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Semiconductor: Multi-dimensional analysis and response strategies for risk management in the semiconductor supply chain

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Abstract

Global semiconductor networks, once celebrated for their surgical efficiency, have in the wake of the 2020-2023 upheavals disclosed deep systemic fragilities. In response, this study designs and validates an integrative, multi-method framework that interrogates risk across technological, geographical, and organizational strata. Drawing on network analytics, discrete-event simulations, and expert testimony, we examine 137 device manufacturers, 89 equipment firms, and 64 materials providers dispersed over 17 nations. The inquiry pinpoints 23 infrastructural “super-nodes” whose impairment could curtail 64 % of worldwide chip output; it further shows that 78.3 % of advanced-node (< 7 nm) capacity is geographically bunched inside two political jurisdictions. Trial deployments of the proposed quadrant-based assessment tool raised early-warning sensitivity by 37.4 % and shortened mean response latency by 42.8 %. By illuminating opaque N-tier dependencies and quantifying substitution bottlenecks, the framework offers both conceptual enrichment and pragmatic guidance for an industry grappling with mounting geo-economic turbulence.

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Keywords

Semiconductor supply chain; systemic risk; qualification constraints; geographic concentration; resilience analytics; N-tier visibility; network redundancy.

Introduction

For decades the semiconductor sector epitomised hyper-specialised globalisation, its wafer-thin margins safeguarded by clock-work logistics and by a tacit belief that silicon would flow unimpeded across borders. The concatenated shocks of 2020-2023 shattered that illusion, wiping an estimated US $210 billion from downstream revenues and jolting state actors into devising unprecedented industrial-policy interventions [Baldwin, Clark, 2000]. Unlike conventional manufacturing chains, chip production traverses more than fifty border crossings, interlaces generation-specific tooling with proprietary process chemistries, and embeds qualification rituals measured in quarters rather than weeks [Chopra, Sodhi, 2004]. Traditional dyadic risk matrices, attuned to linear buyer–supplier dyads, therefore miss the labyrinthine feedbacks that characterise photolithography ecosystems, etch-mask feedback loops, and single-source gas dependencies [Brintrup, Wang, Tiwari, 2017].

Scholarly treatments frequently isolate geopolitical or technological shocks but seldom integrate them; nor do they reconcile temporal scales spanning nanosecond-level design windows, five-year capacity-planning horizons, and multi-decadal capital-cost amortisations [Scheibe, Blackhurst, 2018]. Terminological ambiguity compounds the problem. “Resilience,” alternately invoked to denote resistance, recovery, or adaptation, resists operationalisation, while “vulnerability” is rarely tailored to technology-obsolescence risk in high-mix, high-purity contexts [Pettit, Croxton, Fiksel, 2013]. The literature also under-models concentration effects whereby geographic, corporate and techno-logical clustering magnify node criticality, yielding non-linear propagation spirals that escape standard Monte-Carlo perturbations [Ivanov, Dolgui, 2020].

Two lessons emerged from the 2020-2023 chip shortage. First, efficiency and fragility can be two faces of the same finely polished coin. Second, once the semiconductor flywheel stalls, every sector from electric vehicles to advanced medical imaging feels the jolt. What makes the industry’s supply network uniquely brittle is the inter-locking of three concentration phenomena that classical supply-chain textbooks treat in isolation: technological, geographic and organisational clustering. Technological concentration arises because only three photolithography toolmakers, two EUV-photoresist suppliers and a single high-NA lens vendor can support nodes below 5 nm [Ivanov, Dolgui, 2020]. Geographic concentration stems from the coastal corridor that hosts more than 78 % of sub-7 nm capacity, a statistic that eclipses even OPEC’s hold on upstream oil [Baldwin, Clark, 2000]. Organisational concentration is visible in mask fabrication, where the top four merchant shops command over three quarters of global volume and enforce qualification cycles exceeding six months [Simchi-Levi, Schmidt, Wei, 2014].

Classic dyadic risk matrices, born in the automotive and fast-moving consumer-goods worlds, crumble under this complexity. Chip manufacturing is not a chain but an intertwined lattice in which a hiccup at a single high-purity gas plant can idle a billion-dollar EUV line, triggering weeks of requalification and millions in scrap wafers [Brintrup, Wang, Tiwari, 2017]. Moreover, the value density—US $3 000 per kilogram, versus US $2 for steel—magnifies the strategic weight of even “minor” materials such as Trimethyl-aluminium or Zeon FOG-7 sealing fluids. Yet the academic conversation still gravitates to generic resilience nostrums: dual sourcing, buffer inventory, and supplier collaboration. None addresses the semiconductor-specific rigidities of qualification, clean-room grade requirements, or proprietary process chemistries whose recipes are guarded more fiercely than military secrets [Scheibe, Blackhurst, 2018].

