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Benchmarking supplier performance: How scorecard comparisons and supply risk influence termination decisions

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ABSTRACT

This study examines how supplier termination decisions are influenced by scorecard performance, peer supplier performance, and component supply risk in multisourcing supply chains. While supplier selection has been extensively studied, supplier termination remains underexplored, particularly in dynamic industries like electronics manufacturing. Drawing from agency theory, we examine how relative performance evaluation (RPE) mechanisms and supply risk shape termination decisions. Using proprietary data from a major electronics firm covering 78 suppliers across 15 components over 42 months, we provide novel evidence that firms employ comparative evaluation rather than absolute performance thresholds. Supplier scorecard improvements significantly increase survival probability, while strong peer performance decreases survival probability for other suppliers, demonstrating RPE effectiveness. However, component supply risk systematically moderates these relationships through distinct mechanisms: supplier scarcity weakens both own performance and peer performance effects on termination decisions. In contrast, component specialization selectively reduces peer performance effects but does not moderate own performance effects. These patterns reflect situations where supply constraints limit performance-based termination effectiveness. The study contributes by extending agency theory's RPE to inter-firm settings and demonstrating how different supply risk dimensions selectively moderate different performance evaluation types. These insights guide supply chain managers in understanding when performance-based termination criteria are most effective.

1. Introduction

Supplier selection has long been a central theme in supply chain management research, with extensive studies examining criteria for optimal supplier choice (Choi and Hartley, 1996; Kannan and Tan, 2002). This research has evolved to include multidimensional selection frameworks that consider cost efficiency, quality, delivery reliability, and strategic alignment (Ho et al., 2010). However, supplier selection is only one part of the broader supplier management process, which also involves ongoing performance evaluation and, when necessary, supplier termination. Despite the significant attention given to selection, relatively little research has been dedicated to understanding the critical process of supplier termination (Clough and Piezunka, 2020).

The strategic importance of supplier termination decisions has grown substantially as global supply chains become increasingly complex and competitive pressures intensify. Recent research demonstrates that relationship termination decisions have far-reaching consequences beyond immediate operational impacts—they fundamentally affect firms' innovation capabilities and long-term performance outcomes (Zaefarian et al., 2017; Joseph et al., 2016). This is particularly evident in technology-intensive industries, such as electronics manufacturing, where modular production networks and rapid technological change

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lead to high supplier turnover rates and frequent relationship restructuring (Zhao et al., 2022).[2] Unlike supplier selection, which focuses on adding new capabilities to the supply base, supplier termination involves evaluating ongoing relationships, considering sunk costs and switching expenses, and balancing performance standards against the risks of supply continuity. These decisions directly impact operational stability and can disrupt carefully constructed supply networks, making their understanding essential for effective supplier portfolio management.

Termination decisions become exponentially more strategic in multisourcing environments, where firms typically manage multiple suppliers per component category. In these complex supplier networks, firms often make termination decisions by observing how other supplier relationships are performing (Clough and Piezunka, 2020). Unlike single-sourcing scenarios with clear go/no-go decisions, multisourcing requires firms to balance competing considerations continuously: maintaining performance standards to incentivize all suppliers, managing switching costs that can include retooling and requalification expenses, ensuring supply continuity when removing underperforming suppliers, and avoiding disruptions to carefully orchestrated supplier relationships (Craig et al., 2016; Jamalnia et al., 2023).

To address these complex supplier management challenges, firms have increasingly adopted supplier scorecard systems that provide frameworks for evaluating supplier performance (Andrews and Barron, 2016). The effectiveness of this approach has been documented across various industries, including electronics (Sako, 1992), semiconductor equipment (Cohen et al., 2003), and the automotive sector (Hoyt and Plambeck, 2006). For example, Walmart systematically measures supplier performance across financial, quality, delivery, and environmental dimensions through scorecards to determine strategic supplier engagement levels (Plambeck and Denend, 2011).

While supplier scorecards provide structured performance evaluation systems and have become widely adopted tools for managing supplier relationships (Dey et al., 2015; Hawkins et al., 2020), three critical questions remain unanswered in supplier termination contexts: First, do firms use absolute performance thresholds or comparative evaluation against peer suppliers when making termination decisions? Second, how do supply chain risks and constraints influence the application of performance-based termination criteria? Third, what trade-offs do firms face between maintaining strict performance standards and ensuring supply continuity? These questions are particularly important because termination decisions are often influenced by factors beyond individual supplier performance, including peer supplier performance and broader competitive landscape considerations (Noorizadeh et al., 2021; Jamalnia et al., 2023).

This research addresses these gaps by examining how buying firms use scorecards and relative performance evaluation mechanisms to make supplier termination decisions, particularly considering how component supply risk moderates these relationships. We employ a unique proprietary dataset from a major international electronics firm (TechCorp) covering 78 suppliers and 15 components over 42 months. Our research addresses the fundamental question: How do firms make supplier termination decisions in complex multisourcing environments, and what factors influence the effectiveness of performance-based termination criteria?

We focus on two key performance aspects: the supplier's scorecard performance and that of their primary peer supplier (hereinafter referred to as the peer supplier)—a process we term relative performance evaluation (RPE) (Gong et al., 2011). RPE represents a theoretical framework rooted in agency theory that enables principals to filter out external noise and isolate agent-specific effort by benchmarking performance against comparable peers (Holmström, 1979; Holmström and Milgrom, 1987). By incorporating peer performance measures, RPE helps mitigate information asymmetry and improve incentive alignment in buyer-supplier relationships (Baiman & Rajan, 2002).

We also explore the role of component supply risk in informing supplier termination choices. Component supply risk reflects the potential for supply disruptions based on factors such as supplier availability and component complexity. When supply risk is high, firms face a fundamental trade-off between maintaining performance standards and ensuring supply continuity. This creates what we term "adverse incentive costs"—situations where strict adherence to performance-based termination criteria may result in supply disruptions that are more costly than retaining an underperforming supplier. High-risk components require firms to maintain stronger supplier relationships to ensure supply continuity (Hannan et al., 2008). When the number of approved suppliers is low or component complexity is high, firms may be more reluctant to terminate underperforming suppliers due to switching costs and the risk of supply disruptions (Krause et al., 2007; Ellis et al., 2010).

Our findings reveal that higher component supply risk —proxied by having fewer suppliers— reduces the negative impact of poor supplier performance on termination decisions. Similarly, component supply risk —proxied by component specialization— reduces the positive impact of strong peer supplier performance on supplier termination decisions. This suggests that firms face a fundamental trade-off between performance-based supplier termination and supply chain continuity, particularly when dealing with specialized components or limited supplier alternatives.

Our study makes two significant theoretical contributions to the supplier management literature by extending agency theory and RPE mechanisms to supplier termination decisions. First, we extend supplier termination theory by integrating RPE into supplier termination decisions within multisourcing environments. Prior research emphasizes absolute performance thresholds as primary supplier termination criteria (Hawkins et al., 2020; Dey et al., 2015). However, we demonstrate that firms benchmark suppliers against peer performance rather than evaluating them in isolation. This finding challenges the prevailing assumption that supplier termination decisions are primarily driven by absolute performance failures. Instead, our results reveal that firms employ sophisticated comparative evaluation processes that consider the performance landscape across their entire supplier portfolio (Parmigiani and Rivera-Santos, 2011).

Second, we advance discussions on supplier termination risk and continuity trade-offs (Jindal et al., 2021; Wu et al., 2023). Prior work suggests that high switching costs and regulatory risks deter firms from terminating underperforming suppliers (Wouters et al., 2005; Kaplan and Henderson, 2005). Our study extends this by showing that high-risk environments moderate supplier termination decisions, with firms prioritizing supply continuity over strict performance adherence. This contribution is particularly important because it provides empirical evidence for the theoretical tension between optimal contracting and operational constraints in supply chain management.

2. Related literature and hypothesis development

2.1. Literature review

2.1.1. Factors influencing supplier termination

Supplier termination decisions are shaped by performance evaluations, decision-making biases, strategic considerations, and power dynamics. First, supplier performance is a key determinant of termination decisions, with firms assessing economic, environmental, and risk-related factors before making termination choices (Dey et al., 2015;

[2] Toyota ended its relationship with ChassisCo in 2002 after ongoing quality failures and unresolved nonconformance in key chassis parts, despite repeated Toyota interventions (Fine et al., 2017). In 2022, Apple suspended display orders to BOE after finding unapproved design changes and quality issues in iPhone OLED panels, stressing compliance and delivery standards for suppliers (Digital Trends, 2025, February 9).

Zhang and Du, 2018). Performance evaluation models often integrate multiple criteria, including cost, quality, delivery, and responsiveness (Bhutta and Huq, 2002). Empirical studies indicate that poor results on key performance indicators commonly trigger supplier termination (Hawkins et al., 2020). Joseph et al. (2016) demonstrate that organizational structure influences how performance feedback is processed and termination decisions are made, with centralized structures affecting performance interpretation and aspiration levels that trigger termination. Clough and Piezunka (2020) reveal that termination decisions are also influenced by vicarious performance feedback through network connections, where firms observe how other buyers interact with suppliers to inform their own termination decisions. In industry-specific research, such as in the automotive sector, manufacturers rely on defect rates, delivery reliability, and cost efficiency when making supplier termination decisions (Helper and Sako, 2010). Recent studies suggest that firms dynamically adjust their supplier portfolios based on performance changes, treating supplier entry and exit as strategic options under uncertainty (Noorizadeh et al., 2021).

