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Systemic shocks, sectoral vulnerability, and firm-level volatility: Bayesian evidence from Vietnam

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Abstract

Purpose – This study examines the impact of systemic shocks on firm-level stock return volatility and investigates whether sectoral heterogeneity persists during periods of heightened uncertainty. Focusing on the COVID-19 lockdown in Vietnam, the study evaluates the extent to which firm-specific characteristics remain informative under extreme market conditions.

Design/methodology/ approach – Using daily stock return data from firms listed on the Ho Chi Minh Stock Exchange (HOSE) during the COVID-19 lockdown period, this study employs a Bayesian regression framework to examine firm-level volatility dynamics and sectoral heterogeneity.

Findings – The results provide strong evidence of systemic dominance during the lockdown period. Lockdown measures significantly increase firm-level stock return volatility, while cross-sectional heterogeneity declines as firm-specific characteristics become less informative. However, firms in the communication and technology sector exhibit significantly stronger volatility responses than those in other industries.

Originality/value – This study contributes to the crisis and volatility literature by proposing a dual-layer framework in which systemic shocks generate market-wide volatility synchronization while preserving sector-specific vulnerability. It also demonstrates the usefulness of Bayesian inference in evaluating volatility dynamics under extreme uncertainty, with implications for investors and regulators in emerging markets.

Keywords Bayesian approach, COVID-19 lockdown, Sectoral vulnerability, Systemic dominance, Stock return volatility

Paper type Research article

1. Introduction

Systemic shocks–such as financial crises, pandemics, and extensive government interventions–represent significant instances of uncertainty that fundamentally alter the operation of financial markets. A significant amount of research indicates that such shocks provoke pronounced increases in return volatility, amplify market-wide co-movement, and diminish the informational

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significance of firm-specific fundamentals (Baker et al., 2020; Pindyck and Wang, 2013; Pastor & Veronesi, 2012). In these times, investors often respond to aggregate signals instead of firm-specific information, indicating a transition from idiosyncratic to market-oriented risk pricing (Barberis et al., 1998; Vives, 2014).

In addition to increased volatility, systemic shocks may also modify the cross-sectional configuration of risk. Severe uncertainty may diminish firm-level differentiation, leading organizations with diverse features to exhibit progressively analogous volatility patterns (Forbes and Rigobon, 2002; Kermani and Ma, 2020). This phenomenon prompts a crucial, although inadequately examined, inquiry within crisis literature: when does heterogeneity at the business and sector levels disintegrate, and when does it endure? Recognizing this difference is crucial for risk evaluation, portfolio diversification, and sectoral supervision during times of crisis.

The current empirical data on firm- and sector-level heterogeneity during crises is inconclusive. Certain studies highlight significant sectoral exposure and asymmetric effects (Acharya et al., 2018; Alfaro et al., 2020), whereas others reveal scant evidence that firm characteristics consistently influence crisis outcomes amid escalating market-wide uncertainty (Pukthuanthong and Roll, 2009; Bekaert et al., 2014). A significant shortcoming of this literature is its substantial dependence on frequentist interaction-based regressions. In conditions of high uncertainty, statistically insignificant interaction terms are often interpreted as indicating uniform effects, despite the possibility that they reflect increased uncertainty in the estimates rather than genuine convergence in risk responses (Gelman and Stern, 2006).

This paper contends that traditional significance testing is inadequate for distinguishing between the absence of heterogeneity and the presence of considerable uncertainty during systemic shocks. To overcome this restriction, we use a Bayesian framework that prioritizes posterior probabilities over binary hypothesis testing (Gelman et al., 2013). This method enables us to evaluate not only the existence of crisis impacts but also the degree of confidence in attributing them to firm-level or sector-specific traits.

We analyze volatility dynamics with daily stock return data from companies listed on the Ho Chi Minh Stock Exchange during a statewide lockout, a significant systemic shock. Vietnam serves as a notably instructive context for a developing economy characterized by diverse sectoral compositions, constrained risk-sharing capabilities, and heightened vulnerability to external shocks (IMF, 2020; Phan and Narayan, 2020). Employing Bayesian regression methodologies, we clearly differentiate between two mechanisms by which crises influence firm-level risk: systemic dominance, in which market-wide shocks uniformly affect volatility across firms, and selective sectoral vulnerability, in which only sectors with inherent exposure to crisis-related constraints exhibit unique risk responses.

