Appendix I: Tables and Figures

Table A1: Summary of Experimental Data

Treatment	**Transfer Price**	**N**	**Order**	**Profit**	**Extra Supply**	**Extra Demand**
No Sharing - High Margin	-	26	209.74	3220.00	0.00	0.00
No Sharing - Low Margin	-	24	194.07	1040.31	0.00	0.00
Sharing - High Margin	35	24	206.89	3321.79	25.93	27.97
Sharing - High Margin	15	26	197.79	3293.09	15.41	31.71
Sharing - Low Margin	35	26	187.50	1285.23	23.42	33.10
Sharing - Low Margin	15	26	185.80	1295.06	18.89	39.47
No Sharing - Dec. Support	-	20	225.30	3155.78	0.00	0.00
Sharing - Dec. Support	35	20	216.22	3333.22	24.80	21.07
Sharing - Dec. Support	15	20	209.43	3374.50	24.69	26.21
Fixed Role	35	43	201.28	3051.42	30.94	15.63
Fixed Role	15	40	194.96	3100.98	36.85	21.72
Minimum Send	35	24	208.07	3231.78	22.31	25.69
Minimum Send	15	22	203.84	3226.20	21.49	31.80
Auto Request	35	20	199.69	3208.97	26.07	31.64
Auto Request	15	20	198.75	3268.60	22.09	34.14
Sending Reward	35	24	201.60	3443.90	31.04	30.12
Sending Reward	15	24	201.84	3339.01	25.14	28.38
Customer Transfer	35	24	206.66	3116.69	28.80	24.84
Customer Transfer	15	22	208.01	3221.50	25.55	31.21
Demand Side	35	26	200.09	3231.44	47.02	26.52
Demand Side	15	26	197.02	3244.62	42.31	28.39
Auto Request & Send	35	24	213.53	3376.50	19.54	28.93
Auto Request & Send	15	22	203.29	3285.76	18.75	32.39
Decision Support v.2	35	20	212.94	3391.38	21.27	26.52
Decision Support v.2	15	22	210.07	3405.44	22.42	28.39

Notes. While in general, the average extra supply is below the extra average demand, the opposite can be true as well. Extra supply is averaged only over time periods where requests were made, since extra supply must be zero otherwise. Extra demand is averaged over all time periods, since requests can be made in any period. This difference in the denominator can lead to average extra supply being greater than average extra demand. Further, the sequencing of extra demand/supply is revered in the Demand Side treatment, leading to extra demand being less than extra supply.

Table A2: The Effects of Treatment and Order Quantity on Profitability

	Model 1		Model 2	
	Coef.	SE	Coef.	SE
C2: Low Margin – No Sharing	-2019.42**	(54.85)	-2032.76**	(48.02)
C3: High Margin – Low Transfer Price	185.40**	(53.54)	174.74**	(46.75)
C4: High Margin – High Transfer Price	223.91**	(54.36)	211.51**	(47.52)
C5: Low Margin – Low Transfer Price	-1780.49**	(53.46)	-1787.76**	(46.65)
C6: Low Margin – High Transfer Price	-1792.59**	(53.56)	-1805.65**	(46.75)
Order Quantity @ C1			4.34**	(1.66)
Order Quantity @ C2			-2.72*	(1.38)
Order Quantity @ C3			5.43**	(1.74)
Order Quantity @ C4			7.79**	(1.71)
Order Quantity @ C5			-3.95**	(1.27)
Order Quantity @ C6			0.31	(1.46)
Average Demand (≤200)	11.17**	(2.77)	9.66**	(2.57)
Average Demand (>200)	16.52**	(2.05)	14.96**	(1.88)
Demand Standard Deviation	-11.45**		-12.21**	(1.41)
Constant	1593.91**	(555.6)	1963.08**	(515.6)
N	152		152	
R^2	97%		98%	

Notes. ** p≤0.01. The omitted category is Condition 1, i.e. the high margin, no sharing condition.

