ASSET VOLATILITY ANALYSIS USING THE STRUCTURAL APPROACH EVIDENCE FROM LISTED CONSUMER GOODS FIRMS IN VIETNAM

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Abstract: ***This paper investigates asset volatility (σA) and probability of default (PD) in Vietnam's consumer goods sector using the structural approach pioneered by Merton (1974). The study employs panel data from 101 listed firms on the Ho Chi Minh Stock Exchange (HSX) and Hanoi Stock Exchange (HNX) during the period 2015–2024. Results show that asset volatility is highly cyclical, with peaks during crises such as the COVID-19 pandemic and normalization during recovery years. Sub-sectoral analysis reveals strong heterogeneity: defensive industries such as Household & Personal Products and Essential Retail maintained stable profiles, while cyclical industries such as Consumer Services, Fashion & Durables, and Non-Essential Retail faced elevated risks. Furthermore, the relationship between volatility and default probability is non-linear, highlighting the role of leverage and capital structure in amplifying or mitigating credit risk. These findings have important implications for investors, regulators, and corporate managers in emerging markets, emphasizing the need for sector-specific credit risk monitoring, portfolio diversification strategies, and prudent financial management.***

• Keywords: *asset volatility; probability of default; structural approach.*

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1. Introduction

Vietnam's stock market has developed rapidly since the establishment of the Ho Chi Minh City Stock Exchange (HSX) in 2000, becoming a key channel for capital mobilization, privatization of state-owned enterprises, and private sector growth. By 2024, market capitalization exceeded 90% of GDP, with more than 1,600 listed firms and a diversified structure including derivatives such as futures, warrants, and corporate bonds.

The consumer goods industry plays a critical role, contributing substantially to GDP and employment. Between 2015 and 2024, the sector expanded due to urbanization, rising incomes, and multinational participation. However, firms also faced challenges from input cost pressures, intense competition, shifting consumer behavior, and macroeconomic shocks such as COVID-19 and global financial volatility (Nhung, Le, & Hoang, 2018). These factors highlight the need for accurate measurement of asset and credit risk.

Conventional accounting-based risk measures are often backward-looking and less responsive to real-time conditions in emerging markets. The Structural Approach (Merton, 1974) addresses this by modeling equity as a call option on firm assets, enabling estimation of Distance-to-Default (DD) and Probability of Default (PD) directly from market data (Bharath & Shumway, 2008). Combined with the Geometric Brownian Motion (GBM) model, which captures expected return (μ) and volatility (σ) (Hull, 2018), this provides a comprehensive framework linking stock price dynamics to credit risk.

This paper applies the integrated GBM-Structural Approach to 101 consumer goods firms listed on HSX and HNX from 2015-2024, aiming to deliver empirical insights on asset volatility, default risk, and sectoral heterogeneity that are relevant for investors, regulators, and policymakers.

2. Geometric Brownian Motion (GBM)

Geometric Brownian Motion (GBM) is a widely used model in finance for describing the stochastic behavior of asset prices under continuous time, assuming constant drift and volatility. It underpins option pricing frameworks such as the Black-Scholes-Merton model (Hull, 2018). The stochastic differential equation is:

$$dS_t = \mu S_t dt + \sigma S_t dB_t$$

where S_t is the asset price, the drift (long-term growth rate), the volatility, and B_t standard Brownian motion.

Built on the Efficient Market Hypothesis (EMH), GBM assumes asset prices fully reflect available information, ensuring no long-run arbitrage. It captures randomness in returns while providing a tractable basis for risk and return estimation. Empirical evidence Reddy and Clinton (2016) for Australia, Son (2025) for Vietnam confirms GBM's

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suitability for modeling volatility, especially in large-cap, liquid stocks.

3. Estimating Drift and Volatility of Stock Returns

To apply GBM and the Structural Approach, the first step is to compute the logarithmic return (log return) of stock prices. The log return is calculated as:

$$u_{i,t} = ln\left(\frac{S_{i,t}}{S_{i,t-1}}\right)$$

where $S_{i,t}$ is the closing price at time t. Log returns are additive over time, making them suitable for financial time series analysis (Tsay, 2010).

The annualized stock return volatility (σ_E) is estimated from the standard deviation of daily log returns, adjusted by the number of trading days in a year. The formula is as follows:

$$\sigma_E = \sqrt{\frac{1}{\tau(n-1)}\sum_{t=1}^{n}(u_{i,t} - \overline{u_i})^2}$$

where n is the number of trading days in a year, and τ is the length of the time interval expressed in years. In most cases, with approximately 250 trading days annually, τ is assumed to be 1/250.

