

Supply Chain Decision-Making Across Risk Domains

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ABSTRACT

Risk management has become an increasingly important topic in supply chain management (SCM), but decision-making under conditions of risk remains under-researched. This study used an experiment based on purchasing and the game of roulette to assess dynamic decision-making behaviors in SCM. An analysis of four separate risk domains – including a distinction between quantity- and variability-based decisions – indicated that decision-makers assess risk attitudes independently for each domain and that these attitudes affect subsequent decisions in their respective domains. These findings indicate that SCM represents a distinct decision context. For practitioners, this research demonstrates why standardized risk management approaches that assume consistent risk attitudes may fail, as a manager who appears risk-averse in one type of decision may simultaneously be risk-seeking elsewhere. Organizations can leverage these insights by matching employee risk profiles to decision types and implementing domain-specific training programs.

Keywords: *decision-making; inventory; risk management; roulette; supply chain management.*

1. INTRODUCTION

In an effort to build more resilient, risk-aware supply chains, managers are increasingly turning to technological tools such as artificial intelligence (AI) and real-time visualization for decision support (Ganesh & Kalpana, 2022). While these tools can certainly aid in managing risk, they are most effective when used by a capable decision-maker (Browning *et al.*, 2023). The urgency of understanding risk-based decision-making has intensified following recent global disruptions. In addition to traditional operational risks, supply chain managers now face the compounding effects of geopolitical uncertainties, trade policy shifts, and demand volatility (Katsaliaki *et al.*, 2022; Choudhary *et al.*, 2023). The COVID-19 pandemic revealed the simultaneous interaction of multiple risk domains,

requiring managers to navigate supplier reliability concerns while managing inventory levels amid unprecedented demand uncertainty (Choi *et al.*, 2023; Lücker *et al.*, 2025).

The existing research has not adequately addressed decision-making under conditions of risk and uncertainty in the context of supply chain management (SCM), and therefore more research is needed on this topic (Browning *et al.*, 2023; Heckmann *et al.*, 2015). A critical factor in understanding how decisions are made is an individual's risk attitude. Risk attitudes cannot be studied in a vacuum, however, as they may vary based on the specific risk domain (Frey *et al.*, 2017) or on situational factors (Frey *et al.*, 2023). Within supply chain risk management (SCRM), only 35% of publications include risk attitude (Rajagopal *et al.*, 2017), even though the assumption of a risk-neutral decision-maker is inconsistent with observed decision behavior (Bisière *et al.*, 2015; Ovchinnikov *et al.*, 2015).

This study aims to improve upon and extend the previous research with an experiment-based method of assessing risk attitudes and situational effects in SCM that monitors behaviors across risk domains. The experiment is set up so that individuals make decisions related to inventory- and vendor-related risk in a simulated business scenario, allowing the evaluation of multiple decision criteria simultaneously. As an additional control, the participants completed a roulette-based experiment. This study provides a better understanding of risk-based decision factors in SCM, thus advancing decision-making research and providing managers with a better starting point for understanding and managing supply chain risk.

2. LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

This literature review examines three interconnected areas that inform our research. We first review SCRM to establish the context and identify key decision types. We then examine behavioral decision factors to understand how individuals actually make risk-based decisions. Finally, we develop our hypotheses by integrating risk domain theory with supply chain decision-making contexts.

2.1 Supply Chain Risk Management

Common supply chain risks include natural calamities, transportation failure, employee unavailability, pandemics, information sharing, financial risk, infrastructure, scarcity of resources, lack of coordination, demand uncertainty, and market changes (Dohale *et al.*, 2023). These risks are often addressed through quantitative methods for optimally planning production, inventory, and purchasing, among others (Chopra *et al.*, 2021). Decision-makers may choose to utilize buffers, in which excess resources are maintained as a form of insurance against variations in supply or demand and to reduce dependence on external supply chain entities (Manhart *et al.*, 2020).

Recent global events have intensified supply chain risks in unprecedented ways. The COVID-19 pandemic, geopolitical tensions including trade wars and regional conflicts, and trade policy uncertainties have created new risk dimensions that interact in complex ways (Choi *et al.*, 2023; Lückner *et al.*, 2025; Katsaliaki *et al.*, 2022). Trade tariffs and policy shifts have introduced variability that compounds traditional supplier risk, while demand volatility has increased due to shifting consumer behaviors (Hassan *et al.*, 2024). These contemporary challenges reinforce the need to understand how decision-makers simultaneously navigate multiple, interacting risk domains, as biases and strategic decision-making choices can be particularly influential during times of change (Acciarini *et al.*, 2021).