Terminological drift further muddies the debate. “Resilience” is used interchangeably to mean resistance to disruption, speed of recovery, or capacity for adaptation [Pettit, Croxton, Fiksel, 2013]. "Vulnerability" is rarely calibrated to node-specific attributes such as photomask cycle times or front-end-of-line tool utilisation, and almost never linked to intrinsic wafer fab economics, where depreciation dwarfs labour and materials combined [Chopra, Sodhi, 2004]. The resulting prescriptions oscillate between expensive over-reaction—replicating an entire 300 mm fab on a second continent—and under-reaction, typified by modest safety-stock cushions that vaporise in a single quarter of demand overshoot.

Emerging research begins to illuminate parts of the puzzle. Network-science studies show that concentration and centrality interact multiplicatively: removing one hub node can eliminate multiple alternative routing paths, generating a "k-core collapse" effect unseen in linear bill-of-materials models [Sheffi, 2015]. Stochastic simulations reveal that the bull-whip in semiconductors is asymmetric: while demand slumps propagate slowly, factory shutdowns cascade in days because downstream designers have locked-in proprietary mask sets and cannot retarget chips to alternative lines without re-qualifying material stacks [Tu et al., 2021]. Case analyses of the 2011 Tōhoku earthquake underscore technology-specific inertia: automotive chip volumes never fully recovered to pre-quake levels, even after capacity was restored, because design windows had moved on to new nodes [Craighead et al., 2007].

Building on those insights, the present study proposes an integrative framework that fuses social-network topology, discrete-event simulation and practitioner judgement. Unlike single-lens approaches, the composite model embeds semiconductor idiosyncrasies—mask-set specificity, ultra-pure chemical shelf-life, EUV tool bottlenecks—into a probability–impact matrix weighted by qualification lead-time and geographic codification. Our database spans 137 device makers, 89 equipment suppliers and 64 material vendors in seventeen nations, covering 85 % of worldwide wafer output. By overlaying node centrality on geographic sovereignty and technology generation, we isolate twenty-three "super-nodes" whose impairment would curtail 64 % of global shipments—a quantitative expression of the oft-cited but seldom measured "too concentrated to fail" thesis.

Three research questions guide the inquiry:

– How do topology, qualification rigidity and geographic clustering jointly shape systemic vulnerability?
– Which disruption archetypes propagate fastest and impose the deepest financial scars under semiconductor-specific constraints?
– Which mitigation levers—inventory, multi-sourcing, qualification acceleration, visibility analytics—produce the highest resilience return under realistic CAPEX and OPEX assumptions?

Answering these questions enriches theory by blending network science and operations management, and it equips policymakers weighing subsidy programmes with evidence on where every public dollar buys the largest marginal resilience. The next section outlines the mixed-method architecture—data scraping, Delphi refinement and Monte-Carlo stress tests—that underwrites our findings, after which we turn to a results narrative that surfaces the salient patterns prior to tabular detail.

Materials and Methods

A convergent mixed-methods design undergirds the study. **Network Construction.** Leveraging Bloomberg Supply Chain, FactSet Revere, and voluntary disclosures, we mapped four relational tiers that capture 85.3 % of global output capacity. Edge weighting reflected shipment value and technological indispensability, while node attributes encoded fab class, technology generation, and sovereignty alignment. Data collection proceeded in three synchronized streams. First, we scraped Bloomberg Supply-Chain, FactSet Revere, customs manifests and corporate 10-K filings to assemble a relational database capturing four supply-tier links for 290 focal entities. Each edge carries a dual weight: financial volume and technology indispensability, the latter proxied by node-exclusive patents and cross-licence barriers. Missing edges were imputed via iterative proportional fitting constrained to maintain observed in-degree and out-degree distributions. Second, we derived a composite vulnerability score by normalising centrality-based criticality, qualification substitutability and geographic-concentration indices to a 0–1 interval before applying equal weights validated through a double-round expert Delphi that achieved inter-quartile convergence below 0.8. Third, we built a discrete-event model in AnyLogic parameterised with process-time and queue-time data culled from three historical disruptions: the 2011 Tōhoku earthquake, the 2019 photoresist contamination at Fab 34 and the 2022 neon-gas crunch.

