International Entrepreneurship Review

2026, Vol. 12, No. 2

OPEN ACCESS

10.15678/IER.2026.1202.03

Global supply chain disruptions and United States industries: Winners and losers

Marcin Pietrzak

ABSTRACT

Objective: The article aims to examine how pressure in the global supply chains affects United States industry-level equity returns and volatility, showing which sectors are winners and losers under high- versus low-pressure regimes.

Research Design & Methods: I adopted a quantitative design, modelling 49 U.S. industry-portfolio returns from January 1998 to June 2024 using a two-regime Markov-Switching autoregressive model with transition probabilities that are a function of the global supply chain pressure index (GSCPI).

Findings: Heightened pressure cleaves the cross-section: commodity and capital goods industries enjoy higher long-run returns, while defensives outperform only in tranquil periods, so the regime shift turns winners into losers and vice-versa. Moving into the high-pressure state also amplifies volatility across most sectors and pushes roughly half of them into negative territory, revealing a stark volatility-growth trade-off.

Implications & Recommendations: Regularly tracking supply-chain pressure allows investors and policy-makers to anticipate shifts in sector-level risk-return profiles and to adopt broad, resilience-enhancing strategies to smooth market volatility and sustain economic stability.

Contribution & Value Added: The article introduces a regime-switching model linking global supply-chain disruptions to the U.S. sectoral equity dynamics, uncovering asymmetric effects on returns and volatility that linear models overlook.

Article type:	research article
Keywords:	global supply chains; equity market; volatility; autoregressive model; Markov-switching model
JEL codes:	E32, F23, F47

Received: 28 May 2025 Revised: 14 March 2026 Accepted: 27 March 2026

Suggested citation:

Pietrzak, M. (2026). Global supply chain disruptions and United States industries: Winners and losers. *International Entrepreneurship Review,* 12(2), 47-63. https://doi.org/10.15678/IER.2026.1202.03

INTRODUCTION

Supply chains constitute a fundamental component of the global economy. Recent years have demonstrated the vulnerability of these networks to macroeconomic and financial stress, as evidenced by pandemic shutdowns, transportation bottlenecks, and geopolitical fragmentation, resulting in delays, shortages, and abrupt changes in input prices. Policy responses, including reshoring, 'friendshoring,' and resilience programs, reflect a growing consensus that supply-chain disruptions are recurring rather than exceptional events (Baldwin & Freeman, 2020; Ivanov, 2020). The central question is not whether supply chains are important, but rather which sectors are most exposed and whether certain industries systematically benefit when global supply chains experience stress.

Production network research shows that shocks affecting one firm or sector can spread to other parts of the economy through supplier-customer relationships and input-output linkages. These effects depend on a sector's role in the supply chain (Acemoglu *et al.*, 2012; Barrot & Sauvagnat, 2016; Carvalho *et al.*, 2021). The operations and finance literature shows that firm-level supply chain interruptions reduce shareholder value, hurt performance, and increase equity risk (Hendricks & Singhal, 2003; 2005a; 2005b).

Macrofinancial studies use aggregate supply chain pressure to study inflation and financial conditions (Benigno *et al*., 2022; Ascari *et al*., 2024; Ginn, 2024). However, we know little about how overall supply-chain pressure affects industry equity returns and volatility or if this link is nonlinear.

I addressed this gap by analysing how the GSCPI affects industry equity returns and volatility. I also identified which industries gain or lose as supply-chain pressure rises. In the analysis, I used monthly value-weighted returns for 49 U.S. industry portfolios (January 1998 to June 2024) in a two-regime Markov-switching AR(1) model. I modelled transition probabilities as a logistic function of the GSCPI (Filardo, 1994; Hamilton, 1989), varying over time. This allows expected returns, persistence, and volatility to differ between low- and high-pressure regimes, rather than assuming a constant linear relationship.

The findings show that high supply chain pressure leads to distinct shifts in sector performance rather than a general market decline. Commodity-linked and capital goods industries consistently outperform their own low-pressure-regime returns during periods of high pressure. In contrast, defensive and interest-rate-sensitive industries experience higher returns when supply chain pressures are low. Volatility rises under high-pressure conditions, but the extent of the increase varies across industries. These results highlight a clear shift in risk-return trade-offs as supply constraints intensify. Subsequent sections detail the data, methodology, results, and broader implications.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Supply chain issues became critical during COVID-19 and the recovery. Bottlenecks, input shortages, and delays tracked closely with big swings in inflation, output, and risk. Supply chain stress spreads through networks and affects industries differently. This section reviews evidence and develops hypotheses on how supply pressure impacts sector equity returns.

Macroeconomic research shows input-output links spread firm- or sector-level shocks upstream and downstream, amplifying fluctuations. In network models, local disruptions can have large macro effects if they hit central suppliers or vital input sectors. Acemoglu *et al*. (2012) show that network structure shapes volatility. Empirical studies find that disruptions move through production networks via supplier and customer ties. For example, Barrot and Sauvagnat (2016) use disasters to isolate supplier shocks that then affect customers, with larger effects on specific inputs. Carvalho *et al*. (2021) examined the Great East Japan Earthquake and documented the propagation of supply chain shocks and their macroeconomic impacts.

This suggests that supply chain disruptions affect industries unequally. Upstream, commodity-linked, and input sectors may face demand, price, or capacity shifts, unlike downstream or consumer-facing sectors. Network impacts can be nonlinear; bottlenecks and delays may cause persistent backlogs, not just short-term. Recent empirical work addresses these complexities by using composite global bottleneck measures rather than single indicators. For example, Benigno *et al*. (2022) developed the GSCPI, which combines transportation costs and delivery times into a single worldwide barometer of supply chain pressures.

A complementary macro literature links global supply chain pressures to inflation dynamics and persistence. For example, Ascari *et al*. (2024) found that global supply chain shocks have lasting effects on Euro Area inflation. Tillmann (2024) found that inflation's reaction to supply chain pressures can be asymmetric in Europe, suggesting that adverse shocks may have stronger, longer-lasting impacts than easing events. While these articles focus on inflation, they matter for asset pricing. Supply-driven inflation and activity affect discount rates and risk premia.

Finance and operations research on supply chains began with firm-level event studies. Hendricks and Singhal (2003) showed that supply chain 'glitches' reduce shareholder value. Later, they linked disruptions to weaker performance (2005a) and found longer-term underperformance in stock and higher equity risk (2005b). Hendricks *et al*. (2020) study stock reactions to supply chain shocks from the Great East Japan Earthquake.

The literature shows disruptions affect equity through cash-flow (lost sales, higher costs, or shortfalls) and risk (more uncertainty, higher returns demanded by investors) channels. But identifying firm events does not directly show how broad bottlenecks map onto industry-wide returns or nonlinear effects.

A growing body of asset-pricing research shows that economic linkages and network position shape risk and returns. Cohen and Frazzini (2008) show that information and shocks transmit between linked firms, creating predictable return patterns. Herskovic (2018) outlines production-network asset pricing: network structure creates priced systematic risk. Gofman *et al*. (2020) show that vertical position in networks affects risk premia. Firms farther from end consumers may have different exposure to shocks and returns.

Recent work links supply chain disruptions more directly to asset pricing. Smirnyagin and Tsyvinski (2022) developed a production-based asset-pricing framework. In this framework, 'supply chain disasters' are rare, large negative shocks. These shocks impact both macro outcomes and asset-pricing moments. This perspective supports the idea that supply constraint measures can proxy for shifts in disaster-like risks. It also helps explain why supply chain stress is associated with changes in expected returns and volatility.

Recent studies use supply-chain pressure indices (such as GSCPI) to examine financial outcomes. Hupka (2022) found that global pressure affects firm leverage during stress. Ginn (2024) linked global supply shocks to financial and equity instability. Bouri *et al*. (2025) showed that supply constraints predict international stock returns and volatility, supporting the idea that supply stress influences higher moments and tail risks. Riaz *et al*. (2025) offer sectoral evidence from China, noting negative links between global supply pressure and sectoral returns under certain conditions.

In sum, the literature suggests supply-chain pressure is a key state variable for financial markets. But we still lack clear evidence on how supply chain stress affects U.S. industry returns, and whether the effects are linear, homogeneous, or regime-dependent and varied across industries. Since supply chain shocks may cluster in time and spread nonlinearly, a regime-based approach can help explain both expected returns and differences in volatility across industries.

Guided by the production-network propagation literature and the finance evidence that disruptions affect both cash flows and risk, the empirical analysis tests the following hypotheses using a regime-based framework and industry portfolio returns:

H1: State dependence in expected returns. The long-run expected return (or 'long-run growth' implied by return dynamics) of industry equity portfolios differs between low- and high-supply-chain-pressure regimes.