A relatively recent development in SCRM is the increasing use of AI and other advanced technologies to develop optimal purchasing and inventory policies. Although these tools provide strong analytical capabilities, there is a human element to their usage. Decision-makers may choose to ignore the recommendations of these tools, or may take the recommendations as a baseline and adjust from there (Sturm *et al.*, 2023). In fact, human interjections in forecasting and planning processes may be necessary to achieve an optimal outcome (Browning *et al.*, 2023), as humans have a complementary skill set to machines. Where machines can process information much more quickly, humans have the ability to incorporate broad sets of vague and incomplete information to foresee unusual challenges that may not be evident in data (Sanders, 2017). Browning *et al.* (2023) argue that individuals with varying risk attitudes can strengthen a firm's risk management and resilience.

2.2 Behavioral Decision Factors in SCM

The behavioral aspects of risk-based decisions have been studied through various experiments. In an experiment based on the newsvendor model, Schweizer & Cachon (2000) found that individuals are frequently risk averse and that feedback and training typically did not change this fact. Ovchinnikov *et al.* (2015) compared an analytical version of a newsvendor analysis to a biased human competitor and found that rational decision-making methods lead to superior performance. Other studies have also found that human competitors achieved inferior results compared to optimized decision models (Cannella *et al.*, 2019; Quiroga *et al.*, 2019). Recent behavioral operations research has continued to reveal systematic patterns in how decision-makers deviate from optimal policies, with implications for both technology adoption and training interventions (Perera & Fahimnia, 2024; Kosgoda *et al.*, 2024).

If a systematic bias is identified, then management can put controls in place to reduce the bias. As an example, SCM decision-makers sometimes chase demand by placing higher

orders after a period of high demand and lower orders after a period of low demand. This problem can be reduced through training or by forcing decision-makers to place standing orders for multiple periods, which can potentially cause decision-makers to remain faithful to a rational policy (Bolton & Katok, 2008). However, the effectiveness of such interventions depends on understanding the specific nature of the bias and the decision domain in which it occurs (Acciarini *et al.*, 2021).

These interventions can be more effective if managers have a better understanding of how risks are viewed and approached in SCM. Based on the literature, and supported by decision theory, three specific research questions have emerged and are addressed in the hypotheses tested in this study. The research questions are:

1. Are risk attitudes consistent within the domains of SCM decisions and with non-SCM decisions?
2. Are risk attitudes predictive of behavior within these domains?
3. Are risk-based decisions affected by dynamic situations within these domains?

2.3 Risk Domains & Risk Attitude

We argue that the common risk-based decisions in SCM, which are characterized by quantity- and variability-based decisions, represent distinct risk domains. We, therefore, expect that decision-makers will approach decisions characterized by questions of quantity and variability – in this case, supplier selection (variability) and order total (quantity) – differently due to their unique characteristics.

Some individuals, classified as risk-seeking, prefer a potential big win and the thrill that comes along with it, while others, classified as risk averse, have a stronger fear of the potential big loss and the related anxiety (Weber *et al.*, 2002). Frey *et al.* (2023) found that while an individual may be described as risk-averse or risk-seeking, that characterization may be shaped by additional factors such as the context of the decision, demonstrating that risk preference may vary systematically across domains.

It is important to clearly distinguish SCM as a distinct field of study, so this study tests the SCM decisions alongside roulette decisions. Weber *et al.* (2002) found that gambling decisions were approached differently than business decisions due to the characteristics of their uncertainty, with gambling outcomes exogenously determined and uncontrollable (aleatory uncertainty), while business decisions can be mitigated (epistemic uncertainty). In a gambling decision, the value of an outcome is clearly identifiable, as these decisions have a clear quantity at risk and a clearly defined payout. In a seminal study, March and Shapira (1987) noted that managers often put less emphasis on variability-based factors and instead focus on the value of the potential outcome. Such an approach causes decision-makers to focus on the best or worst outcome, and therefore deviate from purely rational decisions. The decision-maker's risk attitude may affect their decisions by pushing them towards or away from those extreme outcomes. Although the primary interest of this study is SCM, we expect to find that risk attitudes are distinct for quantity and variability risk domains across SCM and gambling scenarios, thus supporting the distinctiveness of each risk domain.

Hypothesis 1: Risk attitudes are inconsistent across quantity and variability risk domains

		Uncertainty Type	
		Epistemic	Aleatory
Risk Type	Variability	SCM – Vendor Risk	Roulette – Odds
	Quantity	SCM – Order Total	Roulette – Bet Size

Figure 1 Risk domain matrix

2.4 Risk Attitude & Decision-Making

Rather than simply identifying distinctions among risk domains, it is important to investigate the predictive capabilities of these distinctions. It is therefore necessary to track whether behavior is consistent with an initial risk attitude over repeated decisions within each risk domain.

Previous experiments involving repeated decisions have resulted in consistent behavior over time (Bisière *et al.*, 2015; Levin *et al.*, 2007), and recent research continues to demonstrate the persistence of anchoring effects in managerial decision-making, even when decision-makers are aware of the bias (Ly *et al.*, 2023; Mahmood *et al.*, 2024). Similar findings in the present context, which includes diverse risk domains, would offer support for the predictive validity of the independent risk domains identified in this study. Building upon and supporting the risk domains developed in Hypothesis 1 and consistent with the concept of anchoring (Furnham & Boo, 2011; Tversky & Kahneman, 1974), we expect risk-based decisions to be consistent with risk attitudes within the specified risk domains.

