How Dominant Market Power Impacts OEM Investments in the Supply Chain – Theory and Experiment

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This study investigates why firms undertake relationship-specific investments in suppliers without formal contractual guarantees of return. We examine how market power, defined as control over wholesale pricing, influences original equipment manufacturer investments in contract manufacturers within dual-channel supply chains. While game-theoretic analysis predicts that OEMs should invest only when they retain pricing control and costs fall below a specific threshold, laboratory experiments with 98 subjects reveal systematic deviations from these equilibrium predictions. Specifically, OEMs underinvest when actions are individually optimal and overinvest when they are profit-diminishing. Our results indicate that decision-makers prioritize salient power dynamics over complex cost calculations, suggesting that bounded rationality constrains optimal decision-making. Paradoxically, these behavioral errors enhance overall supply chain efficiency across all conditions. These findings contribute to coordination theory by demonstrating that market power can substitute for formal contracts. For practitioners, securing pricing control is more critical for capturing returns than executing precise cost-benefit calculations.

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I. INTRODUCTION

The evolution of Lenovo and Acer from low-cost manufacturers for IBM into formidable global rivals illustrates a recurring strategic shift involving the transformation of contract manufacturers (CMs) into direct competitors (Arruñada & Vázquez, 2006). Recent scholarship confirms that this transition remains a pervasive feature of modern supply chains, whether through suppliers entering downstream markets (Zhou et al., 2023) or navigating complex co-opetitive dynamics in sustainable sourcing (Zhang et al., 2024). This creates a dual-channel environment where a supplier serves its client while simultaneously vying for the same end-customers. Paradoxically, original equipment manufacturers (OEMs) frequently make uncontracted, relationship-specific investments in these suppliers' capabilities by providing tools, equipment, and technology upgrades (Yu et al., 2006). They do so despite a lack of formal protection against future rivalry. From a Transaction Cost Economics perspective, firms should eschew such investments due to the risk of opportunistic holdup (Williamson, 1996). Yet, in practice, these investments persist without explicit contracts governing cost-sharing, a phenomenon we term uncontracted investment. This raises a fundamental research question regarding which structural or behavioral mechanisms enable OEMs to recover investment costs and navigate this coordination problem when formal safeguards are absent.

We propose that market power, specifically control over wholesale pricing, serves as the primary structural mechanism for investment recovery. Following Cui and Wu (2016), we operationalize power as a binary state where either the OEM or the CM sets the wholesale price. When the OEM retains pricing power, it can theoretically capture the surplus of investment by setting prices that reflect the reduced marginal costs. Conversely, pricing power for the CM allows the supplier to appropriate these gains, which should theoretically disincentivize OEM investment.

Building on this motivation, we address two specific research questions that jointly span the structural and behavioral dimensions of the problem. RQ1: How does market power, operationalized as control over wholesale pricing, shape OEM decisions to invest in contract manufacturers within dual-channel supply chains? RQ2: How do behavioral factors, particularly bounded rationality and reciprocity norms, cause investment decisions to deviate systematically from game-theoretic equilibrium predictions, and what are the resulting consequences for supply chain efficiency? Together, these questions connect the structural economics of bargaining power to the cognitive and social mechanisms that govern real decision-making.

While reciprocity norms or reputation may facilitate cooperation, we focus on the structural role of bargaining power and investigate how its distribution dictates investment in dual-channel chains. Our analysis specifically addresses how investment costs interact with this power to drive behavior, utilizing a multi-method approach that combines game-theoretic modeling with laboratory experiments. While game theory predicts that OEMs will invest if and only if they control pricing and costs fall below a specific threshold, our experimental data from 98 subjects with 2,940 decisions across four treatments reveal systematic behavioral deviations that challenge traditional equilibrium predictions.

The experimental results yield three primary insights that contribute to the field of behavioral operations management. First, we find that behavior deviates systematically from theoretical benchmarks as OEMs underinvest when it is individually optimal to do so, yet overinvest when it is profit-diminishing. Second, subjects exhibit a selective sensitivity to decision complexity, responding three times more strongly to salient power dynamics than to computationally complex cost thresholds. This suggests that bounded rationality limits optimal decision-making, as managers appear to prioritize bargaining power over mathematical thresholds. Third, we reveal an unexpected efficiency of errors, wherein these behavioral deviations actually increase supply chain efficiency by 10 to 51 percentage points. Despite being individually suboptimal, these investments facilitate coordination and improve system performance across all treatments. This suggests that off-equilibrium behavior may act as a lubricant for supply chain performance when individual and collective incentives diverge.

This research offers three distinct contributions to the supply chain literature. By demonstrating that market power can substitute for formal contracts, we identify a structural mechanism for investment coordination in dual-channel supply chains. Furthermore, by documenting the complexity gap in decision-making, we provide a behavioral explanation for real-world investment patterns that defy standard economic predictions. Finally, we challenge the notion that individual suboptimality is purely detrimental, showing instead how behavioral biases can enhance total system efficiency in competitive environments. These findings suggest that the successful management of modern supply chains requires a nuanced understanding of both the structural power dynamics and the cognitive heuristics that drive investment behavior.

II. LITERATURE REVIEW

Our research integrates four literature streams: dual-channel supply chains, supply chain investment and integration, market power, and behavioral operations management.

The dual-channel supply chain has attracted growing research attention. Hilmola et al. (2005) document industry examples where contract manufacturers compete with their OEM clients. Niu et al. (2015) analyze the pricing game in a dual-channel setting between an OEM and an original design manufacturer (ODM), finding that the partnership remains stable in equilibrium, with the arrangement weakening direct competition. Wang et al. (2013) examine three competition structures and show that the OEM benefits from having the CM as a competitive partner in all cases. Chiang et al. (2003) were among the first to demonstrate formally that introducing a manufacturer's direct channel can be strategically profitable even when it cannibalizes existing retail sales, a finding that motivates the dual-channel structure we model. Tsay and Agrawal (2004) characterize the nature of channel conflict in dual-channel systems and identify conditions under which coordination is achievable, establishing the theoretical foundations for the tension between cooperation and competition that we examine. Cai (2010) extends this work by analyzing pricing coordination between a manufacturer and competing retailers across multiple channel configurations, providing benchmark results against which our bargaining-power manipulation can be assessed. Dumrongsiri et al. (2008) show that the relative efficiency of the direct channel versus the indirect channel, a function of cost structures similar to those we model, determines equilibrium investment in each channel.

However, existing dual-channel research largely assumes formal contracts govern all transactions. Our study extends this literature by examining uncontracted investments, where the OEM invests in the CM without explicit contractual agreements on cost-sharing or benefit distribution.

Transaction cost economics suggests that firms should not invest without formal contracts guaranteeing monetary returns (Williamson, 1996). However, empirical evidence reveals deviations from this prescription. Kang et al. (2009) and Li et al. (2006) provide evidence that firms invest without formal agreements when investments yield potential strategic economic value or maintain sustainable relationships. Dyer (1996) provides foundational evidence that asset-specific investments in supplier–manufacturer relationships can generate substantial competitive advantages even in the absence of full contractual protection, suggesting that relationship-level trust and reputation can function as informal governance mechanisms. Heide and John (1990) identify the conditions under which firms choose relational norms over formal contracts to govern asset-specific investments, establishing governance choice as a function of the expected appropriation risk, a dynamic central to our study. Srinivasan et al.

(2011) document that asymmetric investments emerge systematically in dyadic supply relationships, with the more powerful party typically under-investing, consistent with our game-theoretic predictions for CM-power conditions. Lui et al. (2009) demonstrate empirically that relational norms can substitute for contractual safeguards in sustaining relationship-specific investments, providing empirical motivation for examining how informal behavioral mechanisms, such as the reciprocal pricing we document, can fill contractual gaps.

While this literature identifies conditions under which uncontracted investments occur, it does not examine how market power influences these decisions. We extend this line of research by introducing market power dynamics, specifically control over wholesale pricing, and develop theoretical predictions on how such power influences investment behavior in dual-channel settings.

Market power has been extensively studied in economics and marketing (Frank, 2008). In supply chain contexts, power often manifests through control over key decisions such as wholesale pricing. Galbraith (1952) established the foundational concept of countervailing power, arguing that concentrated market power by one party in a supply relationship tends to generate offsetting power on the other side, a dynamic relevant to how CM pricing authority emerges in our model. Iyer and Villas-Boas (2003) analyze bilateral monopoly settings where both buyers and sellers have pricing authority, demonstrating that equilibrium outcomes depend critically on who moves first in the pricing game; their framework directly informs our binary power operationalization. Raju and Zhang (2005) examine how channel power shifts affect pricing and profitability, showing that the party controlling wholesale pricing captures a disproportionate share of channel surplus, a theoretical prediction we test behaviorally. Ailawadi (2001) documents the real-world consequences of power imbalances in consumer goods supply chains, establishing that pricing authority is a primary mechanism through which channel power is exercised in practice.

However, prior research has not examined how market power interacts with investment decisions in dual-channel settings. We operationalize power as wholesale price-setting authority and examine how this form of power influences uncontracted investment decisions. Our approach connects market power dynamics to investment behavior, providing new insights into supply chain coordination mechanisms.

Research demonstrates systematic deviations between actual human decisions and normative theoretical predictions (Donohue et al., 2018, Schweitzer and Cachon, 2000, Starostyuk et al. 2024). Su (2008) attributes such deviations to bounded rationality and anchoring effects. In supply chain coordination contexts, experimental evidence reveals that individuals often fail to achieve theoretically optimal outcomes due to fairness concerns, strategic uncertainty, and limited computational ability (Chen et al., 2012). Fehr and Schmidt (1999) formalize inequality aversion as a source of behavioral deviation from Nash predictions, showing that many individuals are willing to sacrifice their own payoff to reduce disadvantageous inequality, a mechanism that may explain why power holders in our study set prices generously even when not required to. Bolton and Ockenfels (2000) develop the ERC (Equity, Reciprocity, and Competition) model, which predicts that agents care not only about their absolute payoff but also about their relative share, providing a theoretical foundation for the pricing deviations we document in Section 5.5. Loch and Wu (2008) demonstrate experimentally that social preferences, including status and relationship concerns, can either improve or impair supply chain performance depending on the specific incentive structure, directly relevant to our finding that behavioral deviations enhance efficiency. Katok and Wu (2009) show that fairness concerns and coordination failures persist in supply chain contracting experiments even after extended learning, suggesting that the bounded rationality and reciprocity patterns we identify are not transient features that disappear with experience. Fehr and Gächter (2000) provide foundational experimental evidence that conditional reciprocity, responding cooperatively to cooperative actions, is a robust behavioral phenomenon, consistent with our finding that investment triggers more favorable pricing responses.

These behavioral factors can lead to systematic patterns of under- or over-investment in supply chain relationships. Our experimental approach follows this tradition by examining whether OEM investment decisions conform to theoretical predictions derived from Nash equilibrium. Given the strategic complexity of dual-channel competition combined with investment decisions under different power structures, behavioral deviations are likely. Our experiments identify how market power and investment costs influence actual decision-making patterns.

Despite advances in these four streams, a critical gap remains. Dual-channel research assumes complete contracts, transaction cost economics predicts no investment without formal safeguards, market power studies ignore investment decisions, and behavioral operations research has not examined how decision complexity interacts with power dynamics in dual-channel settings. No prior work integrates these perspectives to examine how market power and behavioral factors jointly influence uncontracted investments when suppliers compete with downstream partners.

Table 2.1 summarizes how our study is positioned relative to each stream. We share with dual-channel research the modeling of simultaneous OEM–CM competition, but depart by introducing uncontracted investments and behavioral subjects. We share with transaction cost economics the focus on relationship-specific investment under holdup risk, but depart by experimentally testing whether power can substitute for formal safeguards, a question the analytical literature has not addressed. We share with market power research the binary power operationalization, but depart by connecting power to investment thresholds and measuring behavioral sensitivity. We share with behavioral operations management the experimental methodology and bounded rationality framing, but depart by documenting a new form of selective complexity sensitivity and showing that behavioral errors can be efficiency-enhancing rather than purely detrimental. This four-way intersection defines the specific contribution of the current study.

TABLE 2.1. POSITIONING OF THE CURRENT STUDY RELATIVE TO FOUR LITERATURE STREAMS

Dimension	**Dual-Channel Supply Chains**	**Supply Chain Investment & TCE**	**Market Power Research**	**Behavioral Ops Mgmt**	**Our Study (Contribution)**
Supply chain structure	Dual-channel (OEM + CM compete)	Dyadic buyer–supplier	Various channel configurations	Newsvendor, contracting games	Dual-channel (OEM + CM compete)
Investment type examined	Not examined	Relationship-specific, uncontracted	Not examined	Effort, inventory, capacity	Uncontracted, cost-reducing

	(assumed contracted)				
Market power operationalization	Implicit via channel structure	Asset specificity as vulnerability	Explicit: pricing authority	Rarely modeled explicitly	Explicit binary: who sets w
Behavioral analysis	Absent (analytical only)	Empirical surveys; no experiments	Absent (analytical only)	Central focus; lab experiments	Central focus; lab experiments
Formal contracts assumed	Yes — complete contracts	Contracts are the research question	Yes — complete contracts	Yes or no, depends on study	No — uncontracted investment
Key gap addressed	No uncontracted investment or BOM	No market power or dual-channel	No investment decisions or BOM	No dual-channel or power dynamics	Integrates all four streams

Our study fills this gap by combining game-theoretic predictions on power-dependent investment thresholds with experimental tests revealing how bounded rationality and reciprocity norms affect actual behavior. This integration yields novel insights into informal coordination mechanisms that operate outside formal contracts.