This hypothesis reflects the idea that aggregate bottlenecks shift either cash-flow expectations (via costs, shortages, pricing power) and/or discount rates in a state-contingent way (Hendricks & Singhal, 2005b; Smirnyagin & Tsyvinski, 2022; Ginn, 2024).

H2: State dependence in volatility with heterogeneous direction. The conditional volatility of industry equity returns differs across supply-chain-pressure regimes.

For the typical industry, high-pressure regimes are expected to be associated with higher uncertainty and thus higher volatility, but the direction need not be uniform across industries because supply chain pressure can reallocate risk and pricing power across the production network (Barrot & Sauvagnat, 2016; Carvalho *et al.*, 2021; Bouri *et al*., 2025). Accordingly, the empirical analysis evaluates both the prevalence of volatility increases and the existence of meaningful exceptions.

H3: Cross-sectional heterogeneity consistent with upstream-downstream exposure. The sign and magnitude of regime-dependent changes in long-run expected returns differ systematically across industries, consistent with differences in production-network position and input dependence.

In particular, upstream or commodity-linked industries may exhibit relatively stronger performance in high-pressure regimes (*e.g*., through price effects or scarcity rents), whereas downstream, input-intensive, and consumer/service industries may exhibit relatively stronger performance in low-pressure regimes (Acemoglu *et al.*, 2012; Herskovic, 2018; Gofman *et al.*, 2020; Gozgor *et al*., 2023).

RESEARCH METHODOLOGY

I used two main data sources: data on supply chain pressure and the market value of the US-listed stocks at the industry level. GSCPI is a measure developed by the Federal Reserve Bank of New York. GSCPI captures *global* supply chain conditions by combining data on shipping costs, delivery times, and backlogs across regions to provide a comprehensive index of GSC conditions. A high index value implies periods of stress in the supply chain.

As for the sectoral stock market returns, I used monthly value-weighted total returns (including dividends) of 49 U.S. industry portfolios – this is public data set available at French (2025). The data sample spans from January 1998 to June 2024. Hence, the sample period included several events that had a profound impact on GSCs: the increasing globalisation of supply chains and the rise of digital and tech-based industries; COVID-19 pandemic supply bottlenecks; geopolitical fragmentation observed following Russia's invasion of Ukraine and China-US tensions. Therefore, this sample allows us to capture structural changes in the relationship between supply chain pressures and equity markets.

I used a Markov switching autoregression (MS-AR) model with time-varying transition probabilities (TVTP) to examine the impact of GSC pressures on equity market returns across different industries. This model captures the dynamic and nonlinear relationships between market returns and supply chain pressures. For more details on this class of models see Hamilton (1989) and Kim and Nelson (2017).

I chose the MS-AR model with TVTP (hereafter MS-AR-TVTP) to understand to what extent GSC pressures account for regime shifts in the equity market and whether these regimes differ from each other. Simple linear models may fail to answer this research question, given that regime changes are inherently nonlinear. This is also the fact shown in Figure 1, which leads to the conclusion that there is no *linear* relationship between supply chain pressures and stock market performance.

The MS-AR-TVTP model addresses these issues by allowing the parameters of the autoregressive process to switch between different regimes, which in this article I interpret as 'low pressure' and 'high pressure' periods. I modelled the transition probabilities between regimes as a logistic function of the GSCPI (Filardo, 1994). This means that as GSC pressures change, the likelihood of switching between regimes changed accordingly. I set the number of regimes to two – this made the interpretation easier (low vs high pressure) and did not change the results. The parameters within each regime, such as the autoregressive coefficients, the constant, and the error variances differed, providing a more flexible modelling approach. For any time series of returns y_t MS-AR-TVTP model can be formulated as follows:

$$y_t = \alpha_{S_t} + \beta_{S_t} y_{t-1} + \varepsilon_{tS_t} \tag{1}$$

in which S_t denotes a state/regime at time t, α_{S_t} is a state-specific constant, β_{S_t} is a state-specific AR(1) coefficient and $\varepsilon_t \sim i.i.d.\ N\left(0, \sigma_{S_t}^2\right)$. Each period, the regime transitioned according to:

$$P(S_t = i | S_{t-1} = j) = \frac{\exp\{x_{t-1}' \beta_{ij}\}}{1 + \exp\{x_{t-1}' \beta_{ij}\}} \tag{2}$$

in which $x_{t-1}$is a vector of GSCPI that determines the transition probabilities from state *j* to *i*. I estimated the model maximum likelihood using the expectation-maximisation algorithm.

For the remainder of this study, I chose AR(1) specification as a baseline for the MS-AR-TVTP model. This parsimonious lag structure provided an intuitive economic interpretation of the model parameters. Long-term expected rate of return in state S_t was given by $\frac{\alpha_{S_t}}{(1-\beta_{S_t})}$. In addition, the AR coefficient β_{S_t} measured the persistence of returns shocks in the state and $\sigma_{S_t}^2$ measured the variability of these shocks. Different combinations of coefficients would correspond to different shapes of the cumulative growth rate of returns. For example, with an AR(1) process, a large positive constant α_{S_t} and a small positive β_{S_t} would correspond to a steep hill, while a lower α_{S_t} would correspond to a hill of milder slope. Zero coefficients would describe a period of no growth, and a negative constant and zero slope would be a collapse period.

RESULTS AND DISCUSSION

Let me begin with descriptive evidence to motivate the nonlinear, regime-based approach. Figure 1 reports correlations between GSCPI and monthly industry portfolio returns. The correlations were modest, suggesting that a linear relationship between supply-chain pressure and sectoral equity returns was weak. This pattern was consistent with the literature, which emphasises that supply shocks may matter most when constraints bind (*e.g.*, through bottlenecks, backlogs, and nonlinear adjustment) rather than continuously and proportionally over time (Acemoglu *et al.*, 2012; Barrot & Sauvagnat, 2016; Carvalho *et al.*, 2021). In that sense, the near-zero unconditional correlations in Figure 1 did not evidence that supply chain stress was irrelevant; instead they suggested that its pricing effects may be state dependent, motivating the Markov-switching framework.

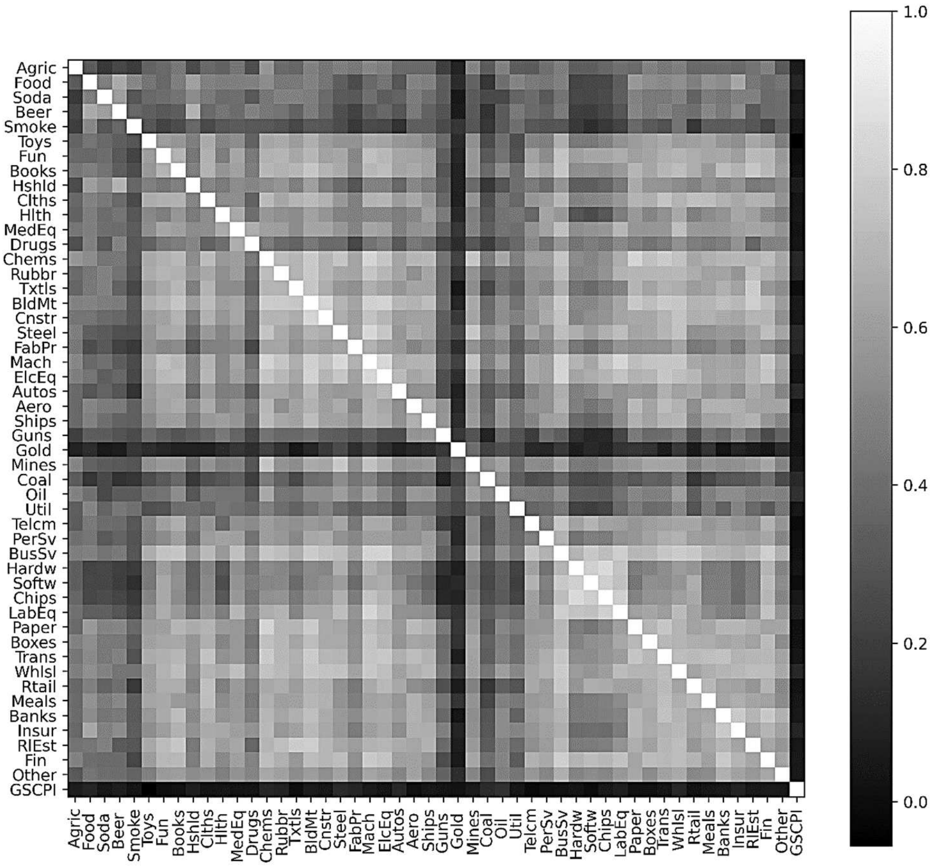

Figure 1. Correlation between the US industry portfolio returns and the GSCPI, 1998-2024

Source: own elaboration.

