focuses on three methods: Ridge Regression, Random Forest, and Gradient Boosting. Table 1 provides variable definitions.

Table 1. Variable definitions

Variable	Definition	Measurement	Expected sign
ROA	Firm performance	Net income / Total assets (%)	
GVC	Global value chain	Position of key export industries	+/-
FVA	Foreign value added	Share of foreign value added in exports (%)	+/-
DVA	Domestic value added	Share of domestic value added in exports (%)	+
Size	Firm size	Natural logarithm of total assets	+
Lev	Financial leverage	Total debt / Total assets (%)	-
Tech	Technological capability	Intangible assets / Total assets (%)	+
SCM	Supply chain management	Inventory turnover ratio	+
Food	Industry dummy (food and beverage)	1 if firm belongs to food and beverage industry, 0 otherwise	+/-
Plastics	Industry dummy (rubber & plastics)	1 if firm belongs to rubber-plastic industry, 0 otherwise	+/-
Chemicals	Industry dummy (pharmaceuticals & chemicals)	1 if firm belongs to pharma-chemical industry, 0 otherwise	+/-
Electronics	Industry dummy (electronics & software)	1 if firm belongs to electronics-software industry, 0 otherwise	+/-

Note: The food processing industry is used as the reference category

Model training and evaluation: The panel data were split by firm to ensure that no observation from the same firm appears in both the training and test samples. Model development used a 70/15/15 (train/validation/test) split with Five-Fold Group Cross-Validation to optimize hyperparameters. We optimized two models (Random Forest & Gradient Boosting) across key hyperparameters such as the total number of decision trees, maximum tree depth, leaf size, and feature sampling; for gradient boosting, we also examined the learning rate and subsampling rate. Based on the minimum cross-validated RMSE, we will select the best combinations of these parameters. For Ridge Regression, we standardized all continuous predictor variables and selected an appropriate value for the Regularization Parameter via a logarithmically spaced Regularization Path (10^{-4}-10^{4}). Finally, we will evaluate the final performance of our models using RMSE, MAE, and R^2 measures. This procedure preserves the structural relationship between firms while eliminating potential information leakage and overfitting.

This study adopts an integrated micro/macro approach using a panel dataset of listed companies in Vietnam's Southeast region for 2020-2024. This period was chosen because it captures the most recent major changes in international trade; the largest shifts in how businesses operate globally since the COVID-19 pandemic disrupted global supply chains; and rising national and regional contributions to GVCs. A purposive sampling strategy was used to construct the sample. Under this strategy, firms were selected from the main export-oriented sectors of the Southeast region. These sectors account for the large majority of the region's total exports and have a high degree of GVC involvement. The sectors identified were food processing; textiles and garments; rubber and plastic products; pharmaceuticals and chemicals; and electronics and software. In addition to firm-level (micro) data, we used industry-level data on GVC indicators, namely foreign value added (FVA), domestic value added (DVA), GVC participation, and GVC position. These indicators are calculated or derived from international input-output (ICIO) tables and trade-in-value-added databases, then linked to firm-level data via industry classification systems. This approach enables simultaneous examination of firm-level and industry-level factors, allowing analysis of how the structural characteristics of global value chains (GVCs) affect listed firms' performance.

4. Empirical results

Table 2 and Table 3 present descriptive statistics of variables and statistical data for 287 observations across five specific industries, respectively. Average return on assets (ROA) was 6.52%, with a high degree of variation in firm performance, as indicated by the 7.34% standard deviation. The lowest ROA was -2.67% and the highest was 52.21%, which indicates that some firms were significantly less effective than others and some were considerably more successful. Descriptive statistics show that the average global value chain indicator (GVC participation index) was 0.14, with a very high standard deviation of 1.39, indicating that firms' participation in global production systems varies widely. Similarly, the foreign value added (FVA) averaged 15.76%, and domestic value added (DVA) averaged 16.79%. This suggests that domestic content remains an essential element within export activity. Firms ranged in size from 3.12 to 11.90, with an average of 6.99 (on a logarithmic scale). Financial leverage (lev), by contrast, averaged 34.23% but showed substantial variation (standard deviation = 24.19); therefore, firms likely vary widely in capital structure and financial risk. In addition, the supply chain efficiency measure (SCM_turnover) averaged 11.02 and showed substantial variation (standard deviation = 28.14); consequently, many firms likely experience differing levels of success in managing their supply chains. Lastly, technological ability (tech) had an average value of 4.45 and showed a very large range (0 to 79.18). Therefore, many firms appear to have varying degrees of technological ability.