III. MODEL SETUP AND THEORETICAL PREDICTIONS

We develop a parsimonious two-player game-theoretic model to isolate the role of market power in investment decisions. Table 3.1 summarizes the notation and parameters used throughout the analysis
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TABLE 3.1. MODEL NOTATION AND PARAMETERS

Symbol	Definition
P	Market price (endogenous)
w	Wholesale price (decision variable)
Q_o, Q_c	OEM and CM quantities (decision variables)
π_{OEM}, π_{CM}	OEM and CM profits
a	Maximum market price (choke price)
b	Price sensitivity to quantity
c	CM production cost per unit (before investment)
c_I	CM production cost per unit (after investment, $c_I < c$)
c_m	CM distribution cost per unit (direct sales only)
I	OEM investment cost (reduces CM production cost from c to c_I)

The model consists of two players: an original equipment manufacturer (OEM) and a contract manufacturer (CM). The CM produces units at cost c per unit and operates two sales channels: (1) wholesale sales to the OEM at price w, and (2) direct sales to end customers at market price P, incurring an additional distribution cost c_m per unit. The OEM purchases from the CM at wholesale price w and resells at market price P. Both the OEM (quantity Q_o) and CM (quantity Q_c) thus compete in the same end market, creating a dual-channel structure.

To isolate the impact of market power, we make several simplifying assumptions. We assume the CM has unlimited production capacity, eliminating capacity constraints as a confounding factor. We further assume that the OEM's market sales quantity (Q_o) equals its order quantity from the CM, eliminating inventory considerations. These assumptions allow clean identification of power effects on investment decisions.

Each simplifying assumption is grounded in both theoretical precedent and real-world industry practice. The unlimited capacity assumption is standard in dual-channel Cournot models (Wang et al., 2013; Niu et al., 2015) and accurately characterizes the operating environment of large electronics contract manufacturers such as Foxconn and Flex Ltd., which maintain substantial structural excess capacity precisely to serve diverse OEM clients on demand. The assumption that OEM order quantity equals market sales quantity follows Cui and Wu (2016) and eliminates inventory dynamics that are orthogonal to our core research questions; this mirrors just-in-time supply arrangements common in consumer electronics, where OEMs order precisely to anticipated demand. The linear inverse demand function is the standard specification in industrial organization and supply chain modeling (Tirole, 1988; Chiang et al., 2003) because it yields tractable closed-form equilibrium solutions that are essential for parameterizing a controlled laboratory experiment. Finally, the binary power operationalization, where either the OEM or the CM sets the wholesale price, but not both, follows Cui and Wu (2016) and reflects real-world market structures: Apple's dominance over suppliers like Foxconn and Pegatron exemplifies OEM-power conditions, while arrangements in which a dominant component supplier serves multiple competing buyers (e.g., TSMC setting terms for fabless chip designers) exemplify CM-power conditions.

The profit functions for each player are:

$$\pi_{OEM} = (P - w)Q_o \tag{1}$$

$$\pi_{CM} = (P - c - c_m)Q_c + (w - c)Q_o \tag{2}$$

The market clears at a price P determined by a standard linear inverse demand function, which depends on total market quantity $(Q_o + Q_c)$:

$$P = a - b(Q_o + Q_c) \tag{3}$$

where a represents the maximum market price and b represents the price sensitivity to quantity.

Theoretical Predictions - OEM Has Market Power

When the OEM has market power and sets wholesale price, the Nash equilibrium (Nash, 1951) wholesale price is $w^* = c$ (equal to the CM's production cost). The derivation appears in Appendix A. The OEM's optimal profit is:

$$\pi_{OEM}^* = \frac{1}{9b}(a - c + c_m)^2 \tag{4}$$

If the OEM invests in the CM's production at cost I, the investment lowers the CM's production cost from c to c_I (where $c > c_I$). We use subscript I to denote variables under investment: P_{I} denotes market price, w_I denotes wholesale price, and Q_{oI} denotes the OEM's quantity. The OEM's profit function with investment is:

$$\pi_{OEMI} = (P_{\mathrm{I}} - w_I)Q_{oI} - I \tag{5}$$

Let Q_{cI} denote the quantity the CM sells to the market. The CM's profit function, assuming the OEM invests, is:

$$\pi_{CMI} = (P_{\mathrm{I}} - c_I - c_m)Q_{cI} + (w_I - c_I)Q_{oI} \quad (6)$$

The market price under investment is:

$$P_I = a - b(Q_{oI} + Q_{cI}) \quad (7)$$

The OEM's optimal wholesale price under investment is $w_I^* = c_I$, and the corresponding optimal profit is:

$$\pi_{OEMI}^* = \frac{1}{9b}(a - c_I + c_m)^2 - I \quad (8)$$

The OEM invests if and only if $\pi_{OEMI}^* > \pi_{OEM}^*$. Substituting equations (4) and (8) and simplifying yields the investment condition:

$$I < \frac{1}{9b}(c_I^2 - c^2 + 2(\mathrm{a} + \mathrm{c}_m)(\mathrm{c} - \mathrm{c_I})) \quad (9)$$

Proposition 1: When the OEM has market power, the OEM invests in the CM if and only if the investment cost falls below the threshold defined in equation (9).

Intuition: When the OEM controls wholesale pricing, it can set $w = c$ (or $w = c_I$ after investment), capturing all the CM's margin from wholesale sales. Investment reduces production costs, which increases total supply chain profits. The OEM, through its pricing power, appropriates these gains. The threshold in equation (9) represents the maximum investment cost at which the profit increase from cost reduction exceeds the investment expenditure. Without pricing power, the OEM cannot capture sufficient benefits to justify the investment cost.

Theoretical Predictions – CM Has Market Power

Next, we consider the case in which the CM has market power and sets the wholesale price. Without OEM investment, the profit functions remain as defined in equations (1) and (2). Under Nash equilibrium, the CM's optimal wholesale price is given in equation (10) (see Appendix A for derivation).

$$w^* = \frac{5a + 5c - c_m}{10} \quad (10)$$

The OEM's optimal profit without investment is:

$$\pi_{OEM}^* = \frac{4c_m^2}{25b} \quad (11)$$

If the OEM invests, the profit functions are given by equations (5) and (6), yielding optimal profit:

$$\pi_{OEMI}^* = \frac{4c_m^2}{25b} - I \quad (12)$$

Since $\pi_{OEMI}^* = \pi_{OEM}^* - I < \pi_{OEM}^*$ for any positive investment cost $I > 0$. Thus, when the CM has market power, the OEM should never invest, regardless of investment cost.

Intuition: When the CM controls wholesale pricing, it sets prices to maximize its own profit, capturing the benefits of any cost reduction. The OEM bears the full investment cost but receives minimal benefit because the wholesale price adjustment exceeds any gains the OEM might realize from increased supply chain efficiency. This creates a fundamental holdup problem: the CM can appropriate the gains from the OEM's investment through strategic pricing. Consequently, investment is never individually rational for the OEM when it lacks pricing power, regardless of how low the investment cost might be.

Given the strategic complexity of dual-channel Cournot competition with investment options, we conduct controlled laboratory experiments to investigate the two research questions stated in the Introduction.

IV. RESEARCH HYPOTHESES AND EXPERIMENTAL DESIGN

We translate our theoretical predictions into testable hypotheses for experimental investigation. Our 2×2 factorial design manipulates market power (OEM vs. CM controls wholesale price) and investment cost (Low vs. High, relative to threshold I^*).

Investment Threshold Hypotheses

Theory predicts investment occurs if and only if the OEM has power and $I < I^*$:

H1a: In the OEM-Low treatment (OEM has power, $I < I^*$), the investment rate equals 100%.

H1b: In the OEM-High, CM-Low, and CM-High treatments, the investment rate equals 0%.

H1c: The investment rate in OEM-Low significantly exceeds the rates in all other treatments.

Hypothesis on Investment Dynamics

H2: Investment rates show no significant change across periods within each treatment.

Investment Determinants

Our 2×2 design permits decomposition of power and cost effects:

H3a: OEM market power positively affects investment rates. Specifically, investment rates are higher when the OEM controls wholesale pricing than when the CM controls it.

H3b: Investment cost negatively affects investment rates. Specifically, investment rates are higher in Low-cost treatments than in High-cost treatments.

Supply Chain Performance

A centralized supply chain would invest when $I < I^*$ (see Appendix A), making OEM-Low closest to the first-best:

H4a: Total supply chain profit is highest in the OEM-Low treatment compared to all other treatments.

H4b: Supply chain efficiency (actual profit as a percentage of centralized optimal profit) is highest in the OEM-Low treatment.

Hypothesis on Pricing Behavior

Theory predicts that the wholesale price should equal $w^* = c$ when the OEM has power, and $w^* = \frac{5a+5c-c_m}{10}$ when the CM has power.

H5: Observed wholesale prices do not significantly deviate from theoretical predictions in each treatment.

Experimental Design

We employ a 2×2 between-subjects factorial design crossing two factors: market power (OEM vs. CM sets wholesale price) and investment cost (Low ($I < I^*$) vs. High ($I > I^*$)), yielding four treatments. Table 4.1 summarizes the 2×2 design and sample sizes (N = 98 total).

TABLE 4.1. EXPEROMENTAL DESIGN AND SAMPLE SIZES

	OEM Has Power	CM Has Power
Investment Cost Low ($I < I^*$)	OEM-Low (n = 24)	CM-Low (n = 24)
Investment Cost High ($I > I^*$)	OEM-High (n = 24)	CM-High (n = 26)

We use game-theoretic analysis to select parameter values that create realistic economic incentives (Table 4.2). Key parameters are held constant across all treatments: $a = 100, b = 0.5, c = 40, c_I = 25, c_m = 5$. The investment cost varies by treatment: $I = 380$ in Low treatments (below the threshold $I^* = 483.33$) and $I = 580$ in High treatments (above the threshold). These values yield equilibrium profits and quantities shown in Appendix B.

TABLE 4.2. PARAMETER CALIBRATION

	OEM-Low	OEM-High	CM-Low	CM-High
Investment cost (I)	380	580	380	580
I^*	483.33	483.33	-	-
Production cost before investment (c)	40	40	40	40
Production cost after investment (c_I)	25	25	25	25
Extra market cost (c_m)	5	5	5	5

Game Sequence

Stage 1 (Investment Decision): OEM observes the power structure and decides whether to invest in reducing the CM's production cost (from $c = 40$ to $c_I = 25$) at cost I.

Stage 2 (Pricing Decision): The player with market power (either OEM or CM, depending on treatment) observes the OEM's investment decision and sets the wholesale price w.

Stage 3 (Quantity Decisions): Both players simultaneously observe all prior decisions and choose their quantities (Q_o for OEM, Q_c for CM).

The Z-Tree software (Fischbacher, 2007) calculates profits and displays all relevant information each period (see Appendix C for screenshots).

Experimental Procedures

Each treatment included approximately 24 participants (12 pairs) randomly assigned to fixed OEM or CM roles. Participants were randomly rematched each period (stranger matching) across 30 periods to minimize repeated-game effects.

We followed standard experimental economics protocols (Chen et al., 2022). Ninety-eight undergraduate business students participated in 90-minute sessions and received monetary compensation based on their performance. After receiving instructions, participants completed a comprehension quiz. Average earnings were $15 (range: $8-$23).

V. EXPERIMENTAL RESULTS

Table 5.1 presents period-averaged results. Investment rates vary substantially across treatments (OEM-Low: 54%; OEM-High: 42%; CM-Low: 33%; CM-High: 36%), reflecting differential responses to power and cost factors.

TABLE 5.1. SUMMARY STATISTICS OF EXPERIMENTAL RESULTS (PERIOD AVERGES)

	OEM-Low	OEM-High	CM-Low	CM-High
Investment Rate	53.61%	41.67%	33.33%	36.41%
Wholesale Price	43	39	72	74
OEM Quantity (Q_o)	41	46	25	32
CM Quantity (Q_c)	51	40	43	48

Market Price (P)	55	58	66	61
OEM Profit (π_{OEM})	-76	370	-256	-797
CM Profit (π_{CM})	665	862	1506	1795
Supply Chain Profit	589	1232	1250	999

Note: All values represent averages across 30 periods. Investment rate calculated as percentage of periods with investment across all subject pairs.