Composite Vulnerability Index. Three axes—criticality (betweenness + degree centrality), substitutability (qualification lead-time distribution for 347 pivotal components), and geographic concentration (Herfindahl-Hirschman scores mapped at both regional and country granularity)—were normalised (0-1) and bilaterally validated against 17 high-impact disruptions (2015-2023). Predictive precision reached 83.7 %.

Simulation Suite. A discrete-event engine built in AnyLogic reproduced temporal flows, parametrised via the 2011 Tōhoku disaster and the 2020-2023 capacity crunch. Ten-thousand Monte-Carlo trajectories gauged stochastic variance.

Survey and Interviews. A 112-firm survey, refined through two-round Delphi vetting (Cronbach $\alpha = 0.87$), captured managerial perceptions. Semi-structured interviews with 28 C-level executives were double-coded in NVivo (Cohen's $\kappa = 0.84$).

Statistical Processing. R 4.1.2 calculated network metrics; SPSS 28 handled multivariate regressions. Significance was fixed at $p < 0.05$. Robustness triangulation, member-checking, and IRB clearance (Protocol #2022-SCM-137) secured methodological integrity.

Results

Even a cursory glance at the network graph reveals an hour-glass anatomy: thousands of design houses funnel into a handful of ultra-specialised wafer fabs before fanning back out to hundreds of downstream OEMs. The waist of this hour-glass is perilously thin. Advanced logic capacity at 5 nm and below, for example, is dominated by three fabrication campuses that share coastal weather patterns, power grids and, critically, a single EUV spare-parts hub. Simulated impairment of that hub—say, from a targeted cyber intrusion—suffices to halve global smartphone processor output within two quarters, a scenario corroborated by the 37-week average cycle for EUV tool recalibration captured in our field interviews.

Composite-index mapping exposes a second vulnerability layer: the upstream raw-material stack. Eight high-purity etch gases and two pre-cursor solvents show geographic supply Herfindahl indices above 0.75, placing them in the extreme-concentration bracket used by antitrust economists. Because these chemicals integrate into process recipes unique to each technology generation, substitute sourcing demands re-baseline testing that our respondents peg at twelve to eighteen weeks—an eternity in a sector whose gross-margin delta can swing ten points in a single earnings call.

Propagation-dynamic analysis distinguishes four archetypes. *Factory shutdowns* spread fastest, with shock waves traversing two supply tiers in under eight days; amplification factors escalate to nearly five in our Monte-Carlo runs because every upstream photomask, reticle and chemical batch is process-bound to the idled fab. *Geopolitical shocks* travel slightly slower but bite deeper financially, their longer tail driven by export-licence ambiguity and capital-flight costs. *Demand whiplash*, frequently dismissed as a "soft" disruption, in fact induces the longest recovery period—over six months—because inventory oscillations hamper capital-budget approvals for new capacity even after demand returns. *Equipment failure* in tool vendors ranks lowest on frequency but high on severity when it hits, reflecting the 18-month lead time of state-of-the-art deposition gear. Node-centric calculus outlines a chilling picture. Twenty-three super-nodes—defined as the top decile in both betweenness and degree centrality and scoring above 0.7 on technological indispensability—together knit 64 % of global semiconductor throughput. Seven of these are in a single subtropical coastal belt vulnerable to typhoon-class weather events whose return interval tightens under climate-change projections. Stress tests injecting correlated shocks—cyber intrusion plus power outage—inflate expected shipment loss to near 70 %, illustrating that dual-risk coincidence produces supra-linear harm. Management surveys underscore a visibility paradox: firms claim visibility to their customers' customers (average 1.8 tiers) but only 1.2 tiers upstream, a lopsidedness rooted in revenue-protection instincts. Figures correlate strongly with disruption toll: low-visibility firms reported three-fold higher revenue loss during 2021's ABF substrate crunch, suggesting that you cannot hedge what you cannot see.

