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Game

Introduction to Reverse Auctions: The BucknellAuto Game

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Abstract. A reverse auction is a common way of executing supply chain sourcing. This article presents a spreadsheet-based game, the BucknellAuto game, that simulates the bidding process in a reverse auction. Students play the seller role and vie for the buyer's demand request by bidding against the automated competitors. The BucknellAuto game allows students to experientially learn not only the competitive bidding process of the reverse auction but also the implications of the auction parameters on the bidding competitiveness. The BucknellAuto game serves as a pedagogical tool for efficiently and effectively introducing the reverse auction to undergraduate students in a fun and interactive way.

Supplemental Material: The game is available at https://doi.org/10.1287/ited.2017.0180.

Keywords: reverse auction • spreadsheet simulation • experiential learning • supply chain sourcing

1. Introduction

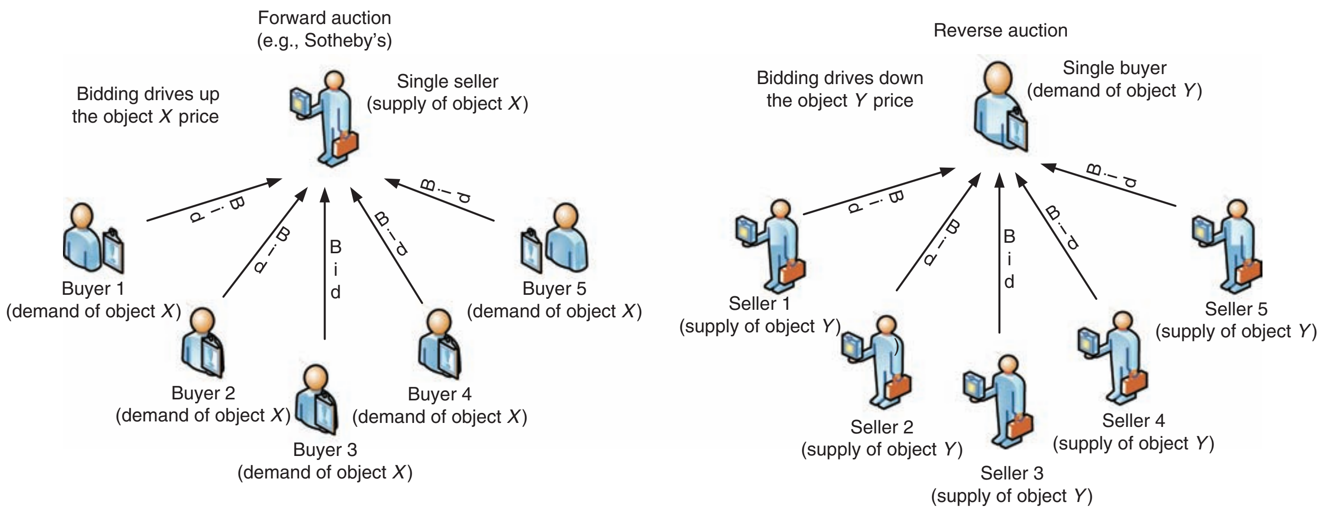
In the context of supply chain management, companies aiming to reduce the procurement costs often execute a strategic procuring approach such as the reverse auction (RA) (Schoenherr 2008, Hawkins et al. 2010). The RA is typically executed electronically, offering a variety of benefits to the supply chain as a whole and has become the standard industry practice (Carter and Stevens 2007, Sanders 2011). Introducing the concept of RAs to students lacking industry experience is a challenge due to the scarcity of relevant pedagogical materials for teaching RA and its operations (Teich et al. 2005). To prepare business and industrial engineering students for the issues that arise in implementing and participating in RAs in practice, we present a pedagogical simulation game with the primary learning goal of allowing students to experientially learn the unique RA bidding process through real-time thoughtful decisions in fictitious scenarios using as little as seven minutes of class time. While much smaller in scale and scope, the game is intended to play a similar role in introducing RAs as classroom games such as the Beer Game has done for issues in supply chain operations (Kaminsky and Simchi-Levi 1998).

Structurally, the RA is a sourcing process in which multiple sellers vie for the demand request from a single buyer (Chen-Ritzo et al. 2005, Engelbrecht-Wiggans and Katok 2006, Wan et al. 2012). Moreover, the bidding price of the auction item is driven downward until the sourcing period ends or no more sellers are willing to bid any lower (Monczka et al. 2011). Figure 1 illustrates the difference between RAs and forward auctions.

Researchers and practitioners have mixed opinions about the RA (Sanders 2011, Monczka et al. 2011, Hawkins et al. 2014). On the one hand, the RA may save buyers substantial procurement-related costs or time; on the other hand, the RA is primarily price-oriented and may hurt sellers' profitability as well as degrade the seller-buyer relationship (Talluri and Ragatz 2004, Giampietro and Emiliani 2007, Kumar and Chang 2007, Pearcy et al. 2007). The debates have much to do with the perceived appropriateness of using RA for the given procurement project (Kumar and Maher 2008). For example, the number of sellers, the administrative costs for participating the RA, the competitors' risk attitudes, and whether the buyer would split the demand quantity among multiple sellers are prominent factors that can affect the competitiveness of the RA bidding process (Engelbrecht-Wiggans et al. 2007, Anton and Yao 1989, Klotz and Chatterjee 1995, Hawkins et al. 2010, Yeniyurt et al. 2011).