Figure 2 complemented this by documenting substantial heterogeneity in unconditional mean returns and volatility across the 49 industry portfolios. The cross-section showed a positive association between the unconditional mean and the unconditional standard deviation, consistent with basic risk-return intuition in asset pricing. Table A1 (Appendix) provides summary statistics and confirms pronounced cross-industry dispersion in both central tendency and tail outcomes. These descriptive results set the stage for the article's main question: whether supply chain pressures are associated with systematic changes in industry return dynamics, expected returns, persistence, and volatility, across regimes.

Next, I summarised the regime-specific estimates. Table A2 (Appendix) contains the regime-specific estimates of the MS-AR(1)-TVTP model, and Figures 3-5 summarise the key parameters graphically. For each industry, the model estimates (i) a regime-specific intercept ('Const'), (ii) a regime-specific AR(1) coefficient ('AR(1)'), and (iii) a regime-specific innovation volatility ('SD of residuals'). I interpreted the two regimes as low- and high-pressure supply chain states because the transition probabilities were modelled as a logistic function of the GSCPI.

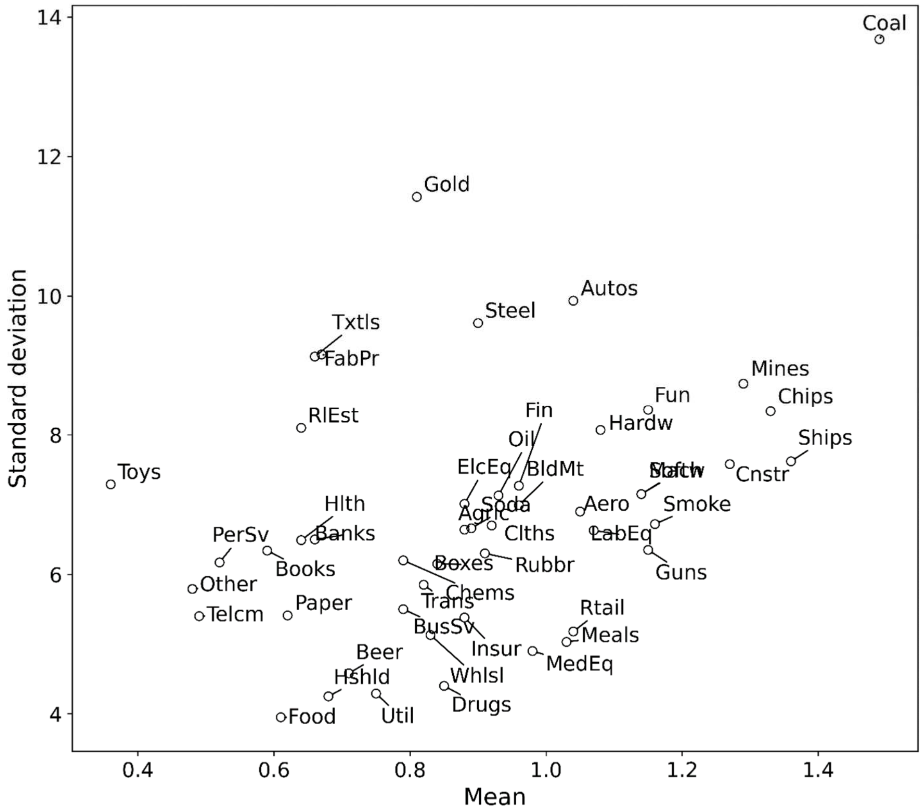

Figure 2. Mean returns and return volatility of the US industry portfolios, 1998-2024

Source: own elaboration.

A clear pattern emerged: several upstream, commodity-linked, and capital-goods industries, including mines, agriculture, steel, and machinery, exhibited higher intercepts in the high-pressure regime. A natural interpretation is that episodes of elevated supply chain pressure often coincide with scarcity conditions and higher input prices, which can raise revenues (or expected margins) for upstream producers and certain capital-goods suppliers, even as they raise costs for downstream users. This interpretation is consistent with production-network logic (Acemoglu *et al.*, 2012; Carvalho *et al.*, 2021) and with evidence that supply chain disturbances can reallocate economic rents and performance across supplier-customer linkages (Barrot & Sauvagnat, 2016). It is consistent with related evidence that global supply-chain stress is connected to commodity-market dynamics (Gozgor *et al.*, 2023).

Conversely, several defensive or rate-sensitive sectors, such as Utilities and Telecom, tended to have higher intercepts in the low-pressure regime. This is consistent with the view that high supply-chain pressure is often associated with upward inflationary pressures and tighter financial conditions (Ascari *et al.*, 2024; Ginn, 2024; Tillmann, 2024), which may be especially adverse for sectors with cash flows discounted at longer horizons and/or those sensitive to interest-rate movements.

Figure 4 compares the AR(1) coefficient across regimes. Interpreting the AR coefficient as capturing the persistence of shocks to industry returns within a regime, the results indicate meaningful heterogeneity in how quickly industries revert after shocks and whether return innovations tend to propagate.

Two patterns were notable. Firstly, some industries displayed greater persistence in the high-pressure regime (*i.e.*, higher AR(1) in the high-pressure state). This is consistent with the idea that when supply bottlenecks bind, adjustment can be slow: backlogs unwind over time, supplier substitution is costly, and shocks can propagate through customer-supplier networks in a persistent manner (Barrot & Sauvagnat, 2016; Carvalho *et al.*, 2021). Secondly, other industries exhibit lower persistence or even stronger mean reversion in the high-pressure regime, consistent with rapid repricing and partial reversals when shocks are recognised as temporary and/or when policy and private responses mitigate constraints. This cross-industry heterogeneity in persistence provides valuable insight, suggesting that supply-chain stress does not merely shift the level of expected returns. It can also alter the time profile of valuation adjustments.

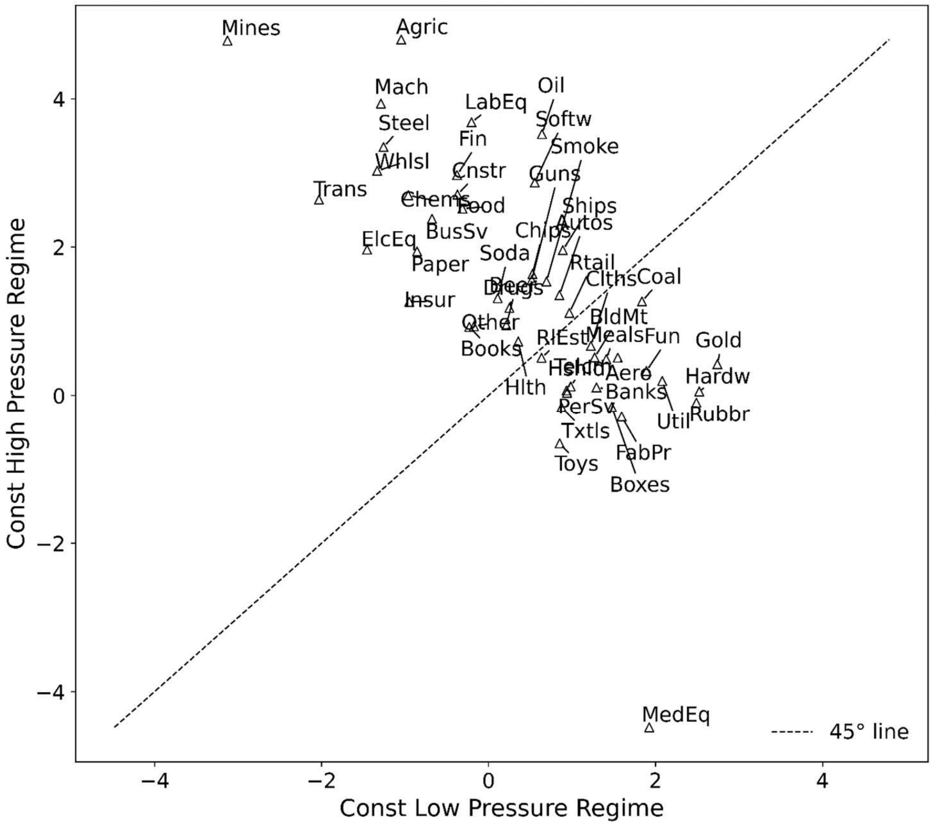

Figure 3. Estimated return intercepts for the US industry portfolios, 1998-2024
Source: own elaboration.

Figure 5 shows the estimated volatility of shocks (innovation volatility) in each regime. For many industries, the high-pressure regime is associated with higher innovation volatility, consistent with the firm-level literature that disruptions elevate uncertainty and equity risk (Hendricks & Singhal, 2003, 2005b; Hendricks *et al.*, 2020) and with more recent evidence that supply bottlenecks help predict the conditional distribution of returns and volatility internationally (Bouri *et al.*, 2025).