5.1. Investment Decisions (H1a-H1c)

Testing Hypothesis 1a: Investment in OEM-Low Treatment

Theory predicts 100% investment in the OEM-Low treatment. However, observed results reveal significant underinvestment. The 12 OEMs invested in only 193 of 360 opportunities (53.61%). A one-sample proportion test ($p < 0.01$) confirms this rate differs significantly from the predicted 100%, rejecting Hypothesis 1a. OEMs systematically underinvested, achieving only 54% of the optimal rate.

A critical insight into why this underinvestment persists comes from examining the profit outcomes experienced by OEMs in this treatment. As shown in Table 5.1, the average OEM profit in OEM-Low is −76, despite investment being theoretically profitable at equilibrium. This loss arises not from the investment decision per se, but from the compound effect of two simultaneous off-equilibrium behaviors: OEMs set wholesale prices substantially above the theoretically optimal level (observed $w = 43$ vs. predicted $w^* = 25$; Table 5.8), compressing their own channel margins, while CMs respond with aggressive quantity decisions that further depress market prices. These joint deviations create conditions in which investment appears to yield losses even though it is individually optimal under equilibrium play.

We argue that this generates a misattribution bias consistent with outcome-based reinforcement learning (Camerer, 1995; Kahneman and Tversky, 1979): subjects observe negative profits in periods where they invest and incorrectly attribute the poor outcome to the investment decision rather than to simultaneous pricing and quantity dynamics. This association between investment and experienced loss suppresses future investment choices, producing rates well below the theoretical optimum. This mechanism is consistent with the learning dynamics documented in Section 5.2, where prior outcomes significantly predict subsequent investment behavior, and explains why the OEM-Low investment rate stabilizes around 53–54% rather than converging upward toward the theoretical 100%.

Testing Hypothesis 1b: Investment in Other Treatments

Theory predicts 0% investment in three conditions: OEM-High (high costs with OEM power), CM-Low, and CM-High (CM has power). However, observed rates significantly exceeded 0% in all three treatments (see Table 5.1). One-sample proportion tests ($p < 0.01$)) confirm these rates differ significantly from predictions, rejecting Hypothesis 1b. OEMs systematically overinvested when theory predicts zero investment, demonstrating consistent deviations in the opposite direction from the OEM-Low treatment.

Testing Hypothesis 1c: Comparative Investment Rates

The OEM-Low's 53.61% investment rate significantly exceeds all other treatments: OEM-High (41.67%), CM-Low (33.33%), CM-High (36.41%); all pairwise comparisons $p <$

0.01. Hypothesis 1c is supported. While absolute levels deviate from theory, the relative pattern follows predicted directions: highest investment occurs when the OEM has power and costs are low.

These systematic deviations (underinvestment when optimal, overinvestment otherwise) suggest bounded rationality or strategic uncertainty affects decisions.

Managerial Insight: OEM managers systematically underinvest when investment is individually profitable, particularly when realized profits are negative due to off-equilibrium pricing dynamics. Organizations should implement structured decision support tools that calculate investment profitability thresholds, flag cognitive biases such as the tendency to attribute pricing-driven losses to the investment decision itself, and alert managers before they forgo profitable supplier investments.

5.2 Investment Dynamics Over Time (H2)

We examine whether investment rates change over 30 periods by comparing early (1–5) versus late (26–30) periods. Table 5.2 shows results from one-sided proportion tests.

TABLE 5.2. INVESTMENT RATES IN EARLY VS. LATE PERIODS

	OEM-Low	OEM-High	CM-Low	CM-High
Periods 1-5 (H_A: p>50%)	63%**	53%	50%	55%
Periods 26-30 (H_A: p<50%)	53%	35%**	26%**	24%**

$^{+}\, p < 0.1$, $^{*}\, p < 0.05$, $^{**}\, p < 0.01$

Investment rates decline significantly in three treatments. In OEM-High, CM-Low, and CM-High, investment drops 18–31 percentage points from early to late periods, falling significantly below 50% by periods 26–30 (all $p < 0.01$). OEM-Low maintains investment around 50–60% throughout.

Regression analysis confirms this pattern. We estimate:

$$Invest_{it} = \beta_0 + \beta_1 Period_t + \varepsilon_{it} \quad (13)$$

where i indexes subjects and t indexes periods. Table 5.3 presents results.

TABLE 5.3. TIME TREND COEFFICIENTS (β_1) FROM LOGISTIC REGRESSION MODELS

Model Specification	OEM-Low	OEM-High	CM-Low	CM-High
Logistic regression	-0.0149	-0.0257*	-0.0413**	-0.0704**
Random effects logistic	-0.0246	-0.0432**	-0.0434**	-0.0761**
Fixed effects logistic	-0.0245	-0.0438**	-0.0435**	-0.0761**

$^{+}\, p < 0.1$, $^{*}\, p < 0.05$, $^{**}\, p < 0.01$

Period coefficients are significantly negative in OEM-High (β=-0.04, p<0.01), CM-Low (β=-0.04, p<0.01), and CM-High (β=-0.08, p<0.01) across all model specifications, but not in OEM-Low. Subjects learn to reduce investment when it harms profits but maintain investment when beneficial.

To examine reinforcement learning, we test whether prior outcomes predict current investment in treatments with initial overinvestment (OEM-High, CM-Low, CM-High). The model includes: prior investment, prior OEM profit, their interaction, and period (Table 5.4).

TABLE 5.4. LEARNING FROM PRIOR OUTCOMES (RANDOM EFFECTS LOGISTIC REGRESSION)

Coefficient	OEM-High	CM-Low	CM-High
Prior Investment $(t-1)$	0.489	0.402	1.025**
Prior OEM Profit $(t-1)$	-0.0007*	-0.0000	-0.0000
Prior Investment * Prior OEM Profit	0.0007*	0.0005+	0.0006**
Period	-0.0111	-0.0302*	-0.0669**

+ p < 0.1, * p < 0.05, ** p < 0.01

The interaction between prior investment and prior profit significantly predicts current investment in CM treatments (both p < 0.05), indicating subjects reinvest more frequently when prior investments were profitable. This demonstrates experience-based learning: subjects discover investment is unprofitable without power and adjust accordingly.

Hypothesis 2 is rejected. Investment rates show significant time trends in three of four treatments, revealing gradual learning rather than immediate equilibrium adoption.

Managerial Insight: Investment behavior is not stable at the outset of a supply chain relationship; it evolves through experience-based learning. In newly formed OEM–CM relationships, both parties may initially over- or under-invest as they learn the incentive structure. Supply chain managers should plan for an adjustment period and accelerate convergence toward cooperation through transparent sharing of investment outcomes and explicit communication of cost-benefit calculations.

5.3 Relative Effects of Power and Cost (H3a, H3b)

We decompose effects of two experimental factors: Power (who sets wholesale price) and Cost (I relative to threshold $I^* = 483.33$). Theory predicts equal effects: Power Effect = 50 percentage points (OEM Power 50% vs. CM Power 0%), Cost Effect = 50 percentage points (Low Cost 50% vs. High Cost 0%).

Observed effects diverge sharply. For Power: OEM Power conditions averaged 48% investment, while CM Power averaged 35%, yielding an observed effect of 13 percentage points. For Cost: Low Cost averaged 43% investment, High Cost averaged 39%, yielding only 4 percentage points. Subjects respond more strongly to power than to cost, suggesting greater sensitivity to salient features than complex calculations. We estimate:

$$\begin{aligned} Invest_{it} &= \beta_0 + \beta_1 Power\ dummy_{it} \\ &+ \beta_2 Cost\ dummy_{it} \\ &+ \beta_3 Power\ dummy_{it} \\ &* Cost\ dummy_{it} + a_i + u_{it} \end{aligned} \tag{14}$$

where the dependent variable represents the investment decision for individual i in period t.

Results (Table 5.5) reveal asymmetric responses. Power marginally affects investment ($\beta_1 = 1.00, p < 0.1$), while cost does not ($\beta_2 = -0.70, p > 0.1$).

When costs are low, power increases investment 20 percentage points (OEM-Low 54% vs. CM-Low 33%), far below the theoretical 100 percentage points difference. When costs are high, power increases investment only 5 percentage points (OEM-High 42% vs. CM-High 36%), despite theory predicting no difference. This persistent overinvestment under OEM power suggests subjects adopt a simple heuristic ("invest when you have power") rather than calculating precise thresholds.

Cost changes have minimal impact. The cost effect (4 percentage points) is five times smaller than the power effect (20 percentage points) and statistically insignificant. Subjects do not adjust behavior based on whether costs fall above or below $I^* = 483.33$, suggesting this calculation exceeds their cognitive capacity.

Hypothesis 3a receives marginal support ($\beta_1 = 1.00, p < 0.1$), confirming power affects investment. Hypothesis 3b is rejected ($\beta_2 = -0.70, p > 0.1$), indicating subjects ignore cost thresholds.

Power also affects quantity decisions. OEM quantity increases 16 units under OEM power ($\beta_1 = 16.09, p < 0.01$), while CM quantity shows no significant response. This asymmetry reflects OEMs' more complex decision space.

These patterns indicate bounded rationality. The power factor is salient and simple—subjects easily identify who controls pricing. The cost threshold requires complex calculation: compare $I \in \{380,580\}$ to $I^* = 483.33$, then integrate this into investment decisions. This computational burden exceeds subjects' cognitive capacity, leading them to focus on observable power dynamics.

Table 5.5 presents full regression results for investment and quantity decisions.

TABLE 5.5. EFFECTS OF POWER AND COST ON BEHAVIORAL DECISIONS RANDOM EFFECTS REGRESSION COEFFICIENTS

Dependent Variable	Power (β_1)	Investment Cost (β_2)	Power * Cost (β_3)
Investment Decision	1.00$^+$	-0.70	0.83
OEM Quantity (Q_o)	16.09**	6.79	-2.27
CM Quantity (Q_c)	7.89	5.00	-16.81
+ p < 0.1, * p < 0.05, ** p < 0.01			

Managerial Insight: Decision-makers respond roughly three times more strongly to the observable power structure than to precise cost-benefit calculations. Practically, this means that securing pricing authority in a supplier relationship is far more effective at driving investment behavior than communicating detailed ROI analyses. Organizations negotiating OEM–CM contracts should prioritize establishing clear, visible pricing power before attempting to optimize investment levels through incentive design.

5.4 Supply Chain Effects (H4a, H4b)

Investment benefits total supply chain profit even when harming individual OEMs. Under centralization, the OEM and CM operate as a single entity maximizing $\pi_{SC} = \pi_{OEM} + \pi_{CM}$. Investment is optimal when:

$$I < I_{Cen}^{*} = \frac{c_I^2 - c^2 - 2ac_I + 2ac}{4b} \quad (15)$$

Comparing centralized and decentralized thresholds, when the following condition holds:

$$-10a + 5c_I + 5c + 8c_M < 0 \quad (16)$$

Using our parameters, both $I = 380$ (Low) and $I = 580$ (High) fall below I_{Cen}^{*}, implying investment maximizes supply chain profit in all treatments.

TABLE 5.6. THEORETICAL SUPPLY CHAIN PROFITS AND

		OEM-Low	OEM-High	CM-Low	CM-High
Decentralized SC Profit	Invest (1)	1981.11	1781.11	2088	1888
	Not Invest (2)	1494.44	1494.44	1530.5	1530.5
Centralized SC Profit	Invest (3)	2432.5	2232.5	2432.5	2232.5
	Not Invest	1800	1800	1800	1800
Channel Efficiency	Invest $\frac{(1)}{(3)}$	81.44%	79.78%	85.84%	84.57%
	Not Invest $\frac{(2)}{(3)}$	61.44%	66.94%	62.92%	68.56%

Theoretical predictions (Table 5.6) show three key findings that highlight fundamental tensions in supply chain coordination. First, investment increases supply chain profit 26-37% across all treatments, creating significant value regardless of power structure or costs. Second, investment increases efficiency 15-20 percentage points across all treatments, moving decentralized supply chains closer to centralized performance. Third, investment creates a coordination problem: it benefits the supply chain in all treatments but harms individual OEMs in three treatments (OEM-High, CM-Low, CM-High). Individually rational decisions (not investing) yield socially suboptimal outcomes, creating tension between individual and collective incentives.

TABLE 5.7. OBSERVED SUPPLY CHAIN PROFITS AND EFFICIENCY (EXPERIMENTAL DATA)

		OEM-Low	OEM-High	CM-Low	CM-High
Observed SC Profit (Average Across Periods)	Invest	1156	1352	1531	1198
	Not Invest	-67	1146	1109	885
Observed Channel Efficiency (% of Centralized Optimum)	Invest	48%	61%	63%	54%
	Not Invest	-3%	51%	46%	40%

Testing H4a: Total Supply Chain Profit

Supply chain profit is consistently higher with investment across all treatments (Table 5.7): OEM-Low (+1223), OEM-High (+206), CM-Low (+422), CM-High (+313). Mann-Whitney tests confirm all differences are significant ($p < 0.01$). H4a is supported: investment significantly increases total supply chain profit across all treatments, confirming theoretical benefits carry over despite behavioral deviations.