The drift parameter (μ_E) is derived from the average daily log return, adjusted for variance, and then annualized as:

$$\mu_E = \frac{\overline{u_i}}{\tau} + \frac{1}{2}\sigma_E^2$$

These measures of drift and volatility are critical inputs for asset risk models, enabling estimation of asset volatility () and probability of default (PD) (Hull, 2018; Tsay, 2010).

4. Structural Approach

The Structural Approach, based on Merton's (1974) model, treats equity as a call option on the firm's assets, where default occurs if asset value falls below debt at maturity. The market value of equity is expressed as:

$$E = V_A N(d_1) - De^{-rT}N(d_2)$$

$$d_1 = \frac{\ln\left(\frac{V_A}{D}\right) + (r + 0.5\sigma_A{}^2)T}{\sigma_A\sqrt{T}}, d_2 = d_1 - \sigma_A\sqrt{T}$$

where V_A is asset value, D debt, σ_A asset volatility, r the risk-free rate, and N(.) the cumulative normal distribution. Asset volatility is linked to equity volatility by:

$$\sigma_A = \frac{1}{N(d_1)} * \frac{E_t}{V_t} * \sigma_E$$

This framework leverages real-time market data, providing forward-looking measures of credit risk superior to accounting-based methods (Hull, 2018; Crosbie & Bohn, 2003). It underpins modern risk management systems, including Moody's KMV model, and has been widely applied to both developed and emerging markets for corporate default estimation.

5. Distance-to-Default (DD) and Probability of Default (PD)

In the Structural Approach, DD measures how many standard deviations a firm's asset value exceeds its debt at maturity, with higher DD indicating lower risk. It is defined as:

$$DD = \frac{\ln\left(\frac{V_A}{D}\right) + (\mu_A + 0.5\sigma_A{}^2)T}{\sigma_A\sqrt{T}}$$

where V_A is asset value, D, μ_A expected asset return, σ_A asset volatility, and T time to maturity.

Once DD is calculated, PD is determined as:

$$PD = N(-DD)$$

where N(.) denotes the cumulative standard normal distribution function.

This framework translates market-based measures of value and volatility into forward-looking credit risk indicators, outperforming traditional accounting-based models (Merton, 1974; Hull, 2018). It underpins systems such as Moody's KMV and Basel II/III IRB (Crosbie & Bohn, 2003; Kealhofer, 2003), and is especially valuable in emerging markets where accounting data are limited. By capturing both systemic and firm-specific risks, the DD-PD framework strengthens credit risk monitoring, financial stability analysis, and investment decision-making.

6. Application of the Model to Consumer Goods Firms Listed in Vietnam

This study analyzes stock return dynamics for 101 consumer goods firms listed on HSX and HNX during 2015-2024. The sector was chosen for its macroeconomic relevance, given its large scale, contribution to GDP, and sensitivity to domestic policy shifts and global financial shocks (Nhung, Le, & Hoang, 2018). To ensure accuracy, illiquid stocks and firms with missing data were excluded. Volatility and drift were calculated using the actual number of trading sessions each year, rather than the standard 252-day assumption, reflecting Vietnam's market conditions. Risk-free rates were proxied by annual yields of Vietnamese government bonds as reported by the State Bank of Vietnam, ensuring consistency with the Structural Approach framework.

Stock Return Drift and Volatility

Table 1: Descriptive Statistics of Stock Return Drift and Volatility

		Mean	Median	Max	Min	Standard Deviation
2024	Volatility	21.10%	20.35%	67.68%	1.45%	9.30%
	Drift	3.01%	1.57%	307.00%	-93.79%	42.69%
2023	Volatility	26.95%	26.99%	57.50%	7.04%	10.80%
	Drift	16.34%	11.01%	162.72%	-60.49%	38.28%
2022	Volatility	38.43%	33.03%	103.12%	4.99%	19.14%
	Drift	-13.36%	-13.62%	241.26%	-132.83%	54.10%
2021	Volatility	35.88%	33.37%	85.70%	10.29%	15.71%
	Drift	63.65%	40.65%	296.55%	-52.49%	79.43%
2020	Volatility	38.19%	31.74%	111.02%	1.76%	20.29%
	Drift	40.37%	26.38%	225.04%	-211.14%	68.75%