Second, research examines the role of cognitive biases in supplier termination decisions. Studies document how cognitive factors can distort termination decisions, with evidence showing that negative framing of performance metrics can lead to premature termination (Wong, 2021) and that subjective biases introduce evaluation inefficiencies (Peng and Lu, 2017). However, the literature also demonstrates that firms can mitigate these biases through structured performance evaluation mechanisms and quantifiable performance data (Peng and Lu, 2017).

Third, strategic considerations beyond immediate performance metrics shape supplier termination dynamics. Zaefarian et al. (2017) demonstrate that firms adopt a capability perspective when making termination decisions, evaluating suppliers' underlying capabilities for innovation and long-term value creation rather than focusing solely on current performance shortfalls. This strategic approach intersects with market power asymmetries, where firms with significant bargaining leverage, such as Apple and Walmart, can strategically rotate suppliers to maintain cost advantages and reduce dependency (Li and Debo, 2009; Gereffi and Christian, 2009). In contrast, smaller firms with weaker bargaining positions often struggle to replace key suppliers, making them more dependent on capability development and relationship management rather than termination as a strategic option (Blasi and Bair, 2019).

2.1.2. *The supplier termination process*

The process of supplier termination involves structured evaluations, risk assessments, and cost considerations to ensure minimal disruption to supply chains. First, before terminating a supplier, firms assess multiple dimensions, including risk exposure, alternative supplier benchmarking, and potential supply chain disruptions (Niu et al., 2019; da Silva et al., 2020). In the aerospace sector, phased termination strategies and redundancy plans are often employed to minimize operational disruptions (Tang et al., 2009). Sustainability governance frameworks further suggest that firms integrate termination risks into broader sustainability management strategies (Jamalnia et al., 2023).

Second, switching suppliers entails significant costs, particularly for specialized components. Firms dependent on specific suppliers may tolerate lower performance levels to avoid transition costs (Barthélemy and Quélin, 2006). Case studies in the semiconductor industry show that supplier switching requires investments in retooling and qualification, prompting firms to continue engagements with underperforming suppliers rather than incur immediate transition costs (Kaplan and Henderson, 2005). Additionally, uncertainty surrounding supplier performance evaluations can delay termination decisions. Firms in volatile industries like pharmaceuticals may retain underperforming suppliers due to regulatory and quality constraints (Wouters et al., 2005). Financial constraints can also prevent optimal termination decisions (Wu et al., 2023).

2.1.3. *Relative performance evaluation in supply chain contracting*

Relative Performance Evaluation (RPE) is a core concept in agency theory which enables principals to filter out external noise and isolate agent-specific effort by benchmarking performance against peers (Holmström, 1979; Holmström and Milgrom, 1987). Its ability to reduce measurement noise and curb opportunism makes it particularly valuable in buyer-supplier relationships (Murphy, 2000; Baiman and Netessine, 2004). For instance, buyers often collaborate with suppliers during product development, leveraging peer benchmarks to improve manufacturing process yields (Gurnani et al., 2000; Cooper and Slagmulder, 2004). By using industry peer groups as benchmarks, principals address information asymmetry and align supplier incentives with buyer goals, such as cost efficiency and quality (Kunz and Pfaff, 2002). RPE's effectiveness is well-documented in contexts such as executive compensation and service systems (e.g., Song et al., 2015; Matsumura and Shin, 2006; Jayaraman et al., 2021).

2.2. *Theoretical framework and hypothesis development*

Our theoretical framework primarily draws on agency theory to explain supplier termination decisions in multisourcing environments.[3] Agency theory, particularly through RPE mechanisms, provides the framework for understanding how firms use comparative performance evaluation to make termination decisions while managing information asymmetry and incentive alignment (Holmström, 1979; Baiman & Rajan, 2002). RPE mechanisms are particularly valuable in supplier termination contexts because they help buyers distinguish between performance problems that are supplier-specific versus those caused by common external factors affecting all suppliers. The application of agency theory to supplier termination decisions involves both performance evaluation challenges and strategic considerations about relationship continuation. When supply risk is high, the effectiveness of performance-based termination criteria may be constrained by operational factors such as switching costs, supplier scarcity, and component specialization, creating a tension between optimal incentive provision and practical constraints.

2.2.1. *Supplier scorecard performance and supplier termination*

Drawing on agency theory, supplier scorecards serve as structured monitoring mechanisms that enable principals (buyers) to evaluate agent (supplier) performance across multiple dimensions (Holmström, 1979; Murphy, 2000). Buyers use scorecard systems to grade suppliers into high and low-performance clusters (Kulp et al., 2004). This grading process serves as both a diagnostic tool for the purchase order decision and a communication mechanism for the parties to discuss the supplier's performance status. Scorecards address the fundamental agency problem of performance observability by providing systematic, multi-dimensional performance measures that reduce information asymmetry between buyers and suppliers (Baiman & Rajan, 2002). The process also provides suppliers with a clear performance improvement roadmap (Ireland and Webb, 2007). For example, Kulp et al. (2004) describe a sourcing process at an automobile manufacturer where suppliers are evaluated on a three-month moving average across multiple dimensions and ranked on a 0–100 scale. Based on their rankings, suppliers are categorized as green, yellow, or red. With management approval, buyers may bypass a 'green' supplier to order from lower-ranked 'yellow' or 'red' suppliers if needed.

[3] While the literature demonstrates that cognitive biases can influence supplier termination decisions (Wong, 2021), our study adopts an agency theory framework that focuses on rational performance evaluation mechanisms. This approach examines how firms use structured scorecard assessments and peer comparisons to systematically evaluate termination decisions, consistent with research showing that quantifiable performance data can help mitigate subjective biases (Peng and Lu, 2017).

Agency theory supports this relationship through its emphasis on performance-based contracting, where poor performance signals indicate declining agent value and increased likelihood of contract termination (Holmström, 1979). When supplier performance deteriorates, the expected future value of the relationship declines from the buyer's perspective, increasing the probability of termination as buyers seek to maintain performance standards and supply chain effectiveness.

In our case setting (explained in Section 3), the scorecard consists of five dimensions (cost, quality, delivery, service and technology) (see Table 1). Every month, suppliers are scored on these dimensions, and procurement teams use this scoring to speed up their purchase order decision process, as well as provide underperforming suppliers with a clear performance improvement roadmap (Ireland and Webb, 2007; Wever et al., 2012). Therefore, based on agency theory predictions about performance-based contracting, we hypothesize.

H1. Ceteris Paribus, the supplier's termination decision is a negative function of the supplier's scorecard performance change.

2.2.2. *Peer supplier scorecard performance and supplier termination*

The theoretical foundation for incorporating peer supplier performance is based on the informativeness principle of agency theory, which states that any informative signal about an agent's effort should be incorporated into optimal incentive contracts to enhance contracting efficiency (Holmström, 1982). Peer performance provides information about the focal supplier's efforts when suppliers face "common shocks." Common shocks represent external factors that affect all suppliers in a component category similarly, such as raw material price fluctuations, regulatory changes, or technology disruptions. By comparing a focal supplier's performance to peer suppliers facing similar external conditions, buyers can better isolate supplier-specific effort from environmental factors (Banker and Datar, 1989).

This filtering mechanism is particularly valuable in supplier termination decisions because it helps buyers distinguish between performance problems that are supplier-specific (indicating potential termination candidates) versus industry-wide challenges that may not warrant termination. From an agency theory perspective, strong peer supplier performance provides a benchmark that makes underperforming suppliers more salient and increases termination likelihood. When peer suppliers demonstrate superior performance, it signals that better performance levels are achievable, making retention of poorly performing suppliers less justifiable from a contracting efficiency standpoint (Li and Debo, 2009).

Besides relying on the supplier's performance as indicated by their scorecard, we expect that firms will incorporate supplier RPE into the supplier termination decision process. We predict a positive association between the performance of peer suppliers and the termination decision for other suppliers within each component category. This prediction aligns with agency theory insights about the comparative efficiency of performance evaluation and contracting mechanisms. Thus, we hypothesize.

H2. Ceteris Paribus, the supplier's termination decision is a positive function of the peer supplier's scorecard performance change.

Table 1
Supplier scorecard at TechCorp.

Scorecard measure[a]	Subdimensions[b]	Evaluator
Operating scorecard measures		
Delivery (*DEL*) (20 %) TechCorp's measurement of the supplier on its delivery	1-1. Supplier on time and in full delivery 1-2. Transportation provider on-time pick-up 1-3. Order picking accuracy 1-4. Transportation provider on-time delivery 1-5. Transportation provider reports loss and damage	*Made by the procurement unit.* Purchase manager
Cost (*COST*) (30 %) TechCorp's measurement of the supplier's cost	2-1. Average unit price of raw material purchases 2-2. Target cost attainment rate 2-3. Total distribution cost reduction year over year 2-4. Distribution cost per unit shipped 2-5. Freight bill accuracy	*Made by the procurement unit.* Purchase manager
Quality (*QUAL*) (35 %) TechCorp measures the supplier's quality.	3-1. Implementation rates of SOP for quality assurance 3-2. Pre-delivery defects 3-3. Post-delivery defects 3-4. Number of delivery complaints received	*Made by the production unit.* Production manager
Qualifying strategic scorecard measures		
Technology (*TECH*) (8 %) TechCorp's measurement of the supplier on its technology	4-1. Achievement in hardware-software system integration 4-2. Technology resources	*Made by the component engineering team* Engineering manager
Service (*SVC*) (7 %) TechCorp's measurement of the supplier on its service	5-1. Response to sample requests 5-2. Supplier response to problems	*Made by the procurement unit.* Purchase manager

Notes.
[a] Percentages in brackets represent the weights assigned by TechCorp. Technology and service responsiveness are qualifying scorecard measures with less weight (15 %) in the order allocation decision. The measures are 'qualifiers' for becoming an approved supplier and are used to manage the suppliers' technological and service capabilities.
[b] We could not get data on any of the scorecard subdimensions.