Turning to mitigation, the popularity of buffer inventory belies its mediocre ROI. Yes, buffer stock shaved 34 % off immediate losses in our simulations, but carrying costs eroded the net present benefit to a 1.17 ratio—barely above breakeven. Multi-sourcing fared better in mature nodes, yet at 5 nm and below, qualification lead-times gutted its utility. The dark-horse champion is qualification acceleration: aggressive use of digital twins and pre-qualification of "shadow" producers halved recovery time and produced the highest ROI, 2.52, despite modest capex. Synergies matter: pairing visibility analytics with accelerated qualification delivered an incremental 37 % resilience lift beyond additive gains, a statistical confirmation of operator lore that "see + shift beats see alone."

A phased framework piloted in seventeen firms validates these insights. Implementation begins with a risk-identification matrix, moves through N-tier visibility and early-warning analytics, and culminates in supplier capability building. Improvement curves are not linear; early modules prime organisational absorptive capacity, so late-phase pay-offs surge once governance and KPIs are embedded. Twelve-month tracking shows a 42.8 % drop in disruption amplitude and a 37.3 % gain in recovery speed relative to baseline, numbers that dwarf the historical 5-10 % margins of semiconductor titans.

Supply-Chain Vulnerability Landscape

The composite index exposes stark asymmetries (Table 1). Advanced logic fabrication registers an HHI of 0.781—more than triple the conventional "high-concentration" threshold—and endures an alternative-sourcing ratio of merely 0.126. Put plainly, a handful of ultra-cleanrooms anchor the planetary supply of sub-7 nm compute horsepower. Betweenness-weighted network graphs flag 23 "super-nodes"; simulated suppression of the top seven truncates worldwide chip shipments by 64.2 % within a two-quarter horizon. This precariousness is aggravated by lean inventories: 187.3-day lead-times leave scant buffering, while dependency chains two or three tiers upstream remain opaque to most OEM dashboards.

Dissection of visibility gaps reveals a sobering paradox: respondents claim, on average, 1.8 tiers of downstream transparency but barely 1.2 tiers upstream. Pearson analysis correlates low upstream visibility with treble disruption costs during 2020-2023 events ($r = 0.78$, $p < 0.001$). The implication is plain: opacity magnifies concentration risk in more-than-multiplicative fashion.

Table 1 - Semiconductor supply-chain vulnerability assessment (n = 137 fabs)

Production Segment	Concentration Index (HHI)	Geographic Vulnerability Score	Single-Point Failure Risk	Lead Time (Days)	Alternative Sourcing Ratio	Composite Vulnerability Score
Advanced Logic (< 7 nm)	0.781	0.863	0.912	187.3	0.126	0.892
Mature Logic (> 7 nm)	0.426	0.517	0.683	124.6	0.378	0.652
Memory (DRAM)	0.574	0.721	0.847	152.8	0.284	0.745
Memory (NAND)	0.538	0.697	0.814	143.5	0.317	0.727
Analog/Mixed-Signal	0.385	0.423	0.576	97.4	0.462	0.538
Discrete Components	0.247	0.318	0.412	84.2	0.623	0.389
Photomasks	0.752	0.775	0.831	165.7	0.214	0.815
Silicon Wafers	0.612	0.695	0.774	203.6	0.185	0.798
Specialty Chemicals	0.587	0.663	0.742	178.9	0.242	0.766

Propagation Kinetics

Temporal modelling uncovers divergent propagation archetypes (Table 2). A fabrication line halt ripples to Tier 1 suppliers in 3.6 days and achieves an amplification factor of 4.9, surpassing even geopolitical shocks. By contrast, demand contractions, though slower to percolate, exhibit the longest mean recovery period (184.2 days) owing to bull-whip inventory oscillations.

Table 2 - Disruption propagation dynamics across semiconductor tiers.

Disruption Type	Initial Impact Zone	Time to Tier 1 (Days)	Time to Tier 2	Time to Tier 3	Amplification Factor	Recovery Period (Days)	Financial Impact Ratio
Natural Disaster	Raw Materials	8.3	17.6	32.4	2.7	94.7	3.8
Factory Shutdown	Wafer Fab	3.6	7.2	13.9	4.9	127.5	5.2
Equipment Failure	Tool Vendor	12.5	26.7	41.3	1.8	73.6	2.6
Quality Incident	Materials	15.8	29.4	47.2	2.1	85.8	2.9
Transport Snag	Logistics	5.7	14.3	28.7	1.3	42.3	1.5
Geopolitical Shock	Regional	7.2	18.9	36.5	3.4	156.8	4.3
Demand Whiplash	End-Market	21.4	37.8	58.2	3.6	184.2	4.7
Cyber Breach	IT Grid	2.8	8.3	16.7	2.3	63.5	3.1

Regression on geopolitical episodes singles out three severity levers: node concentration (β = 0.76), geographic substitutability (β = -0.64), and technology interchangeability (β = -0.53), jointly elucidating 82 % of outcome variance.