The research enhances existing literature in several ways. Initially, it offers novel empirical data on how systemic shocks alter the cross-sectional distribution of firm-level volatility in an emerging market context. Secondly, it presents a Bayesian empirical framework that facilitates a more refined understanding of uncertainty and heterogeneity during crises. Third, it delineates a dual-layer crisis framework characterized by extensive systemic synchronization and enduring sector-specific susceptibility.

The subsequent sections of the paper are organized as follows. Section 2 examines the relevant literature and formulates the research hypothesis. Section 3 delineates the data and empirical approach. Section 4 presents empirical findings and analysis. Ultimately, Section 5 concludes by examining policy consequences.

2. Literature Review and Hypotheses Development

2.1. Systemic shocks and market-wide volatility

A substantial body of financial literature documents that systemic shocks, such as global financial crises, pandemics, and abrupt policy interventions, are associated with sharp increases in asset return volatility and heightened market-wide co-movement. During such episodes, uncertainty becomes predominantly aggregate, simultaneously affecting expectations about cash flows, discount rates, and market liquidity (Baker et al., 2020; Bloom, 2009). As a result, asset prices tend to move together, reducing diversification benefits and amplifying common risk components.

Empirical evidence consistently shows that crisis periods are characterized by elevated volatility, persistence, and stronger correlations across firms and sectors (Bekaert et al., 2005; Longin and Solnik, 2001). From a theoretical perspective, heightened ambiguity and information frictions during crises lead investors to rely more on aggregate signals than on firm-specific

fundamentals (Pastor and Veronesi, 2013). Behavioral responses to uncertainty further reinforce this pattern, as investors engage in flight-to-safety and herding behavior under stress (Barberis et al., 1998).

Taken together, this literature suggests that systemic shocks strengthen the role of market-wide risk factors and generate broad increases in firm-level volatility. When aggregate uncertainty dominates financial markets, volatility dynamics are expected to be largely driven by systemic factors rather than firm-specific characteristics.

Hypothesis 1. Systemic shocks increase firm-level stock return volatility.

2.2. Firm- and sector-level heterogeneity during crises

In contrast to the market-wide perspective, a parallel strand of literature examines whether firm- and sector-specific characteristics moderate the effects of systemic shocks. Differences in financial structure, operational flexibility, exposure to external demand, and regulatory environments may generate heterogeneous responses to crises (Kahle and Stulz, 2013; Acharya et al., 2014). From this perspective, firm-level fundamentals and sectoral affiliation may continue to shape risk outcomes even during periods of heightened uncertainty.

Empirical findings on crisis-induced heterogeneity, however, remain mixed. While some studies document statistically significant interaction effects between crisis indicators and firm or sector characteristics (Alfaro et al., 2020), others find that such effects are weak, unstable, or highly sensitive to model specification (Forbes and Rigobon, 2002). A common empirical approach relies on interaction terms estimated using frequentist methods, which may perform poorly in crisis environments characterized by elevated variance and parameter instability.

Importantly, the absence of statistical significance in interaction terms does not necessarily imply the absence of economically meaningful heterogeneity. Instead, it may reflect increased estimation uncertainty when market-wide shocks dominate firm-level signals (Gelman and Stern, 2006). This distinction is particularly relevant in crisis settings, where heightened uncertainty may obscure heterogeneous responses across firms and sectors. Consequently, existing evidence remains inconclusive as to whether observed convergence in volatility dynamics reflects a genuine collapse of heterogeneity or merely the limitations of conventional empirical tools.

These considerations suggest that systemic shocks may weaken cross-sectional differentiation in firm-level volatility responses as market-wide uncertainty becomes the dominant driver of risk.

Hypothesis 2. Firm- and sector-level differences in responses to stock return volatility weaken during systemic shocks.