Hypothesis 2: Risk-based decisions are consistent with an individual’s initial risk strategy within a specified risk domain

2.5 Situational Factors in Decision-Making

Situational factors are also important to understanding risk attitudes in decision theory (Bromiley & Curley, 1992). The information that is processed in the course of a decision may come from personal experience or external description, and the results of each gambling or business event provide new information to be processed (Erev & Barron, 2005). To further understand how SCM decisions are made, the influence of positive or negative outcomes on subsequent decisions is considered in this study.

Whereas gambling decisions result in a clear win or loss from a single bet, outcomes from SCM decisions may be less obvious. For example, in an inventory-related decision, the outcomes can be perceived as positive when customers are supported and inventory levels are low enough that they do not significantly raise costs. Alternatively, an outcome can be viewed negatively if excess inventory leads to high costs or if inventory is insufficient to fill customer orders. In a purchasing scenario, negative outcomes are those in which

delays, disruptions, or quality issues occur, whereas a positive scenario is one in which those outcomes are avoided and the purchase price is acceptable. In both the inventory and purchasing decisions, there may also be intermediate outcomes consisting of minor delays or moderately elevated inventory levels, but not enough to cause a financial loss. There may also be a temporal aspect to these decisions, as the results of operational decisions may take days or weeks to take effect, thus delaying any feedback regarding a decision. These complex and somewhat unclear outcomes provide a unique context for analyzing SCM decisions.

Previous outcomes can shape decisions by helping decision makers to understand probabilities (Barron & Erev, 2003) or improve reasoning (Hertwig & Ortmann, 2001), but can also reveal biases. The house money effect, for example, demonstrates that individuals take on larger risks following a positive outcome (Thaler & Johnson, 1990). Conversely, Bisière *et al.* (2015) argue that new information does not affect attitudes towards risk. We argue that the specificity of the risk domain will help to clarify these effects within each risk domain. Considering the biases inherent in decision-making, and consistent with the house money effect, we suspect that individuals will take on larger risks following a positive outcome, and lower levels of risk following a negative outcome within each risk domain (Thaler & Johnson, 1990).

Hypothesis 3: Positive (negative) outcomes lead to higher (lower) levels of future risk-taking within each risk domain

3. METHODOLOGY

This section describes the experimental methodology used to test our hypotheses. We first discuss the rationale for using an experiment-based approach and explain how our dual-experiment design allows us to test risk attitudes across multiple domains. We then detail the specific design of each experiment.

3.1 Assessment Tools

Assessing risk attitudes and behaviors is a complex and dynamic task. Surveys have notable limitations for measuring dynamic risk behavior (Shou & Olney, 2021), thus pointing to the need for a dynamic, experiment-based

research method. Risk-taking depends on the context of the decision, so risk attitude should be assessed in context- and process-sensitive ways, with a decision task that is as close to the real decision scenario as possible (Weber & Johnson, 2009, p. 137). Previous experiment-based studies in SCM have yielded results that show clear distinctions between behavior-based decisions and analytically-based decision methods (Ovchinnikov *et al.*, 2015; Quiroga *et al.*, 2019). Given these outcomes, an experiment is a well-suited method for assessing behavior in dynamic, risk-based decisions.

To assess the hypotheses while simultaneously considering the wider context, a control test is included in the experiment in the form of roulette. In comparing the two experiments, this study can test for differences between the two SCM risk domains, as well as similar quantity- and variability-based risk domains in roulette. Pairing the risk types and the uncertainty types results in a 2x2 matrix, as depicted in Figure 1. Inside the matrix are the four risk domains of interest in this study.

3.2 Experiment Design

The experiment participants were students in business courses who were provided with an incentive structure related to their course grades. Students who participated in the experiment received a 0-2% increase in their grade depending on their performance in the experiments.

A pilot test of the experiments was conducted using a Microsoft Excel-based program. Based on feedback obtained during the pilot study, the instructions and the gameplay were refined, and a web application was developed to manage the experiment and to gather decision data. The experiment was conducted as described in the next two sections.

3.2.1 Roulette Experiment

Roulette is a casino game in which a ball is spun along a wheel with numbered slots. Each bet can cover between 1 and 18 of the slots, and bets are paid out based on the slot in which the ball lands, with a relative payout based on the number of slots covered by the bet. The range of odds that a participant can choose is from 2-1 through 36-1 (Appendix). Although the roulette wheel used in this experiment has 38 slots, the payback calculations are based on a 36-slot wheel (e.g. a bet that covers one slot pays back 36-1, but the odds of winning are 1 in 38), thus yielding a 94.8% payback rate for most bets and giving the casino a 5.2% advantage (Casino.org, 2024). Although the long-term expected value of each bet is consistent, the variability for the bets varies widely. Betting with safe odds (i.e. 2-1) yields relatively consistent returns, whereas betting with riskier odds (i.e. 36-1) can result in a larger win or loss in the short term.