		Mean	Median	Max	Min	Standard Deviation
2019	Volatility	29.06%	22.82%	98.69%	0.00%	20.55%
	Drift	7.52%	2.00%	212.11%	-82.09%	50.34%
2018	Volatility	34.24%	31.99%	92.30%	1.74%	18.78%
	Drift	12.63%	2.48%	339.63%	-114.54%	72.51%
2017	Volatility	29.33%	24.70%	90.72%	7.14%	15.56%
	Drift	17.38%	4.98%	278.28%	-72.44%	60.63%
2016	Volatility	34.90%	31.84%	93.54%	8.44%	16.02%
	Drift	3.90%	3.31%	239.67%	-226.28%	72.03%
2015	Volatility	29.31%	26.21%	76.00%	6.48%	14.44%
	Drift	19.57%	10.35%	267.24%	-86.45%	58.96%

Source: Author's calculations based on listed firms' data

Table 1 summarizes stock return volatility (σ) and drift (μ) for 101 consumer goods firms from 2015-2024. The results show strong temporal variation, with volatility rising during crises and stabilizing during recovery. Between 2015-2019, volatility was relatively stable at 29-35% with positive returns, reflecting robust domestic consumption and investor confidence. In 2020, COVID-19 triggered volatility of 40.37% and returns of -18.19%, underscoring supply chain disruptions and market uncertainty. The market rebounded in 2021 with volatility of 63.65% and returns of 40.37%, but conditions deteriorated again in 2022 as volatility peaked at 83.43% and returns dropped to -13.86%. Recovery followed in 2023-2024, with volatility falling to 26.95% and 21.10% and returns stabilizing at 16.34% and 3.01%.

Cross-sectional heterogeneity was also pronounced. Maximum annual returns reached 212.11% in 2019, while the minimum fell to -138.73% in 2021, illustrating firm-specific vulnerabilities such as leverage and capital structure. Standard deviations exceeded 70% in 2015 and 2020, confirming wide dispersion of outcomes.

Overall, three insights emerge: volatility in Vietnam's consumer goods sector is cyclical and shock-sensitive; return dynamics follow alternating boom-and-bust patterns; and firm fundamentals amplify systemic shocks, with highly leveraged firms experiencing disproportionate losses. These findings highlight the sector's vulnerability to crises and the importance of market-based risk indicators for credit risk analysis.

Firm Asset Volatility and Probability of Default

To estimate asset volatility (σ_A), distance-to-default (DD), and probability of default (PD), the Structural Approach requires both market-based and macro-financial inputs. A key parameter is the risk-free rate, proxied by annual yields on Vietnamese government bonds with five-year maturity. Between 2015 and 2018, rates remained relatively stable at 4.5-5%. They declined to 3.2% in 2019 and further to 2.8% in 2020, reflecting monetary easing and liquidity injections during the COVID-19 crisis. The lowest level was observed in 2021 at 2.5%, after which rates recovered to 4.5% in 2022 and stabilized around 3.5% in 2023-2024, consistent with post-pandemic macroeconomic normalization. Other assumptions include a constant payout ratio of 2% and bankruptcy costs fixed at 50% of asset value, in line with established structural credit risk modeling practices (Hull, 2018).

The sample comprises 101 consumer goods firms listed on HSX and HNX, divided into 51 consumer discretionary and 50 consumer staples companies. To capture sectoral heterogeneity, the firms were classified into seven sub-sectors: Food, Beverage & Tobacco (46 firms), Household & Personal Products (2 firms), Retail-Essential (2 firms), Retail-Non-Essential (22 firms), Consumer Services (5 firms), Fashion & Durables (19 firms), and Automobiles & Components (5 firms). This classification highlights the structural diversity of Vietnam's consumer goods sector and enables a comparative analysis of risk profiles between cyclical and defensive industries. Examining these sub-sectors provides deeper insights into how asset volatility, distance-to-default, and probability of default vary with firms' economic functions and exposure to macroeconomic shocks.