Testing H4b: Supply Chain Efficiency

Investment consistently increases efficiency across all treatments: OEM-Low (+51 points), OEM-High (+10 points), CM-Low (+17 points), CM-High (+14 points). Mann-Whitney tests confirm all improvements are significant ($p < 0.01$). H4b is supported: investment significantly increases supply chain efficiency, reducing coordination losses in decentralized supply chains and moving performance closer to centralized optimum despite behavioral deviations.

Managerial Insight: Even in conditions where investment harms the individual OEM, it consistently increases total supply chain value by 17–104%. OEMs considering whether to invest in supplier capabilities should account not only for direct financial returns but also for the relational signal that investment sends, the resulting reciprocal pricing response from CMs (documented in Section 5.5) partially compensates the OEM and helps sustain the partnership.

5.5 Wholesale Pricing Behavior (H5)

Testing Hypothesis 5: Pricing Deviations from Theory

H5 predicted wholesale prices would conform to theory. Data reveal systematic deviations: OEMs with power set prices higher than optimal; CMs with power set prices lower than optimal.

TABLE 5.8. OBSERVED VS. PREDICTED WHOLESALE PRICES

	OEM-Low		OEM-High		CM-Low		CM-High	
	Invest	Not Invest	Invest	Not Invest	Invest	Not Invest	Invest	Not Invest
Observed Price	36.44	49.96	31.59	44.97	63.16	76.59	59.50	81.53

Predicted Price	25	40	25	40	62	69.5	62	69.5
Difference	+**	+**	+**	+**	-**	-**	-**	12.03

** p < 0.01 (two-sample t-test comparing observed to predicted)
Note:
+ indicates observed > predicted (price setters are generous to partners).
- indicates observed < predicted. Predicted prices from Nash equilibrium (equations in Section 3).
OEMs with power consistently set prices above optimal, benefiting CMs.
CMs with power consistently set prices below optimal, benefiting OEMs.

OEMs with power consistently set prices above optimal, benefiting CMs. CMs with power consistently set prices below optimal, benefiting OEMs. The observed pricing patterns reveal systematic deviations from theoretical predictions in both OEM-power and CM-power treatments, with striking implications for how power holders exercise their pricing authority.

In the OEM-power treatments, OEMs consistently set wholesale prices 5 to 11 units above the theoretically optimal levels, in both invest and no-invest scenarios. All of these deviations are statistically significant at the $p < 0.01$ level. This 'generous' pricing strategy leaves money on the table for the OEM while increasing the CM's profit margin. Similarly, in the CM-power treatments, CMs demonstrate their own form of pricing generosity by setting wholesale prices 1 to 12 units below the theoretically optimal levels in most scenarios. Three of the four comparisons show statistically significant deviations.

TABLE 5.9. EFFECT OF INVESTMENT ON PRICING DEVIATIONS (DEPENDENT VARIABLE: OBSERVED PRICE-PREDICTED PRICE)

Model Specification	OEM-Low	OEM-High	CM-Low	CM-High
OLS Regression	1.47	1.62	-5.93	-14.53**
Random Effects	9.69**	2.83*	-5.96	-15.18**
Fixed Effects	11.58**	3.20**	-5.98	-16.66**

Note:
Positive coefficients indicate that investment increases the pricing deviation (OEMs set even higher prices, or CMs set even lower prices, when investment occurs).
This magnified generosity when investment occurs suggests reciprocal behavior: power holders reward investment with more favorable pricing.

OEM Pricing with Investment: OEMs increase their pricing deviation when they invest. In OEM-Low, the deviation increases by 9.69 points ($p < 0.01$); in OEM-High, by 2.83 points ($p < 0.05$). This magnified generosity when investing suggests reciprocal motivation—OEMs share investment benefits with CMs through favorable pricing.

CM Pricing with Investment: When OEMs make relationship-specific investments, CMs respond by decreasing wholesale prices even further below the theoretically optimal levels, demonstrating enhanced pricing generosity. This effect is particularly pronounced in the CM-High treatment, where the pricing deviation increases in magnitude by 15.18 points ($p < 0.01$). This finding indicates that investment by the OEM triggers a systematic and substantial pricing response from the CM.

These reciprocal patterns of generous pricing, where each party when in power sets prices that benefit their counterpart rather than fully extracting available surplus, suggest the emergence of implicit cooperation or reciprocity norms not captured by standard Nash equilibrium predictions. The results decisively reject Hypothesis 5.

Reciprocity versus Altruism: Distinguishing the Mechanisms

The generous pricing patterns documented above are consistent with two distinct behavioral mechanisms that warrant explicit differentiation. The first is pure altruism or inequality aversion, formalized by Fehr and Schmidt (1999) and Bolton and Ockenfels (2000), which predicts that power holders set favorable prices unconditionally, regardless of whether their partner has invested, because they derive intrinsic disutility from unequal payoff distributions. The second is conditional reciprocity, formalized by Fehr and Gächter (2000) and Charness and Rabin (2002), which predicts that pricing generosity is specifically triggered by, and proportional to, the partner's prior cooperative action.

Our data allow us to distinguish these mechanisms by examining whether pricing deviations are unconditional (favoring altruism) or conditionally larger following investment (favoring reciprocity). The baseline pricing deviations in the no-invest conditions, OEMs pricing 5–10 units above optimal and CMs pricing 1–12 units below optimal, are consistent with a baseline preference for fairness or relationship maintenance. However, the statistically significant incremental deviations triggered by investment (Table 5.9), particularly the 15.18-point increase in CM pricing generosity in CM-High ($p < 0.01$) and the 9.69-point increase in OEM-Low ($p < 0.01$), are more consistent with conditional reciprocity than with pure altruism. An altruism explanation would predict no systematic difference between invest and no-invest pricing, a prediction our data firmly reject.

We therefore interpret the pricing behavior as a two-layer phenomenon: a baseline layer of fairness preferences producing unconditional generosity, overlaid by a conditional reciprocity layer that amplifies generosity in response to observed investment. This interpretation aligns with the behavioral supply chain coordination literature (Loch and Wu, 2008; Katok and Wu, 2009) and provides a richer behavioral foundation for the emergent informal coordination mechanism we document.

Managerial Insight: The reciprocal pricing behavior documented here, where power holders voluntarily offer favorable terms to partners who have invested, suggests that informal coordination can partially substitute for formal investment-sharing contracts. Supply chain managers should structure repeated interactions with transparent outcome visibility to allow such reciprocity norms to develop organically. These informal mechanisms work best when relationships are long-term, mutual benefits are substantial, and investment decisions are observable to the pricing party.

VI. MANAGERIAL IMPLICATIONS AND DISCUSSION

Our controlled laboratory experiments reveal systematic behavioral deviations from game-theoretic predictions in dual-channel supply chain investment decisions. This section synthesizes our empirical findings, articulates theoretical contributions to multiple literature streams, derives managerial implications, and acknowledges study limitations. Our central finding is that individual decision errors can inadvertently facilitate supply chain coordination through emergent reciprocity norms.

6.1 Summary of Key Findings

Our experiments reveal four robust patterns that diverge from theoretical predictions.

Finding 1: Systematic Investment Biases. OEMs underinvest when investment is individually optimal (54% vs. 100% predicted in OEM-Low) but overinvest when it is suboptimal (33–42% vs. 0% predicted in other treatments).

Finding 2: Differential Sensitivity to Decision Complexity. Market power's effect on investment (13 percentage points) is three times larger than investment cost's effect (4 points), both falling far short of theoretical predictions (50 points each).

Finding 3: Asymmetric Learning Dynamics. Investment rates decline over time in suboptimal conditions but remain stable in optimal conditions, indicating experience-based learning to avoid losses but not to capture gains.

Finding 4: Reciprocal Pricing and Coordination. Both OEMs and CMs set prices benefiting partners rather than maximizing individual profits, with deviations intensifying when investment occurs, creating an emergent coordination mechanism.

6.2 Theoretical Contributions

Our research advances four distinct literature streams.

Contribution to Dual-Channel Supply Chain Literature. We extend dual-channel models (Wang et al., 2013; Niu et al., 2015) by incorporating uncontracted investments and endogenous market power structures. While prior analytical work assumes complete contracts govern all transactions, we examine settings where OEMs invest without formal guarantees of return appropriation. Our game-theoretic model demonstrates that investment optimality depends critically on market power: OEMs should invest only when they control wholesale pricing and costs fall below a calculable threshold. Our behavioral results reveal that the complexity inherent in dual-channel competition, where firms simultaneously cooperate as supply chain partners and compete as market rivals, exceeds bounded human computational capacity.

Contribution to Transaction Cost Economics and Investment Theory. We provide the first experimental test of Williamson's (1996) transaction cost economics prediction that firms should not make relationship-specific investments without contractual safeguards against opportunistic holdup. Results document systematic violations: OEMs invest without protection in 33–42% of cases where theory predicts zero, while underinvesting (54% vs. 100%) when power ensures returns. These patterns challenge the foundational assumption that firms act as profit maximizers. The persistence of these deviations across 30 periods of experience suggests fundamental cognitive constraints rather than learning failures.

Contribution to Behavioral Operations Management. We document a novel behavioral pattern: selective sensitivity to decision complexity. Decision-makers respond strongly to simple, salient features (who controls pricing) but fail to respond to computationally complex calculations (whether costs exceed equilibrium thresholds). This extends prior work on bounded rationality in supply chains (Su, 2008; Loch and Wu, 2008) by demonstrating that not merely decision complexity per se, but specifically the computational complexity of decision rules, drives deviations from optimality. Furthermore, the misattribution bias we document in OEM-

Low, where OEMs associate negative profits with investment rather than with off-equilibrium pricing dynamics, represents a novel form of attribution error in supply chain decision-making. This extends the bounded rationality literature by identifying a specific cognitive failure mode: the inability to disentangle the profitability of an investment decision from the confounding effects of concurrent pricing and quantity deviations. Future research should examine whether providing OEMs with counterfactual profit information (i.e., what they would have earned without investing) can correct this attribution bias and improve investment rates toward the theoretical optimum.

Contribution to Supply Chain Coordination Theory. We document an emergent coordination mechanism arising from behavioral deviations. Individual suboptimality, specifically overinvestment by OEMs lacking power and generous pricing by power holders, generates system-level benefits. Supply chain efficiency increases 10–20 percentage points when investment occurs, even in treatments where investment harms the investing OEM individually. This challenges the standard assumption that off-equilibrium play necessarily reduces welfare.

6.3 Managerial Implications

Our findings offer specific guidance for supply chain decision-makers.

Implications for OEMs Making Investment Decisions. OEMs make systematic errors in evaluating supplier investments, underinvesting when profitable and overinvesting when not. To mitigate these biases, managers should implement structured decision frameworks incorporating the theoretical investment threshold from our model. Specifically, when an OEM controls wholesale pricing, investments are profitable when costs fall below $I^* = \frac{1}{9b}(c_I^2 - c^2 + 2(a + c_m)(c - c_I))$. However, our experimental evidence reveals that even sophisticated decision-makers struggle with this calculation. Managers should therefore develop decision support systems that automatically calculate thresholds and flag situations where cognitive biases are likely.

Investment value depends critically on market power. Cost-reduction investments in suppliers are individually profitable only when the investing firm can capture benefits through favorable wholesale pricing. Before making uncontracted investments, OEMs should negotiate pricing authority or establish contracts specifying price adjustments contingent on investment.

Even when investments do not maximize short-term individual profits, they may improve long-term supply chain performance. Our data demonstrate that total supply chain profit increases 17–104% with investment across all experimental treatments, even when individual OEM profit decreases. OEMs seeking sustained partnerships should view cost-reduction investments as relationship-building mechanisms that signal commitment and facilitate cooperation through triggered reciprocity.

Implications for CMs Responding to Investments. Contract manufacturers should interpret OEM investments, particularly unprotected investments when the CM controls pricing, as costly commitment signals. Our experimental evidence shows that CMs spontaneously reciprocate such investments by setting wholesale prices 2–12 units below individually optimal levels, partially compensating OEMs for investment costs. To sustain cooperative relationships, CMs should make such reciprocity explicit through transparent cost-sharing or pass-through arrangements.

Implications for Supply Chain Coordinators. Our results reveal that informal coordination mechanisms can emerge from repeated interactions when decisions are mutually observable. Supply chain managers should structure relationships to facilitate such emergence by increasing interaction frequency, enhancing transparency of decisions and outcomes, and explicitly recognizing mutual benefits from cooperation. However, our findings also reveal the importance of designing for bounded rationality. Complex decision rules based on threshold calculations are poorly executed. Simpler heuristics ('invest when you control pricing and expected ROI exceeds two years') are more likely to be followed, even if theoretically inferior.

Finally, managers should recognize that informal mechanisms, such as uncontracted investments combined with reciprocal pricing, can achieve coordination when formal contracts are costly or difficult to enforce. These informal mechanisms work best when relationships are long-term, interactions are repeated, and mutual benefits are substantial.