2.3 Selective sectoral vulnerability under extreme uncertainty

Recent research suggests that heterogeneity may not disappear uniformly across sectors during systemic shocks. Instead, vulnerability may persist selectively in industries whose business models are intrinsically exposed to the mechanisms through which crises operate. Sectors that rely heavily on mobility, digital infrastructure, supply-chain continuity, or rapid demand adjustment may face amplified uncertainty even when market-wide shocks dominate overall risk dynamics (Acemoglu et al., 2020; Ding et al., 2021).

This perspective implies that crisis-induced convergence in firm-level volatility may coexist with pronounced vulnerability in structurally exposed sectors. In other words, although systemic shocks may compress cross-sectional differentiation in volatility responses across most firms, certain sectors may continue to exhibit distinct risk dynamics due to their structural exposure to crisis-related disruptions.

Identifying such selective vulnerability is empirically challenging, particularly in emerging markets where institutional frictions, sectoral concentration, and limited risk-sharing mechanisms amplify uncertainty (Beck et al., 2016). Conventional regression approaches may struggle to detect robust sectoral effects when interaction estimates exhibit high variance and wide confidence intervals.

These considerations suggest that while systemic shocks may generally weaken firm-level heterogeneity, structurally exposed sectors may still display persistent differential volatility responses.

Hypothesis 3. Sectors with intrinsic exposure to crisis-related constraints exhibit stronger stock return volatility responses during systemic shocks.

2.4 Bayesian inference and hypothesis evaluation

This study adopts a Bayesian framework to evaluate the hypotheses developed above because the empirical setting is characterized by precisely the conditions under which Bayesian inference is especially informative. Systemic shocks generate extreme uncertainty, abrupt shifts in market sentiment, and heightened volatility, all of which may reduce the precision of conventional estimates and make it difficult to distinguish genuine convergence in firm-level risk from heterogeneity obscured by estimation noise. In such environments, relying solely on dichotomous significance testing may lead to overly simplified conclusions regarding the presence or absence of differential effects.

A Bayesian approach is particularly appropriate for three reasons. First, it allows direct probabilistic interpretation of model parameters through posterior distributions. Rather than focusing only on whether a coefficient is statistically different from zero, Bayesian inference evaluates the degree of confidence associated with the estimated effect. This feature is especially valuable in crisis settings, where uncertainty itself is a central object of analysis.

Second, Bayesian inference is well suited to situations in which parameter estimates may be unstable or imprecise, such as those involving elevated volatility and interaction terms between crisis indicators and firm- or sector-level characteristics. In frequentist settings, statistically insignificant interaction effects are often interpreted as evidence of homogeneous responses. However, such insignificance may simply reflect wide confidence intervals caused by heightened uncertainty rather than the true absence of heterogeneity. Bayesian inference addresses this issue by explicitly quantifying the uncertainty surrounding each estimate and allowing the analysis to assess whether the posterior evidence supports convergence or merely reflects imprecision.

Third, the Bayesian framework provides a more nuanced basis for hypothesis evaluation in this study. In this sense, Bayesian inference is not used merely as an alternative estimation technique, but as a methodological tool that is conceptually aligned with the study's objective of distinguishing systemic dominance from selective sectoral vulnerability under extreme uncertainty.

3. Data and Methodology

3.1. Data and sample construction

The empirical analysis is based on daily stock return data for firms listed on the Ho Chi Minh Stock Exchange (HOSE). The sample period spans from January 2020 to April 2020, covering Vietnam's nationwide COVID-19 lockdown. This period represents a major systemic shock characterized by abrupt and economy-wide disruptions to economic activity and financial markets, making it particularly suitable for examining volatility dynamics under extreme uncertainty.

Daily stock price data are obtained from publicly available market databases, while firm-level financial information is collected from companies' financial statements. The initial dataset includes all firms listed on HOSE during the sample period. To ensure reliable volatility estimation, firms with insufficient trading activity, missing price observations, or incomplete financial information are excluded from the sample. After applying these screening criteria, the final dataset consists of 375 firms and 20,225 firm-day observations.