Importantly, the volatility effect is not uniform. A nontrivial set of industries exhibits lower innovation volatility in the high-pressure regime. One interpretation is that supply chain stress can compress the dispersion of outcomes for certain upstream sectors when price effects prevail, and cash-flow expectations become more tightly linked to a common factor (*e.g.*, commodity conditions). Another interpretation is that the 'low-pressure' regime, defined with respect to supply-chain conditions, can still contain episodes of financial and macro volatility unrelated to supply chains, which may raise the estimated innovation volatility for specific portfolios. This helps explain why one should treat volatility comparisons across regimes as industry-specific empirical facts rather than imposed by a priori assumptions.

Taken together, Figures 3-5 provide evidence consistent with the article's hypotheses: expected return dynamics and risk are state-dependent and heterogeneous across industries.

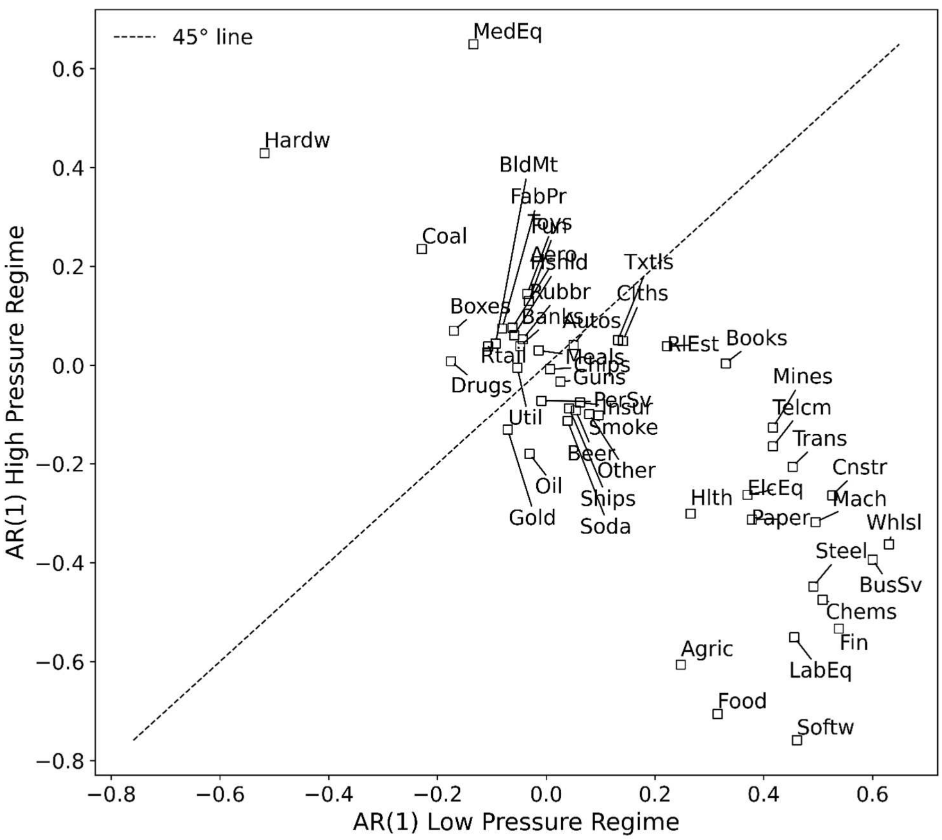

Figure 4. Estimated return persistence for US industry portfolios, 1998-2024

Source: own elaboration.

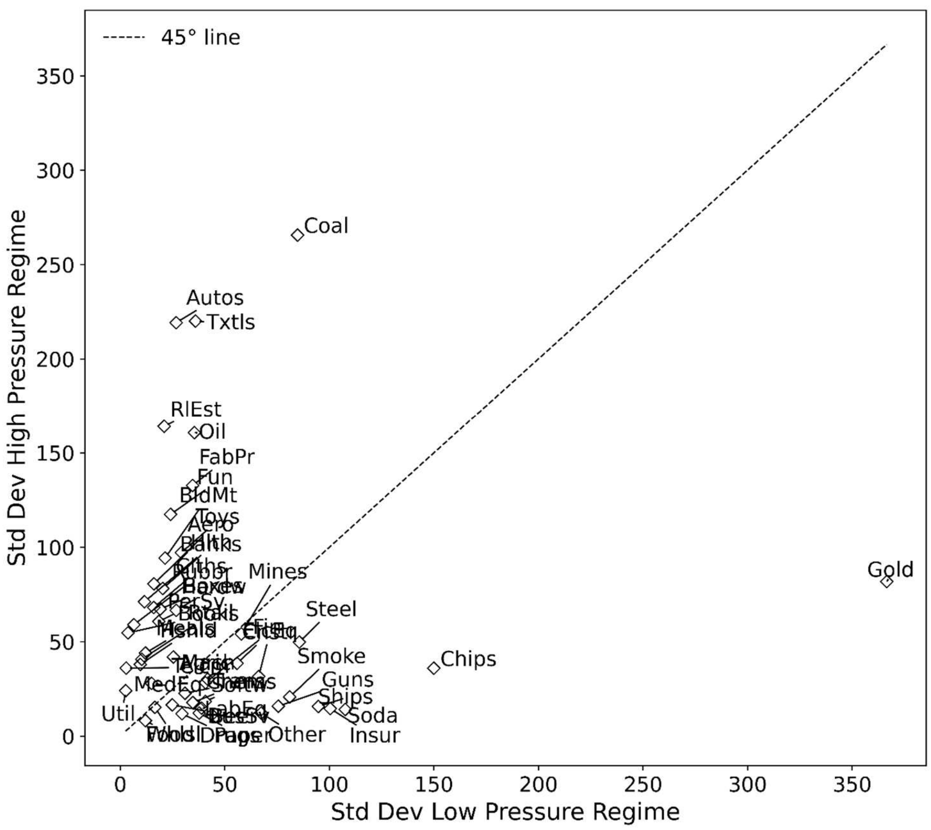

Figure 5. Estimated standard deviation for US industry portfolios, 1998-2024

Source: own elaboration.

Because the model was AR(1) within each regime, it was natural to summarise conditional expected performance using the implied long-run mean return within regime (as reported in Table A2). Figure 6 plots these implied long-run returns for the low- and high-pressure regimes and provides a transparent 'winners and losers' classification. Three results are central:

1. Substantial regime dependence (H1)
   Many industries exhibited economically meaningful differences in implied long-run returns across regimes. This state dependence is consistent with the view that supply chain stress can change both expected cash flows (through costs and shortages) and discount rates (through inflation and financial conditions) in a regime-contingent manner (Ascari *et al.*, 2024; Ginn, 2024; Smirnyagin & Tsyvinski, 2022).
2. Ranking reversals across regimes.
   Several industries that performed relatively well in the high-pressure regime performed relatively poorly in the low-pressure regime, and vice versa. This 'ranking reversal' is precisely the kind of nonlinear cross-sectional behaviour that a linear specification would find it challenging to capture.
3. Cross-industry heterogeneity consistent with production-network exposure (H3).
   Industries that plausibly benefited from scarcity pricing or upstream positioning, such as mines, agriculture, steel, and machinery, tended to exhibit stronger long-run returns in the high-pressure regime. In contrast, a set of sectors performed better in the low-pressure regime, consistent with either downstream input dependence or greater sensitivity to tightening financial conditions in high-pressure episodes. This pattern is consistent with the production-network and network-asset-pricing literature, which emphasises that upstream-downstream positions and network structure shape exposures to real shocks and risk premia (Acemoglu *et al.*, 2012; Herskovic, 2018; Gofman *et al.*, 2020).