Table A3: Robustness Test with Decision Support

	Coef.	SE
C3*: High Margin – Low Transfer Price	-14.56**	(5.18)
C4*: High Margin – High Transfer Price	-7.42	(5.09)
Average Demand (≤200)	0.73**	(0.35)
Average Demand (>200)	0.42**	(0.30)
Constant	78.96	(67.11)
N	60	
R^2	29%	

Notes. **p≤0.01. C3* indicates that this condition is similar to C3 with the addition of decision support. The omitted category is C1*. All coefficients measure differences in order quantities compared to this condition.

Figure A1: Comparison of Order Quantities in the Sharing and No-sharing Situations under Risk-Aversion

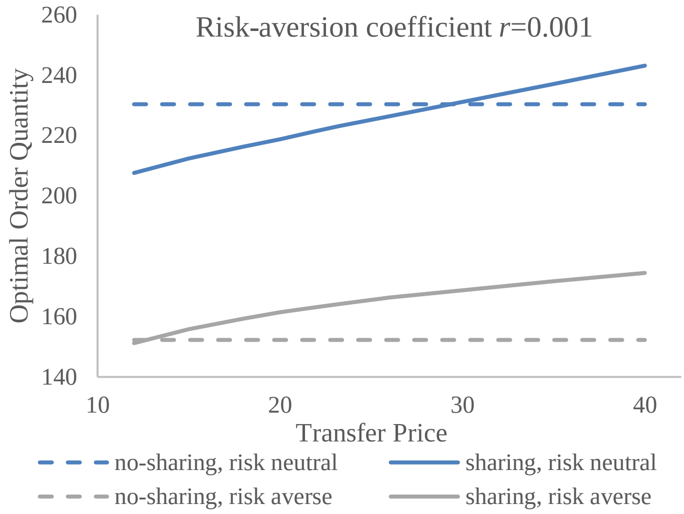


Figure A2: Screen Shots of the Base Study - Initial Stocking Decision

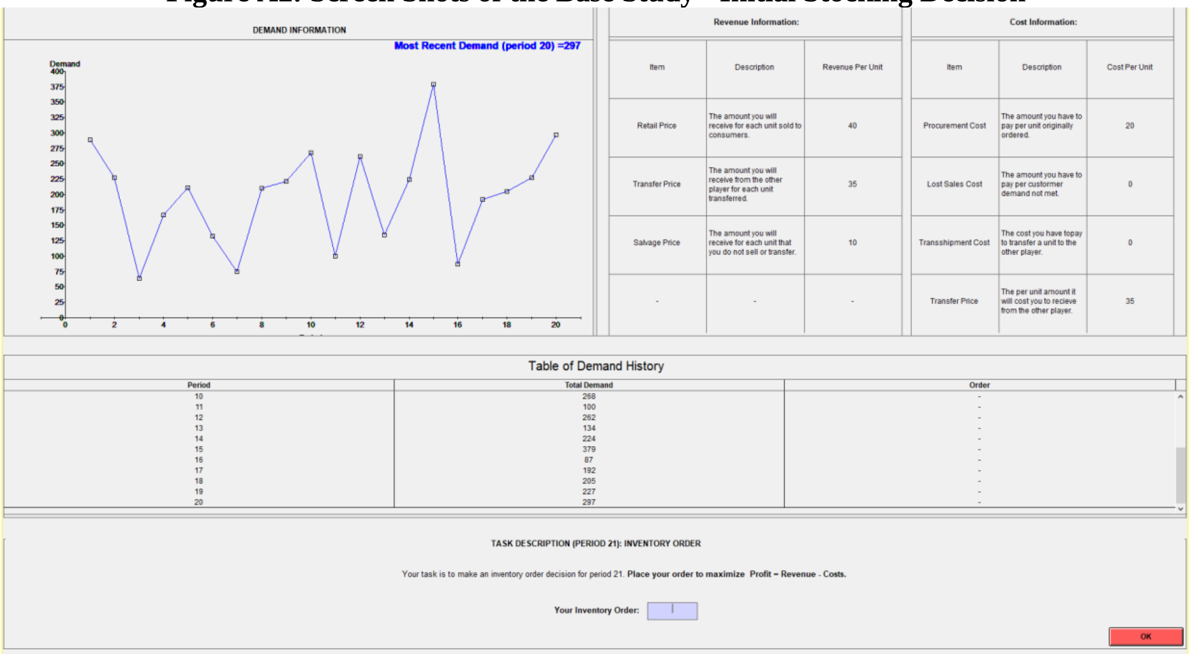


Figure A3: Screen Shots of the Base Study - Requesting Decision

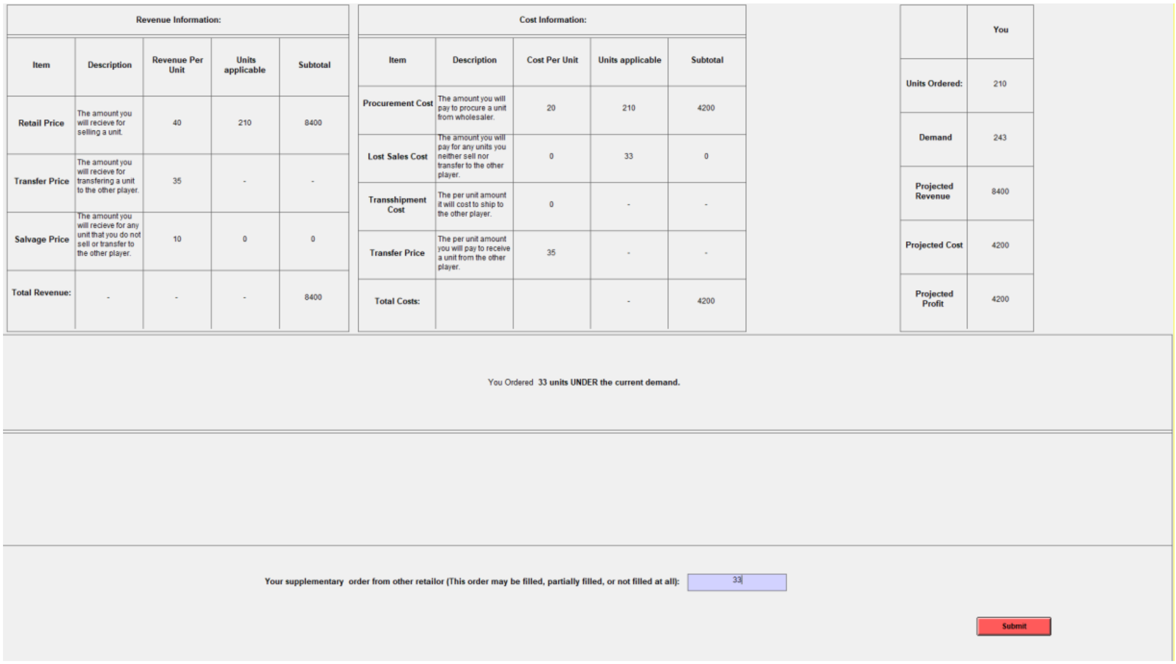
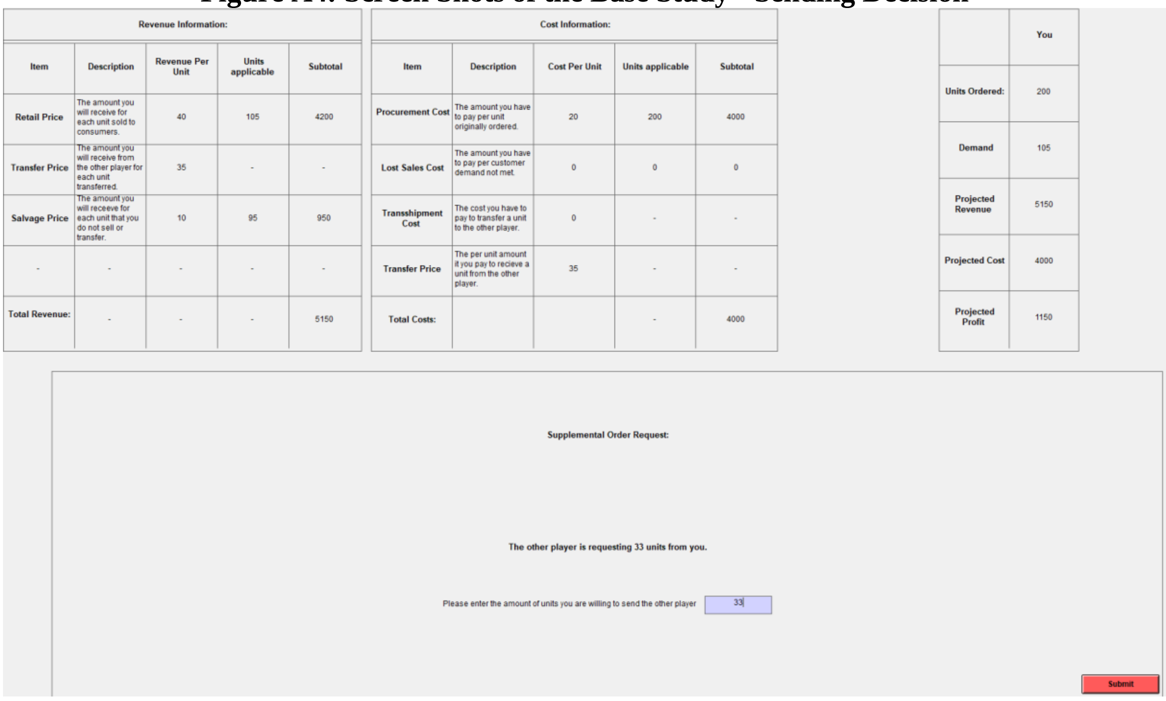