In the experiment, the participants began with 1,000 chips and were required to play until they reached 25 spins or until they ran out of chips. With each spin, the participant could bet any amount from one chip to their entire balance of chips, and it could be placed on any of the eligible bets. The bet odds and bet amount, as well as the results, were recorded in a database for each round. Because the expected value from any bet is less than the amount of the bet, the optimal decision from a financial perspective is to not play the game. This experiment forces participants to play, so betting the minimum amount yields the optimal expected return. Any deviation from the minimum bet and the safest odds can be considered an increase in risk.

3.2.2 SCM Experiment

The participants also completed an SCM-based experiment in which they purchased inventory from three different suppliers carrying different levels of cost and risk, with the goal of maximizing their profit. The suppliers ranged from high cost with low lead time and uncertainty (Alabama) through low cost with high lead time and uncertainty (China), with a moderate option (Brazil) in between. The experiment design focuses on relative differences among suppliers rather than absolute magnitudes. For example, the differences between Alabama (high cost, low risk) and China (low cost, high risk) create clear trade-offs that mirror real-world purchasing decisions where managers typically evaluate supplier options based on comparative advantages rather than absolute values. The specific parameter values were calibrated through pilot testing to ensure that no single strategy dominated and that participants faced meaningful trade-offs between cost and reliability. The experiment parameters are presented in the Appendix, Table A1. Results were then generated by the application based on these parameters, and the decisions and results were saved in a database. These results included the level of demand, the number of units received with acceptable quality from each supplier, whether any of the shipments were delayed until the following week, and the financial results.

In the web application, the order entry fields included a default value that was equal to the average weekly demand, with inventory being purchased in equal amounts from the three suppliers. Participants could adjust their risk level by shifting purchases towards the riskier or less risky supplier, or by reducing their inventory level. An optimal strategy in this experiment was to reduce inventory as low as possible without stocking out, while also purchasing at a relatively low cost. There is inherent conflict between these objectives, however, as purchasing from a risky supplier makes it more difficult to maintain a low, stable inventory level.

4. RESULTS

This section presents the experimental findings. We first provide overall descriptive statistics for both experiments to establish baseline decision patterns. We then systematically test each hypothesis, beginning with risk domain independence (H1), followed by the predictive validity of risk attitudes (H2), and concluding with situational effects (H3).

A total of 144 participants completed the experiment. Although the experiments ran longer than twenty rounds, only the results from the first twenty rounds were included to avoid any changes in decision-making at the end of the experiments for individuals making risky final decisions to win the competition. The overall results are presented first, followed by a more detailed analysis of the decisions in relation to the hypotheses.

4.1 Overall Results

In the SCM experiment, the two primary risk metrics were Order Total and Vendor Risk. The Order Total was calculated as the total number of units ordered from the three suppliers. The Vendor Risk metric captured the relative number of units purchased from the high-risk supplier as

Table 1 Descriptive statistics and correlation matrix of risk attitudes

	Descriptive Statistics		Correlation Matrix			
	Mean	Std. Dev	Order Total	Vendor Risk	Bet Size	Odds
Order Total	5,574.89	110.72	1.000	0.021	-0.004	0.028
Vendor Risk	-48.48	811.53		1.000	0.092	-0.123
Bet Size	112.45	220.65			1.000	-0.127
Odds	11.83	14.03				1.000

Table 2 Results for Hypotheses 2 & 3

	Domain	Risk Attitude (Hypothesis 2)			Situation (Hypothesis 3)			
	Order Total	Risk Attitude	Order Total	Vendor Risk	Profit-Loss	Order Total Change	Low Inventory	Order Total Change
SCM	Order Total	Low Risk (High OT) (n=361)	5860.2	127.18	Profit (n=2213)	68.77	Yes (n=602)	212.97
		High Risk (Low OT) (n=1007)	4482.12	-266.43	Loss (n=523)	-481.76	No (n=2,134)	-105.21
		p-value	0.000***	0.000***	p-value	0.000***	p-value	0.001***
	Vendor Risk	High Risk (High VR) (n=627)	5271.68	587.15	Profit (n=2213)	-31.15	Yes (n=602)	-20.37
		Low Risk (Low VR) (n=950)	5040.70	-324.73	Loss (n=523)	135.71	No (n=2,134)	6.50
		p-value	0.079	0.000***	p-value	0.40*	p-value	0.731
Roulette	Bet Size	High Risk (High Bet) (n=969)	141.36	4.99	Win (n=858)	8.98		
		Low Risk (Low Bet) (n=1503)	89.89	7.43	Loss (n=614)	0.04		
		p-value	0.002***	0.000***	p-value	0.221		
	Odds	High Risk (High Odds) (n=997)	134.8	10.65	Win (n=858)	1.09		
		Low Risk (Low Odds) (n=1475)	93.35	2.66	Loss (n=1614)	-1.01		
		p-value	0.000***	0.000***	p-value	0.000***		

compared to the low-risk supplier. A positive value indicates that a higher number of units was purchased from the high-risk supplier. Most rounds in the SCM experiment resulted in a profit, and the average profit at the end of the twenty rounds was \$51,661.47 (σ =\$63,664.52). For the roulette experiment, Bet Size and Odds were the primary metrics. At the conclusion, the average chip balance was 948.79 (σ =797.38).