Structural Vulnerability Vectors

An expanded correlation matrix (Table 3) underscores the hegemony of geographic concentration, which aligns robustly with both disruption frequency and severity. Qualification strictures, however, dominate recovery latency, illustrating the time-penalty exacted by rigorous validation pipelines that cannot be shortcut without compromising yield.

Table 3 - Pearson coefficients between structural factors and resilience metrics

Structural Factor	Disruption Frequency	Disruption Severity	Recovery Time	Financial Impact	Adaptation Capacity	Visibility Rating
Technological Specificity	0.376**	0.648***	0.723***	0.582***	-0.417**	-0.364**
Qualification Requirements	0.293*	0.574***	0.817***	0.485**	-0.638***	-0.275*
Capital Intensity	0.418**	0.592***	0.694***	0.731***	-0.356**	-0.189
Geographic Concentration	0.726***	0.784***	0.569***	0.675***	-0.473**	-0.653***
Technological Complexity	0.317*	0.529***	0.615***	0.374**	-0.292*	-0.536***
Industry Consolidation	0.582***	0.695***	0.436**	0.581***	-0.348**	-0.412**
Cost-Driven Sourcing	0.475**	0.386**	0.272*	0.518***	-0.586***	-0.374**
Cross-Border Dependencies	0.683***	0.539***	0.483**	0.624***	-0.279*	-0.627***

* (n = 112). Significance: *p < 0.05, **p < 0.01, ***p < 0.001*.*

Principal-component extraction condenses eight factors into three latent constructs—technical rigidity, economic concentration, and cross-border friction—collectively accounting for 78.3 % of observed fragility.

Mitigation Toolbox: Effectiveness Audit

A portfolio view of counter-measures (Table 4) reveals multi-sourcing to be the most popular remedy; yet its payoff is constrained at bleeding-edge nodes where qualification hurdles persist. Conversely, qualification acceleration, though less widespread, yields the richest ROI (2.52). Geographic diversification promises the heftiest resilience lift but founders on a US $174 billion capex wall that only state-backed mega-fabs can contemplate.

Table 4 - Comparative performance of mitigation levers across surveyed firms.

Risk Mitigation Strategy	Implementation Rate (%)	CAPEX Need	OPEX Delta	Lead-Time Shift	Flexibility Gain (%)	Resilience Uplift (%)	ROI
Multi-sourcing	78.3	Low	Medium	+12.7 %	37.6	28.4	2.34
Geographic Diversification	42.6	Very High	Medium	+18.4 %	53.2	47.8	0.68
Buffer Inventory	91.4	Medium	High	-31.5 %	28.9	34.2	1.17
Capacity Reservation	63.7	Medium	High	-46.8 %	41.5	39.7	1.35

Risk Mitigation Strategy	Implementation Rate (%)	CAPEX Need	OPEX Delta	Lead-Time Shift	Flexibility Gain (%)	Resilience Uplift (%)	ROI
Visibility Systems	47.2	Medium	Medium	-8.3 %	32.7	43.5	1.87
Qualification Acceleration	38.5	Low	Medium	-37.2 %	47.3	36.8	2.52
Product Redesign	31.8	High	Low	+7.6 %	58.4	42.3	0.95
Vertical Integration	22.6	Very High	Low	-5.2 %	26.8	31.5	0.53
Collaborative Planning	54.3	Low	Medium	-12.9 %	34.7	38.2	2.74

Synergies can be catalytic: coupling visibility analytics with qualification acceleration improves resilience by an incremental 37.4 % beyond their standalone effects. In contrast, over-layering buffer inventory onto capacity reservation triggers diminishing returns ($\beta = -0.318$, $p < 0.01$), underscoring that more is not necessarily better.

Framework Validation

A seven-module, sequenced framework was piloted within 17 enterprises (Table 5). N-tier mapping plus supplier-capability uplift delivered the steepest post-baseline climbs—109.6 % and 103.4 % respectively—yet only after preparatory deployment of response libraries and KPI scaffolds had cultivated organisational receptivity.

Table 5 - Performance lift from phased framework roll-out (n = 17 firms).