2.2.3. *Component supply risk as a moderator*

Component supply risk, supplier scorecard performance and supplier termination decisions are intricately linked, as the impact of supplier and peer supplier scorecard performance on termination decisions depends on the level of supply chain uncertainty and information asymmetry created by component supply risk. Information asymmetry in this context refers to the buyer's limited ability to accurately assess supplier performance and capabilities when supply risk is high (Cannon and Perreault, 1999). High supply risk environments are characterized by greater uncertainty about supplier capabilities, market conditions, and alternative supply sources, making it more difficult for buyers to make optimal termination decisions based solely on performance metrics.

Component supply risk reflects the buyer's perception of potential losses from supply disruptions and is influenced by two key factors: the number of suppliers and the degree of component specialization (Ellis et al., 2010). From an agency theory perspective, high component supply risk constrains the buyer's ability to use performance-based termination effectively because the costs and risks of supplier switching may outweigh the benefits of maintaining strict performance standards. In high component supply risk situations, buyers must maintain supplier relationships to ensure continuity, often by keeping them 'warm' (Plambeck and Taylor, 2006). This leads buyers to retain underperforming suppliers in high-risk or high-dependency scenarios (Akrout and Woodside, 2024).

First, fewer suppliers increase supply risk due to higher switching costs and reduced information flow. A larger pool of suppliers fosters competition, incentivizing better performance and providing buyers with more flexibility to switch suppliers in response to poor performance (Ellis et al., 2010). Conversely, buyers face greater information asymmetry when fewer suppliers exist because thin markets limit access to comparable performance benchmarks and alternative supply sources (Cannon and Perreault, 1999). This scarcity creates both higher switching costs and greater uncertainty about alternative suppliers' capabilities, amplifying the risks associated with termination decisions. This scarcity of options amplifies the negative consequences of poor supplier performance, as switching becomes costly and difficult (Barthélemy and Quélin, 2006; Gassenheimer and Manolis, 2001).

Second, specialized components further elevate supply risk due to their customization and integration into early-stage product development (Ittner et al., 1999; Hegde et al., 2005; Perdue and Summers, 1991). Unlike generic components, specialized components often require extensive collaboration and adaptation, increasing design and production risks (Bajari and Tadelis, 2001; Cohen et al., 2003). These components involve relationship-specific investments and tacit knowledge that create switching costs and information asymmetries (Dyer, 1996; Gulati and Singh, 1998). These components are sourced earlier in the product lifecycle, necessitating substantial supplier-buyer interdependence (Cooper and Slagmulder, 2004). Such interdependence heightens information asymmetry and performance risks, including design failures or production ramp-up issues (Dekker, 2004; Dyer, 1996; Gulati and Singh, 1998). Performance risk includes the possibility that one or more of these suppliers will experience a design failure or fail to ramp up production yields to acceptable levels for cost-efficient high-volume production by the product launch date (Cohen et al., 2003).

2.2.4. Theoretical predictions for moderation effects

In such high component risk cases, the supplier's and peer supplier's scorecard performance might not fully reflect the supplier's true capabilities or the full costs and benefits of termination, thus creating adverse incentive costs (Murphy, 2000). From an agency theory perspective, high supply risk increases the noise in performance signals, reducing the informativeness of scorecard measures for termination decisions (Holmström, 1979). Additionally, high supply risk creates contracting constraints that make performance-based termination less viable, as switching costs and supply disruption risks may outweigh the benefits of terminating poorly performing suppliers. For example, Joshi (2023) finds that supplier performance incentives are less effective when technological dynamism is high. In contrast, low supply risk environments make generic component buyer-supplier exchanges more conducive to performance-based termination decisions, reducing adverse incentive costs and supply disruption risks. This increases the likelihood that supplier and peer supplier scorecard performance will impact the termination decision. Summarizing the theoretical predictions for both proxies of component supply risk.

H3a. The negative association between the supplier's scorecard performance and supplier termination is weaker when there is a high component supply risk (i.e., fewer suppliers).

H3b. The negative association between the supplier's scorecard performance and supplier termination is weaker when there is high component supply risk (specialized components).

H4a. The positive association between the peer supplier's scorecard performance and supplier termination is weaker when there is a high component supply risk (i.e., fewer suppliers).

H4b. The positive association between the peer supplier's scorecard performance and supplier termination is weaker when there is high component supply risk (specialized components).

3. Research site

3.1. Company background and research access

TechCorp (a pseudonym used to protect company confidentiality) is a major international smartphone manufacturer based in Taiwan, ranking among the top five global smartphone manufacturers during our study period (2009–2012). The company shipped over 30 million smartphones annually, maintaining a substantial global market presence (Gartner, 2014). TechCorp operates one of the industry's most extensive supplier ecosystems, managing relationships with over 500 active suppliers who provide billions of components annually across 15 major component categories that comprise approximately 90 % of smartphone value content (see Appendix A for order volume details).[4] The company operates in the highly dynamic smartphone industry characterized by short product life cycles ranging from six to nine months and intense competitive pressures. TechCorp employs sophisticated multisourcing strategies to manage supply chain risks, providing flexibility and enabling competitive benchmarking among suppliers within each component category. The company's procurement decisions are guided by a systematic supplier scorecard system that evaluates performance across multiple dimensions monthly.

We examine the termination decisions for suppliers that had been on TechCorp's accredited list for over two years and received regular allocations. During field visits, interviews were conducted with the Global Logistics Manager, Purchasing Manager, Senior Accountant, and Chief Operations Officer to understand factors influencing supplier selection and termination decisions. These interviews explored how sourcing decisions are guided by TechCorp's systematic supplier scorecard system, which conducts monthly evaluations across five dimensions: delivery, cost, quality, technological capability, and service. Through these interviews, we gained detailed insights into TechCorp's supplier management processes. We obtained access to proprietary data on supplier performance evaluations and termination decisions over 42 months from July 2009 to December 2012.

3.2. Supplier scorecard system at TechCorp

The scorecard measures five categories of performance: delivery, cost, quality, technology, and service responsiveness (*DCQTS,* see Table 1). Once production of a new product begins, the supplier scorecard measures for that component are updated monthly based on feedback from the vendor management team members. Delivery is assessed based on the supplier's transportation provider's ability to ensure on-time pick-up and delivery, accurate reporting of loss or damage, and order-picking precision. Adjustments to the rating may reflect whether the supplier offers shorter lead times or demonstrates supply flexibility by maintaining a surplus capacity to guarantee uninterrupted supply to TechCorp. Cost is evaluated through the average unit price of raw materials, target cost attainment rate, distribution costs, and freight bill accuracy. A key aspect of cost evaluation is the supplier's ability to maintain a 70 % yield rate on new components, directly impacting TechCorp's operational efficiency. Quality is rated by the quality team in collaboration with the production manager, focusing on four sub-indicators: adherence to standard operating procedures for quality assurance, pre- and post-delivery defect rates, and the volume of

[4] Our research setting enhances generalizability beyond a single-firm study in several ways. TechCorp's 15 core component categories represent standard production requirements across all major smartphone manufacturers (Dedrick and Kraemer, 2017). The scale of operations—with individual suppliers receiving orders exceeding one billion units monthly—reflects the complexity characteristic of leading global electronics manufacturers. TechCorp's multi-sourcing approach (2–11 suppliers per component) represents standard industry practice (Sodhi and Tang, 2012).

delivery complaints. The quality team actively tracks costs and manages cost-down targets through regular supplier visits, monitoring process consistency, and holding quarterly meetings to address performance gaps.

Technology assesses the supplier's technological resources and their proficiency in hardware and software integration. While initial technology assessment is critical for supplier approval, ongoing evaluations emphasize sustainability—whether the supplier can maintain their technological capabilities over three years. Service measures the supplier's responsiveness to sampling requests, issue resolution within 24 h ("corrective action response"), and proactive communication of schedule or specification changes. Suppliers earn higher ratings for promptness in addressing service requests and providing samples upon demand, ensuring alignment with TechCorp's operational needs.

3.3. Data and variable measures

Our study encompasses a 42-month observation period, spanning from July 2009 to December 2012. Our dataset captures detailed transactional and performance information for 78 suppliers across 15 components, resulting in 3066 supplier-month observations (see Table 2). Individual supplier-component relationships vary in duration due to suppliers entering or exiting during this observation window. Many suppliers maintained relationships for the whole 42-month period, while others had shorter durations depending on when they entered TechCorp's supplier base or were terminated (see Appendix A).

The unbalanced nature of our panel reflects the reality of supplier relationships, where some suppliers maintain longer relationships than others due to performance, strategic changes, or market conditions. We also report on the level of supplier continuity for each of the 15 components, noting that our data for some components is limited to 21 months (component 5) while others extend to the full 42 months (component 14) (see Table 2). The data relates to one contract for the supply of a smartphone component for the length of each supplier's continuity. To address potential concerns about the unbalanced panel structure, we conducted several robustness tests, detailed below, and reported the results in Section 4.4.