Figure A4: Screen Shots of the Base Study - Sending Decision



Appendix II: Representative Instructions for Experiment (Base Study, Condition 3)

This is an experiment in inventory decision making. During the experiment, you will play a game from which you will receive cash earnings based on your performance. Upon completion of the game, you will be paid your total earnings in cash plus a $5 show-up fee. If you have any questions, feel free to raise your hand and we will assist you. Please do not communicate with other participants in the game, and please refrain from using your cell phones.

Description of the Game. You are a retailer selling a product. To be able to sell the product, you must first place inventory orders in advance of knowing the exact customer demand for that period. If the realized customer demand during the selling period is less than the number of units you order (Order > Demand), there will be some units that you ordered but cannot sell. While leftover units can be salvaged at a price which is below the cost to order units, these units do not carry over to the next selling period. Conversely, if the customer demand is greater than the number of units ordered (Demand > Order), there will be some consumer demand that cannot be met.

There will be a total of 30 selling periods for your product. You will be randomly matched with a new player in each selling period. After demand in a selling period is revealed, you will get a chance to request additional inventory from that other player, and the other player will be provided with a similar opportunity. Your goal is to maximize your total profits over all 30 selling periods.

Revenue/Cost Information

Retail Price (the amount you will receive for each unit sold to consumers):	40
Transfer Price (the amount you receive from the other player for each unit transferred):	15
Salvage Price (the amount you will receive for each unit that you do not sell or transfer):	10
Procurement Cost (the amount you have to pay per unit originally ordered):	20
Lost Sales Cost (the amount you have to pay per customer demand not met):	0
Transhipment Cost (the cost you have to pay to transfer a unit to the other player):	0

The other players with whom you will be matched face the same price/cost parameters.

Demand Information. Demand in each selling period is drawn from a Normal Probability Distribution. Average demand is 200, with a standard deviation of 70.71. Demand in one selling period is uncorrelated with demand in the next period.

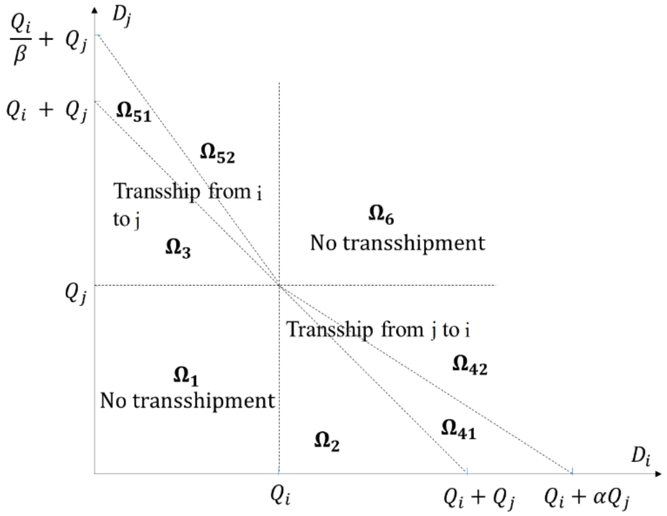
Payoffs. The computer program will calculate your profits in every selling period. Your cash earning in each selling period will be approximately