Table 2. Descriptive statistics of variables

Variable	Obs	Mean	Std. Dev	Min	Max
ROA	287	6.52	7.34	-2.67	52.21
GVC	287	0.14	1.39	-0.68	3.50
FVA	287	15.76	8.33	5.11	26.75
DVA	287	16.79	8.23	8.11	27.12
Size	287	6.99	1.79	3.12	11.90
Lev	287	34.23	24.19	0	75.57
SCM	287	11.02	28.14	0	229.01
Tech	287	4.45	11.47	0	79.18

Table 3. Number of observations by industry

Year	Food	Textile	Plastics	Chemical	Electronics	Total
2020	26	15	6	9	3	59
2021	23	15	7	9	4	58
2022	25	17	6	9	3	60
2023	24	16	9	10	4	63
2024	20	11	5	10	1	47
Obs	118	74	33	47	15	287

The correlation matrix (Table 4) suggests that most explanatory variables have low-to-moderate correlations with one another. However, ROA is highly and positively correlated ($r = 0.691$) with its lagged value (ROA_1), reflecting the persistent effect of past performance on current firm performance. The correlation between LFVA and LDVA is very strong ($r = 0.987$), which indicates serious multicollinearity between the two GVC indicators. Foreign Value Added (FVA) and Domestic Value Added (DVA) both include lagged terms to allow for the time necessary for FVA and DVA from prior periods to influence firm productivity, costs, and overall performance during the current period, as well as to help reduce concerns about simultaneity between firms' participation in GVC and their overall performance. Although FVA and DVA are highly correlated, each captures different aspects of economic phenomena; thus, removing one or the other could reduce the amount of relevant data used. Ridge regression is suitable because it uses L2 regularization to shrink and stabilize coefficient estimates for highly correlated predictors instead of dropping them. As such, ridge regression reduces the negative impacts of multicollinearity and improves the model's stability and predictability (Figure 1).

Although the data are panel-structured, these machine learning models (Table 5) are designed primarily for prediction rather than traditional panel data inference. To address pseudo-replication and potential information leakage from multiple observations of each firm in the sample, we split the data into training and test/validation groups at the firm level, and included year and industry control variables to account for unobserved trends across time and sectors. The results of the machine learning models should therefore be interpreted in terms of predictive performance, not causality or statistical significance. Substantial differences were found in the predictive performance of the models. Unlike earlier studies in machine learning, ridge regression outperformed every model used in almost all of the measures evaluated.

Table 4. Correlation matrix of variables

Variable	ROA	ROA_1	GVC	LFVA	LDVA	Size	Lev	SCM	Tech
ROA	1.000	0.691	-0.021	0.076	0.055	0.173	-0.319	-0.030	-0.135
ROA_1	0.691	1.000	-0.012	-0.015	-0.043	0.173	-0.280	-0.035	-0.124
GVC	-0.021	-0.012	1.000	-0.134	-0.088	-0.083	-0.047	-0.062	0.023
LFVA	0.076	-0.015	-0.134	1.000	0.987	-0.012	0.002	-0.001	-0.030
LDVA	0.055	-0.043	-0.088	0.987	1.000	0.010	0.020	-0.004	0.004
Size	0.173	0.173	-0.083	-0.012	0.010	1.000	0.245	-0.280	-0.030
Lev	-0.319	-0.280	-0.047	0.002	0.020	0.245	1.000	-0.085	0.266
SCM	-0.030	-0.035	-0.062	-0.001	-0.004	-0.280	-0.085	1.000	0.187
Tech	-0.135	-0.124	0.023	-0.030	0.004	-0.030	0.266	0.187	1.000

Table 5. Regression results using machine learning models

No.	Model	RMSE	MAE	R^2
1	Random Forest	5.139902	2.894693	0.544855
2	Ridge(*)	4.971037	2.780705	0.574270
3	Gradient Boosting	5.204642	2.777226	0.533317

(*) indicates the best-performing model.