Table 2: Descriptive statistics for asset volatility (σ_A) across the sample period

Year	Mean	Median	Max	Min	Standard Deviation
2024	12.35%	10.64%	66.39%	0.17%	8.74%
2023	14.89%	13.70%	48.99%	0.32%	8.95%
2022	20.14%	16.16%	93.88%	0.18%	14.73%
2021	21.90%	17.99%	71.03%	0.95%	13.97%
2020	19.67%	14.11%	93.99%	0.16%	16.27%
2019	13.76%	8.87%	90.62%	0.11%	13.82%
2018	15.65%	12.30%	66.46%	0.13%	13.09%
2017	13.66%	10.98%	58.62%	0.43%	11.32%
2016	17.02%	13.44%	80.10%	0.84%	15.19%
2015	13.23%	10.89%	55.64%	0.56%	10.55%

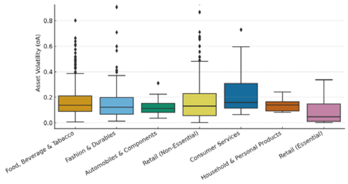
Source: Author's calculations based on listed firms' data

The descriptive statistics in Table 3 show that average σ_A fluctuated between 12.35% in 2024 and 21.90% in 2021, with a median consistently below the mean, confirming the right-skewed distribution of volatility. This indicates that while most firms exhibited moderate risk profiles, a subset of highly leveraged or distressed firms disproportionately elevated sectoral volatility. Maximum σ_A values reached 55.64% in 2015 and peaked near 98.12% in 2021, underscoring the influence of extreme outliers during crisis conditions. Standard deviations were highest in 2016 (15.19%) and 2020 (21.71%), coinciding with global trade tensions and the COVID-19 crisis.

Interestingly, during the relatively calm period of 2018-2019, σ_A averaged 15.65% and 13.76%, respectively, reflecting a stable macroeconomic environment prior to the pandemic (Reddy & Clinton, 2016). By contrast, volatility escalated to 19.20% in 2020, consistent with rising financial distress across emerging markets. By 2022-2024, σ_A gradually normalized, falling to 20.14% in 2022, 14.89% in 2023, and 12.35% in 2024, reflecting improved financial stability and investor confidence.

Figure 1 shows substantial heterogeneity in asset volatility (σ_A) across sub-sectors. Consumer Services and Fashion & Durables display the widest interquartile ranges and most outliers, with σ_A values exceeding 0.7-0.9, reflecting their cyclical and discretionary nature. In contrast, Household & Personal Products and Retail (Essential) exhibit tightly clustered, low volatility (medians around 0.13-0.17), confirming their defensive role. Food, Beverage & Tobacco occupies an intermediate position, with moderate averages but occasional spikes linked to commodity price shocks. Automobiles & Components show mixed outcomes: some firms remain stable near σ_A = 0.1, while others face high volatility, underlining exposure to demand cycles and capital intensity.

Figure 1: Distribution of asset volatility across consumer-related sub-sectors



Source: Author's calculations based on listed firms' data

Using the Merton model, the Probability of Default (PD) was estimated for 101 firms during 2015-2024. Results reveal significant temporal variation, closely aligned with shifts in market volatility and macroeconomic shocks.

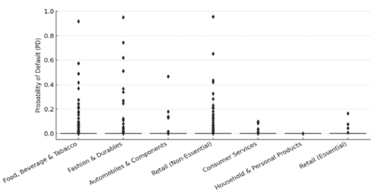
Table 3: Descriptive statistics for Probability of Default (PD) across the sample period

Year	Mean	Median	Max	Min	Standard Deviation
2024	0.3031%	0.0000%	12.2938%	0.0000%	1.5686%
2023	0.1565%	0.0000%	12.6656%	0.0000%	1.2772%
2022	5.3145%	0.0003%	65.2638%	0.0000%	12.3523%
2021	0.0154%	0.0000%	0.9077%	0.0000%	0.0945%
2020	1.3638%	0.0000%	94.8436%	0.0000%	9.5348%
2019	1.4183%	0.0000%	43.4786%	0.0000%	5.3942%
2018	2.5723%	0.0001%	41.9347%	0.0000%	7.8083%
2017	0.3365%	0.0000%	14.0377%	0.0000%	1.5813%
2016	5.6812%	0.0000%	95.5134%	0.0000%	17.6386%
2015	0.5819%	0.0000%	17.8939%	0.0000%	2.3545%

Source: Author's calculations based on listed firms' data

Between 2015 and 2019, average PDs remained modest (0.33%-2.57%), though outliers reached 14-43%, indicating that a minority of firms carried disproportionately high credit risk. Dispersion across firms was evident, with standard deviations up to 7.8% (Campbell, Lettau, Malkiel, & Xu, 2001). The COVID-19 crisis caused a sharp escalation: in 2020, PDs peaked at 94.84% with a mean of 5.68%, the highest in the sample. Elevated risks persisted in 2021-2022, with outliers again exceeding 90% and average values at 1.64% and 3.51%. These results confirm that discretionary sectors particularly Retail (Non-Essential) and Fashion & Durables were most exposed to credit distress due to reliance on household demand and supply chain stability.