The notably high standard deviation in Vendor Risk (σ =811.53) relative to its mean (μ =-48.48) reveals substantial heterogeneity in supplier selection strategies among participants. This wide variance indicates that while the average participant slightly favored low-risk suppliers (negative mean), individual strategies ranged from heavy reliance on high-risk suppliers to complete avoidance of them. This finding suggests that standardized procurement policies may not align with natural decision-making tendencies across all employees, and that organizations may benefit from either deploying employees whose risk profiles match strategic objectives or implementing decision support systems that account for individual variation in risk tolerance.

4.2 Hypothesis Testing

Hypothesis 1 tested the individual’s risk attitude based on their initial strategy in each experiment. For roulette, each individual’s first bet was used to determine their initial strategy, which was used as a proxy for their risk attitude. The distribution of initial bet sizes (μ =112.45; σ =220.65, skewness=3.06, kurtosis=9.04) and odds (Odds: μ =11.83, σ =14.03, skewness=1.04, kurtosis=-0.74) was fairly normal in the first round, although the skewness and kurtosis levels were relatively high for bet size. The individual’s initial strategy was deemed to be high or low based on whether their first-round bet was above or below the median for both bet size and odds. Values equal to the median were retained with the low group due to the proximity to the lower values and to maintain balanced group sizes.

In the first round of the SCM experiment, more than half of the participants ordered the default values (order total equal to the average weekly demand, distributed evenly among the suppliers), so the variability among participants was low for both metrics. The level of variability increased in Round 2, so to achieve sufficient variability in the sample, the average of Rounds 1 & 2 was used (Order Total:

Table 3 Summary of Hypotheses

Hypothesis 1: Risk attitudes are inconsistent across quantity and variability risk domains	
Test:	Correlation among initial strategies.
Result:	No significant correlation
Supported:	Yes
Hypothesis 2: Risk-based decisions are consistent with an individual's initial risk strategy within a specified risk domain	
Test:	T-test comparing subsequent decisions between groups with different initial strategies
Result:	Decisions in alignment with initial strategies within risk domain. High-risk decisions often balanced with low-risk decisions in other within-experiment domain
Supported:	Yes
Hypothesis 3: Positive (negative) outcomes promote higher (lower) levels of risk-taking within risk type	
Test:	T-test comparing decisions following positive and negative outcomes
Result:	The results were significantly different between some groups.
Supported:	Partial support

$\mu=5574.89$, $\sigma=110.72$; kurtosis=7.47; skewness=-0.33; Vendor Risk: $\mu=-48.48$, $\sigma=811.53$; kurtosis=5.10; skewness=0.24). The risk inherent in using multiple rounds is that the results of Round 1 can influence the Round 2 decisions, but it is unlikely that these results had a meaningful effect, as there is a multiple-round lead time for orders, and the results of the Round 1 decisions would typically not be realized until Round 3. The individuals whose orders were equal to the median could not be categorized as high or low and were therefore removed from the analysis of the initial strategy hypothesis.

For Hypothesis 1, the individuals' initial strategies among the four risk domains were compared via correlation tests, and no statistically significant relationships were found (Table 1). Each pair of risk domains was also graphed on scatter plots, and no relationship patterns were detected. In summary, each risk factor appears to be independent of the others, supporting the notion that risk preference is domain-specific, consistent with recent findings in risk preference research (Frey *et al.*, 2023). To test Hypothesis 2, the decisions in the subsequent rounds were compared with the initial strategy. For each risk domain, the total dataset was split into high and low initial strategies, and t-tests were performed to compare the average values across the groups (Table 2, "Risk Attitude" column). All four risk domains yielded results in which the subsequent decisions were consistent with the corresponding risk attitudes. Interestingly, significant relationships were also found between each of the risk domains and the other within-experiment risk domains (Table 2).

Testing Hypothesis 3 required an analysis of changes in decision factors following positive or negative outcomes (Table 2, "Situations" columns). The situational factors were profit vs. loss and high vs. low inventory in the SCM experiment and win vs. loss in the roulette experiment.