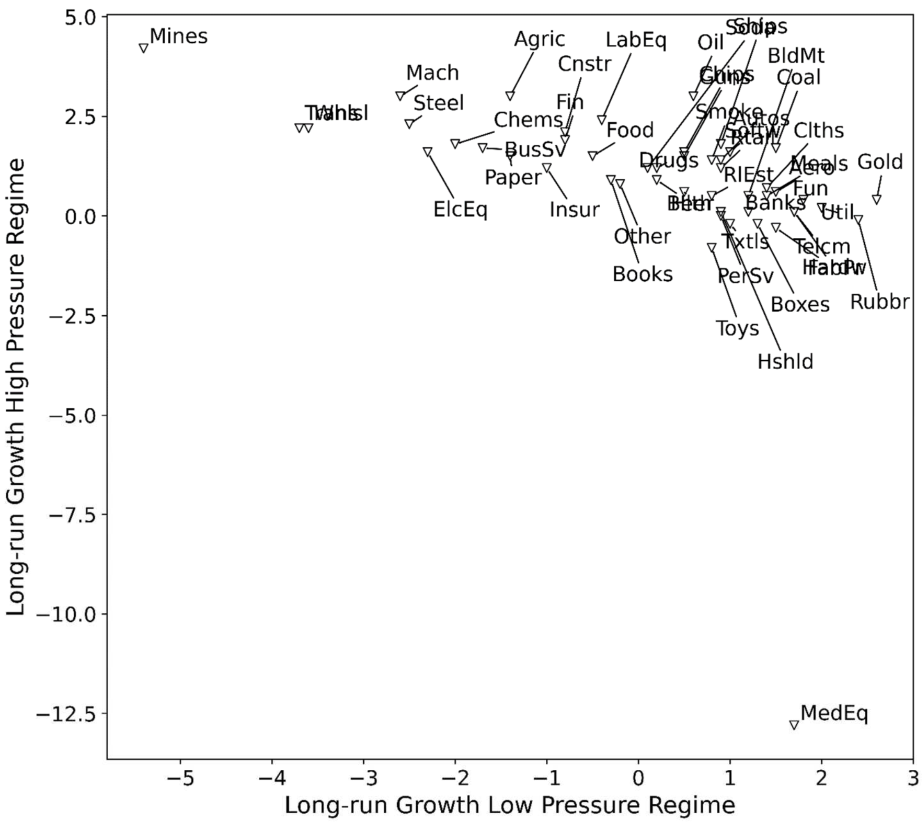

Figure 6. Implied long-run expected returns for US industry portfolios, 1998-2024
Source: own elaboration.

Crucially, these results complement, but also refine, the firm-level event-study literature. Whereas disruption announcements are associated with negative abnormal returns on average (Hendricks &

Singhal, 2003, 2005b), the industry-portfolio evidence here indicates that aggregate supply-chain stress is not uniformly negative across sectors. In an interconnected economy, stress can redistribute profits and risk across the production network, creating both relative winners and losers.

Within the Regime Rate of Return and Standard Deviation

Figure 7 jointly plots implied long-run returns and innovation volatility within each regime, providing a compact summary of how the risk-return trade-off shifts across supply chain states. The low-pressure regime features a relatively tight cluster: many industries combine moderate long-run returns with comparatively contained volatility. In the high-pressure regime, the cross-section becomes more dispersed: some industries pair strong long-run returns with elevated volatility, while others face weaker long-run performance with higher uncertainty. This widening dispersion is consistent with recent evidence that supply chain pressures can influence not only the mean but also higher moments and tail risks of equity returns (Bouri *et al.*, 2025).

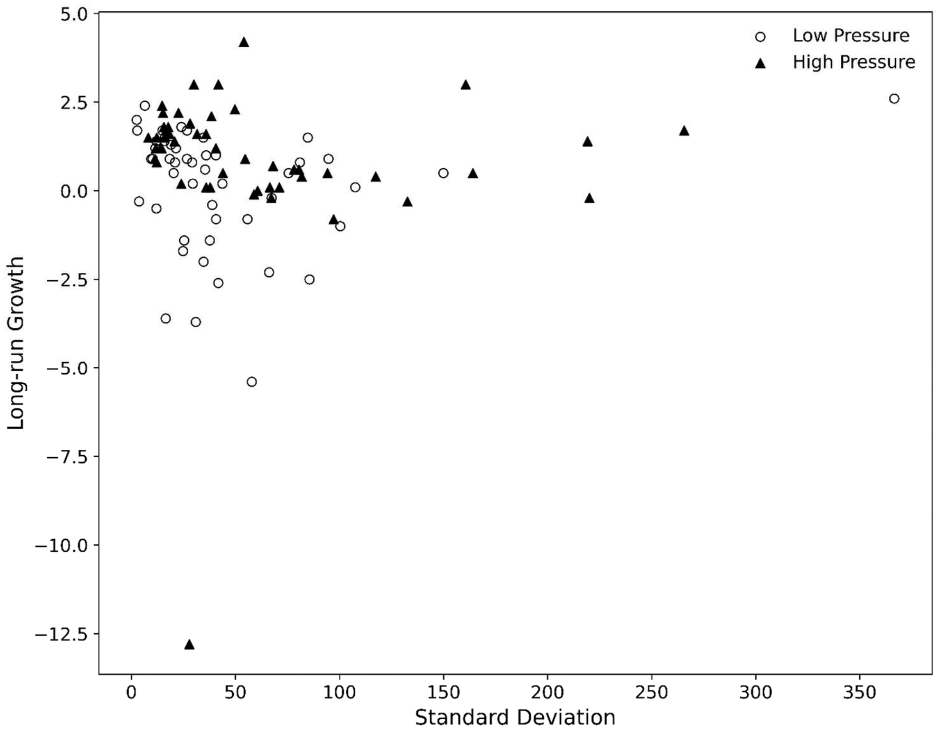

Figure 7. Implied long-run expected returns and volatility of US industry portfolios, 1998-2024
Source: own elaboration.

Figure 8 makes these comparisons more directly interpretable by plotting the differences between regimes in long-run returns and innovation volatility, yielding four economically meaningful quadrants.

1. ΔReturn > 0 and ΔVolatility > 0: industries whose conditional performance improves in high-pressure regimes but at the cost of higher uncertainty. This pattern is consistent with 'scarcity rent' channels in upstream sectors and capital-goods suppliers.
2. ΔReturn > 0 and ΔVolatility < 0: industries whose performance improves while volatility falls under high pressure, suggesting resilience and/or enhanced pricing power that stabilises expectations.
3. ΔReturn < 0 and ΔVolatility > 0: industries that lose under high pressure and become riskier – arguably the clearest 'vulnerable' group from a supply-chain perspective.
4. ΔReturn < 0 and ΔVolatility < 0: industries that underperform in high-pressure regimes but with lower volatility, consistent with a shift in the nature of risk rather than a simple 'more volatility under stress' narrative.

This decomposition is useful because it clarifies why a single blanket statement – 'high supply chain pressure increases volatility' – is incomplete. The empirical evidence supports heterogeneous volatility responses (H2), which is consistent with production-network propagation and reallocation effects (Barrot & Sauvagnat, 2016; Carvalho *et al.*, 2021).

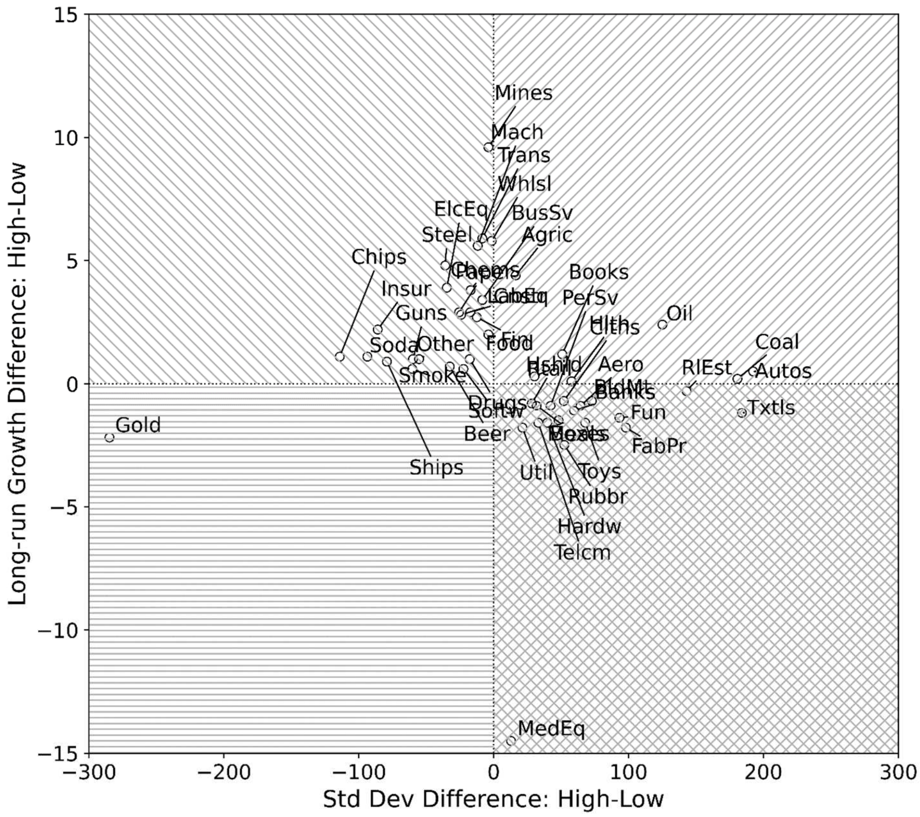

Figure 8. Differences in implied long-run expected returns and volatility between regimes for US industry portfolios, 1998-2024
Source: own elaboration.