Implications for AI-Powered Decision Support Tools. As artificial intelligence increasingly shapes supply chain decision making, our findings provide a theoretical foundation for the design of AI-powered decision support systems (Jackson et al., 2024; Su et al., 2026). We identify a specific bounded rationality constraint, decision makers' difficulty in executing complex threshold calculations, that is particularly well suited to AI intervention. By automating the evaluation of investment costs relative to the critical threshold I^*, AI-driven decision support systems can systematically incorporate market power considerations and process real-time data at a scale that exceeds human cognitive limits.

6.4 Robustness and Generalizability

A central concern when interpreting behavioral findings from a single parametric calibration is whether the theoretical benchmark against which deviations are measured is itself an artifact of the chosen parameters. We address this concern through two analytical simulations. We note an important boundary at the outset: the observed 3:1 sensitivity ratio (13 percentage points for power versus 4 percentage points for cost) is an empirical result produced by human subjects. No numerical simulation can project what this behavioral ratio would be under different parameter values; answering that question would require running additional experiments. The two simulations below instead address the structural questions that determine whether the conditions for observing such a finding are robust.

Simulation 1: The 50/50 Theoretical Benchmark Is a Structural Property of the 2×2 Design. The equal-sensitivity prediction, 50 percentage points each for the power effect and the cost effect, is not a product of our specific parameter values for a, b, and Δc $(c - c_I)$, but rather a structural property of the binary investment decision embedded in a 2×2 design: whenever the two experimental cost levels bracket the equilibrium threshold (i.e., $I_{Low} < I^* < I_{High}$), Nash equilibrium always predicts exactly 100% investment in OEM-Low and 0% in all other three conditions, yielding theoretical power and cost effects of exactly 50 percentage points each by construction. We note that the threshold I^* itself is not parameter-invariant, from equation (9), I^* scales inversely with b and linearly with a, so the bracketing condition $I_{Low} < I^* < I_{High}$ does not hold universally for fixed cost levels of 380 and 580 across all parameter combinations, but the invariance claim is accordingly precise: it concerns the structure of the Nash prediction conditional on a valid bracket, not the cost values themselves. To verify this numerically, we compute I^* across a grid spanning $a \in [80, 150], b \in [0.25, 1.0]$, and $\Delta c \in [5, 25]$, and present results in Appendix D. Panel A of Figure D1 displays a two-dimensional heatmap over the (a, b) parameter space, color-coded by whether the bracketing condition holds: the green region, which encompasses the experimental calibration point ($a = 100, b = 0.50$, marked with a star), identifies all parameter combinations for which the design is valid, while orange and purple regions indicate where fixed cost levels of 380 and 580 would require recalibration. Panel B of Figure D1 then plots the theoretical power effect and cost effect computed at each of the 1,230 valid grid cells within this region: every single cell produces exactly 50 percentage points for both effects, with no deviation whatsoever across the entire valid parameter space. Our experimental calibration ($a = 100, b = 0.5, \Delta c = 15, c_m = 5$) produces $I^* = 483.33$, which comfortably satisfies the bracketing condition and sits well within the green region of Figure D1, Panel A. The 3:1 behavioral deviation we document is therefore measured against a fixed, structurally determined 50/50 benchmark that does not shift with parameter choices, provided the bracketing condition is maintained.

Simulation 2: The Efficiency-of-Errors Result Is Structurally Robust. Our finding that investment always increases total supply chain profit, even in treatments where it harms the individual OEM, rests on both I_{Low} and I_{High} falling below the centralized threshold I_{Cen}^*. Comparing equations (9) and (15), $I_{Cen}^* > I^*$ whenever condition (16) holds: $-10a + 5cI + 5c + 8cm < 0$. With our parameters, $I_{Cen}^* \approx 1012.5$, well above $I^* = 483.33$, so both experimental cost levels (380 and 580) sit strictly below the centralized optimum and investment is always socially efficient regardless of treatment. The graphical evidence for this result is presented in Appendix D (Figures D2–D4). Figure D2 plots both I_{OEM}^* (solid blue) and I_{SC}^* (dashed green) against market size $a \in [80, 150]$, Figure D3 plots the same two thresholds against price sensitivity $b \in [0.25, 1.0]$, and Figure D4 plots them against cost reduction $\Delta c \in [0, 35]$. Across all three figures, the green dashed line (I_{SC}^*) lies strictly and substantially above the blue solid line (I_{OEM}^*) throughout the entire parameter range, with no crossing, no narrowing to zero, and no region where the ordering reverses. Notably, in Figure D3, both experimental cost levels of 380 and 580 remain below I_{SC}^* within the valid bracketing region, confirming that the dominance of social over private investment incentives persists wherever the experimental design is properly calibrated. To further verify condition (16) analytically, we evaluate it across a grid spanning $a \in [80, 150], b \in [0.25, 1.0], \Delta c \in [5, 25]$, and $c_m \in [2, 10]$, confirming that the condition is satisfied across all combinations in this economically meaningful range, the most demanding case ($a = 80, \Delta c = 5, c_m = 10$) yields −345, far below zero. Consequently, I_{Cen}^* strictly exceeds both experimental cost levels throughout the grid, and investment always increases total supply chain profit relative to no investment. The behavioral overinvestment observed in CM-power conditions is therefore always efficiency-enhancing: not a coincidence of our specific parameter calibration, but a structural property of this class of dual-channel model in which the social value of cost reduction reliably exceeds its private value to the investing party.

Taken together, these two simulations establish that the theoretical 50/50 benchmark is parameter-invariant within the valid design region, and that the efficiency benefits of behavioral errors are structurally guaranteed across the full economically meaningful parameter space. The precise magnitude of the behavioral 3:1 sensitivity ratio under different parameter settings remains an open empirical question that we identify as a priority direction for future experimental research, and we have stated this explicitly in Section 7.

6.5 Limitations

While our findings offer valuable insights, certain limitations provide a roadmap for future research. First, we examine a single parametric calibration with fixed demand and cost parameters. While chosen to reflect realistic economic incentives, our results may not generalize across all parameter ranges or market structures. Future research should systematically vary demand elasticity, cost structures, and market concentration to establish boundary conditions for our behavioral patterns.

Second, our experimental design provides complete information about costs, demand, and investment effectiveness. Real supply chains involve substantial uncertainty about investment outcomes, information asymmetries regarding costs and capabilities, and demand volatility. These factors may strengthen investment incentives (if uncertainty creates option value) or weaken them (if risk aversion dominates).

Third, our subjects are undergraduate business students rather than practicing supply chain managers. While student samples are standard in experimental operations research and our design includes extensive training and salient financial incentives, managers may exhibit different risk preferences, strategic sophistication, or time preferences. Fourth, our 30-period horizon captures medium-term dynamics but not very long-term relationships spanning years or decades. Fifth, we examine only wholesale price contracts. Sixth, laboratory experiments may not capture all real-world complexity.

VII. CONCLUSION AND FUTURE RESEARCH

This study demonstrates that systematic behavioral deviations from Nash equilibrium can inadvertently facilitate supply chain coordination. Our game-theoretic model identifies market power as the critical determinant of investment optimality, yet experimental evidence reveals persistent violations driven by bounded rationality. Subjects respond strongly to salient features but fail to execute complex threshold calculations.

Despite individual suboptimality, these behavioral errors generate system-level benefits. Investment increases supply chain efficiency by 10–51 percentage points across all treatments, even when harming individual investors. Combined with reciprocal pricing behaviors, these deviations create emergent coordination mechanisms that challenge the conventional view that off-equilibrium play necessarily reduces welfare.

Our findings advance transaction cost economics by providing the first experimental evidence that firms invest without contractual protections, extend behavioral operations management by documenting selective sensitivity to computational complexity, and offer practitioners a key insight: simple heuristics may outperform complex analytical rules when bounded rationality constrains decision-making.

Future research should examine six extensions. First, alternative contract forms (revenue-sharing, buy-back, quantity discounts) to test whether our coordination mechanism survives different governance structures. Second, information asymmetries and outcome uncertainty to enhance realism and test how incomplete information affects investment and reciprocity. Third, longer time horizons to study reciprocity evolution and learning dynamics. Fourth, network structures with multiple suppliers or buyers to test competitive effects on uncontracted investment. Fifth, field experiments or empirical studies of actual OEM–CM relationships to enhance external validity. Sixth, manager subjects and organizational decision-making to test whether experience mitigates biases and how group dynamics differ from individual choices. Seventh, future research should systematically vary the key parameters of our model, particularly the cost gap ($c - cI$), demand sensitivity b, and the ratio I/I^*, to empirically establish boundary conditions for the behavioral sensitivity patterns we document. While our analytical simulations in Section 6.4 confirm that the theoretical benchmark and efficiency findings are structurally robust, the precise magnitude of the 3:1 power-to-cost behavioral sensitivity ratio under different parametric calibrations can only be resolved through additional experiments with human subjects.

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APPENDIX A. PROOFS NASH EQUILIBRIUM SOLUTIONS

Solution when OEM has power.

Not Invest.

$$\pi_{OEM} = (P - w) * Q_o = (\, a - b(Q_o + Q_c) - w) * Q_o \quad (17)$$

$$\pi_{CM} = (P - c - c_m) * Q_c + (w - c) * Q_o = (\, a - b(Q_o + Q_c) - c - c_m) * Q_c + (w - c) * Q_o \quad (18)$$

$$\frac{d\pi_{OEM}}{dQ_o} = a - 2b * Q_o - b * Q_c - w \quad (19)$$

$$\frac{d\pi_{CM}}{dQ_c} = a - b * Q_o - 2b * Q_c - c - c_m \quad (20)$$

Let $Q_o^* = \arg\max\,(\pi_{OEM})$ and $Q_c^* = \arg\max\,(\pi_{CM})$,

$$Q_o^* = \frac{a - b * Q_c - w}{2b} \quad (21)$$

$$Q_c^* = \frac{a - b * Q_o - c - c_m}{2b} \quad (22)$$

So,

$$Q_o^* = \frac{a - 2w + c + c_m}{3b} \quad (23)$$

$$Q_c^* = \frac{a - 2c - 2c_m + w}{3b} \quad (24)$$

Let $\pi_{OEM}^* = \max(\pi_{OEM})$,

$$\pi_{OEM}^* = \frac{1}{9b} * (a + c + c_m - 2w)^2 \quad (25)$$

$$\frac{d\pi_{OEM}}{dw} = -\frac{4}{9b}(a + c + c_m - 2w) \quad (26)$$

Let $w^* = \arg\max\,(\pi_{OEM})$

$$w^* = \frac{a + c + c_m}{2} \quad (27)$$

Since $c < w$, when $w^* = c$, π_{OEM} will be the equilibrium.

$$\pi_{OEM}^* = \frac{1}{9b} * (a - c + c_m)^2 \quad (28)$$

Invest.

$$\pi_{OEMI} = (P_{\mathrm{I}} - w_I) * Q_{oI} - I = (\, a - b(Q_{oI} + Q_{cI}) - w) * Q_{oI} - I \quad (29)$$

$$\pi_{CMI} = (P_{\mathrm{I}} - c_I - c_m) * Q_{cI} + (w_I - c_I) * Q_{oI} = (\, a - b(Q_{oI} + Q_{cI}) - c_I - c_m) * Q_{cI} + (w_I - c_I) * Q_{oI} \quad (30)$$

$$\frac{d\pi_{OEMI}}{dQ_{oI}} = a - 2b * Q_{oI} - b * Q_{cI} - w_I \quad (31)$$

$$\frac{d\pi_{CMI}}{dQ_{cI}} = a - b * Q_{oI} - 2b * Q_{cI} - c_I - c_m \quad (32)$$

Let $Q_{oI}^* = \arg\max\,(\pi_{OEMI})$ and $Q_{cI}^* = \arg\max\,(\pi_{CMI})$,

$$Q_{oI}^* = \frac{a - b * Q_{cI} - w_I}{2b} \quad (33)$$

$$Q_{cI}^* = \frac{a - b * Q_{oI} - c_I - c_m}{2b} \quad (34)$$

So,

$$Q_{oI}^* = \frac{a - 2w_I + c_I + c_m}{3b} \quad (35)$$

$$Q_{cI}^* = \frac{a - 2c_I - 2c_m + w_I}{3b} \quad (36)$$

Let $\pi_{OEMI}^* = \max(\pi_{OEMI})$,

$$\pi_{OEMI}^* = \frac{1}{9b} * (a + c_I + c_m - 2w_I)^2 - I \quad (37)$$

$$\frac{d\pi_{OEMI}}{dw_I} = -\frac{4}{9b}(a + c_I + c_m - 2w_I) \quad (38)$$

Let $w_I^* = \arg\max\,(\pi_{OEMI})$

$$w_I^* = \frac{a + c_I + c_m}{2} \quad (39)$$

Since $c < w_I$, when $w_I^* = c_I$, π_{OEMI} will be maximum.

$$\pi_{OEMI}^* = \frac{1}{9b} * (a - c_I + c_m)^2 - I \quad (40)$$

The condition that OEM would invest is when $\pi^*_{OEMI} > \pi^*_{OEM}$, that is

$$\frac{1}{9b} * (a - c_I + c_m)^2 - I > \frac{1}{9b} * (a - c + c_m)^2 \quad (41)$$

The condition that OEM would invest is

$$I < \frac{1}{9b}\left(c_I^2 - c^2 + 2(\mathrm{a} + \mathrm{c}_m)(\mathrm{c} - \mathrm{c_I})\right) \quad (42)$$

Solution when CM has power.