Figure 2: Distribution of asset volatility across consumer-related sub-sectors



Source: Author's calculations based on listed firms' data

In contrast, Household & Personal Products consistently recorded near-zero PDs, confirming its defensive nature. Retail (Essential) also maintained low risk, reflecting the stabilizing role of staple goods. Food, Beverage & Tobacco showed intermediate outcomes, with occasional PD spikes linked to sector-specific shocks such as regulation or commodity price fluctuations.

Figure 2 shows that PD distributions are highly right-skewed: while most firms report near-zero PDs, a subset records extreme values. Outliers are concentrated in Retail (Non-Essential) and Fashion & Durables, where several firms reached PDs above 60% or close to 100%, reflecting their vulnerability to demand shocks and supply chain disruptions (Campbell, Lettau, Malkiel, & Xu, 2001). These sectors face not only greater operational volatility but also tighter liquidity constraints, amplifying default risk during downturns.

By contrast, Household & Personal Products consistently recorded negligible PDs, reinforcing its defensive nature. Retail (Essential) also showed stable, near-zero PDs, highlighting the protective effect of staple goods. Food, Beverage & Tobacco occupied an intermediate position: average PDs were low, but occasional spikes appeared due to regulatory shifts or commodity price shocks. Overall, defensive sectors remained resilient, while discretionary sectors amplified systemic credit risk.

To provide deeper insights into firm-level risk, asset volatility (σ_A) and probability of default (PD) were analyzed across sub-sectors of the Vietnamese consumer goods industry between 2015 and 2024.

Table 4: Summary Statistics of Asset Volatility and Probability of Default by Sub-sector

Consumer Services		Consumer Discretionary				Consumer Staples		
		Fashion & Durables	Retail (Non-Essential)	Automobiles & Components	Household & Personal Products	Food, Beverage & Tabacco	Retail (Essential)	
Asset Volatility σ_A	Average	22.8173%	15.2152%	16.9890%	12.1050%	13.6778%	16.5159%	9.0046%
	Max	73.0016%	93.8838%	93.9883%	31.1505%	24.1627%	80.0978%	33.5244%
	Min	6.5012%	1.2379%	0.1071%	3.6512%	8.1269%	0.6842%	0.1845%
	Medium	15.9502%	12.1438%	12.9769%	11.1696%	13.7684%	13.7303%	4.7159%
	Standard Deviation	17.3895%	13.7609%	16.0558%	5.2952%	4.3291%	11.5995%	10.0261%
Probability of Default PD	Average	0.6458%	2.5960%	2.4816%	1.8763%	13.6778%	1.3160%	9.0046%
	Max	9.6945%	94.8436%	95.5134%	46.7555%	24.1627%	91.7082%	33.5244%
	Min	0.0000%	0.0000%	0.0000%	0.0000%	8.1269%	0.0000%	0.1845%
	Medium	0.0000%	0.0000%	0.0000%	0.0000%	13.7684%	0.0000%	4.7159%
	Standard Deviation	1.9750%	11.3307%	9.7426%	7.4226%	4.3291%	6.8359%	10.0261%

Source: Author's calculations based on listed firms' data

Consumer Services consistently exhibited the highest volatility, with an average σ_A of 22.8% and a maximum of 73%. This volatility pattern reflects the cyclical and demand-sensitive nature of the sector, which is highly exposed to household consumption shocks. Firms such as DAH and NVT showed pronounced PD spikes during the COVID-19 crisis, at times exceeding 8.5%, confirming the sector's fragility when tourism, hospitality, and service-related activities contracted under lockdowns and demand restrictions. These results suggest that service-oriented firms face elevated systemic risk due to their dependence on discretionary spending and their limited capacity to absorb income shocks.

Fashion & Durables and Retail (Non-Essential) displayed similarly elevated σ_A levels (15-17%), coupled with extreme PDs surpassing 90% for some firms.

These values highlight the pro-cyclical character of discretionary retail, where firms' performance is closely tied to fluctuations in household disposable income and consumer sentiment. The volatility within these segments is magnified by inventory cycles, supply chain disruptions, and their reliance on non-essential demand, making them particularly vulnerable during macroeconomic downturns. The sharp PD outliers in these sub-sectors reinforce their role as amplifiers of systemic instability.