The empirical results provide three contributions to existing work.

Firstly, the results show that aggregate supply chain stress is associated with nonlinear, heterogeneous industry dynamics that are not evident in unconditional correlations. This complements macro-finance evidence that supply chain shocks can be destabilising for aggregate output, inflation, and equity returns (Ginn, 2024), by showing that aggregate effects can mask meaningful cross-sectional divergence. In other words, even if a supply chain shock reduces aggregate (or index-level) equity returns, certain industries can still exhibit improved conditional performance.

Second, the 'winners and losers' pattern is consistent with the production-network view, which holds that shocks propagate through supplier-customer relationships and can create asymmetric exposures across vertical positions (Acemoglu *et al.*, 2012; Gofman *et al.*, 2020; Herskovic, 2018). The empirical finding that upstream and commodity-linked industries more often display stronger high-pressure performance is also consistent with evidence that supply chain stress is tied to commodity-price dynamics (Gozgor *et al.*, 2023) and with the broader view that supply constraints can behave like 'disaster-type' shocks with priced implications (Smirnyagin & Tsyvinski, 2022).

Third, the volatility results show that supply chain stress is not a purely 'high-volatility regime' phenomenon across all sectors. While many industries become riskier when pressures rise (consistent with disruption-based increases in equity risk documented by Hendricks & Singhal, 2005b), others exhibit lower innovation volatility in the high-pressure regime, implying that the composition and transmission of uncertainty change across regimes rather than rising uniformly.

Practical Implications

For investors, the data show that the GSCPI is a useful indicator for sectoral risk management. Since industries differ in both regime-dependent expected returns and regime-dependent volatility, a 'one-size-fits-all' approach to hedging supply chain risk is inappropriate. This complements recent evidence that supply chain pressures have predictive content for the conditional distribution of stock returns and volatility (Bouri *et al.*, 2025). A cautious interpretation is warranted: the model identifies conditional patterns rather than causal effects, so the results should be used as inputs into risk monitoring and scenario analysis rather than as mechanical trading rules.

For corporations, the results show that supply chain stress can coincide with large shifts in the market value dynamics of industries. This reinforces the importance of resilience investments (*e.g.*, supplier diversification, inventory and logistics flexibility, and monitoring upstream bottlenecks), which is consistent with the supply-chain resilience literature that emerged after COVID-19 (Ivanov, 2020). The cross-industry heterogeneity documented here suggests that returns aimed at resilience may be particularly high in sectors that fall into the 'ΔReturn < 0 and ΔVolatility > 0' quadrant of Figure 8.

Supply chain pressures have been shown to matter for inflation dynamics and macro-financial conditions (Ascari *et al.*, 2024; Tillmann, 2024; Ginn, 2024). Therefore, from a policy perspective, the industry heterogeneity documented here suggests that monitoring supply-chain indicators may also help identify sector-specific financial vulnerabilities under high-pressure conditions episodes. This does not imply that sector-by-sector intervention is always desirable; rather, it highlights that aggregate supply chain stress can coincide with uneven sectoral effects on risk and valuation, which may be relevant for stress testing and targeted diagnostics.

CONCLUSIONS

In this study, I investigated whether global supply chain pressures, measured by GSCPI, are reflected in the risk and return dynamics of U.S. industry equity portfolios. Using monthly value-weighted returns for 49 industries over January 1998-June 2024, I estimated a two-regime Markov-switching AR(1) model with time-varying transition probabilities driven by the GSCPI (Benigno *et al.*, 2022; Filardo, 1994). The empirical motivation was straightforward: unconditional correlations between the GSCPI and sectoral returns are generally weak, consistent with the view that supply bottlenecks and their financial effects are state dependent rather than linear and constant over time. Thus, a regime-switching framework was well suited to characterise how expected returns, persistence, and volatility change across low- and high-pressure supply-chain states.

The results show that supply chain stress reorders the cross-section of industry performance. In the high-pressure regime, several upstream and commodity- or capital-goods-linked sectors (*e.g.*, mines, agriculture, steel, machinery) exhibit stronger implied long-run expected returns than in the low-pressure regime, while a set of more interest-rate-sensitive or defensive industries (*e.g.*, utilities and telecom) tend to perform relatively better in low-pressure periods. This 'winner-loser reversal' is consistent with production-network logic: disruptions propagate through supplier-customer relationships, but the net equity-market effect depends on whether an industry is positioned to benefit from scarcity pricing or instead suffers primarily from input shortages and cost shocks (Acemoglu *et al.*, 2012; Barrot & Sauvagnat, 2016; Carvalho *et al.*, 2021). The findings further strengthen the view that supply constraints can behave like macro shocks, shifting both cash-flow expectations and discount rates, helping explain why supply-chain pressure is associated with meaningful changes in expected returns across states (Ginn, 2024; Smirnyagin & Tsyvinski, 2022).

A second main finding is that the high-pressure regime is typically, though not universally, associated with higher return volatility. This is consistent with firm-level evidence that disruptions increase equity risk and can erode shareholder value (Hendricks & Singhal, 2003, 2005b; Hendricks *et al.*, 2020), as well as macro-finance evidence linking supply chain shocks to deteriorating financial conditions and weaker equity returns (Ginn, 2024). Simultaneously, the volatility response was heterogeneous: for some industries, estimated innovation volatility was not higher under high pressure, and a few show the opposite pattern. This heterogeneity yields useful information rather than being problematic. It is consistent with the idea that supply-chain stress can reallocate risk and pricing power across the production network, raising uncertainty for some sectors while compressing outcome dispersion for others, rather than functioning as a uniform 'high-volatility state' for the entire market (Barrot & Sauvagnat, 2016; Carvalho *et al.*, 2021). Moreover, the implied long-run growth estimates indicate that high supply-chain pressure pushes a sizable subset of industries toward near-zero or negative long-run performance, highlighting an economically meaningful volatility-growth trade-off: some sectors experience higher risk without compensating improvements in long-run expected returns.

The results contribute to the literature as follows. Firstly, they extend the firm-level disruption literature by showing that aggregate, global supply bottlenecks can generate systematic *cross-industry* divergence in equity outcomes, not just negative average effects for directly disrupted firms (Hendricks & Singhal, 2003, 2005b). Secondly, they complement production-network asset-pricing research by delivering empirical evidence consistent with the view that network position and exposure to upstream bottlenecks shape risk-return dynamics (Herskovic, 2018; Gofman *et al.*, 2020). Thirdly, they demonstrate that treating the GSCPI as a state variable is empirically useful: linear correlations understate the relationship, whereas a regime-dependent approach reveals economically meaningful nonlinearity and heterogeneity. This matters for the interpretation of 'supply chain shocks' in macro-finance settings, where the same aggregate stress can plausibly hurt some sectors while supporting others (Smirnyagin & Tsyvinski, 2022).

Limitations

One should interpret the article's conclusions with several limitations in mind. Firstly, the empirical design is primarily associational: although the regime classification is informed by the GSCPI, the analysis does not claim a fully identified causal effect of supply-chain pressure on returns, and supply-chain stress may co-move with other macro-financial forces (*e.g.*, demand shocks, monetary tightening, commodity cycles). Secondly, the two-regime MS-AR(1) structure is intentionally parsimonious; it captures nonlinear state dependence but may not fully represent richer dynamics (multiple regimes or higher-order persistence) that could matter for some industries. Thirdly, the use of industry portfolios can mask substantial within-industry heterogeneity across firms in exposure, pricing power, and supply-chain organisation.

Several directions for future research occur naturally. One priority is to connect the estimated regime sensitivities to observable industry characteristics (input intensity, import dependence, upstream/downstream position from input-output tables, supplier concentration), providing a sharper mapping from economic mechanisms to empirical heterogeneity. A second extension is to integrate additional indicators of supply-chain tightness (*e.g.*, delivery-time indices, shipping measures, or industry-specific bottleneck proxies) to test whether results are specific to the GSCPI or robust across measurement approaches. Thirdly, firm-level work could unpack within-industry dispersion and test whether firms with greater supplier diversification or resilience investments show systematically different regime responses, thereby linking more directly to the resilience literature. Finally, cross-country replication would clarify how institutional structure, trade exposure, and market composition mediate the financial transmission of global supply-chain stress.

REFERENCES

Acemoglu, D., Carvalho, V.M., Özdaglar, A., & Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, *80*(5), 1977-2016. https://doi.org/10.3982/ECTA9623

Ascari, G., Bonam, D., & Smadu, A. (2024). Global supply chain pressures, inflation, and implications for monetary policy. *Journal of International Money and Finance*, *142*, 103029. https://doi.org/10.1016/j.jimonfin.2024.103029

Baldwin, R., & Freeman, R. (2020). *Trade conflict in the age of Covid-19. VoxEU.org*. Retrieved from https://cepr.org/voxeu/columns/trade-conflict-age-covid-19 on May 22, 2020.