3.3.1. Dependent variable

Supplier termination (*TERMINATE*) – Our dependent variable captures actual supplier termination events that occurred during our 42-month observation period (July 2009 to December 2012). For each supplier-month observation, the variable equals 0 if the supplier continued their relationship with TechCorp and equals 1 in the month when the supplier was terminated.

We identify suppliers as terminated based on: (1) cessation of purchase orders for at least three consecutive months, (2) no subsequent reinstatement during our observation period and (3) confirmation through management interviews that the relationship was formally discontinued. No suppliers had cessation of purchase orders in the final 2 months. Indeed, many suppliers had zero orders for one (22 suppliers) or two months (6 suppliers) only and were not terminated (see Appendix A). This distinction was crucial for accurately identifying genuine termination events versus temporary disruptions in our dataset. Using this approach, we identified 13 suppliers (16.7 % of our sample) who were terminated during our 42-month observation period. These suppliers showed cessation of purchase orders and confirmed relationship discontinuation, with no subsequent reinstatement during the remaining observation period. This methodology ensures we capture meaningful termination decisions rather than temporary order allocation adjustments.

3.3.2. Independent variables

Supplier Scorecard Measures *(DCQTS)* - To measure supplier performance, we constructed metrics across five key dimensions: delivery (20 %), cost (30 %), quality (35 %), technology (8 %), and service (7 %) (see Table 1). These dimensions were weighted based on their importance in TechCorp's operations and are updated monthly. These individual measures were aggregated into a weighted scorecard metric, *W_DCQTS*, which provides a comprehensive evaluation of supplier performance. Our model used the month-on-month change (ΔW_DCQTS) to capture performance trends.

Peer Supplier's Scorecard Measures *(DCQTS_PEER)* - The peer supplier's performance (*W_DCQTS_PEER*) is measured using the same five-dimensional scorecard applied to all suppliers but represents the performance of the benchmark supplier against whom others are compared. The peer supplier identification and performance measurement process requires a detailed explanation due to its central role in our RPE

Table 2
Component/supplier details.

Component Number/Name		No. of Suppliers	Suppliers[a]	Data range (# months) supplier continuity[b]	Specialization code (0–1)[c]
Strategic lead suppliers – key suppliers					
1	Battery	3	8, **20**, 23	41	1
2	Mechanical (Housing and outside casing)	10	1, 11, **17**, 32, 33, 39, 42, 36, 51, 59	30	1
3	Mechanical (Antenna)	3	**61**, 62, 71	31	1
4	Liquid Crystal display module	6	3, **18**, 19, 37, 40, 58	23	1
5	Touch window	5	21, 25, **29**, 48, 50	21	1
6	Camera module	2	68, **72**	24	1
Generic component suppliers					
7	Pouch	3	5, **14**, 26	37	0
8	Linear	9	13, 19, **28**, 35, 41, 45, 55, 56, 60	29	0
9	Radio Frequency Integrated Circuit RFIC	6	2, **16**, 22, 36, 49, 54	37	0
10	Bare Printed Circuit Board PCB	4	15, 24, **27**, 38	40	0
11	Connector	11	4, 10, **12**, 30, 31, 34, 43, 44, 47, 53, 57	30	0
12	Adapter, Plug	4	**6**, 7, 9, 52	22	0
13	Ceramic capacitor	4	67, 70, **73**, 77	41	0
14	Resistor carbon film	4	65, 74, 76, **78**	42	0
15	Diode	5	63, 64, **66**, **69**, 75	25	0
	Total	78	1~78		

Notes.
[a] The primary peer supplier of each component is shown in **bold**. For component 15, the primary peer supplier was 69 until it was replaced by supplier 66 after month 25. For component 6, there was only one supplier for months 25–42; therefore, only the observations for months 1–24 for this component are included.
[b] Supplier continuity represents how long the supply is continuous within each component before a supplier is dropped.
[c] Specialization code – High level (1) strategic lead suppliers of liquid crystal display modules (optical), touch window, camera module, battery, mechanical housing, and antenna. Low level (0) Suppliers of generic components that are mass-produced and require little coordination with the transacting party. For example, linear, RFIC, PCB, connectors, and various components.

framework. For each component category, we identified the primary peer supplier as the consistently dominant supplier in terms of order volume and strategic importance to TechCorp. The primary peer suppliers identified through this process maintained average purchase order shares ranging from 23 % (component 11) to 76 % (component 6), reflecting their dominant positions within their respective component categories (see Appendix A). This variation in peer supplier dominance provides natural variation in the strength of peer effects across component categories. This identification was validated through interviews with procurement managers who confirmed these suppliers' roles as key benchmarks for performance evaluation. *PEER_SUP* is a dummy variable that equals 1 if a supplier is identified as the primary peer supplier for a component and 0 otherwise.

Importantly, when we examine the termination decision for the peer supplier itself, we use the performance of the second-most-dominant supplier in that component category as the comparative benchmark. This approach ensures that every supplier has a meaningful peer comparison while avoiding the logical inconsistency of comparing a supplier against itself. The month-on-month change in peer supplier performance (*ΔW_DCQTS_PEER*) captures how the benchmark supplier's performance evolution affects termination decisions for other suppliers in the same component category.

Component Supply Risk *(FEWER_SUP & SPECIALIZE) -* We proxy the component supply risk level in terms of the number (fewer) of suppliers or whether the component is specialized. We created the fewer suppliers (*FEWER_SUP*) variable by reversing the sign of the number of suppliers (*NUMBER_SUP*) for each component for any given month, so that higher values of *FEWER_SUP* represent fewer available suppliers (i.e., higher supply risk). The mode of the number of suppliers held for each component was four throughout this study. The number of suppliers used to source complex and generic components have similar ranges: two to eleven suppliers for complex components and three to eleven suppliers for generic components.

Component specialization (*SPECIALIZE*) was constructed based on the amount of *customization*, how critical the component is to the product design's specifics, and the *lead time* needed to bring the component into the product development process (see Table 2). We create an indicator variable for the level of component specialization (Kim and Wilemon, 2003) by grouping the 15 types of components into two categories representing distinct levels of customization and critical lead time coordination between the buyer and supplier (see Table 2). At the high level (1), six components (liquid crystal display modules (optical), touch window, camera module, battery, mechanical housing, and antenna) exhibit high component specialization, necessitating extensive coordination with the transacting party. The remaining nine components (generic) have low component specialization (0) to the extent that they are more likely to be mass-produced, are not part of the final product (e.g., pouch), and require little coordination with the transacting party.

This component specialization grouping was confirmed through interviews with the chief operations officer, who noted, "The product development lifecycle lasts 16 weeks, and the customized and critical components are designed during the first four weeks; in other words, they are baked into the process with a 12 to 16-week lead time." In reference to specific components, the COO notes, the battery is a "critical" component where the supplier is chosen based on "the shortest lead time on what we want based on a mechanical design." Similarly, the Liquid Crystal display module is "customized," with the COO noting they know "every display provider for every project and every allocation because that is important to our success." In contrast, generic components are readily available and do not significantly impact the smartphone's unique features or performance. The COO notes, "the capacity for Linear ICs and RF ICs is typically never an issue - we can order millions and millions of them," and for Radio Frequency Integrated Circuits, the COO states, "I do not care - that is decided way down in the engineering chain." Even customizable accessories like the pouch are considered "generic" because they are "not critical and separate from the smartphone."

3.3.3. Control variables

Supplier Capacity *(SIZE)* is constructed based on three capacity levels provided by TechCorp. Size takes the following values: 1, 2, or 3, where 3 is the largest supplier. 1 = a minimum capacity of 100 million units per month, 2 = a maximum capacity of 1 billion units per month, and 3 = a maximum capacity of more than 1 billion units. For example, 24 of the 78 suppliers had orders exceeding one billion units in one month (see Appendix A). A peer supplier (PEER_SUP) is the leading supplier that TechCorp consistently sources for each component, so controlling its scorecard performance and order volume is essential. Order Volume Growth (*VOL_GROWTH*) represents the month-on-month percentage growth in total order volume across all suppliers. Purchase order volume (*PO_VOL*) represents the total number of units purchased from a supplier on a monthly basis.

Table 3 presents the descriptive statistics of the dependent and independent raw variables. Except for technology and service, the scorecard measures delivery, quality, and cost variables, which exhibit considerable realized variance, as assessed by their standard deviations and ranges in their means. We report on the correlations between the variables used in the models in Table 4.

3.4. Empirical models

We estimated both logistic regression models and Linear Probability Models (LPM) using fixed-effects regression to ensure robustness of our findings. The LPM approach offers several advantages: (1) coefficients directly represent marginal effects on survival probability, facilitating interpretation; (2) it provides a useful robustness check against potential specification issues in nonlinear models; and (3) it enables formal testing for heteroskedasticity using the Modified Wald statistic. Given the binary nature of our dependent variable and to facilitate comparison with prior literature, we report the logistic regression results in our main analysis. Table 5 presents the logistic regression coefficients (log-odds changes). The LPM results are consistent with our reported findings and available upon request.