By contrast, defensive industries such as Household & Personal Products and Retail (Essential) demonstrated markedly lower risk profiles. Both recorded σ_A levels in the range of 8-9% and maintained near-zero PDs throughout the period, even during the COVID-19 crisis. This resilience reflects the relatively inelastic demand for necessities such as cleaning products, hygiene items, and staple goods, which tend to remain stable despite fluctuations in income levels or broader economic conditions (Hull, 2018). These results provide strong empirical support for the defensive sector hypothesis, where essential goods act as stabilizers for both consumers and investors during turbulent periods.

Food, Beverage & Tobacco firms occupied an intermediate position. While average σ_A stood at 16.5%, occasional PD spikes were observed, particularly in response to regulatory changes, commodity price volatility, and disruptions in agricultural inputs. This mixed performance illustrates the dual character of the sub-sector: demand for food and beverages is relatively stable, but exposure to external shocks in raw materials and taxation policies can destabilize firm valuations and credit profiles.

Finally, Automobiles & Components displayed the most heterogeneous outcomes. The sector recorded a moderate average σ_A of 12.1%, but PD values varied widely across firms. While some manufacturers maintained near-zero PDs, others experienced spikes above 40%, particularly during global trade frictions and supply chain disruptions in 2016 and 2022. This divergence reflects the capital-intensive nature of the industry, its reliance on imported inputs, and its sensitivity to cyclical demand shifts in both domestic and export markets.

Across all sub-sectors, the crisis period of 2020-2022 amplified both volatility and default risk. Several firms in discretionary industries recorded PDs exceeding 80-90%, confirming their vulnerability to systemic shocks. However, the recovery years of 2023-2024 showed a sharp reversal: volatility moderated, and PD values declined broadly, with most firms returning to PD = 0%. This normalization signals improved macroeconomic management, stabilization of household demand, and renewed investor confidence, consistent with the post-pandemic recovery trajectory of Vietnam's economy.

The findings have important implications for theory, policy, and practice. First, they confirm structural credit risk models (Merton, 1974), showing that higher asset volatility raises default probability, but also reveal strong sectoral heterogeneity. Ignoring these differences risks obscuring critical contrasts between defensive and cyclical industries. Second, results highlight the need for sector-specific risk assessment in emerging markets like Vietnam, where the COVID-19 crisis showed that essential retail and household goods remained resilient, while discretionary sectors faced disproportionate stress (Reddy & Clinton, 2016). Third, the relationship between volatility (σ_A) and default probability (PD) is non-linear: firms with high leverage and weak balance sheets may default under moderate volatility, while stronger firms remain stable despite higher σ_A (Crosbie & Bohn, 2003). Finally, joint evaluation of σ_A and PD provides valuable guidance for investors and policymakers. Defensive sectors strengthen portfolio resilience, while cyclical sectors amplify systemic risk. Sub-sector PD distributions can serve as stress-testing tools, helping identify fragile industries and supporting policies for capital structure optimization and financial stability (Hull, 2018).

7. Conclusion

This study applied the Structural Approach, using the Merton model, to assess asset volatility (σ_A) and probability of default (PD) for 101 Vietnamese consumer goods firms (2015-2024). Three main insights emerge. First, σ_A is cyclical and shock-sensitive, with crises such as COVID-19 driving sharp spikes in both σ_A and PD, followed by post-crisis stabilization. Second, strong sectoral heterogeneity was observed: defensive sub-sectors (Household & Personal Products, Retail-Essential) maintained low volatility and near-zero PDs, while cyclical sub-sectors (Consumer Services, Fashion & Durables, Retail-Non-Essential) showed elevated risk. Third, the σ_A-PD relationship proved non-linear: firms with moderate volatility but high leverage faced greater default risk, whereas firms with high σ_A but stronger asset bases remained secure.

These findings highlight the need for sector-specific risk assessment in emerging markets. For policymakers, sub-sector PD distributions can serve as stress-testing tools, while for investors, sectoral allocation is vital for portfolio resilience. From a corporate governance perspective, firms in cyclical industries should strengthen capital structures, extend debt maturities, and maintain liquidity buffers. Overall, the Structural Approach offers valuable insights into credit risk dynamics in Vietnam's consumer goods sector, underscoring the interaction between volatility, leverage, and default probabilities in shaping financial stability.

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