Not Invest.

$$\pi_{OEM} = (P - w) * Q_o$$
$$= (\, a - b(Q_o + Q_c) - w) * Q_o \quad (43)$$

$$\pi_{CM} = (P - c - c_m) * Q_c + (w - c) * Q_o$$
$$= (\, a - b(Q_o + Q_c) - c - c_m) * Q_c + (w - c) * Q_o \quad (44)$$

$$\frac{d\pi_{OEM}}{dQ_o} = a - 2b * Q_o - b * Q_c - w \quad (45)$$

$$\frac{d\pi_{CM}}{dQ_c} = a - b * Q_o - 2b * Q_c - c - c_m \quad (46)$$

Let $Q_o^* = \arg\max\,(\pi_{OEM})$ and $Q_c^* = \arg\max\,(\pi_{CM})$,

$$Q_o^* = \frac{a - b * Q_c - w}{2b} \quad (47)$$

$$Q_c^* = \frac{a - b * Q_o - c - c_m}{2b} \quad (48)$$

So,

$$Q_o^* = \frac{a - 2w + c + c_m}{3b} \quad (49)$$

$$Q_c^* = \frac{a - 2c - 2c_m + w}{3b} \quad (50)$$

Let $\pi^*_{CM} = \max(\pi_{CM})$,

$$\pi^*_{CM} = \frac{1}{9b} * (a - 2c - 2c_m + w)^2 + \frac{1}{3b} * (w - c)(a - 2w + c + c_m) \quad (51)$$

$$\frac{d\pi_{CM}}{dw} = \frac{1}{9b}(5a + 5c - c_m - 10w) \quad (52)$$

Let $w^* = \arg\max\,(\pi_{CM})$

$$w^* = \frac{5a + 5c - c_m}{10} \quad (53)$$

Since $c < w^* < P$, when $w^* = \frac{5a+5c-c_m}{10}$, π_{CM} will be maximum.

$$\pi^*_{CM} = \frac{5a^2 - 10ac - 10ac_m + 5c^2 + 10cc_m + 9c_m^2}{20b} \quad (54)$$

$$\pi^*_{OEM} = \frac{4c_m^2}{25b} \quad (55)$$

Invest.

$$\pi_{OEMI} = (P_\mathrm{I} - w_I) * Q_{oI} - I$$
$$= (\, a - b(Q_{oI} + Q_{cI}) - w) * Q_{oI} - I \quad (56)$$

$$\pi_{CMI} = (P_\mathrm{I} - c_I - c_m) * Q_{cI} + (w_I - c_I) * Q_{oI}$$
$$= (\, a - b(Q_{oI} + Q_{cI}) - c_I - c_m) * Q_{cI} + (w_I - c_I) * Q_{oI} \quad (57)$$

$$\frac{d\pi_{OEMI}}{dQ_{oI}} = a - 2b * Q_{oI} - b * Q_{cI} - w_I \quad (58)$$

$$\frac{d\pi_{CMI}}{dQ_{cI}} = a - b * Q_{oI} - 2b * Q_{cI} - c_I - c_m \quad (59)$$

Let $Q_{oI}^* = \arg\max\,(\pi_{OEMI})$ and $Q_{cI}^* = \arg\max\,(\pi_{CMI})$,

$$Q_{oI}^* = \frac{a - b * Q_{cI} - w_I}{2b} \quad (60)$$

$$Q_{cI}^* = \frac{a - b * Q_{oI} - c_I - c_m}{2b} \quad (61)$$

So,

$$Q_{oI}^* = \frac{a - 2w_I + c_I + c_m}{3b} \quad (62)$$

$$Q_{cI}^* = \frac{a - 2c_I - 2c_m + w_I}{3b} \quad (63)$$

Let $\pi^*_{CMI} = \max(\pi_{CMI})$,

$$\pi^*_{CMI} = \frac{1}{9b} * (a - 2c_I - 2c_m + w_I)^2 + \frac{1}{3b} * (w_I - c_I)(a - 2w_I + c_I + c_m) \quad (64)$$

$$\frac{d\pi_{CMI}}{dw_I} = \frac{1}{9b}(5a + 5c_I - c_m - 10w_I) \quad (65)$$

Let $w_I^* = \arg\max\,(\pi_{CMI})$

$$w_I^* = \frac{5a+5c_I-c_m}{10} \quad (66)$$

Since $c_I < w_I^* < P$, when $w_I^* = \frac{5a+5c_I-c_m}{10}$, π_{CM} will be maximum.

$$\pi_{CMI}^* = \frac{5a^2-10ac_I-10ac_m+5c_I^2+10c_Ic_m+9c_m^2}{20b} \quad (67)$$

$$\pi_{OEMI}^* = \frac{4c_m^2}{25b} - I \quad (68)$$

Since $\frac{4c_m^2}{25b} - I < \frac{4c_m^2}{25b}$,

$$\pi_{OEMI}^* < \pi_{OEM}^* \quad (69)$$

Solution for centralized supply chain.

Not Invest.

$$\pi_{SC} = (P - \mathrm{c}) * Q_{SC}$$
$$= (\,a - b * Q_{SC} - \mathrm{c}) * Q_{SC} \quad (70)$$

$$\frac{d\pi_{SC}}{dQ_{SC}} = a - 2b * Q_{SC} - \mathrm{c} \quad (71)$$

Let $Q_{SC}^* = \arg\max\,(\pi_{SC})$,

$$Q_{SC}^* = \frac{a-\mathrm{c}}{2b} \quad (72)$$

Let $\pi_{SC}^* = \max(\pi_{SC})$,

$$\pi_{SC}^* = \frac{(\mathrm{a-c})^2}{4b} \quad (73)$$

Invest.

$$\pi_{SCI} = (P_I - \mathrm{c_I}) * Q_{SCI}$$
$$= (\,a - b * Q_{SCI} - \mathrm{c_I}) * Q_{SCI} - I \quad (74)$$

$$\frac{d\pi_{SCI}}{dQ_{SCI}} = a - 2b * Q_{SCI} - \mathrm{c_I} \quad (75)$$

Let $Q_{SCI}^* = \arg\max\,(\pi_{SCI})$,

$$Q_{SCI}^* = \frac{a-\mathrm{c_I}}{2b} \quad (76)$$

Let $\pi_{SCI}^* = \max(\pi_{SCI})$,

$$\pi_{SCI}^* = \frac{(\mathrm{a-c_I})^2}{4b} - I \quad (77)$$

The condition that OEM (now is also the centralized supply chain) would invest is when $\pi_{SCI}^* > \pi_{SC}^*$, that is

$$\frac{(\mathrm{a-c_I})^2}{4b} - I > \frac{(\mathrm{a-c})^2}{4b} \quad (78)$$

The condition that OEM (now is also the centralized supply chain) would invest is

$$I < \frac{c_I^2-c^2-2ac_I+2ac}{4b} \quad (79)$$

Comparing the centralized and decentralized supply chain

Let I_{DeCen}^* = threshold for OEM to invest in the decentralized supply chain

I_{Cen}^* = threshold for OEM to invest in the centralized supply chain

$$I_{DeCen}^* = \frac{1}{9b}\left(c_I^2 - c^2 + 2(\mathrm{a} + \mathrm{c_M})(\mathrm{c} - \mathrm{c_I})\right)$$

$$I_{Cen}^* = \frac{c_I^2 - c^2 - 2ac_I + 2ac}{4b}$$

$$I_{DeCen}^* - I_{Cen}^*$$
$$= \frac{1}{9b}\left(c_I^2 - c^2 + 2(\mathrm{a} + \mathrm{c_M})(\mathrm{c} - \mathrm{c_I})\right) - \frac{c_I^2 - c^2 - 2ac_I + 2ac}{4b}$$
$$= \frac{(c - c_I)(-10a + 5c_I + 5c + 8c_M)}{36b}$$

When $-10a + 5c_I + 5c + 8c_M < 0$, $I_{DeCen}^* < I_{Cen}^*$

APPENDIX B. CALIBRATIONS

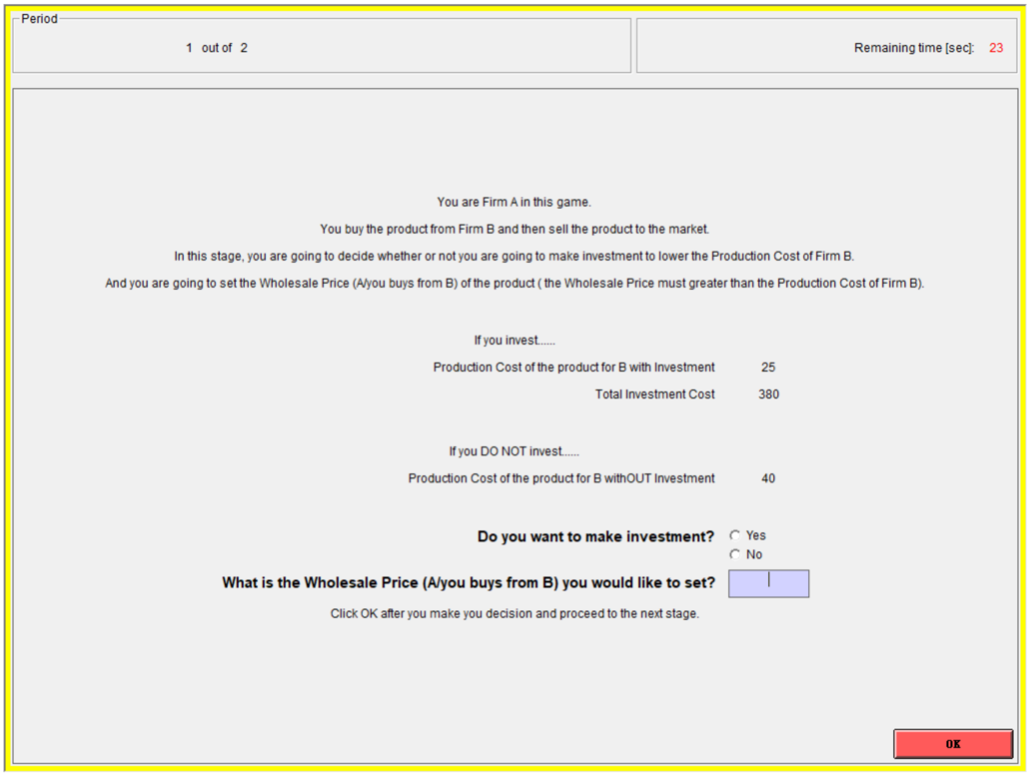
TABLE 1. PARAMETER CALIBRATION

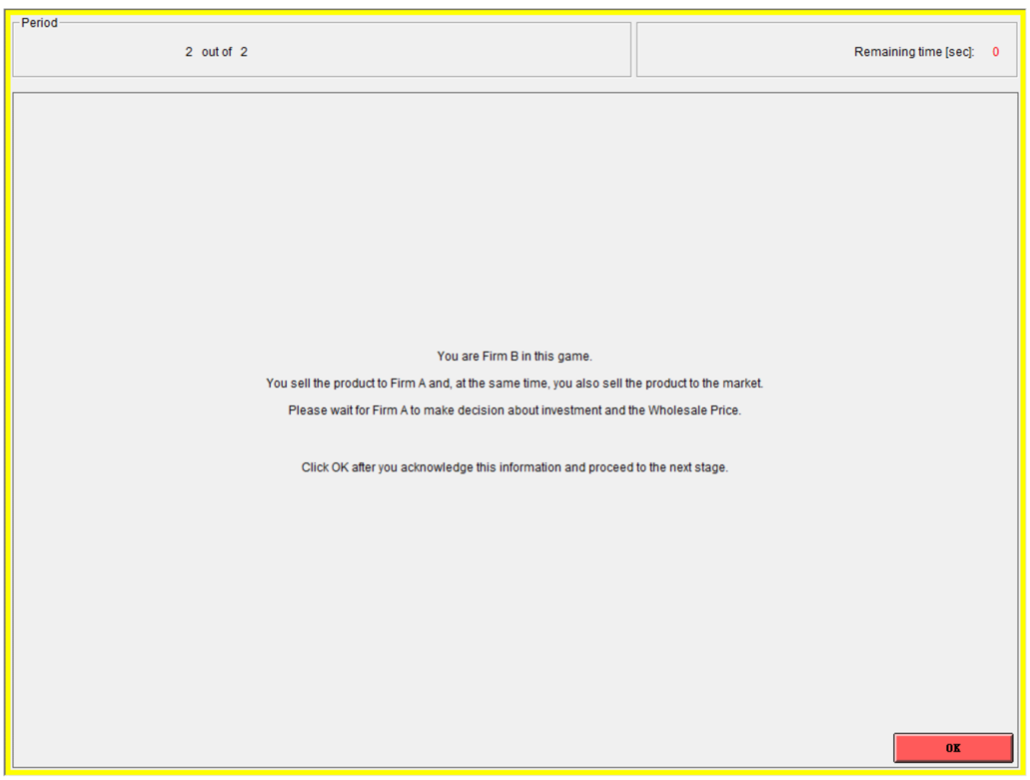
	OEM-Low	OEM-High	CM-Low	CM-High
Investment cost (I)	380	580	380	580
I^*	483.33	483.33	-	-
Production cost before investment (c)	40	40	40	40
Production cost after investment (c_I)	25	25	25	25
Investment Percentage	100%	0%	0%	0%
Quantity of OEM (Q_o^*/Q_{oI}^*)	53	43	4	4
Quantity of CM (Q_c^*/Q_{cI}^*)	43	33	53	53
Wholesale Price (w^*/w_I^*)	25	40	69.5	69.5
Market Price (P^*)	51.67	61.67	71.5	71.5
Profit of OEM (π_{OEM}^*/π_{OEMI}^*)	1042.22	938.89	8	8
Profit of CM (π_{CM}^*/π_{CMI}^*)	938.89	555.56	1522.50	1522.50
Profit of Supply Chain (Profit of OEM+ Profit of CM)	1981.11	1494.44	1530.5	1530.5