Given the panel nature of our data, we conducted diagnostic tests to identify potential econometric issues before estimation. The Modified Wald test (Greene, 2000) revealed significant heteroskedasticity across suppliers ($\chi^2 = 247.83$, $p < 0.001$), and Wooldridge tests detected significant first-order autocorrelation in model residuals across all specifications. To address these identified issues, we implemented cluster-robust standard errors grouped at the supplier level (not component or time level), following Petersen (2008)'s recommendations for handling standard errors in panel data. This one-way clustering approach accounts for both heteroskedasticity and within-cluster correlation of error terms across the 78 supplier clusters, which is particularly appropriate for our setting, where supplier-specific factors may create dependence in the error structure across time periods for the same supplier, while maintaining independence assumptions across different suppliers. The comparison of unclustered versus clustered standard errors across key variables demonstrates the empirical impact of this clustering approach on our parameter estimates.[5]

While the LPM assumes a linear relationship between covariates and probability, the consistency of results across both approaches

[5] The comparison reveals that clustered standard errors are consistently smaller than their unclustered counterparts across all variables, with the most pronounced reductions observed in composite and interaction terms (e.g., *SPECIALIZE* x *ΔW_DCQTS_ PEER*: 0.037 vs 0.016) (untabulated results available upon request). In this dataset, supplier clustering appears to eliminate noise rather than account for dependence, suggesting either well-balanced cluster structures with minimal intra-cluster correlation (Petersen, 2008).

Table 3
Descriptive summary.

Variable[c]	Obs.[a]	Mean	Median	Std. Dev.	Normal Range	Min.	Max.
TERMINATE	3066	0.17	0.00	0.40	0~1	0.00	1.00
W_DCQTS	2919	77.09	80.00	16.62	5~100	11.22	100.00
W_DCQTS_PEER	2827	76.24	80.00	16.78	5~100	25.12	100.00
NUMBER_SUP	3066	6.30	5.00	2.86	0~11	1.00	11.00
SPECIALIZE	3066	0.57	0.00	0.82	0~1	0.00	1.00
SIZE	3066	2.16	3.00	0.95	1~3	1.00	3.00
PEER_SUP	3066	0.19	0.00	0.39	0~1	0.00	1.00
VOL_GROWTH	3066	0.70	0.00	19.68		−96.49	123.97
PO_VOL[b]	3066	1979.82	120.44	7871.40		0.00	111,607.00

TERMINATE	The supplier termination variable was given 0 if the supplier survived and 1 if the supplier was terminated.
W_DCQTS	= Weighted summation of five measures = Del (*0.2) + Cost (*0.3) + Qual (*0.35) + Tech (*0.08) + Svc (*0.07)
W_DCQTS_PEER	= Weighted summation of the DCQTS measures of the peer supplier of the component
ΔW_DCQTS	= the month-on-month change in the weighted supplier scorecard measure *W_DCQTS*
ΔW_DCQTS_PEER	= the month-on-month change in the weighted peer supplier scorecard measure *W_DCQTS_PEER*
FEWER_SUP	= Defined as −1 times the number of suppliers (*NUMBER_SUP*) per component per month (so higher values = fewer suppliers, indicating higher supply risk).
SPECIALIZE	= Indicator variable that takes the value of 1 (high component specialization) and 0 (low component specialization). See Table 2 for details.
SIZE	= Supplier capacity - takes the following values: 1, 2, or 3, where 3 is the largest supplier.
PEER_SUP	= Dummy variable that takes the value of 1 if a supplier is identified as the primary supplier for that component, 0 otherwise.
VOL_GROWTH	= Raw growth in millions of units = (*Po_vol* – *Po_vol* in period t-1)/1,000,000
PO_VOL	= Purchase order volume for each supplier each month

Notes.
[a] = Sample size: 3066. *Component*: 1–15; *Supplier*: 1–78; *Month*: 1–42. The data spans 42 months (July 2009 to December 2012).
[b] = Figures represent 10,000s.
[c] = Variable definitions and descriptions.

Table 4
Pearson correlation statistics.

Correlation	1	2	3	4	5	6	7	8
1, TERMINATE	1							
2. W_DCQTS	−0.01	1						
3. W_DCQTS_PEER	−0.01	0.47***	1					
4. FEWER_SUP	−0.07***	−0.01	−0.01	1				
5. SPECIALIZE	−0.13***	−0.01	0.01	0.16***	1			
6. SIZE	−0.15***	−0.01	0.01	−0.41***	−0.31***	1		
7. PEER_SUP	−0.07***	−0.01	0.01	0.01	0.03	−0.20***	1	
8. VOL_GROWTH	−0.01	−0.02	−0.03*	−0.01	−0.01	−0.03	0.02	1
9. PO_VOL	−0.17***	−0.01	0.01	−0.02	0.05***	0.05***	0.38***	0.05***

Notes.
***, **, * indicate p-values of ≤0.01, 0.05, and 0.10 in a two-tailed test.

strengthens confidence in our conclusions. Given the binary nature of our dependent variable and to facilitate comparison with prior literature, we report the logistic regression results in our main analysis. We developed six logistic regression models to systematically examine the relationships between supplier performance, peer performance, component supply risk, and termination decisions. Our general empirical specification takes the form:

$$\text{Logit } TERMINATE_{it} = \beta_0 + \beta_1 \Delta W\_DCQTS_{it} + \beta_2 \Delta W\_DCQTS\_PEER_{it} + \beta_3 FEWER\_SUP_{it} + \beta_4 SPECIALIZE_{it} + \beta_5 SIZE_{it} + \beta_6 PEER\_SUP_{it} + \beta_7 VOL\_GROWTH_{it} + \beta_8 PO\_VOL_{it-1} + y_t + \varepsilon_{it}$$

Where i denotes each supplier index, t denotes time in months, and γ_t represents month fixed effects to control for time-varying factors affecting all suppliers. For interaction models, we add the relevant interaction terms (e.g., $\beta_9 FEWER\_SUP_{it} \times \Delta W\_DCQTS_{it}$) to capture the moderating effects of component supply risk.

Our empirical specification directly corresponds to the theoretical framework presented in Fig. 1, where the main effects (H1, H2) and moderation effects (H3, H4) are tested through the systematic progression of Models 1–6. Our modelling approach follows a structured progression from baseline effects to complex interaction models, allowing us to isolate the specific mechanisms underlying termination decisions:

Model 1 (Baseline effects): Tests the fundamental relationships between supplier scorecard performance change (Δ*W_DCQTS*) and peer supplier scorecard performance change (Δ*W_DCQTS_PEER*) on termination probability, including basic control variables. This model provides the foundation for hypotheses H1 and H2.

Model 2 (Full interaction): Incorporates all interaction terms between performance measures and both component supply risk proxies (*FEWER_SUP* and *SPECIALIZE*) simultaneously, testing all moderation hypotheses (H3a, H3b, H4a, H4b) within a single specification.

Models 3 & 4 (Individual supplier performance interactions): Model 3 isolates supplier performance × supplier scarcity interactions (H3a); Model 4 examines supplier performance × component specialization interactions (H3b). These models allow us to assess each supply risk dimension separately for supplier performance effects.

Models 5 & 6 (Individual peer performance interactions): Model 5 focuses on peer performance × supplier scarcity interactions (H4a); Model 6 examines peer performance × component specialization interactions (H4b). These models isolate each supply risk dimension for peer performance effects.

This structured progression from baseline to interaction models allows us to assess how supply risk moderates performance-termination relationships and identify which supply risk dimensions are most important for different types of performance effects.

Table 5
Logistical regression results for supplier termination decision.

		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
		Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat			Coeff	T-Stat	Coeff	T-Stat
ΔW_DCQTS	H1–	−0.10	−5.61***	−0.06	−3.80***	−0.08	−5.03***	−0.08	−5.05***	−0.06	−3.90***	−0.06	−3.83***
ΔW_DCQTS_PEER	H2+	0.07	4.84***	0.03	2.68***	0.05	3.81***	0.06	4.35***	0.03	3.59***	0.03	3.60***
FEWER_SUP$_{it}$		−0.07	−2.71***	−0.05	−1.83*	−0.06	−2.44**	−0.06	−2.27**	−0.04	−1.72*	−0.04	−1.69
SPECIALIZE$_i$		−0.04	−0.50	−0.01	−0.19	−0.01	−0.14	−0.01	−0.13	−0.01	−0.09	−0.01	−0.10
FEWER_SUP x *ΔW_DCQTS*	H3a–			−0.01	−2.15**	−0.01	−3.46***						
SPECIALIZE x *ΔW_DCQTS*	H3b–			0.01	0.01			−0.01	−0.08				
FEWER_SUP x *ΔW_DCQTS_PEER*	H4a–			−0.01	−1.40					−0.01	−1.84*		
SPECIALIZE x *ΔW_DCQTS_ PEER*	H4b–			−0.04	−2.74***							−0.03	−5.97***
SIZE$_i$		2.52	3.40***	0.14	1.91*	0.20	2.82***	0.20	2.81***	0.14	1.93*	0.14	1.93*
PEER_SUP$_{i,t}$		0.21	1.01	0.09	0.44	0.14	0.68	0.14	0.68	0.08	0.43	0.08	0.43
VOL_GROWTH$_{i,t}$		0.01	1.47	0.01	1.26	0.01	1.18	0.01	1.28	0.01	1.32	0.01	1.36
PO_VOL$_{t-1}$		−0.06	−0.99	−0.04	−0.66	−0.05	−0.78	−0.04	−0.73	−0.04	−0.62	−0.04	−0.62
Pseudo R^2		0.02		0.03		0.03		0.02		0.02		0.03	
LR Wald Chi-square		52.82		91.59		51.38		39.74		33.28		57.71	
Pr > *F*:		0.00		0.00		0.00		0.00		0.00		0.00	
Observations		2532		2532		2532		2532		2532		2532	
Clustered SE variable		Supplier		Supplier		Supplier		Supplier		Supplier		Supplier	
Month FE		Yes		Yes		Yes		Yes		Yes		Yes	

3.5. Robustness checks and econometric procedures

To further validate our findings, we conducted bootstrap regression models with cluster-level resampling by supplier, maintaining the same 78 supplier structure as our main analysis. We used the bias-corrected and accelerated bootstrap method with 1000 replications, which provides more reliable confidence intervals than standard approaches by adjusting for bias and skewness in the distribution (Efron and Hastie, 2021). By avoiding strict parametric distributional assumptions, the bootstrap provides additional protection against potential autocorrelation and cross-sectional dependence. This approach is particularly valuable because it empirically validates our inference, addressing both intra-cluster correlation and potential deviations from parametric error assumptions identified during diagnostic testing. The detailed results and validation of robustness using bootstrap methods are presented in Section 4.