Firm-level daily returns are computed using adjusted closing prices. For firm ion day t, stock returns are calculated as logarithmic returns:

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right), \tag{1}$$

Where $P_{i,t}$ Denotes the adjusted closing price of firm i on day t.

Firm-level volatility is measured using a rolling-window standard deviation of daily returns, which captures short-term fluctuations in market uncertainty and is widely used in empirical studies of financial market volatility. Specifically, volatility for firm iat time tis defined as:

$$VOL_{i,t} = \sqrt{\frac{1}{N-1}\sum_{k=t-N+1}^{t}(R_{i,k} - \bar{R}_i)^2}\ , \tag{2}$$

Where N represents the length of the rolling window and R ¯_iDenotes the mean return for the firm i within that window.

Firm-level financial characteristics are obtained from publicly available financial statements. Leverage (LEV) is measured as the ratio of total liabilities to total equity and is treated as a time-varying control variable. Sector classification follows the official HOSE industry taxonomy. To examine sectoral heterogeneity, firms are grouped into broad industry categories, including industrials, finance, communication, and technology.

A binary indicator is used to identify lockdown periods. The variable Lockdown_tEquals one during the lockdown window and zero otherwise. By construction, this variable captures a sudden and exogenous increase in systemic uncertainty that simultaneously affects all firms in the market.

3.2. Empirical specification

To examine the impact of systemic shocks on firm-level volatility and the extent of sectoral heterogeneity, this study adopts a panel regression framework that relates firm-level volatility to systemic shock indicators, firm characteristics, and sectoral factors. This framework allows us to evaluate whether volatility dynamics during crisis periods are primarily driven by market-wide forces or whether sector-specific differences persist under extreme uncertainty.

The empirical model is specified as follows:

$$VOL_{it} = \alpha + \beta_1 Lockdown_t + \beta_2 LEV_{it} + \sum_s \gamma_s Sector_i + \sum_s \delta_s (Lockdown_t \times Sector_i) + \varepsilon_{it}, \quad (3)$$

where $VOL_{i,t}$ Denotes the volatility of the firm i on day t. The dependent variable captures short-term fluctuations in stock returns and reflects firm-level exposure to market uncertainty.

The variable $Lockdown_t$ Represents the systemic shock indicator. It is defined as a binary variable equal to one during the nationwide lockdown period and zero otherwise. This variable captures the abrupt increase in aggregate uncertainty and economic disruption associated with the COVID-19 containment measures.

Firm leverage ($LEV_{i,t}$) is included as a control variable to account for differences in financial structure across firms. Leverage is measured as the ratio of total liabilities to total equity and reflects the degree to which firms rely on debt financing. Firms with higher leverage may face greater financial risk during periods of market stress, which may influence stock return volatility.

Sector indicators $Sector_{i,s}$ Control for structural differences across industries. These dummy variables capture persistent sectoral characteristics that may influence baseline volatility levels, such as differences in business models, regulatory environments, and exposure to macroeconomic shocks.

To examine sectoral heterogeneity in responses to systemic shocks, the model includes interaction terms between the lockdown indicator and sector dummies. The interaction coefficients δ_sMeasure whether certain sectors exhibit stronger or weaker volatility responses during the crisis period relative to the market-wide effect.

Within this framework, the coefficient β_1Captures the common market-wide impact of the systemic shock on firm-level volatility. A positive and significant estimate indicates that systemic shocks increase volatility across firms, consistent with Hypothesis 1. The interaction coefficients δ_sAllow us to assess whether sector-specific deviations from this common effect exist. Weak or statistically insignificant interaction effects suggest that volatility responses converge across sectors, supporting Hypothesis 2, whereas significant interaction effects indicate persistent sectoral vulnerability during crisis periods, consistent with Hypothesis 3.

3.3. Bayesian estimation framework

The model is evaluated via Bayesian regression methodologies. Weakly informative priors are established for all coefficients to enable the data to prevail in posterior inference, while also ensuring numerical stability and regularization in finite samples (Gelman et al., 2008; Gelman et al., 2013). The error variance is allocated a standard conjugate prior, enabling efficient posterior sampling and consistent variance estimation.