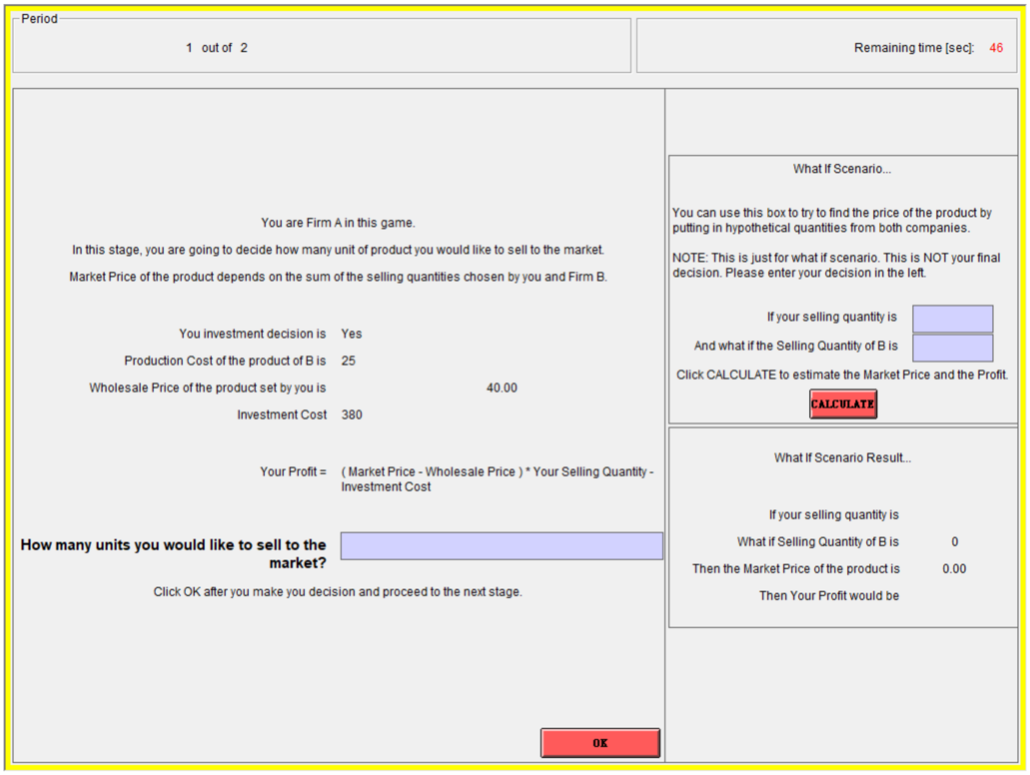
TABLE 2. PARAMETER CALIBRATION – CENTRALIZED SUPPLY CHAIN

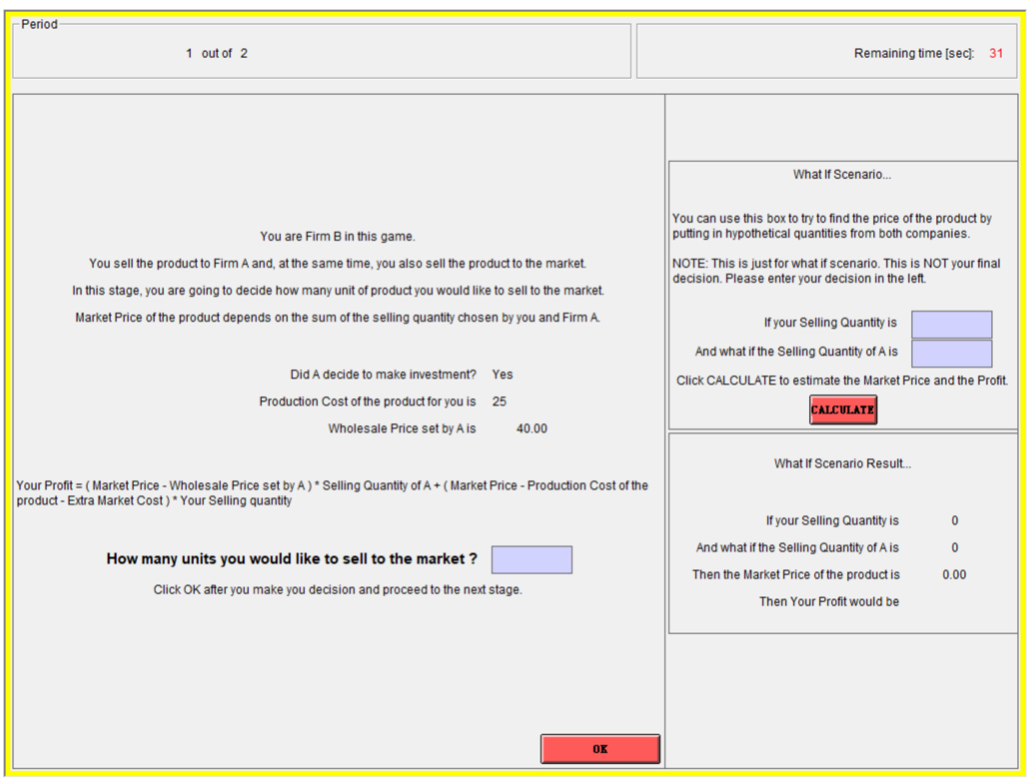
	Low	High
Investment cost (I)	380	580
I^*	1012.5	1012.5
Production cost before investment (c)	40	40
Production cost after investment (c_I)	25	25
Investment Percentage	100%	100%
Quantity of Supply Chain (Q_{SC}^*/Q_{SCI}^*)	75	75
Wholesale Price (w^*/w_I^*)	25	25
Market Price (P^*)	62.5	62.5
Profit of Supply Chain (π_{SC}^*/π_{SCI}^*)	2432.5	2232.5