Real Cash Earning ($) = Profits x 0.0095%.

For example, if your Profits in a turn are equal to 3500, your Real Cash Earnings that period will be about 33 cents. Note that your cash earnings will be negative if your profit for that round goes below 0. Your total cash earnings in this experiment will be $6 plus your total cash earnings for the 30 decisions rounds. The computer program will calculate your cash earnings for each selling period and your total cash earnings for all the periods you have completed. We will pay your total earnings upon the completion of the game by rounding them to the highest dollar amount and making sure that you receive at least $6 (show-up fee). The maximum Earnings that we will pay out per participant is $24.

Appendix III: Proof of Proposition 1

To solve the optimal order $Q_s(\alpha,\beta)$, we partition the demand space (D_1, D_2) as shown below.



Given realized demand (D_1, D_2) in each of the regions of the above figure, the corresponding transshipment (T_{ij}, T_{ji}), shortage (Z_i, Z_j), leftover (L_i, L_j) and sales (R_i, R_j) are summarized below.

	Transship(T_{ij}, T_{ji})	Shortage (Z_i, Z_j)	Leftover (L_i, L_j)	Sales (R_i, R_j)
Ω_1	0,0	0,0	$Q_i - D_i, Q_j - D_j$	D_i, D_j
Ω_2	$0, D_i - Q_i$	0,0	$0, Q_i + Q_j - D_i - D_j$	D_i, D_j
Ω_{41}	$0, D_i - Q_i$	$0, D_i + D_j - Q_i - Q_j$	0,0	$D_i, Q_j + Q_i - D_i$
Ω_{42}	$0, \alpha(D_j - D_j)$	$D_i - Q_i - \alpha(Q_j - D_j)$, $D_j - Q_j + \alpha(Q_j - D_j)$	0,0	$Q_i + \alpha(Q_j - D_j)$, $Q_j - \alpha(Q_j - D_j)$
$\Omega_{3,51}$	$\beta(D_j - Q_j)$,0	$0, (1-\beta)(D_j - Q_j)$	$Q_i - D_i - \beta(D_j - Q_j), 0$	$D_i, Q_j + \beta(D_j - Q_j)$
Ω_{52}	$Q_i - D_i, 0$	$0, D_j + D_i - Q_j - Q_i)$	0,0	$D_i, Q_j + Q_i - D_i$
Ω_6	0,0	$D_i - Q_i, D_j - Q_j$	0,0	Q_i, Q_j

Hence, player *i*'s expected profit is

$$\Pi_i(Q_i, Q_j; \alpha, \beta) = \int_{\Omega} (r_i R_i + s_i L_i + c_{ij} T_{ij} - c_{ji} T_{ji}) dD_i dD_j - c_i Q_i.$$

Thus, we have the following first-order condition with respect to Q_i,

$$\frac{\partial \Pi_i(Q_i, Q_j; \alpha, \beta)}{\partial Q_i} = v_i Pr(\Omega_{42} + \Omega_6) + c_{ij} Pr(\Omega_2 + \Omega_{41} + \Omega_{52}) + s_i Pr(\Omega_1 + \Omega_3 + \Omega_{51}) - c_i$$

Since both players are symmetric, we have $Q_i = Q_j = Q_s(\alpha,\beta)$ at equilibrium. Thus, we can solve $Q_s(\alpha,\beta)$ through the above first-order condition $\partial \Pi_i(Q_i, Q_j; \alpha, \beta)/\partial Q_i = 0$. Next, we show that $Q_s(\alpha,\beta)$ decreases as α increases and decreases as β decreases.