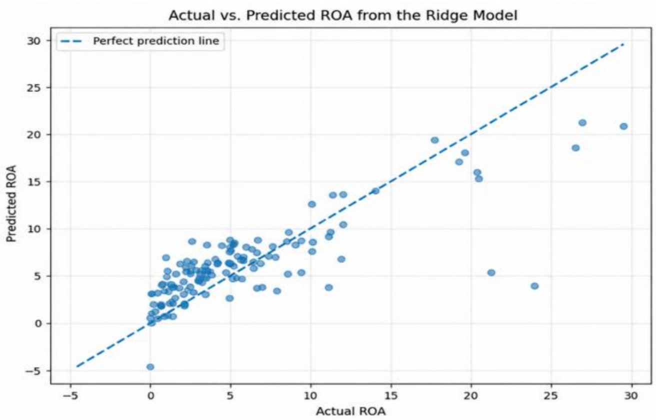

Figure 1. Actual vs. predicted ROA from the ridge model

It produced the largest R-Squared value (0.57) and the smallest root mean square error (RMSE = 4.97) and mean absolute error (MAE = 2.78). This demonstrates that global value chains (GVCs) and firm performance are likely related linearly within the study population. More specifically, foreign value added (FVA) and domestic value added (DVA) appear to predictably add to firm performance rather than interact nonlinearly. In contrast to studies that found tree-based models best identify nonlinearities and/or high-dimensional interactions [19,20], these results support the idea that regularized linear models perform well when the data-generating process is continuous, and multicollinearity exists among the independent variables. Because predictor variables in enterprise financial data are often strongly correlated, Ridge regression provides more stable coefficient estimates and improved prediction accuracy.

The random forest model was the next best-performing model (R-squared =0.54, RMSE = 5.14), indicating that while non-linearities may exist, they are insufficient in both magnitude and prevalence to outperform a regularized linear specification. Conversely, the gradient boosting model performed the worst (R-squared = 0.53, RMSE = 5.20). Several factors could explain this poor performance, including sample size constraints and noise in the firm-level data, which can negatively affect boosting algorithms. While Friedman [21] notes that gradient boosting can capture complex relationships, it is also prone to overfitting and should be carefully tuned for small/noisy datasets. Overall, the findings presented herein illustrate the importance of choosing an appropriate model in empirical analyses of GVC participation and firm performance. While recent studies in finance and supply chain management continue to report advantages from machine learning methods [19], these results suggest that appropriately regularized linear models can still perform as well as, or better than, machine learning methods when the underlying relationships are stable and additive. In economic terms, these results suggest that firm performance in the context of GVCs is shaped by two types of influence: first, the intensity of GVC participation (e.g., FVA and DVA), and second, systematic firm characteristics (e.g., size, leverage, technological capability), whose effects can be captured well within a linear framework.

The study provides ample evidence that the extent of influence of each independent variable on firm performance (ROA) varies considerably (Figure 2). The lagged dependent variable (previous-year ROA) had a strong positive impact on current-year ROA. This significance lies in the fact that firm performance is highly persistent over time and heavily influenced by historical events. Therefore, this research corroborates both prior research on firm dynamics and prior studies utilizing dynamic panel data. The conclusions of this study are congruent with the concepts of path dependence and capability accumulation found throughout the literature [22]. Furthermore, firms exhibit operational inertia and learning-by-doing. Among all independent variables studied in this research, GVC participation (GVC) was the second-largest predictor of firm performance after the lagged dependent variable. Therefore, incorporation into a Global Value Chain (GVC) is strongly associated with increased firm performance.

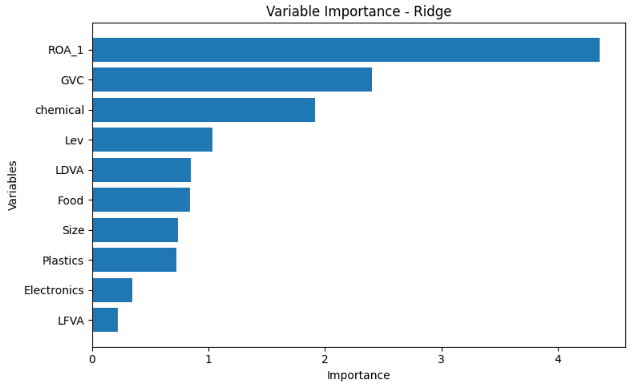

Figure 2. Importance of influencing factors (Variable importance in the Ridge model is measured as the absolute magnitude of the standardized Ridge coefficients)