Barrot, J.N., & Sauvagnat, J. (2016). Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks, *The Quarterly Journal of Economics*, *131*(3), August 2016, 1543-1592. https://doi.org/10.1093/qje/qjw018

Benigno, G., di Giovanni, J., Groen, J.J.J., & Noble, A.I. (2022). The GSCPI: A new barometer of global supply chain pressures (*Staff Report No. 1017*). Federal Reserve Bank of New York. Retrieved from https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr1017.pdf on May 22, 2020.

Bouri, E., Cepni, O., Gupta, R., & Liu, R. (2025). Supply chain constraints and the predictability of the conditional distribution of international stock market returns and volatility. *Economics Letters*, *247*, 112176. https://doi.org/10.1016/j.econlet.2025.112176

Carvalho, V.M., Nirei, M., Saito, Y.U., & Tahbaz-Salehi, A. (2021). Supply Chain Disruptions: Evidence from the Great East Japan Earthquake. *The Quarterly Journal of Economics*, *136*(2), 1255-1321. https://doi.org/10.1093/qje/qjaa044

Cohen, L., & Frazzini, A. (2008). Economic links and predictable returns. *The Journal of Finance*, *63*(4), 1977-2011. https://doi.org/10.1111/j.1540-6261.2008.01379.x

Filardo, A.J. (1994). Business-cycle phases and their transitional dynamics. *Journal of Business & Economic Statistics*, *12*(3), 299-308. https://doi.org/10.1080/07350015.1994.10524545

French, K.R. (2025, May 7). *49 Industry Portfolios*. Dartmouth College. Retrieved from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html on May 5, 2025.

Ginn, W. (2024). Global supply chain disruptions and financial conditions. *Economics Letters*, *239*, 111739. https://doi.org/10.1016/j.econlet.2024.111739

Gofman, M., Segal, G., & Wu, Y. (2020). Production networks and stock returns: The role of vertical creative destruction. *The Review of Financial Studies*, *33*(12), 5856-5905. https://doi.org/10.1093/rfs/hhaa034

Gozgor, G., Khalfaoui, R., & Yarovaya, L. (2023). Global supply chain pressure and commodity markets: Evidence from multiple wavelet and quantile connectedness analyses. *Finance Research Letters*, *54*, 103791. https://doi.org/10.1016/j.frl.2023.103791

Hamilton, J.D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica*, *57*(2), 357-384. https://doi.org/10.2307/1912559

Hendricks, K.B., Jacobs, B.W., & Singhal, V.R. (2020). Stock market reaction to supply chain disruptions from the Great East Japan Earthquake. *Manufacturing & Service Operations Management*, *22*(4), 683-699. https://doi.org/10.1287/msom.2019.0777

Hendricks, K.B., & Singhal, V.R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management*, *21*(5), 501-522. https://doi.org/10.1016/j.jom.2003.02.003

Hendricks, K.B., & Singhal, V.R. (2005a). Association between supply chain glitches and operating performance. *Management Science*, *51*(5), 695-711. https://doi.org/10.1287/mnsc.1040.0353

Hendricks, K.B., & Singhal, V.R. (2005b). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations Management*, *14*(1), 35-52. https://doi.org/10.1111/j.1937-5956.2005.tb00008.x

Herskovic, B. (2018). Networks in production: Asset pricing implications. *The Journal of Finance*, *73*(4), 1785-1818. https://doi.org/10.1111/jofi.12684

Hupka, Y. (2022). Leverage and the global supply chain. *Finance Research Letters*, *50*, 103269. https://doi.org/10.1016/j.frl.2022.103269

Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review*, *136*, 101922. https://doi.org/10.1016/j.tre.2020.101922

Kim, C.J., & Nelson, C.R. (2017). *State-space models with regime switching: classical and Gibbs-sampling approaches with applications*. MIT Press.

Riaz, A., Ullah, A., & Muhammad, B. (2025). The impact of global supply chain pressure on the stock market: A sectoral view. *Humanities and Social Sciences Communications*, volume 12, Article 284. https://doi.org/10.1057/s41599-025-04634-0

Smirnyagin, V., & Tsyvinski, A. (2022). Macroeconomic and asset pricing effects of supply chain disasters (*NBER Working Paper No. 30503*). National Bureau of Economic Research. https://doi.org/10.3386/w30503

Tillmann, P. (2024). The asymmetric effect of supply chain pressure on inflation. *Economics Letters*, *235*, 111540. https://doi.org/10.1016/j.econlet.2024.111540

Appendix A: Additional tables

Table A1 below denotes the average, standard deviation, minimum, maximum, 25th, 50th, and 75th percentiles of each U.S. industry portfolio returns over January 1998–June 2024. Values of GSCPI are in the last row of this table.

Table A2 contains estimated values of model parameters.

Table A1. Summary statistics for monthly United States industry portfolio returns and the GSCPI, January 1998–June 2024

VARIABLE	AVERAGE	STANDARD DEVIATION	MIN	25%	50%	75%	MAX
AGRIC	0.88	6.64	-18.21	-3.27	0.55	4.42	28.56
FOOD	0.61	3.95	-11.12	-1.74	0.82	2.95	17.38
SODA	0.89	6.66	-26.03	-2.19	1.23	4.55	38.9
BEER	0.71	4.58	-19.74	-1.79	0.8	3.54	16.46
SMOKE	1.16	6.72	-24.96	-2.74	1.89	4.92	32.46
TOYS	0.36	7.29	-23.27	-3.8	0.81	4.56	23.14
FUN	1.15	8.36	-32.25	-3.36	1.33	6.06	41.27
BOOKS	0.59	6.34	-24.7	-2.68	0.4	3.69	30.57
HSHLD	0.68	4.25	-14.77	-1.55	0.78	3.23	18.71
CLTHS	0.92	6.7	-22.39	-2.67	1.23	4.66	24.99
HLTH	0.64	6.49	-23.22	-3.44	0.94	4.47	19.95
MEDEQ	0.98	4.9	-19.39	-1.44	1.23	4.48	13.93
DRUGS	0.85	4.4	-11.3	-2.08	1.08	3.86	13.63
CHEMS	0.79	6.2	-21.06	-2.78	1.15	4.38	22.01
RUBBR	0.91	6.3	-20.88	-2.42	1.62	4.08	32.09
TXTLS	0.66	9.13	-36.03	-4.29	1.29	5.53	59.18
BLDMT	0.96	6.99	-31.97	-2.56	1.62	4.72	34.6
CNSTR	1.27	7.58	-32.14	-3.45	1.35	6.3	22
STEEL	0.9	9.61	-32.41	-4.78	0.71	6.53	30.67
FABPR	0.67	9.16	-33.71	-4.82	0.3	6.01	35.79
MACH	1.14	7.15	-29.93	-2.88	1.48	5.62	23.03
ELCEQ	0.88	7.01	-24.82	-2.88	0.93	5.22	22.82
AUTOS	1.04	9.93	-36.42	-4.13	0.89	5.44	49.45
AERO	1.05	6.9	-35.8	-2.21	1.22	5.18	32.53
SHIPS	1.36	7.62	-23.55	-2.71	1.56	5.32	29.33
GUNS	1.15	6.35	-30.08	-2.1	1.27	4.7	25.43
GOLD	0.81	11.42	-33.6	-5.72	-0.02	6.75	79.52
MINES	1.29	8.74	-34.8	-4.72	0.91	7.58	26.99
COAL	1.49	13.68	-40.89	-7.36	1.58	9.88	44.04
OIL	0.93	7.13	-34.66	-2.87	0.79	4.75	32.89
UTIL	0.75	4.29	-12.94	-1.75	1.31	3.56	11.76
TELCM	0.49	5.4	-15.56	-2.45	0.75	3.8	22.11
PERSV	0.52	6.17	-25.3	-3.14	0.63	4.09	18.68
BUSSV	0.79	5.5	-23.25	-2.51	1.37	3.97	18.12
HARDW	1.08	8.07	-33.92	-3.18	1.66	5.76	25.39
SOFTW	1.14	7.15	-22.89	-2.74	1.62	4.96	26.11
CHIPS	1.33	8.34	-31.8	-3.21	2.25	6.4	26.79
LABEQ	1.07	6.63	-23.38	-2.88	1.58	5.08	21.33
PAPER	0.62	5.41	-18.32	-2.74	1.09	3.71	23.44
BOXES	0.84	6.15	-21.47	-2.88	0.97	4.69	18.98
TRANS	0.82	5.85	-17.81	-2.79	1.13	4.47	17.44
WHLSL	0.83	5.13	-21.09	-2.23	1.19	4.27	15.99
RTAIL	1.04	5.18	-14.56	-1.88	1.04	3.94	18.63
MEALS	1.03	5.03	-22.12	-1.99	1.25	4.13	18.67

VARIABLE	AVERAGE	STANDARD DEVIATION	MIN	25%	50%	75%	MAX
BANKS	0.66	6.5	-27.84	-2.89	1.21	4.14	19.85
INSUR	0.88	5.38	-26.98	-1.76	1.38	3.78	23.34
RLEST	0.64	8.1	-36.75	-3.01	1.2	4.44	65.22
FIN	0.96	7.27	-26.2	-3.49	1.4	5.8	19.42
OTHER	0.48	5.79	-23.71	-2.2	0.52	4.1	18.7
GSCPI	0.01	1.01	-1.56	-0.6	-0.25	0.2	4.37

Source: own study.