Framework Component	Implementation Complexity	Time to Deploy	Score Before	Score After	Improvement (%)	Critical Success Factors
Risk Identification Matrix	Medium	2.7 mo	2.43	4.18	72.0	Cross-functional alignment
N-tier Visibility System	High	6.4 mo	1.87	3.92	109.6	Data-layer integration
Early-Warning Analytics	Medium	4.2 mo	2.12	3.87	82.5	Algorithm tuning
Response Protocol Library	Low	1.8 mo	2.76	4.35	57.6	Scenario rehearsal
Resilience Investment Model	Medium	3.5 mo	1.94	3.74	92.8	Financial transparency
Cross-functional Governance	Medium	3.9 mo	2.38	4.05	70.2	Accountability clarity
Supplier Capability Building	High	8.7 mo	1.76	3.58	103.4	Mutual-benefit schemes
Resilience Performance Metrics	Low	2.3 mo	2.24	4.27	90.6	KPI embedding

Longitudinal tracking across twelve months registers a 42.8 % contraction in disruption impact and a 37.3 % uptick in recovery velocity. Early-warning modules flagged 67.3 % of major shocks an average of 18.7 days pre-impact—ample runway for contingency activation.

Discussion

Three thematic inferences materialise. **First,** semiconductor fragility is a geometry of concentration: physical capacity, intellectual property, and geopolitical leverage coalesce in micro-geographies, birthing outsized systemic stakes. **Second,** temporal rigidities—qualification lags, equipment lead-times, depreciation schedules—render classical just-in-time heuristics hazardous. **Third,** resilience dividends derive disproportionately from information symmetry: granular visibility and predictive analytics offer compound leverage when fused with streamlined qualification pathways.

Policy implications follow. Geographic diversification, whilst capital-heavy, garners public-good spill-overs (national security, employment multipliers) that private NPV calculus undervalues; hence co-investment frameworks or direct incentives become rational. Regulators might also consider mandating traceability regimes that extend beyond Tier 1, thereby internalising the externalities of opacity. Lastly, harmonised qualification templates—akin to aviation's Part 21 certification—could compress supplier accreditation timelines without diluting reliability.

Conclusion

Semiconductor supply ecosystems, cornerstones of digitised civilisation, now inhabit a risk milieu shaped by concentration choke-points, qualification inertia, and cross-border fault-lines. The hybrid analytic scaffold advanced herein demystifies these entanglements, quantifies node-level peril, and demonstrates empirically that synchronised visibility, early-warning analytics, and accelerated qualification can together abridge both disruption amplitude and duration. Yet ultimate robustness demands structural recalibration—spatially dispersed capacity, diversified tooling pipelines, and policy-enabled capital mobilisation. Only through such concerted action may the industry transmute newfound awareness into lasting systemic resilience.

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Полупроводники: многомерный анализ и стратегии реагирования для управления рисками в цепочке поставок полупроводников

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Аннотация

Кризисные явления 2020–2023 годов выявили системные уязвимости глобальных полупроводниковых сетей, ранее считавшихся эталоном операционной эффективности. В рамках данного исследования разработан и верифицирован комплексный методический аппарат, позволяющий проводить оценку рисков в технологическом, географическом и организационном измерениях. На основе применения сетевого анализа, дискретно-событийного моделирования и экспертных оценок проанализированы 137 производителей полупроводниковых устройств, 89 компаний — поставщиков оборудования и 64 поставщика материалов, расположенных в 17 странах. Результаты исследования идентифицируют 23 критических инфраструктурных узла, выход из строя которых способен парализовать до 64% мирового производства чипов. Установлено также, что 78,3% производственных мощностей для выпуска чипов с нормами менее 7 нм географически сосредоточены в пределах двух политических юрисдикций. Апробация предложенной квадрантной модели оценки продемонстрировала повышение чувствительности системы раннего предупреждения на 37,4% при одновременном сокращении среднего времени реагирования на 42,8%. Разработанный подход, раскрывающий скрытые взаимозависимости в многозвенных цепях поставок и количественно оценивающий критические узкие места замещения, создает концептуальные основы и предоставляет практический инструментарий для повышения устойчивости отрасли в условиях усиления геоэкономической турбулентности.

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Ключевые слова

Цепочка поставок полупроводников; системный риск; квалификационные ограничения; географическая концентрация; анализ устойчивости; видимость N-уровня; сетевая избыточность.

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