4. Results

4.1. Descriptive statistics and correlations

Table 3 presents descriptive statistics for all variables in our analysis. The termination rate in our sample is 20 %, indicating that approximately one in five supplier relationships ended before reaching our 40-month threshold. This termination rate is consistent with industry benchmarks in the electronics sector, where supplier turnover is relatively high due to technological changes and competitive pressures (Ernst, 2005; Sturgeon, 2002).

The supplier scorecard measures (*W_DCQTS*) show substantial variation with a mean of 77.09 and a standard deviation of 16.62, indicating meaningful performance differences across suppliers. Similarly, peer supplier performance (*W_DCQTS_PEER*) exhibits comparable variation (mean = 76.24, SD = 16.78), providing sufficient variation to test our RPE hypotheses. The number of suppliers per component averages 6.30 with substantial variation (SD = 2.86), while 57 % of our observations involve specialized components, creating natural variation in our supply risk measures.

Table 4 shows correlation statistics among key variables. Notably, the correlation between supplier and peer supplier performance is moderate (0.47), suggesting these measures capture related but distinct performance dimensions. The relatively low correlations between our supply risk measures and performance variables reduce concerns about multicollinearity affecting our interaction term interpretations.

4.2. Hypotheses tests

Table 5 presents results from six logistic regression models with robust standard errors clustered at the supplier level (78 clusters). As previously described, clustering standard errors at the supplier level adjusts for within-supplier correlation, providing robust inference for our results.

4.2.1. Baseline performance effects (H1 and H2)

Model 1 in Table 5 presents results for our baseline hypotheses examining the direct effects of supplier and peer supplier performance on termination decisions. H1 posits that the supplier's termination probability is a negative function of the change in the supplier's scorecard performance (Δ*W_DCQTS*). The results in Model 1 show that the Δ*W_DCQTS* coefficient is −0.10 and highly significant ($p < 0.01$). This supports H1 and confirms the argument that the supplier's scorecard performance change serves as a critical input for termination decisions. From a theoretical perspective, this finding aligns with predictions from agency theory regarding performance-based contracting.

H2 posits that the supplier's termination probability is a positive function of the peer supplier's performance change (Δ*W_DCQTS_PEER*). The results in Model 1 reveal that the Δ*W_DCQTS_PEER* coefficient is

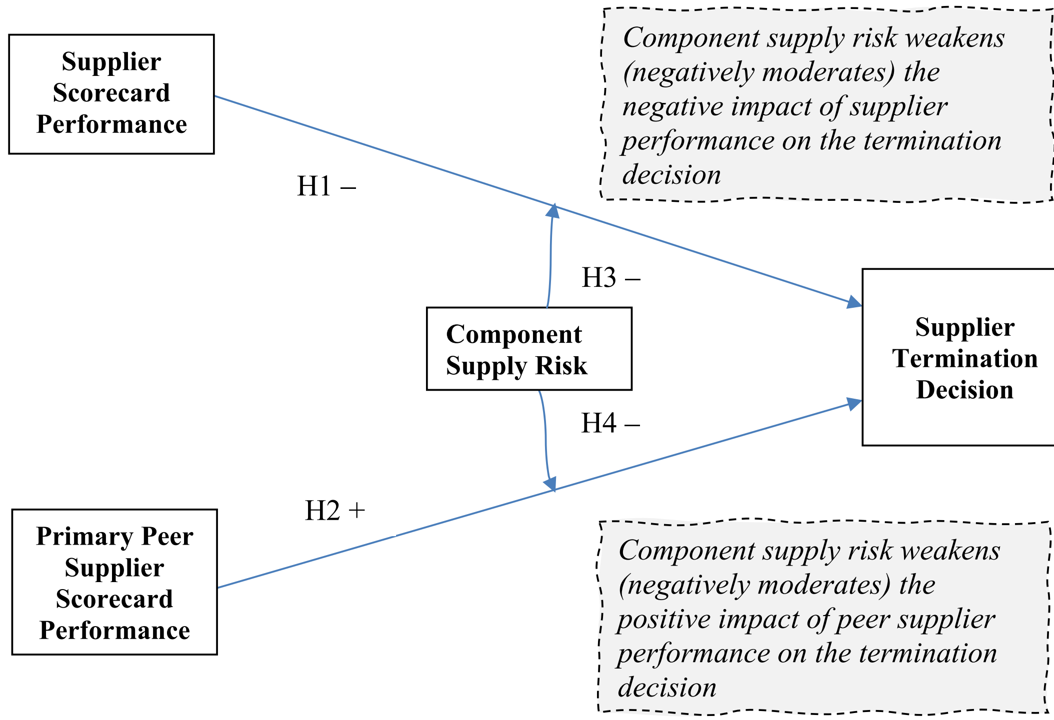

Fig. 1. Summarizes our theoretical framework, showing how supplier and peer performance influence termination decisions (H1, H2), and how component supply risk moderates these relationships (H3, H4).

0.07 and highly significant ($p < 0.01$). This finding strongly supports H2 and provides novel empirical evidence for RPE mechanisms in supplier termination decisions. The positive coefficient confirms that strong peer performance makes termination of other suppliers more likely, consistent with agency theory's informativeness principle and the effectiveness of comparative performance evaluation in contracting.

4.2.2. *Supplier performance moderation (H3)*

H3 posited that the negative association between the supplier's scorecard performance and supplier termination would be weaker when component supply risk is high. Model 2 presents our full interaction specification, while Models 3 and 4 examine each supply risk dimension separately to provide detailed insights into the moderation mechanisms.

Consistent with H3a, the interaction coefficient for supplier performance and *FEWER_SUP* is −0.01 and significant ($p < 0.01$) in Model 2. The negative coefficient indicates that the termination-reducing effect of good supplier performance becomes weaker when there are fewer suppliers available. This finding is reinforced in Model 3, where the isolated interaction shows a coefficient of −0.01 ($p < 0.001$), confirming the robustness of this moderation effect.

However, the interaction between supplier performance and component specialization (*SPECIALIZE*) shows inconsistent results across models. In Model 2, the coefficient is statistically insignificant (0.01, $p > 0.10$), and Model 4 confirms this lack of significance. This suggests that H3b is not supported, indicating that component specialization alone does not significantly moderate the supplier performance-termination relationship.

The differential results for H3a versus H3b provide important theoretical insights. Supplier scarcity appears to create more binding constraints on termination decisions than component specialization, possibly because scarcity directly limits the availability of alternative options. In contrast, specialization represents capability requirements that might be met through supplier development rather than termination.

4.2.3. *Peer performance moderation (H4)*

H4 posited that the positive association between peer supplier scorecard performance and supplier termination would be weaker when component supply risk is high. The results show more complex patterns than predicted, with both supply risk dimensions playing important roles.

For H4a, Model 2 shows that the interaction between peer supplier performance and *FEWER_SUP* is −0.01, but it is not statistically significant ($p > 0.10$). However, Model 5, which isolates this interaction, reveals a marginally significant coefficient of −0.01 ($p < 0.10$). This provides weak support for H4a, suggesting that supplier scarcity somewhat reduces the impact of peer performance on termination decisions, but the effect is not as strong as predicted.

The results for H4b are much stronger and more consistent. The interaction between peer supplier performance and *SPECIALIZE* is −0.04 and highly significant ($p < 0.01$) in Model 2, and this finding is confirmed in Model 6 with a coefficient of −0.03 ($p < 0.001$). This provides strong support for H4b, indicating that component specialization significantly weakens the positive relationship between peer supplier performance and termination decisions.

The stronger results for specialization versus supplier scarcity in peer performance moderation (H4b vs H4a) suggest different mechanisms at work. Component specialization may create relationship-specific investments and switching costs that make peer comparisons less relevant for termination decisions, while supplier scarcity affects the availability of alternatives regardless of performance comparisons.

4.3. *Model comparisons and bootstrap validation*

Comparing across our six model specifications provides additional insights into the robustness and mechanisms underlying our findings. The progression from Model 1 (baseline effects) through Models 2–6 (various interaction specifications) reveals consistent patterns, with some notable nuances. The model fit statistics indicate that the interaction models (Models 2–6) provide a significantly better fit than the baseline model, with Pseudo R^2 values ranging from 0.02 to 0.03 and LR

Wald Chi-square statistics all highly significant ($p < 0.001$). These low Pseudo R^2 values are expected in fixed-effects logistic panel models and do not undermine the validity of our findings. This improvement in model fit confirms that supply risk moderation effects are both empirically and economically meaningful.

To further validate the robustness of our findings, we conducted bootstrap regression analysis with cluster-level resampling by supplier, maintaining the same 78 supplier structure as our main analysis. Bootstrap methodology provides non-parametric validation that does not rely on strict distributional assumptions and offers additional protection against potential autocorrelation and cross-sectional dependence issues identified in our diagnostic testing. Bootstrap results using 1000 replications with bias-corrected confidence intervals replicate the same model specifications as Table 5, confirming the robustness of all reported coefficients and significance levels (untabulated results available upon request).