Firms included in more complex global value chains may be able to reap the rewards of access to international markets and knowledge spillovers, and/or use high-quality inputs to increase productivity and profitability. Therefore, the results of this study serve as evidence for the GVC literature, suggesting that firms can be "upgraded" through their inclusion in GVCs [4,5]. The industry-specific variable for the chemical sector (chemical) demonstrated a somewhat larger association than many other industry-specific variables. Specifically, this finding suggests that some industries may see larger increases in firm performance when they participate in GVCs because of greater technological complexity or a more upstream position in the value chain. However, this does not necessarily indicate considerable differentiation among industries in improvements in firm performance stemming from GVC participation. Rather, it appears that, generally speaking, industries differ little in the improvements in firm performance stemming from GVC participation. Additionally, firms in industries with higher knowledge content or at an early stage in the value chain are likely to experience greater performance advantages. Financial leverage (Lev) continued to show a strong association with firm performance and thus confirms that capital structure remains an important determinant of firm performance. This finding aligns with capital structure theory, suggesting that financial leverage affects both the cost of capital and the financial risk associated with equity financing [10,23]. Likewise, LDVA demonstrated a moderate association with firm performance, thereby supporting the notion that a company's ability to create internal value additions influences its performance [24]. Finally, LFVA showed the weakest association with firm performance. Reliance on imported inputs therefore does not appear to be linked to improved profitability. Similar evidence has been identified throughout GVC literature. GVC researchers have suggested that when domestic firms become integrated into GVCs, they can take advantage of long-term upgrading possibilities [4]. Of the remaining firm-level variables included in this study (i.e. size and the supply chain efficiency measure), none were found to exhibit substantial positive associations. Although relevant, these variables appear to play secondary roles relative to the principal drivers of firm performance, i.e., prior performance and GVC participation. Likewise, most industry dummies (Food, Plastics, Electronics) showed little or no association. This suggests that performance gaps among firms stem primarily from firm-specific characteristics and positioning within a GVC rather than from industry differences. Overall, the results identify three interrelated mechanisms that shape firm performance: (1) the dynamic persistence of past performance (ROA); (2) the degree of integration into GVCs; and (3) the ability of a firm to create value-added internally. Most notably, identifying persistence and GVC participation as the two key factors contributing to firm performance provides empirical support for recent research in both the GVC and firm performance literatures on the importance of the historical accumulation of capabilities and relationships with external organizations.

5. Conclusions

The study analyzes how participation in global value chains and the distribution of value-added affect enterprise performance in Vietnam's Southeast region. It uses three machine learning models: ridge regression, random forest model, and gradient boosting model. Each offers a different perspective on the linear and non-linear relationships among the variables under study. Ridge regression forecasts firm performance more accurately than the tree-based models. This suggests that the relationship between GVC indicators and firm performance is largely linear as opposed to highly non-linear or interactive. The findings clarify the nature of the relationships between GVC indicators and firm performance and demonstrate the continued relevance of regularized linear models at the firm level when dealing with collinearity and small samples. In addition, a linear model adequately captured the marginal effects of the main explanatory variables (GVC participation, DVA, financial leverage) on Vietnamese firms' performance. Another key finding is the temporal stability of corporate performance, as shown by the strong influence of the prior period's ROA on current performance. This indicates that corporate performance is both dynamic and shaped by past development trajectories, influenced by factors such as accumulated knowledge, learning effects, and organizational inertia. Persistence in firm performance also supports the view that short-term performance gains are closely tied to long-term capability building and strategic positioning within value chains. Regarding GVC-related factors, our results confirm that DVA explains firm performance better than FVA. This reinforces our earlier observations on the importance of quality, rather than quantity, of GVC participation. Accordingly, while a firm may be active in multiple GVCs, its ability to build sustainable internal capacity for value creation allows it to develop its operations and ultimately achieve improved financial performance. Conversely, heavy reliance on FVA may reduce profit margins, as it reflects potential concentration in low value-adding segments of a GVC (processing/assembling). Finally, firm-specific characteristics, including financial leverage and firm size, continue to explain firm performance. Financial leverage balances tax benefits and financial risk, while firm size reflects both potential economies of scale and potential organizational rigidity. Moreover, technological capability has a positive but relatively minor effect; digitalization and intangibles add to firm performance, yet their total impact has not been fully realized across all firms.

Therefore, much variability remains among developing nations in technology adoption, as firms' capacities to absorb new technologies differ widely. From a policy perspective, the study findings provide several critical recommendations for policymakers. First, policymakers should stop focusing solely on encouraging participation in global value chains and instead promote higher-quality participation through increased domestic value creation. Policymakers would then need to support industrial upgrades, innovation, and developments in supporting industries. Second, firms need to build internal capabilities in supply chain management and technology adoption to translate GVC participation into superior financial returns. Third, policymakers should attend to firms' financial structure and risk management practices, since excessive leverage can damage a firm's financial condition during periods of global economic instability. The authors attempted to conduct this study accurately, but a few drawbacks could affect its validity: using national-level export data as a proxy for each region's "participation" may introduce measurement error. The results should therefore be interpreted with caution and validated by testing sensitivity to the proxy data. Another limitation is the lack of thorough robustness tests and alternative model specifications. Most of the present analysis relies on ROA and a single model specification. Future research should test other specifications and samples, including excluding lagged ROA from the models; using alternative performance metrics (e.g., ROE); removing ROA outliers; and estimating the models by industry.

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Ethical issue
The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere. All survey participants provided informed consent before participating, and the anonymity and confidentiality of all respondents were strictly maintained throughout the research process.

Data availability statement
The manuscript contains all the data. However, additional data will be provided by the corresponding author upon reasonable request.

Conflict of interest
The authors declare no potential conflict of interest.

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