In summary of Hypothesis 3, the situational factors appear to affect certain risk domains but not others. In both experiments, there is one decision factor that stands out as the primary response mechanism. In roulette, the odds decision (the variability-based risk) is the primary response to the win-loss situation; whereas in the SCM experiment, the order total decision (the quantity-based risk) is the primary response to both the profit-loss and the low inventory situations. As a post-hoc test, each of the situations was tested in conjunction with risk attitude, and there were no notable differences. Based on the results of the experiment, Hypotheses 1 & 2 were fully supported, and Hypothesis 3 was partially supported. This finding indicates a complex relationship between risk strategies and situational factors (Table 3).

5. DISCUSSION

This section interprets our findings from both theoretical and practical perspectives. We begin by examining the theoretical contributions to decision-making research and supply chain management theory. We then translate these findings into actionable insights for practitioners managing supply chain risks.

5.1 Theoretical Implications

In an era of increasing reliance on technology, research has shown that when humans are aided by technology, they can outperform technology alone. To support this point, a greater understanding of the behavioral aspects of decision-making is required (Browning *et al.*, 2023). Previous research has shown distinctions among various risk types (Bao & Datta, 2014; Frey *et al.*, 2023; Rohrmann, 2005; Weber *et al.*, 2002), including gambling and business scenarios (March & Shapira, 1987), but the specific risk domains of SCM have not previously been tested. This study introduced the quantity-versus-variability distinction in the form of decisions related to the critical SCM-based risk factors of order quantity and supplier selection (Cannella *et al.*, 2019). By using the decision-maker's initial strategy as a proxy for their risk attitude within each risk domain, this study was able to identify independent risk attitudes for each of the four domains, with little correlation among them, thus providing evidence that SCM decisions should be considered as a standalone context.

These findings have particular relevance in today's uncertain environment. Recent supply chain disruptions and macroeconomic issues have revealed that managers must simultaneously navigate supplier reliability concerns (variability-based risk) while managing inventory levels amid demand uncertainty (quantity-based risk) (Choi *et al.*, 2023; Lücker *et al.*, 2025). Our finding that these risk domains are assessed independently suggests that organizations need specialized strategies for each domain rather than unified risk management approaches.

The experiments further indicated that risk attitudes can predict behavior within each risk domain. As noted by Frey *et al.* (2023), the psychometric structure of risk preference is multidimensional and may vary widely across domains. This study found similar results, implying that risk can be managed best when customized to the specific SCM risk domains. Quantity- and variability-based risks are certainly not exclusive to SCM questions, and studying these factors as distinct risk domains enables future studies to address even more domains with increased precision.

Furthermore, complex relationships were identified between initial risk attitudes and subsequent behaviors in

related risk domains. Consistent with Hanoch *et al.* (2006), this study showed that rather than being truly risk-seeking, decision-makers may be more accepting of risk in specific areas, but may be risk-neutral or averse in others, thus counteracting the initial risks. By including related risk factors in the experiment (i.e. quantity and variability), an individual can make a direct comparison between the two factors and select the form of risk that they consider more acceptable. For example, in the roulette experiment, participants with a high initial bet strategy continued to make high bets, but they also bet with significantly safer odds than those with a low bet strategy. Of the four risk domains, the only one that demonstrated alignment across the within-experiment risk domains was the odds decision in the roulette experiment, in which participants who made risky bets also bet large amounts. The roulette experiment is characterized by aleatory uncertainty with a clearly defined level of uncertainty and a rapid feedback mechanism, so those placing bets with high odds were demonstrating an apparent propensity for risk and were therefore also willing to take risks in terms of the size of their bets. No such alignment was found in the SCM scenario. This finding lends further support for the need to focus on specific risk domains, as well as specific decisions of interest.

Situational factors were also found to shape behavior, outweighing risk attitude in some domains. The initial odds position was still relevant, however, in that those who started with high odds varied their bets around their high or low initial value. The same holds true for the order total decision. These findings are consistent with the anchoring bias, which states that decisions are affected by being anchored to an initial starting point (Furnham & Boo, 2011). Within each risk domain, an individual's initial decision provides an anchor that affects subsequent decisions. Considering the notion of risk attitude being either constructed or stable and enduring (Lichtenstein & Slovic, 2006), this study seems to support the constructed risk attitude approach because initial positions vary widely based on the individual's interpretation of the situation, and decisions may slowly shift away from initial strategies over time. It is important, therefore, to define the decision as specifically as possible to generate the most accurate results from risk assessments, including factors such as the function (e.g. SCM) and the decision criteria (e.g. quantity vs. variability).

No conclusive results could be determined regarding variability- and quantity-based risks. In the SCM experiment, the order total (quantity-based risk) was the primary risk adjustment mechanism, rather than vendor risk. We speculate that the order total may be a relatively easy decision to adjust, as changing the vendor risk (variability-based risk) through a shift in suppliers takes time to enact due to the extended lead times, and in this way is representative of real-world purchasing decisions. In the roulette experiment, the results were the opposite, with odds (variability-based risk) utilized as the primary risk adjustment mechanism, with bet size (quantity-based risk) as a relatively minor decision for calibrating the level of risk. Future research could focus on the ease of change or the temporal nature of variables as decision drivers.