The bootstrap results were reassuring. Standard errors closely matched our cluster-robust estimates—for instance, the bootstrap standard error for our key performance variable (ΔW_DCQTS) was 0.0184 versus our original 0.0185, well within normal sampling variation. The bootstrap validation confirmed our core results: supplier performance improvements significantly reduced termination probability, while peer performance improvements increased termination risk for other suppliers. All key relationships remained statistically significant across the different confidence interval methods, with bias estimates generally small (less than 5 % of coefficient values), suggesting that our original estimates were largely unbiased. This alignment between our parametric cluster-robust and the non-parametric bootstrap methods gives us confidence that our findings aren't simply artifacts of our chosen estimation technique.

4.4. Sensitivity tests

We conducted several sensitivity analyses to assess the robustness of our findings and address potential concerns about our research design.

4.4.1. Supplier capacity constraints

The RPE framework assumes that suppliers have sufficient capacity to receive additional orders if they outperform peers. We examined supplier capacity utilization by analyzing the distribution of order volumes relative to suppliers' maximum observed orders. Our analysis reveals substantial flexibility in order allocation: the difference between minimum and maximum orders ranged from 80 % to 100 % of maximum capacity across suppliers, and order size distributions were consistently skewed toward the lower end (negative skewness for 76 of 78 suppliers). This indicates that TechCorp maintained substantial flexibility in order allocation and was not constrained by supplier capacity limitations that might compromise RPE mechanisms.

4.4.2. Order volume growth patterns

Our theoretical framework assumes that overall demand growth provides opportunities for performance-based reallocation rather than requiring termination due to declining orders. Analysis of growth patterns across 60 component-years revealed negative growth in only 11 instances, primarily concentrated in component 7 (accessories), which experienced negative growth in all years. When we exclude these component-years from our analysis, all main results remain qualitatively unchanged, confirming that our findings are not driven by demand decline-induced terminations.

4.4.3. Temporal stability and alternative threshold specifications

To assess whether our results are driven by specific time periods or market conditions, we estimated our models for different subperiods within our 40-month observation window. Results remain consistent across early (months 1–21) versus late (months 22–40) periods, indicating that our findings reflect stable behavioral patterns rather than temporary market conditions. We also tested alternative thresholds for our termination variable (e.g., 36 months instead of 40 months) to ensure our results are not sensitive to the specific cutoff choice. Results remain consistent across these alternative specifications, with coefficient magnitudes and significance levels showing minimal variation.

5. Discussion and implications

Our empirical findings provide strong support for agency theory mechanisms in understanding supplier termination decisions in multisourcing environments, with one primary theoretical contribution and important boundary conditions that reveal when these mechanisms are most effective.

5.1. Relative performance evaluation in supplier termination

Our primary contribution demonstrates that firms employ sophisticated relative performance evaluation (RPE) mechanisms rather than relying solely on absolute performance thresholds in supplier termination decisions. This finding provides the first empirical evidence of RPE application to supplier termination contexts and challenges the prevailing assumption that termination decisions are primarily driven by absolute performance failures (Hawkins et al., 2020; Dey et al., 2015).

Our findings reveal that TechCorp systematically benchmarks suppliers against peer performance, with strong peer supplier performance significantly increasing termination probability for other suppliers (H2 supported). The robust statistical significance of these relationships indicates that RPE mechanisms represent a fundamental component of supplier management practices in multisourcing environments, rather than ad hoc decision-making processes. This supports agency theory's informativeness principle in inter-firm settings, showing that buyers use peer performance signals to filter out common market shocks and isolate supplier-specific performance issues (Li and Debo, 2009). These findings demonstrate that firms employ sophisticated comparative evaluation processes that consider the performance landscape across their entire supplier portfolio (Parmigiani and Rivera-Santos, 2011).

5.2. Boundary conditions: supply risk moderation of RPE effectiveness

Our findings reveal important contingencies that moderate the effectiveness of RPE mechanisms, demonstrating when performance-based termination criteria become constrained by operational factors. Component supply risk systematically moderates performance-termination relationships through distinct mechanisms: supplier scarcity weakens the positive relationship between supplier performance and survival (H3a supported), while component specialization weakens the negative relationship between peer supplier performance and termination (H4b supported).

When suppliers are scarce, firms become reluctant to terminate even poorly performing suppliers (Bai et al., 2021; Ellis et al., 2010). The results show that performance-based termination effects are weakened when supplier availability is limited. For peer performance effects, component specialization creates constraints, as relationship-specific investments and switching costs make peer comparisons less relevant (Kaplan and Henderson, 2005). These findings illustrate how information asymmetry and switching costs operate in high-risk supply environments, highlighting the boundary conditions of performance-based contracting and explaining why performance-based supplier management practices vary in effectiveness across different contexts (Helper and Sako, 2010; Zhang and Du, 2018).

These theoretical mechanisms extend beyond electronics manufacturing to other complex multisourcing environments. Helper and Sako (2010) demonstrate similar performance evaluation and supplier comparison mechanisms in automotive manufacturing, while Tang et al. (2009) show how supply risk constraints affect supplier management decisions in aerospace. This suggests that RPE processes, supply risk moderation of performance-based decisions, and performance-constraint tensions represent fundamental challenges across technology-intensive industries with complex supplier networks.

5.3. Practical implications

Our results demonstrate that traditional performance-based termination criteria become less predictive when supply risk is high, creating situations where strict adherence to performance criteria may lead to supply disruptions that are more costly than retaining underperforming suppliers. This highlights the tension between optimal incentive provision and operational constraints in supply chain management, where firms must balance performance standards with supply continuity concerns (Jindal et al., 2021; Wouters et al., 2005). These findings provide actionable guidance for supply chain managers: RPE mechanisms can be applied effectively for components with multiple suppliers and low specialization. In contrast, high-risk components require more cautious approaches that prioritize relationship maintenance and supplier development over strict performance-based termination (Krause et al., 2007).

6. Conclusions and future research

This study helps us better understand how companies decide to terminate suppliers by applying agency theory in environments where firms use multiple suppliers. Using detailed data from a major international electronics manufacturer that tracked 78 suppliers across 15 components over 42 months, we found evidence that companies use RPE when making termination decisions, and that supply risks significantly influence these choices.

Our study has important limitations that affect how we should interpret and apply these findings, though they also point to promising directions for future work. First, studying just one company naturally raises questions about broader applicability. However, several factors suggest our results are likely relevant beyond this single case. TechCorp operates as one of the world's largest smartphone manufacturers, managing over 500 suppliers - a scale and complexity typical of major global technology companies. The systematic performance tracking and competitive supplier strategies we observed are now standard practice across consumer electronics manufacturing (Strange and Zucchella, 2017; Baldwin and Lopez-Gonzalez, 2015).

More importantly, the core mechanisms we uncovered—how companies compare suppliers against each other, how supply risks shape performance-based decisions, and the ongoing tension between demanding high performance while ensuring supply continuity—represent challenges that many companies face when managing complex supplier networks. These agency theory principles and RPE mechanisms likely apply well beyond electronics manufacturing to other industries where companies juggle multiple suppliers while balancing performance expectations with operational continuity (Gereffi, 2017; Shih, 2020).

Our second major limitation involves the data itself. The monthly performance data and our inability to access detailed scorecard subdimensions constrained our analysis. Additionally, our supplier capacity measurement in three broad categories and component specialization as binary classification represent relatively crude measures that may obscure more nuanced effects. Our 42-month observation period may not capture very long-term relationship patterns, and we lack complete information about specific termination reasons.

Future research can address these limitations through several directions. Multi-industry extensions could examine how RPE mechanisms operate across various industries, including automotive (Helper and Sako, 2010), pharmaceuticals (Wouters et al., 2005), and aerospace (Tang et al., 2009), to establish boundary conditions and identify contextual factors that enhance the effectiveness of comparative performance evaluation. Additionally, supplier behavioral response research should examine how suppliers modify their behavior under RPE-based evaluation systems, whether competitive benchmarking creates productive dynamics, and design features that maximize positive incentive effects while minimizing unintended consequences. Understanding how decision-making biases might influence the application of RPE or the weighting of supply risk would provide valuable behavioral insights into supplier termination decisions. Trust and relationship quality studies could explore how interpersonal relationships, shared investments, and mutual trust moderate performance-termination relationships, investigating how different buyer-supplier relationship types (transactional, collaborative, strategic partnerships) exhibit different evaluation and termination patterns.

In conclusion, this study offers valuable insights into supplier termination decisions for both researchers and practitioners, while highlighting opportunities for future research. The application of agency theory and RPE mechanisms provides a foundation for continued theoretical development in supplier management, while our empirical findings provide practical guidance for supply chain managers navigating complex performance evaluation and supplier relationship management challenges.

CRediT authorship contribution statement

Neale G. O'Connor: Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Investigation, Conceptualization. **Jorge Romero:** Validation, Methodology, Formal analysis, Data curation. **Kaveh Asiaei:** Writing – review & editing, Methodology.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used CLAUDE AI and Grammarly for rechecking references, spelling, and grammar in various parts. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

APPENDIX A

Descriptive summary

We summarize the order quantity of 78 suppliers to show the range of orders, the mean percentage of the maximum order, and the average order percentage obtained by each supplier.