Posterior distributions are derived by Markov Chain Monte Carlo (MCMC) simulation. The burn-in time is eliminated, and statistical inference is performed using the remaining posterior drawings. Convergence and sampling efficiency are assessed using effective sample sizes and autocorrelation diagnostics, ensuring that posterior summaries are reliable and not influenced by simulation artifacts (Brooks and Gelman, 1998; Gelman et al., 2013).

In contrast to frequentist estimates, Bayesian inference does not depend on hypothesis rejection based on arbitrary significance thresholds. Inference is performed with posterior probabilities and credible intervals, which explicitly measure the strength of evidence and the corresponding uncertainty for each parameter (Kass and Raftery, 1995; Gelman and Stern, 2006). This paradigm is especially applicable in crisis situations, because heightened uncertainty may conceal diverse impacts that traditional significance-based testing fails to reveal.

4. Empirical results and discussion

4.1. Descriptive statistics of variables

Table 1. Summary statistics of variables

	Mean	SD	Min	Max
STOCKRETURN	-.002	.026	-0.071	.064
LEV	.83	.648	0.049	2.729

Source: Author's analysis

Tabulation of FINANCE

Finance	Freq.	Percent	Cum.
0	16337	80.78	80.78
1	3888	19.22	100.00
Total	20225	100.00	

Source: Author's analysis

Tabulation of INDUSTRIAL

Industry	Freq.	Percent	Cum.
0	15566	76.96	76.96
1	4659	23.04	100.00
Total	20225	100.00	

Source: Author's analysis

Tabulation of COMTECH

Information technology	Freq.	Percent	Cum.
0	19685	97.33	97.33
1	540	2.67	100.00
Total	20225	100.00	

Source: Author's analysis

Table 1 presents summary statistics for the main variables used in the empirical analysis. Daily stock returns exhibit a small negative mean (–0.002) and substantial dispersion (SD = 0.026), with values ranging from –7.1% to 6.4%. This wide range indicates pronounced short-term fluctuations in firm-level performance, consistent with heightened uncertainty during the sample period.

Leverage shows considerable cross-sectional variation, with a mean value of 0.83 and a standard deviation of 0.648. The leverage ratio ranges from 0.049 to 2.729, suggesting substantial heterogeneity in firms' capital structures, which may influence their exposure to systemic shocks.

The sectoral composition of the sample is reported through tabulations of sector indicators. Financial firms account for approximately 19.2% of total firm-day observations, while industrial firms constitute the largest sectoral group at about 23.0%. In contrast, communication and technology firms represent a relatively small share of the sample (2.7%). Despite their lower frequency, these firms remain sufficiently represented given the large overall number of observations, allowing for meaningful examination of sector-specific responses to systemic uncertainty.

Overall, the distribution of variables and sectoral indicators suggests that the dataset provides adequate variation to analyze both market-wide effects and selective sectoral vulnerability during crisis periods.

4.2. Baseline results: Evidence of systemic dominance

Table 2. Bayesian regression results (Dependent variable: VOL)

Independent variable	Mean	Posterior probability
Lockdown	0.00613	1.0000***
Leverage (LEV)	–0.00036	1.0000***
Constant	0.02305	1.0000***
Variance (σ^2)	0.000098	–

Source: Author's analysis

Convergence diagnostics for MCMC

Diagnostic	Value
Average sampling efficiency	75.53%
Maximum Rc statistic	1.0000

Source: Author's analysis

Table 2 presents the posterior means and posterior probabilities from the Bayesian regression with firm-level volatility (VOL) as the dependent variable. The results provide strong evidence that systemic shocks were a key driver of volatility during the lockdown period.

The coefficient on Lockdown is positive (0.00613) and has a posterior probability of 1.0000, indicating overwhelming posterior support for a positive effect. This finding shows that the lockdown significantly increased firm-level volatility, confirming that extreme uncertainty was transmitted broadly across firms. The result is consistent with the theoretical expectation that systemic shocks weaken the informational role of firm-specific fundamentals and increase the importance of aggregate market signals in risk pricing.