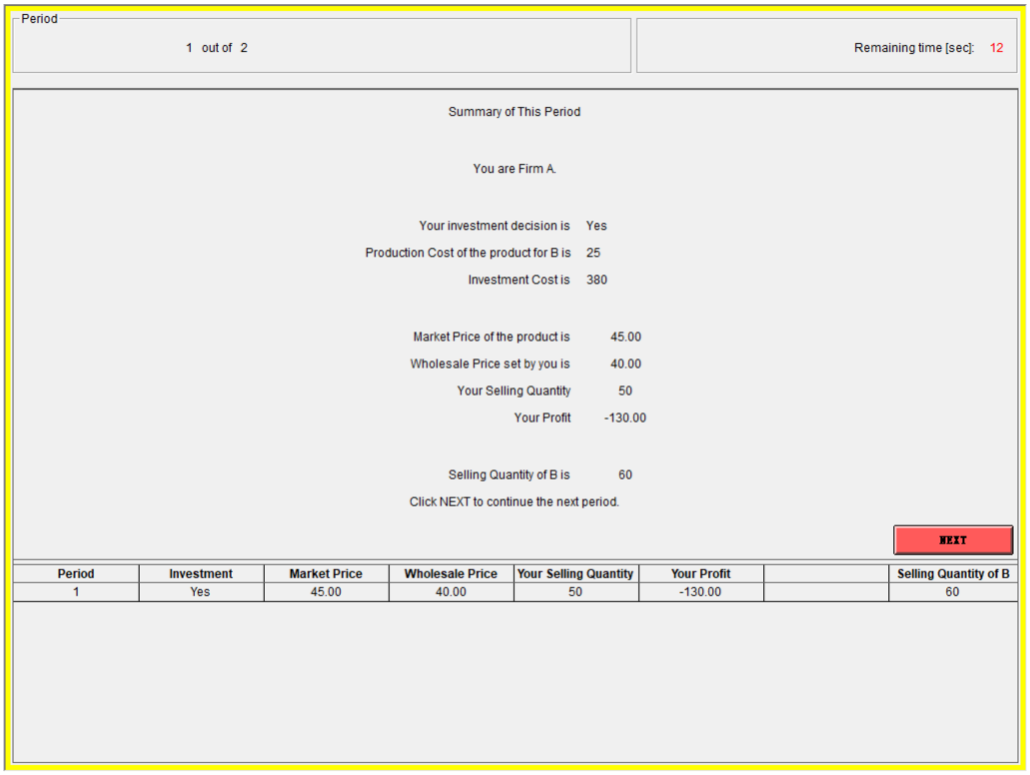
APPENDIX C. EXPERIMENT SCREENSHOTS

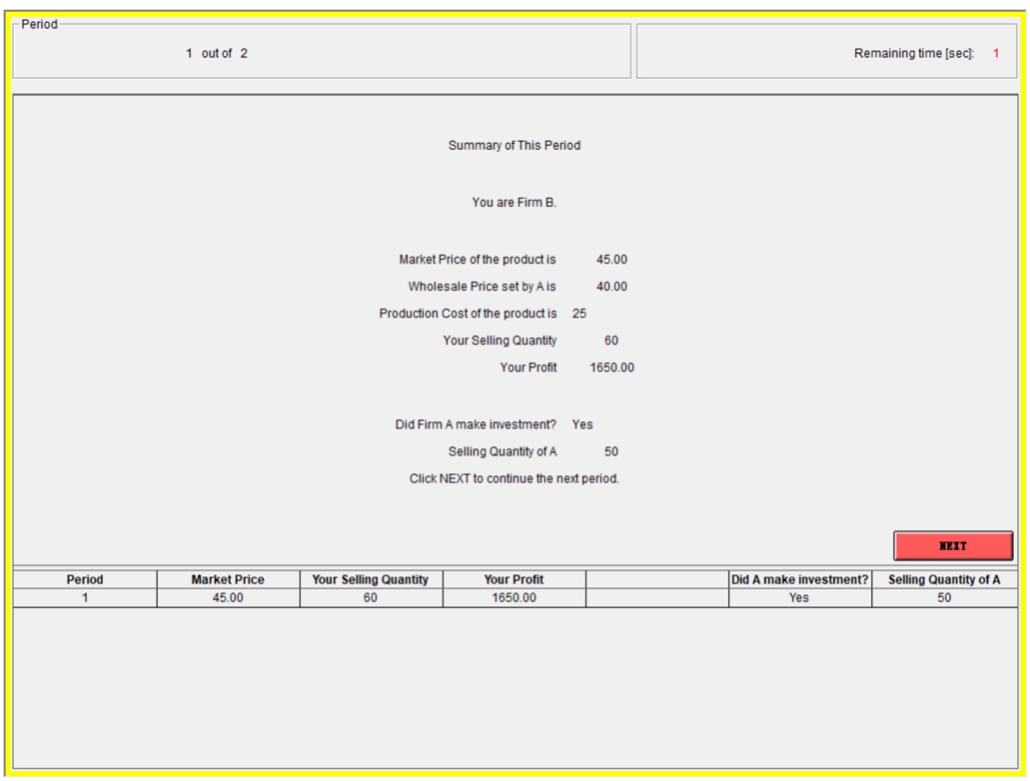




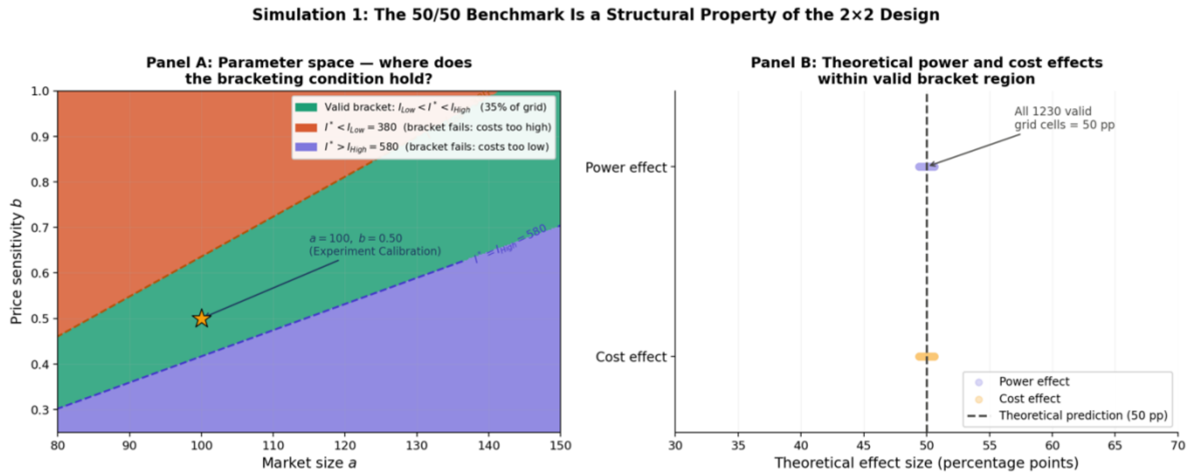

Period
1 out of 2
Remaining time [sec]: 46
You are Firm A in this game.
In this stage, you are going to decide how many unit of product you would like to sell to the market.
Market Price of the product depends on the sum of the selling quantities chosen by you and Firm B.
You investment decision is Yes
Production Cost of the product of B is 25
Wholesale Price of the product set by you is 40.00
Investment Cost 380
Your Profit = (Market Price - Wholesale Price) * Your Selling Quantity - Investment Cost
How many units you would like to sell to the market?
Click OK after you make you decision and proceed to the next stage.
OK
What If Scenario...
You can use this box to try to find the price of the product by putting in hypothetical quantities from both companies.
NOTE: This is just for what if scenario. This is NOT your final decision. Please enter your decision in the left.
If your selling quantity is
And what if the Selling Quantity of B is
Click CALCULATE to estimate the Market Price and the Profit.
CALCULATE
What If Scenario Result...
If your selling quantity is
What if Selling Quantity of B is 0
Then the Market Price of the product is 0.00
Then Your Profit would be

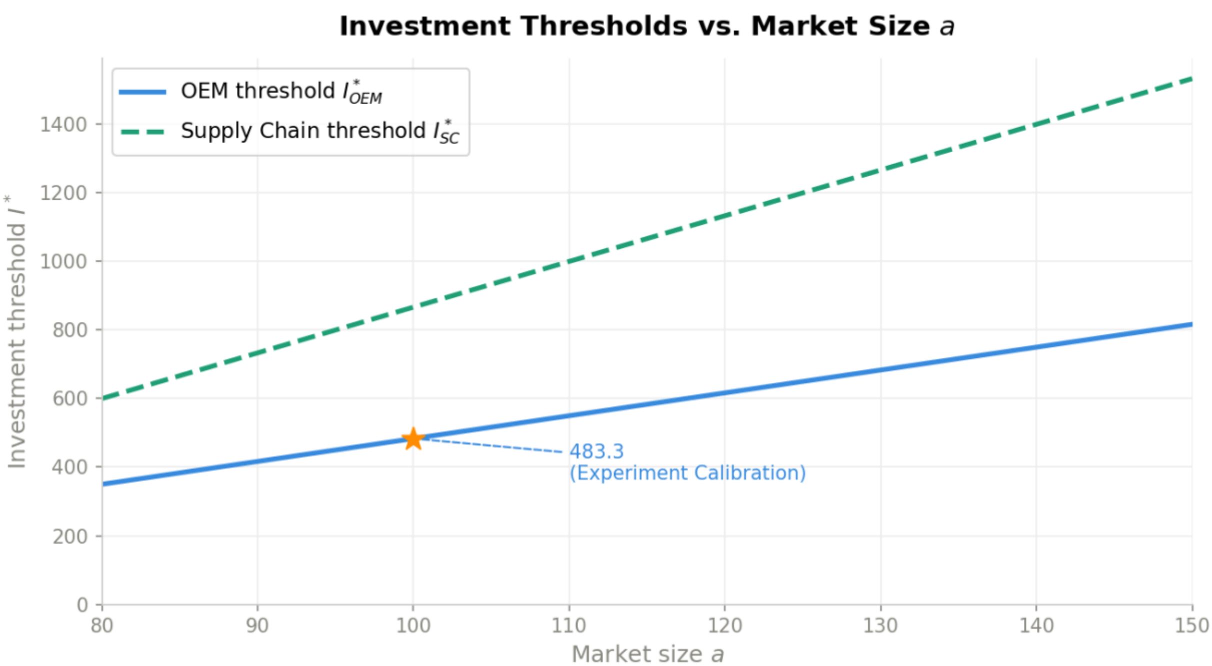

Period
1 out of 2
Remaining time [sec]: 31
You are Firm B in this game.
You sell the product to Firm A and, at the same time, you also sell the product to the market.
In this stage, you are going to decide how many unit of product you would like to sell to the market.
Market Price of the product depends on the sum of the selling quantity chosen by you and Firm A.
Did A decide to make investment? Yes
Production Cost of the product for you is 25
Wholesale Price set by A is 40.00
Your Profit = (Market Price - Wholesale Price set by A) * Selling Quantity of A + (Market Price - Production Cost of the product - Extra Market Cost) * Your Selling quantity
How many units you would like to sell to the market ?
Click OK after you make you decision and proceed to the next stage.
OK
What If Scenario...
You can use this box to try to find the price of the product by putting in hypothetical quantities from both companies.
NOTE: This is just for what if scenario. This is NOT your final decision. Please enter your decision in the left.
If your Selling Quantity is
And what if the Selling Quantity of A is
Click CALCULATE to estimate the Market Price and the Profit.
CALCULATE
What If Scenario Result...
If your Selling Quantity is 0
And what if the Selling Quantity of A is 0
Then the Market Price of the product is 0.00
Then Your Profit would be

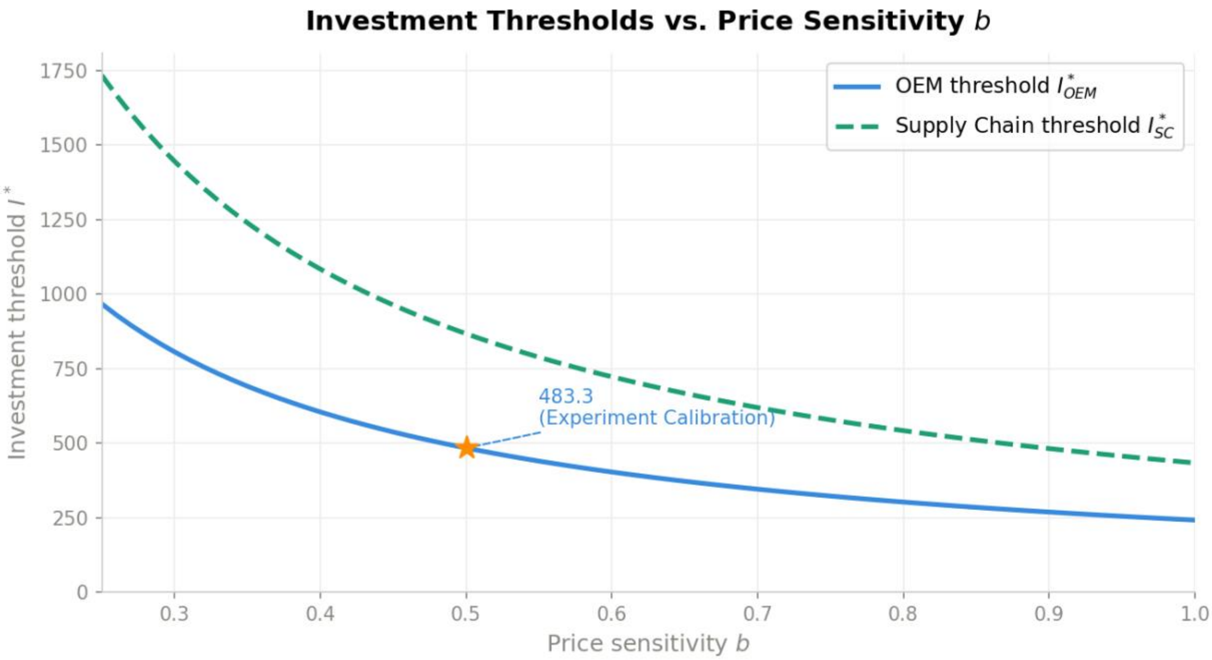

Period
1 out of 2
Remaining time [sec]: 12
Summary of This Period
You are Firm A.
Your investment decision is Yes
Production Cost of the product for B is 25
Investment Cost is 380
Market Price of the product is 45.00
Wholesale Price set by you is 40.00
Your Selling Quantity 50
Your Profit -130.00
Selling Quantity of B is 60
Click NEXT to continue the next period.
NEXT
Period | Investment | Market Price | Wholesale Price | Your Selling Quantity | Your Profit | | Selling Quantity of B
1 | Yes | 45.00 | 40.00 | 50 | -130.00 | | 60

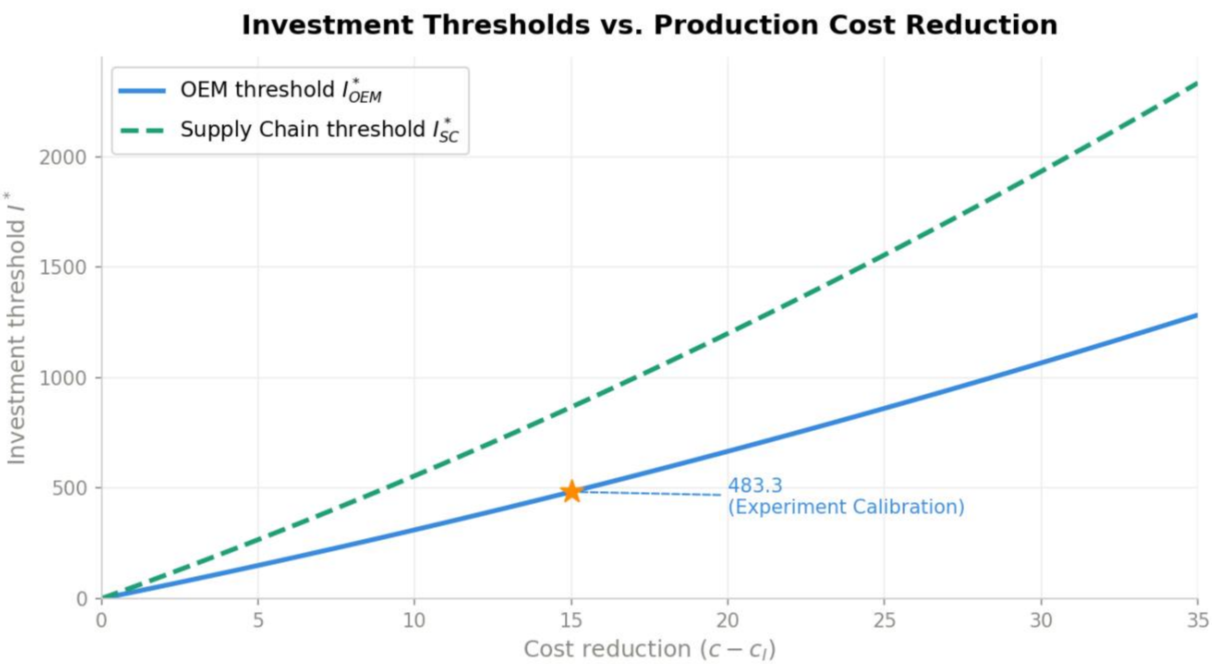

Period
1 out of 2
Remaining time [sec]: 1
Summary of This Period
You are Firm B.
Market Price of the product is 45.00
Wholesale Price set by A is 40.00
Production Cost of the product is 25
Your Selling Quantity 60
Your Profit 1650.00
Did Firm A make investment? Yes
Selling Quantity of A 50
Click NEXT to continue the next period.
NEXT
Period | Market Price | Your Selling Quantity | Your Profit | | Did A make investment? | Selling Quantity of A
1 | 45.00 | 60 | 1650.00 | | Yes | 50

APPENDIX D. SIMULATION GRAPHS






Investment Thresholds vs. Price Sensitivity b
OEM threshold I^*_{OEM}
Supply Chain threshold I^*_{SC}
Investment threshold I^*
Price sensitivity b
483.3
(Experiment Calibration)
0
250
500
750
1000
1250
1500
1750
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0


Investment Thresholds vs. Production Cost Reduction
OEM threshold I^*_{OEM}
Supply Chain threshold I^*_{SC}
Investment threshold I^*
Cost reduction $(c - c_I)$
483.3
(Experiment Calibration)
0
500
1000
1500
2000
0
5
10
15
20
25
30
35