Component #	Supplier #	Obs.	Mean	Median	Min.	Max.	Volume Range as % of Max.	Skewness	Mean % of Max Order	Average Purchase Order %[c]
1	8	42	85,953,229	79,940,908	5,346,304	295,481,800	98 %	1.806	29 %	37 %
1	20*	41	74,811,701	66,862,689	22,039,720	165,567,916	87 %	0.706	45 %	37 %
1	23	41	60,182,799	47,473,414	7,194,486	156,265,359	95 %	0.717	39 %	29 %
2	1	42	815,448,019	621,825,422	91,432,227	3,017,155,162	97 %	1.303	27 %	11 %
2	11	42	1,867,031,701	1,771,558,050	394,201,540	4,753,422,339	92 %	0.932	39 %	22 %
2	17*	42	2,930,015,083	2,793,630,217	992,601,164	5,064,891,687	80 %	0.144	58 %	37 %
2	32	42	873,311,861	803,619,981	18,200,582	1,945,318,446	99 %	0.280	45 %	8 %
2	33	42	384,739,871	204,326,926	4,580,897	2,187,077,170	100 %	2.524	18 %	6 %
2	39	41	905,085,117	819,859,390	5,437,296	2,180,346,736	100 %	0.166	42 %	6 %
2	42	41	260,651,182	295,127,123	53,504,384	516,875,293	90 %	0.075	50 %	3 %
2	46	30	8,615,221	6,752,247	426,774	23,005,389	98 %	0.412	37 %	1 %
2	51	42	287,655,221	245,266,706	54,587,144	687,135,592	92 %	0.666	42 %	3 %
2	59	42	391,015,207	342,752,675	130,285,922	930,537,461	86 %	0.949	42 %	5 %
3	61*	41	33,797,872	18,721,852	0	200,049,294	100 %	1.879	17 %	47 %
3	62	41	15,265,694	584,169	0	213,315,558	100 %	4.003	7 %	10 %
3	71	31	49,432,269	23,603,593	0	194,707,001	100 %	1.387	25 %	48 %
4	3	42	46,182,170	44,497,630	8,275,762	193,335,035	96 %	2.360	24 %	18 %
4	18*	42	106,106,555	92,153,947	6,240,488	319,427,457	98 %	0.813	33 %	36 %
4	19	42	58,929,429	51,895,194	9832	155,038,018	100 %	0.316	38 %	23 %
4	37	38	14,614,260	4,388,365	9218	76,712,990	100 %	1.702	19 %	14 %
4	40	42	7,231,186	46,087	4356	66,002,393	100 %	2.511	11 %	10 %
4	58	23	4,308,068	3,358,286	3388	19,249,490	100 %	2.116	22 %	2 %
5	21	21	79,381,917	70,534,234	31,034,718	153,384,695	80 %	0.604	52 %	41 %
5	25	40	37,171,821	32,325,591	2,337,366	119,399,677	98 %	1.230	31 %	17 %
5	29*	41	138,561,081	119,270,791	13,615,582	334,905,388	96 %	0.456	41 %	38 %
5	48	41	40,432,623	10,016,420	1,095,726	138,329,748	99 %	0.932	29 %	7 %
5	50	41	24,176,547	12,471,518	63,335	393,778,000	100 %	5.779	6 %	10 %
6	68	24	49,543,739	53,521,365	123,696	94,363,570	100 %	−0.214	53 %	30 %
6	72*	24	265,658,388	270,948,415	46,281,955	736,916,300	94 %	0.587	36 %	76 %
7	5	40	10,466,742	8,139,400	288,031	40,990,302	99 %	1.460	26 %	52 %
7	14*	37	10,398,242	8,745,506	744	42,639,126	100 %	1.261	24 %	41 %
7	26	40	2,890,135	1,642,882	60,747	14,499,584	100 %	1.893	20 %	10 %
8	13	41	358,954,228	311,152,204	26,095,486	974,219,046	97 %	0.503	37 %	15 %
8	19	29	455,757,101	433,525,847	28,431,647	998,025,039	97 %	0.939	46 %	23 %
8	28*	42	1,366,194,679	1,215,988,550	84,178,457	4,187,759,624	98 %	0.898	33 %	41 %
8	35	24	172,896,652	174,628,911	8,465,312	542,754,735	98 %	1.153	32 %	7 %
8	41	42	40,510,095	29,809,172	3,072,765	127,206,441	98 %	1.040	32 %	2 %
8	45	38	131,935,861	113,604,289	341,460	467,449,262	100 %	0.960	28 %	5 %
8	55	42	52,171,035	36,207,768	3059	231,807,426	100 %	1.581	23 %	2 %
8	56	42	64,799,630	30,778,031	4200	238,727,351	100 %	0.967	27 %	6 %
8	60	36	3,023,868	1,571,366	65,986	16,399,861	100 %	2.123	18 %	1 %
9	2	42	253,547,126	237,331,258	49,747,988	550,318,429	91 %	0.650	46 %	20 %
9	16*	42	852,944,316	777,994,450	221,640,607	2,025,406,202	89 %	0.795	42 %	63 %
9	22	37	89,058,262	80,956,496	2,299,824	414,115,056	99 %	2.868	22 %	8 %
9	36	42	132,769,255	121,508,123	1,263,453	401,489,703	100 %	1.137	33 %	6 %
9	49	42	46,453,337	34,423,725	98,526	170,551,461	100 %	1.662	27 %	2 %
9	54	39	8,902,183	455,926	1917	34,168,323	100 %	0.799	26 %	1 %
10	15	42	115,597,540	93,969,350	92,098	377,747,321	100 %	1.157	31 %	24 %
10	24	42	155,960,501	150,746,101	3,585,682	341,009,355	99 %	0.046	46 %	29 %
10	27*	42	125,984,727	110,238,361	10,397,055	364,804,939	97 %	0.928	35 %	35 %
10	38	40	24,430,677	17,532,204	5364	84,900,229	100 %	0.926	29 %	12 %
11	4	41	471,660,813	409,910,139	72,082,412	1,131,915,992	94 %	0.860	42 %	15 %
11	10	41	769,693,372	723,177,098	73,680,848	1,881,550,953	96 %	0.438	41 %	21 %
11	12*	41	807,062,572	717,124,505	115,906,466	2,390,076,464	95 %	0.838	34 %	26 %
11	30	41	197,077,428	124,737,984	13,862,121	902,179,551	98 %	2.095	22 %	4 %
11	31	38	50,828,637	44,891,599	402,124	182,975,341	100 %	0.931	28 %	2 %
11	34	30	43,499,425	34,475,734	55,854	177,181,618	100 %	1.687	25 %	2 %
11	43	41	231,721,013	166,818,604	18,252,605	652,914,893	97 %	0.993	35 %	8 %
11	44	40	90,511,295	75,563,680	55,854	268,171,197	100 %	0.681	34 %	5 %
11	47	42	501,603,289	276,306,170	9,193,418	5,445,174,200	100 %	4.861	9 %	8 %
11	53	38	40,009,722	32,056,224	199,045	167,509,543	100 %	1.534	24 %	2 %
11	57	41	364,314,802	311,431,196	113,192,368	820,849,366	86 %	0.697	44 %	11 %
12	6*	40	132,492,701	95,985,678	25,809,498	357,782,974	93 %	1.018	37 %	57 %
12	7	41	70,376,226	43,666,480	941,700	209,248,971	100 %	1.027	34 %	16 %
12	9	41	46,763,411	27,423,704	29,759	256,923,407	100 %	1.892	18 %	26 %
12	52	22	1,995,598	2,089,350	45,750	4,463,321	99 %	0.390	45 %	1 %
13	67	41	6,166,906,215	4,103,540,880	48,486,704	25,606,791,667	100 %	1.620	24 %	9 %
13	70	42	35,616,492,627	32,057,158,105	1,900,112,010	1.11607 E+11	98 %	1.335	32 %	40 %
13	73*	41	43,433,834,699	40,142,615,982	9,051,804,482	95,543,179,302	91 %	0.659	45 %	51 %
13	77	42	2,010,233,769	1,951,557,678	184,987,036	6,657,990,813	97 %	1.455	30 %	3 %
14	65	42	14,336,116,002	13,290,613,771	2,522,149,429	28,080,665,144	91 %	0.417	51 %	42 %
14	74	42	1,657,660,084	749,682,210	155,483,883	8,583,755,345	98 %	2.203	19 %	6 %
14	76	42	2,474,970,271	2,437,352,248	158,114,086	5,841,574,064	97 %	0.576	42 %	6 %
14	78*	42	18,124,075,578	17,521,368,367	1,513,342,312	37,966,888,563	96 %	0.169	48 %	46 %

(*continued on next page*)

(*continued*)

Component #	Supplier #	Obs.	Mean	Median	Min.	Max.	Volume Range as % of Max.	Skewness	Mean % of Max Order	Average Purchase Order %[c]
15	63	41	370,541,967	284,393,479	7,389,791	1,222,467,706	99 %	1.121	30 %	15 %
15	64	41	371,480,891	303,162,978	96,457,561	979,562,914	90 %	1.180	38 %	10 %
15	66**	42	1,804,764,432	1,636,889,072	17,843,559	5,651,319,600	100 %	0.456	32 %	25 %
15	69*	25	2,257,846,300	2,328,597,739	7,380,088	4,417,968,380	100 %	−0.069	51 %	50 %
15	75	41	463,312,672	388,837,164	32,755,184	1,613,664,140	98 %	1.133	29 %	6 %

Notes.
* = Primary peer supplier for each component (shaded grey). ** = Supplier 66 became a primary peer supplier after month 25.

Data availability

Data will be made available on request.

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