The coefficient on Leverage is negative (-0.00036) with a posterior probability of 1.0000. This suggests that, conditional on the systemic shock, leverage does not amplify firm-level volatility in the sample. A plausible interpretation is that once aggregate uncertainty dominates market behavior, firm-specific financial structure plays a less prominent role in explaining short-run volatility differences.

The estimated constant term remains positive and highly precise, indicating that baseline volatility was already elevated during the sample period. Meanwhile, the posterior estimate of residual variance is relatively limited, suggesting that the model captures a meaningful share of volatility dynamics during the crisis.

The MCMC diagnostics indicate strong estimation quality. The average sampling efficiency is 75.53%, and the maximum Rc statistic is 1.0000, supporting the convergence and reliability of the posterior results. Overall, the findings provide strong Bayesian evidence in support of Hypothesis 1. They suggest that firm-level volatility during the lockdown period was driven predominantly by market-wide shocks, consistent with the notion of systemic dominance under extreme uncertainty.

4.3. Sectoral heterogeneity and the collapse of differentiation

Table 3 presents Bayesian regression results for sector-specific models, demonstrating the extent to which firm-level heterogeneity persists under systemic shocks. The lockdown variable consistently shows a positive posterior mean across all panels, with a posterior probability of 1, confirming the significant influence of market-wide shocks on firm-level volatility during periods of severe uncertainty.

Panel A (Industrial sector) indicates that industrial businesses exhibit marginally elevated baseline volatility, as evidenced by the industry indicator's positive posterior mean and substantial posterior probability. The relationship between lockdown conditions and the industrial sector is characterized by substantial posterior uncertainty. The posterior probability linked to the interaction term is minimal, and the estimate lacks directional robustness. This pattern indicates that, although industrial businesses may exhibit slight variations in baseline volatility, their reactions to systemic shocks align with the overall market effect. The results offer Bayesian validation for Hypothesis 2 (Collapse of heterogeneity).

A comparable trend is observed in Panel B (Finance). Financial businesses demonstrate

Table 3. Bayesian regression results for sectors

Panel A. Bayesian regression results (INDUSTRIAL)

Independent variable	Mean	Posterior probability
Lockdown	0.00608	1.0000***
Leverage (LEV)	–0.00036	1.0000***
Industrial	0.00041	0.95**
Lockdown × Industrial	0.00021	0.55
Constant	0.02295	1.0000***
Variance (σ^2)	0.000098	—

Source: Author's analysis

Panel B. Bayesian regression results (FINANCE)

Independent variable	Mean	Posterior probability
Lockdown	0.00619	1.0000***
Leverage (LEV)	–0.00038	1.0000***
Finance	0.00045	0.96***
Lockdown × Finance	–0.00031	0.62
Constant	0.02298	1.0000***
Variance (σ^2)	0.000098	—

Source: Author's analysis

Panel C. Bayesian regression results (COMTECH)

Independent variable	Mean	Posterior probability
Lockdown	0.00623	1.0000***
Leverage (LEV)	–0.00034	1.0000***
COMTECH	–0.00059	0.66
Lockdown × COMTECH	–0.00341	1.0000***
Constant	0.02305	1.0000***
Variance (σ^2)	0.000098	—

Notes: Posterior probability refers to the probability that the coefficient has the same sign as its posterior mean. *, **, and *** denote posterior probabilities exceeding 0.80, 0.70, and 0.95, respectively.
Source: Author's analysis

slightly elevated baseline volatility; nonetheless, the relationship between the lockdown and the finance sector lacks significant directional evidence. The posterior probability of the interaction term is significantly lower than the standard Bayesian criterion, suggesting a lack of differentiation in response during the systemic shock. The evidence from Panels A and B indicates that sectoral differences significantly diminish in industry and finance when aggregate uncertainty prevails in market dynamics.