Finally, Browning *et al.* (2023) argued that more research on the behavioral aspects of risk preferences is necessary, and they questioned the effects of more or less conservative agents on risk and resilience. This study

addresses this gap by providing a superior method for understanding risk preferences. The experiment-based research design in this study can overcome the limitations of surveys (Shou & Olney, 2021) and build upon previous behavior-based methods (Schweitzer & Cachon, 2000) in a dynamic context like SCM (Appelt *et al.*, 2011; Lichtenstein & Slovic, 2006). Although Schweitzer and Cachon (2000) utilized an inventory-based experiment, their decision-makers focused on a single decision and calculated an optimization problem beforehand. We offer a more complex and arguably more realistic experiment, and for comparison, we also included a more straightforward experiment in the form of roulette. In future research, similar experiments can be conducted in various contexts by adapting the decision criteria.

While this study focuses on relative differences among experimental parameters, we acknowledge that absolute magnitudes may also influence behavior. For instance, a 20% price difference at a \$10 purchase price may be perceived differently than the same percentage difference at a \$1,000 price point, potentially revealing threshold effects in risk perception. Similarly, the absolute level of demand variability (as opposed to relative differences among suppliers) could affect risk-taking behavior. Future research should investigate whether such threshold effects exist and how absolute versus relative framings affect risk-taking behavior across domains. Our experimental design, however, prioritizes internal validity through controlled relative comparisons, which we argue captures the essential nature of supply chain trade-offs that managers face when evaluating among multiple options.

5.2 Managerial Implications

Firms must manage risk to be able to manage critical strategic elements of SCM such as customer service, integration with suppliers (Zhao *et al.*, 2013), and resilience in the face of disruptions (Browning *et al.*, 2023). Risk attitudes can affect SCM decisions in numerous ways, including contract length and type, willingness to make a purchase, supplier selection, purchase size, and inventory level. It can also affect whether decision-makers factor some elements of risk into decisions (McWilliams *et al.*, 2022). Despite any automation or decision support technology that may be in place, individual decision-makers have a major impact on outcomes (Browning *et al.*, 2023). Humans and machines have opposite strengths and weaknesses, with humans able to detect patterns that machines might miss, which can lead to the generation of novel insights (Sanders, 2017). More specifically, technology may provide superior decision support capabilities for lower-level operational decisions (Sturm *et al.*, 2023), but as decisions become more complex and strategic in nature, they require more human intervention.

Previous research has offered recommendations for stabilizing decisions such as thinning the set of order options (Feng *et al.*, 2011) and forcing employees to use standing orders (Ovchinnikov *et al.*, 2015). Achieving a better understanding of employee risk attitude may offer further support for management in setting such policies.

Understanding risk domains matters for supply chain managers because traditional risk assessments that treat all supply chain risks as homogeneous will miss critical nuances in how decision-makers actually behave. A purchasing

manager who appears risk-averse in order quantity decisions may simultaneously be risk-seeking in supplier selection, leading to unexpected outcomes. This disconnect means that standard risk profiling tools may not accurately predict behavior across all SCM decision types. Organizations cannot assume that an employee who demonstrates caution in one area will demonstrate similar caution in another. A manager who maintains conservative inventory buffers (quantity risk aversion) might simultaneously source from high-risk, low-cost suppliers (variability risk seeking), creating a mismatch between risk exposure and organizational strategy.

Training programs that focus on general risk management principles may be ineffective because risk attitudes vary by specific decision type. Instead, organizations need targeted training programs that address specific decision domains. The situational sensitivity of certain risk domains means that managers need different monitoring and intervention strategies depending on the type of risk. For example, the substantial variance in vendor risk strategies observed in our experiment (Table 1) suggests that supply chain organizations face significant variability in how employees approach supplier selection decisions. Organizations can buffer against this variability through portfolio approaches to risk management, where purchasing responsibilities are distributed across managers with complementary risk profiles. Decision boundaries that provide clear parameters while allowing individual discretion can balance standardization with flexibility. For critical sourcing decisions, cross-functional teams that include both risk-averse and risk-seeking individuals can leverage variance to generate more thorough evaluations. Organizations should assess risk profiles within specific decision domains and assign responsibilities accordingly, recognizing that the same individual may be appropriate for different types of decisions across domains.

In the SCM experiment, maintaining an appropriate inventory level was tied closely to high profitability. Participants who followed a riskier vendor strategy could potentially benefit from lower purchase costs, but the variability associated with these suppliers made it more difficult to maintain appropriate inventory levels and maximize profit. Rather than a straight-line risk profile, inventory provides an inverted U-shaped profit level, wherein by reducing order levels and inventory, the participant took on some risk but could potentially reduce their cost and increase their profit; on the other hand, failing to reduce order totals could lead to elevated inventory levels and increased costs. Recognizing such risk factors in a purchasing decision is more complex than assessing the odds in a roulette bet, but this point reflects the fact that business decisions are complex, with poorly understood risk factors. While general training on risk management would likely be beneficial to decision-makers, specific training may be required for the management of specific risk domains, as current SCM educational resources do not adequately contain such coverage (Ferguson & Drake, 2021).