Based on the derivative of implicit function, we have $\frac{\partial Q(\alpha,\beta)}{\partial \alpha} = -\frac{\partial^2 \Pi}{\partial Q \partial \alpha} / \frac{\partial^2 \Pi}{\partial Q^2}$. Since $\frac{\partial^2 \Pi}{\partial Q^2} < 0$ at the optimal $Q_s(\alpha,\beta)$, it suffices to show that $\frac{\partial^2 \Pi}{\partial Q \partial \alpha} < 0$. We have

$$\frac{\partial^2 \Pi}{\partial Q \partial \alpha} = v_i \frac{\partial Pr(\Omega_{42})}{\partial \alpha} + c_{ij} \frac{\partial Pr(\Omega_{41})}{\partial \alpha} = -(v_i - c_{ij}) \frac{\partial \Pr(\Omega_{41})}{\partial \alpha} < 0,$$

Therefore, we have proved that $Q_s(\alpha, \beta)$ decreases as α increases.

Likewise, we can show that

$$\frac{\partial^2 \Pi}{\partial Q \partial \beta} = s_i \frac{\partial Pr(\Omega_{51})}{\partial \beta} + c_{ij} \frac{\partial Pr(\Omega_{52})}{\partial \beta} = \left(c_{ij} - s_i\right) \frac{\partial \Pr(\Omega_{52})}{\partial \beta} > 0$$

Thus, we have proved that $Q_s(\alpha, \beta)$ decreases as β decreases. By definition, for rational players, $Q_s^* = Q_s(\alpha = 1, \beta = 1)$. Hence, when $\alpha = 1$ and $\beta < 1$, we have $Q_s^* > Q_s(\alpha, \beta)$; and when $\alpha > 1$ and $\beta = 1$, we have $Q_s^* > Q_s(\alpha, \beta)$.

Appendix IV: Structural Estimation of the Behavioral Model

Given a set of behavioral parameters $\theta = (\alpha, \beta, \delta_o, \delta_u)$, we can solve the equilibrium order quantity predicted by the behavioral model. In particular, for the no-sharing case, we can solve Q_n through the modified critical fractile formula $Q_n = F^{-1}\left(\frac{v-c+\delta_u}{v-s+\delta_u+\delta_o}\right)$.

For the inventory sharing case, we can solve the predicted order quantity $Q_s(\theta)$ through the following first-order condition,

$$\frac{\partial \Pi_s}{\partial Q_s} = (v + \delta_u) \Pr(\Omega_{42} + \Omega_6) + c_{ij} \Pr(\Omega_2 + \Omega_{41} + \Omega_{52}) + (s - \delta_o) \Pr(\Omega_1 + \Omega_3 + \Omega_{51}) - c = 0$$

For the fixed role treatment, we can solve the predicted order quantity for the recipient, i.e., $Q_s^r(\theta)$, through the following first-order condition,

$$\frac{\partial \Pi_s^r}{\partial Q_s^r} = (v + \delta_u) \Pr(\Omega_{42} + \Omega_6) + c_{ij} \Pr(\Omega_2 + \Omega_{41}) + (s - \delta_o) \Pr(\Omega_1 + \Omega_3 + \Omega_5) - c = 0,$$

and solve the predicted order quantity for the source, i.e., $Q_s^s(\theta)$, through the following first-order condition,

$$\frac{\partial \Pi_s^s}{\partial Q_s^s} = (v + \delta_u) \Pr(\Omega_2 + \Omega_4 + \Omega_6) + c_{ij} \Pr(\Omega_{52}) + (s - \delta_o) \Pr(\Omega_1 + \Omega_3 + \Omega_{51}) - c = 0$$