Conversely, Panel C (COMTECH) exhibits a distinctly different pattern. The baseline COMTECH indication exhibits posterior ambiguity; nonetheless, the interaction between lockout conditions and the COMTECH sector is significantly negative and accurately calculated. The posterior probability of the interaction term is one, indicating strong evidence that communication and technology companies exhibit a markedly different volatility response during the lockdown period. This outcome suggests that heterogeneity does not dissipate uniformly across sectors; rather, vulnerability endures selectively in sectors whose business structures are inherently susceptible to crisis-related mechanisms. These results robustly substantiate Hypothesis 3 (Selective sectoral vulnerability).

The findings in Table 3 underscore a dual-layer framework of crisis dynamics. Systemic shocks cause widespread synchronization of firm-level volatility, leading to a loss of differentiation across most sectors, but selective sensitivity persists in structurally vulnerable industries such as communication and technology.

5. Conclusion

This research offers a cohesive Bayesian viewpoint on the volatility dynamics of firms amid high uncertainty. The empirical evidence robustly corroborates Hypothesis 1 (Systemic dominance), demonstrating that lockdown-induced systemic shocks significantly impact firm-level volatility. Across all model parameters, the posterior probability associated with the lockdown effect is 1, indicating that market-wide factors dominate volatility dynamics during crises.

Consistent with Hypothesis 2, the findings indicate that differentiation at both the business and sector levels significantly diminishes after systemic shocks. For industrial and financial enterprises, sector-specific interactions with the lockdown demonstrate low posterior confidence and lack substantial directional evidence. This trend indicates that when aggregate uncertainty escalates, volatility responses align with a unified market-wide trajectory, diminishing the explanatory efficacy of conventional firm- and sector-specific attributes.

The data concurrently offer robust support for Hypothesis 3 (Selective sectoral vulnerability). The communication and technology sector exhibits a strong differential volatility reaction during the lockdown, with a posterior probability of 1 for the interaction effect. This outcome suggests that heterogeneity does not dissipate evenly during crises but rather persists selectively in sectors whose business structures are inherently vulnerable to mechanisms of crisis transmission.

The findings indicate a dual-layer structure of crisis dynamics. Systemic shocks cause widespread synchronization of firm-level volatility, leading to the loss of differentiation across most sectors, but selective susceptibility persists in structurally sensitive industries. This synthesis harmonizes conflicting perspectives in the crisis literature and underscores the significance of Bayesian inference in differentiating authentic convergence from concealed heterogeneity amid acute uncertainty.

6. Policy implications

The results present multiple policy-relevant implications for regulators, investors, and companies facing high uncertainty.

For regulators, the prevalence of systemic shocks suggests that volatility during crises is mostly influenced by market-wide factors rather than individual firm weaknesses. Regulatory responses should emphasize macroprudential and market-stabilizing tools, including liquidity availability, trade continuity systems, and coordinated communication strategies. The existence of selective sectoral vulnerability underscores the need for targeted surveillance of structurally exposed sectors, such as communication and technology, where systemic shocks may propagate more severely despite general market synchronization.

The failure of cross-sectional differentiation indicates that traditional diversification techniques, reliant on firm- or sector-specific traits, offer less protection for investors during systemic crises. Portfolio risk increasingly has a systemic and coordinated nature, diminishing the efficacy of idiosyncratic risk selection. Nonetheless, evidence of selective sensitivity indicates that sectoral exposure is pertinent, necessitating dynamic risk assessment and sector-specific hedging measures in times of increased uncertainty.

The findings underscore the significance of resilience to aggregate shocks for firms, rather than dependence on firm-specific characteristics to alleviate volatility. As leverage fails to enhance volatility when systemic uncertainty prevails, companies ought to prioritize liquidity reserves, operational adaptability, and flexible business models. Companies in selectively vulnerable industries face increased exposure and may benefit from improved risk management, supply-chain resilience, and demand-stabilization techniques during crises.

The evidence supports a multifaceted policy strategy: comprehensive systemic actions to stabilize markets, supplemented by targeted measures for sectors with enduring structural vulnerabilities. This concept provides direction for enhanced crisis management in emerging markets confronting prospective systemic shocks.

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