It is also important to assess risk attitudes in relation to the outcomes of the experiments. The results of both experiments indicated that to achieve a high score, a participant must take on an elevated level of risk. The majority of participants were somewhat risk-averse, and

those who were more risk-averse achieved average results. Taking on increased levels of risk yielded a high level of variance, with some individuals experiencing very negative results and others experiencing very positive results. These findings are consistent with risk-reward models in finance (Lundblad, 2007). They also support the assertion of Lovallo *et al.* (2020) that managers take on too little risk, with the result being low levels of innovation.

6. CONCLUSION

Ovchinnikov *et al.* (2015, p. 1783) noted that “decision-makers are irrational, but somewhat predictable”. This study has made progress toward predictability in SCM decisions by addressing three research questions. The first two questions asked whether risk attitudes were consistent across SCM decisions and whether they predicted behavior. The experiment showed that decision-makers assess each risk domain independently, rather than applying a single risk attitude to all domains. However, within each risk domain, risk attitude is predictive of behavior. These findings suggest that the benefits of understanding risk attitudes are limited to the specific domain. Moreover, in defining the risk domains, this study has identified two specific risk types – variability and quantity – that can be applied to various SCM decisions and beyond. By showing that these same risk types are applicable in a business setting and a gambling setting, it reveals the versatility of these concepts.

The third research question addressed the role of situational factors in SCM decision-making, and the results indicate inconsistent behavior across the risk domains. Notably, the two new risk types - variability and quantity - yielded opposing results in the situational experiments. This partial finding opens up the possibility of future research to find further nuance concerning the causes of these behaviors. Future research can also build upon this finding by testing additional risk types or applying this distinction in different settings.

Finally, we have utilized a risk assessment method that can capture the dynamics of the complex decisions that occur in the field of SCM. As noted by Charness *et al.* (2020), “while the external validity of measures of risk attitude holds in closely related frameworks, this validity is compromised in more remote settings”. Only a dynamic assessment method such as the one used in this study can capture the changes in behaviors over time and across risk domains. These findings, therefore, contribute to the risk management and decision theory literature beyond SCM.

Some limitations of the study must also be acknowledged. While the risk assessment method used in this study is dynamic, it is not as complex as real-world decision scenarios, which would encompass significantly more sources of uncertainty, both internal and external to the organization. Future research can measure behaviors in a business setting to overcome the limitations of this study. The experimental design focuses on relative differences among options rather than exploring potential threshold effects or the influence of absolute magnitudes. Future research should investigate whether absolute magnitude thresholds exist that fundamentally alter decision-making behavior.

The field of SCRM continues to evolve, with more emphasis placed on strategic risk factors such as resilience and the ability to weather disruptions (Browning *et al.*, 2023). Our findings suggest that effective risk management in today's complex environment (Choi *et al.*, 2023; Lücker *et al.*, 2025) requires moving beyond generic risk assessments to domain-specific approaches that recognize the multidimensional nature of risk preference. Gaining a better understanding of the individuals who make these decisions can help drive this field toward maturity and provide a foundation for future research on risk management in SCM.

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Appendix – Experiment Data

Table A1: Parameters for SCM and roulette experiments

SCM Experiment Data				
Sales Data				
Selling Price	\$2.00 per unit			
Holding Cost	\$0.25 per unit per round			
<i>Costumer</i>	<i>1</i>	<i>2</i>	<i>3</i>	
Average Sales	3000	2000	1000	
Std. Dev. Of Sales	1200	1000	400	
Purchasing Data				
<i>Vendor</i>	<i>Alabama</i>	<i>Brazil</i>	<i>China</i>	
Price	\$1.50	\$0.90	\$0.60	
Exchange Rate	0	±10%	±20%	
Average Acceptance Rate	99%	94%	90%	
Lead Time (rounds)	1	2	3	
On Time Rate	98%	90%	85%	
Roulette Experriment Data				
# of Slots Covered by Bet	Odds	Payout	Expected Value	
1	1 in 38	36 to 1	36/38 (94,7%)	
2	2 in 38	18 to 1	36/38 (94,7%)	
3	3 in 38	12 to 1	36/38 (94,7%)	
4	4 in 38	9 to 1	36/38 (94,7%)	
5	5 in 38	7 to 1	36/38 (94,7%)	
6	6 in 38	6 to 1	36/38 (94,7%)	
12	12 in 38	3 to 1	36/38 (94,7%)	
18	18 in 38	2 to 1	36/38 (94,7%)	