Table A2. Two-regime MS-AR(1)-TVTP estimates for monthly United States industry portfolio returns, January 1998–June 2024

INDUSTRY	LOW PRESSURE REGIME					HIGH PRESSURE REGIME				
	CONST	AR(1)	SD OF RESIDUALS	LONG-RUN GROWTH	AVG EXPECTED DURATION	CONST	AR(1)	SD OF RESIDUALS	LONG-RUN GROWTH	AVG EXPECTED DURATION
AGRIC	-1.046*	0.247***	25.439***	-1.4%	3.139	4.798***	-0.606***	41.874***	3.0%	1.467
FOOD	-0.312	0.315***	12.074***	-0.5%	3.224	2.519***	-0.706***	8.171***	1.5%	1.450
SODA	0.110	0.039	107.618***	0.1%	1.460	1.311***	-0.113*	14.067***	1.2%	3.174
BEER	0.213	0.054	43.794***	0.2%	1.410	0.948***	-0.091	11.285***	0.9%	3.439
SMOKE	0.694	0.096	81.035***	0.8%	1.643	1.536***	-0.102	20.717***	1.4%	2.556
TOYS	0.852**	-0.035	29.252***	0.8%	3.001	-0.652	0.144	97.172***	-0.8%	1.500
FUN	1.891***	-0.032	24.095***	1.8%	2.108	0.329	0.130	117.412***	0.4%	1.903
BOOKS	-0.230	0.330***	3.763*	-0.3%	1.429	0.924	0.004	54.660***	0.9%	3.329
HSHLD	0.935***	-0.059	9.602***	0.9%	3.428	0.067	0.061	37.917***	0.1%	1.412
CLTHS	1.226***	0.141	16.049***	1.4%	1.820	0.668	0.049	68.092***	0.7%	2.219
HLTH	0.356	0.265***	20.367***	0.5%	3.172	0.728	-0.301*	78.148***	0.6%	1.460
MEDEQ	1.925***	-0.134	14.985***	1.7%	6.841	-4.481**	0.649***	27.917***	-12.8%	1.171
DRUGS	0.250	-0.175*	29.556***	0.2%	1.633	1.181***	0.008	11.817***	1.2%	2.580
CHEMS	-0.962	0.508***	34.753***	-2.0%	1.959	2.699***	-0.475***	17.755***	1.8%	2.042
RUBBR	2.490***	-0.043	6.532***	2.4%	1.666	-0.098	0.053	58.973***	-0.1%	2.502
TXTLS	0.875*	0.132*	35.996***	1.0%	3.953	-0.161	0.051	220.034***	-0.2%	1.339
BLDMT	1.271***	-0.093	21.456***	1.2%	2.699	0.513	0.044	94.267***	0.5%	1.589
CNSTR	-0.372	0.526***	55.862***	-0.8%	1.816	2.709***	-0.264***	38.521***	2.1%	2.225
STEEL	-1.258	0.491***	85.652***	-2.5%	1.905	3.350***	-0.448***	49.786***	2.3%	2.104
FABPR	1.595***	-0.081	34.636***	1.5%	2.047	-0.290	0.074	132.681***	-0.3%	1.955
MACH	-1.289	0.495***	41.836***	-2.6%	1.996	3.936***	-0.318**	30.086***	3.0%	2.004
ELCEQ	-1.455	0.370***	66.230***	-2.3%	1.412	1.966***	-0.263***	31.562***	1.6%	3.426
AUTOS	0.849*	0.050	26.752***	0.9%	2.689	1.352	0.041	219.169***	1.4%	1.592
AERO	1.548***	-0.062	16.115***	1.5%	2.077	0.509	0.076	80.596***	0.6%	1.928
SHIPS	0.890	0.042	94.759***	0.9%	2.123	1.960***	-0.087	15.673***	1.8%	1.890
GUNS	0.518	0.026	75.615***	0.5%	1.678	1.556***	-0.033	15.821***	1.5%	2.475
GOLD	2.741	-0.071	366.569***	2.6%	1.193	0.421	-0.131**	81.832***	0.4%	6.176
MINES	-3.127***	0.417***	57.925***	-5.4%	1.765	4.785***	-0.127	54.067***	4.2%	2.308
COAL	1.838**	-0.229**	84.814***	1.5%	1.972	1.268	0.235**	265.573***	1.7%	2.029
OIL	0.640*	-0.031	35.478***	0.6%	9.057	3.524*	-0.180	160.674***	3.0%	1.124
UTIL	2.081***	-0.053	2.614***	2.0%	1.432	0.195	-0.005	24.022***	0.2%	3.316
TELCM	0.984**	0.417***	2.868*	1.7%	1.373	0.121	-0.165*	35.987***	0.1%	3.681
PERSV	0.940***	-0.009	18.469***	0.9%	2.195	0.036	-0.072	60.673***	0.0%	1.837
BUSSV	-0.677	0.600***	24.899***	-1.7%	1.985	2.382***	-0.394***	16.518***	1.7%	2.015
HARDW	2.524***	-0.518***	26.793***	1.7%	1.763	0.054	0.429***	66.581***	0.1%	2.311
SOFTW	0.554	0.461***	40.677***	1.0%	2.415	2.871***	-0.759***	18.325***	1.6%	1.707
CHIPS	0.526	0.007	149.972***	0.5%	1.410	1.637***	-0.008	35.941***	1.6%	3.436
LABEQ	-0.204	0.456***	38.912***	-0.4%	2.629	3.683***	-0.551***	14.810***	2.4%	1.614
PAPER	-0.856	0.378**	37.764***	-1.4%	1.816	1.942***	-0.313***	12.184***	1.5%	2.226
BOXES	1.476***	-0.170**	19.116***	1.3%	2.748	-0.157	0.070	67.268***	-0.2%	1.572
TRANS	-2.031	0.453**	30.996***	-3.7%	1.634	2.641***	-0.206**	22.644***	2.2%	2.577
WHLSL	-1.334**	0.630***	16.580***	-3.6%	2.015	3.029***	-0.363***	15.221***	2.2%	1.985
RTAIL	0.968***	-0.107	10.340***	0.9%	1.854	1.112**	0.038	40.649***	1.2%	2.171
MEALS	1.410***	-0.014	12.105***	1.4%	2.470	0.489	0.030	43.975***	0.5%	1.680

INDUSTRY	LOW PRESSURE REGIME					HIGH PRESSURE REGIME				
	CONST	AR(1)	SD OF RESIDUALS	LONG-RUN GROWTH	AVG EXPECTED DURATION	CONST	AR(1)	SD OF RESIDUALS	LONG-RUN GROWTH	AVG EXPECTED DURATION
BANKS	1.293***	-0.048	11.594***	1.2%	1.972	0.107	0.039	71.134***	0.1%	2.028
INSUR	-0.949	0.062	100.449***	-1.0%	1.187	1.263***	-0.075	14.558***	1.2%	6.353
RLEST	0.635	0.222***	21.018***	0.8%	3.270	0.508	0.039	164.065***	0.5%	1.441
FIN	-0.377	0.538***	40.758***	-0.8%	2.305	2.971***	-0.533***	28.274***	1.9%	1.766
OTHER	-0.175	0.079	67.452***	-0.2%	1.593	0.933***	-0.099	12.198***	0.8%	2.686

Source: own study.

Author

Marcin Pietrzak

Assistant Professor at the Institute of Economics, Polish Academy of Sciences. His research interests include financial economics, time series econometrics and financial markets.

Correspondence to: dr Marcin Pietrzak, Institute of Economics, Polish Academy of Sciences, ul. Nowy Świat 72, 00-330 Warszawa, Poland, e-mail: mpietrzak@inepan.waw.pl

ORCID https://orcid.org/0000-0002-5401-9917

Acknowledgements and Financial Disclosure

Not applicable.

Use of Artificial Intelligence

The author declares that Grammarly was used for proofreading.

Conflict of Interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Copyright and License

Published by Krakow University of Economics – Krakow, Poland