Note that $\Omega_4 = \Omega_{41} \cup \Omega_{42}$, $\Omega_5 = \Omega_{51} \cup \Omega_{52}$. Essentially, given a set of parameters $\theta = (\alpha, \beta, \delta_o, \delta_u)$, we can solve predicted order quantity (Q_n, Q_s, Q_s^r, Q_s^s). The observed order quantities in the experiments, however, do not perfectly coincide with the model predictions due to various noises at players' decision processes. To capture the variation of the observed order quantities, we assume that the average order quantity placed by a player *i* in the experiments is normally distributed with mean specified by the behavioral model predication, i.e.,

$$q_{i,n} \sim N(Q_n(\delta_o, \delta_u), \sigma_n^2)$$
$$q_{i,s,c_{ij}} \sim N\left(Q_{s,c_{ij}}(\alpha, \beta, \delta_o, \delta_u), \sigma_{sc_{ij}}^2\right)$$
$$q_{i,s,c_{ij}}^r \sim N\left(Q_{s,c_{ij}}^r(\alpha, \delta_o, \delta_u), \left(\sigma_{s,c_{ij}}^r\right)^2\right)$$
$$q_{i,s,c_{ij}}^s \sim N\left(Q_{s,c_{ij}}^s(\beta, \delta_o, \delta_u), \left(\sigma_{s,c_{ij}}^s\right)^2\right)$$

where $c_{ij} \in \{15, 35\}$ indicates the high or low transfer price.

The noise parameters $\sigma^2 = \left(\sigma_n^2, \sigma_{sc_{ij}}^2, \left(\sigma_{s,c_{ij}}^r\right)^2, \left(\sigma_{s,c_{ij}}^s\right)^2\right)$ are specific to each treatment, while the behavioral parameters $\theta = (\alpha, \beta, \delta_o, \delta_u)$ are specified to be common across all treatments because they affect all players across these treatments. We estimate parameters θ and σ^2 through maximum likelihood estimation (MLE), as described below.

For shorthand, let t denote the index for different treatments and N_t denote the number of players in treatment *t*. Let $i = 1, .., N_t$ be the index for player in each treatment. Thus, the MLE is to find θ and σ^2 so as to maximize the log-likelihood function for the observed order quantity, i.e.,

$$\max_{\theta,\sigma^2} \ln\left(L(\theta,\sigma^2)\right) = -\frac{1}{2}\ln(2\pi)\sum_t N_t + \sum_t \sum_{i=1}^{N_t}\left(-\frac{1}{2}\ln(\sigma_t^2) - \frac{\left(q_{it} - Q_t(\theta)\right)^2}{2\sigma_t^2}\right)$$
$$= -\frac{1}{2}\ln(2\pi)\sum_t N_t - \frac{1}{2}\sum_t N_t\left(\ln(\sigma_t^2) + \frac{\sigma_{q_t}^2 + \left(\bar{q}_{it} - Q_t(\theta)\right)^2}{\sigma_t^2}\right)$$

where $\bar{q}_{it} = \frac{\sum_{i=1}^{N_t} q_{it}}{N_t}$, i.e., the average observed order for treatment *t*, and $\sigma_{q_t}^2 = \frac{\sum_{i=1}^{N_t}(q_{it} - \bar{q}_t)^2}{N_t}$, i.e., the variance of the observed order for treatment *t*.

Taking the first derivative of the log-likelihood against σ^2 gives

$$\frac{\partial \ln L}{\partial \sigma_t^2} = -\frac{N_t}{2}\left(\frac{1}{\sigma_t^2} - \frac{\sigma_{q_t}^2 + \left(\bar{q}_{it} - Q_t(\theta)\right)^2}{\sigma_t^2}\right)$$

Thus, given θ, we can solve the corresponding MLE estimator of σ_t^2 as

$$\sigma_t^2 = \sigma_{q_t}^2 + \left(\bar{q}_{it} - Q_t(\theta)\right)^2$$

Substituting σ_t^2 back into the log-likelihood function, we have

$$\ln L(\theta) = -\frac{1}{2}(\ln(2\pi) + 1)\sum_t N_t - \frac{1}{2}\sum_t N_t\left(\ln\left(\sigma_{q_t}^2 + \left(\bar{q}_{it} - Q_t(\theta)\right)^2\right)\right)$$

Thus, we can obtain the MLE estimator of θ through $\max_{\theta} \ln L(\theta)$, which can be done using commercial optimization software such as Matlab.