In recent years, using spreadsheet applications in teaching management knowledge or decision-making skills for undergraduate business students has become common (Bell 2000, Teich et al. 2005, Jaureguiberry and Tappata 2015). In this teaching note, we create a simple simulation game that can effectively highlight the essence and issues of the RA for students (Lojo 2016). Classroom games such as the famous Beer Game have been recognized as a simple yet effective way of illustrating complex ideas not easily taught through

Figure 1. Illustrations of the Forward and the Reverse Auctions



traditional lectures (Griffin 2007). Similarly, computer simulation games such as the Littlefield Technologies are also widely used for teaching a variety of operations management concepts (Miyaoka 2005, Lojo 2016). Given that most students are comfortable with these types of activities, the RA simulation game presented here is of high pedagogical value.

To this end, we present an RA spreadsheet-based bidding game, called the BucknellAuto game. To our knowledge, this is the first such spreadsheet-based simulation teaching tool to introduce the concept of the RA to students. In the BucknellAuto game, students vie for the buyer's demand quantity on 20 automotive part items in the auctions by bidding against automated competitors. The individual student's objective depends on the instructor's goal with the course since the game can easily and meaningfully accommodate single or multiple objectives. For example, the instructor can evaluate a student's performance by at least two measures: the number/percentage of bids won and the total/average profit. That is, the students can focus on winning as many auction bids as possible, being as profitable as possible or both at the same time, while being aware that the two objectives require different strategies. The instructors may take advantage of this game and discuss the trade-off between these two measures in the eventual performance evaluation. Regardless of which objectives are implemented for the game, the instructor should fully clarify the student's objective before the game is played . Our recommendation is to take both measures into consideration by asking the students to maximize the average profit and win at least a certain number of auctions, which may be the case the students will face in practice. That way, the game becomes more challenging to the students than the game with a single objective. Considering the increased future use of RA , we aim to design a game that motivates students' learning of RA in a contextualized setting (Tassabehji et al. 2006, Atkinson 2008).

With respect to auction structure, the BucknellAuto game can be played as a first-price auction or as a second-price auction. The first-price auction is a very common and simple auction type yet a stepping stone for learning other relatively more complex auction types (Engelbrecht-Wiggans and Katok 2007). We suggest playing the first-price auctions in the beginning for two reasons. First, the auction winner in a first-price auction is bound to supply the items at the price actually bid by the winner. As such, the first-price setting is easily understandable to the auction participants due to a straightforward awarding process. Second, sellers in a first-price auction tend to place a bid greater than their true costs to assure a positive profit if their bid is selected. However, the optimal amount of markup is not obvious, thus increasing the risk and competitive nature of the game. We think struggling over how much to bid above the true cost adds a realistic dilemma that makes the game more appealing.

To increase the pedagogical value and flexibility of the game, we allow the users to easily enable/disable the second-price auction setting using a simple check box in the game interface. In the conventional second-price forward auction, the winner, or the highest bidder, honors the second highest bidding price. By the same token, in the second-price reverse auction, the lowest bidder honors the second lowest bidding price, and the second lowest bidder honors the third lowest bidding price. In terms of game play, the second-price auction may lack some of the drama of the first-price auction because risk-neutral sellers in a second-price auction would likely always choose to bid at their true costs due to the actual price being determined by the next highest bid (Milgrom and Weber 1982, Milgrom 1989, Kagel and Levin 1993). That is, for those who are familiar with the auction theory, the dominant bidding strategy in the second-price auction can be obvious. This could also provide an opportunity to instructors to allow students to constructively discover this dominant strategy in the course of the game.

The target users of the BucknellAuto game are undergraduate business majors. Apart from basic spreadsheet application proficiency, no specific skill sets or knowledge are needed to play. The game can be played by individual students independently or by pairs of students sharing the same computer screen. Also, the game can be used as a standalone session or accompany regular RA lectures. To date, 109 students from the Quantitative Reasoning or the Global Supply Chain Management course at Bucknell University have played the game. In addition to positive qualitative student feedback , the statistical tests on the survey results strongly support that the game will improve student's understanding of RAs.

The remainder of the paper is organized as follows. In Section 2, we explain the spreadsheet-based RA simulation BucknellAuto game. In Section 3, we report the evaluation on the game effectiveness. In Section 4, we conclude the paper with a summary.

2. Bidding Game

Students playing the BucknellAuto game are expected to experience and struggle with the trade-offs between profit margin in a submitted bid and the probability of winning the auction. That is, the sellers' trade-off is that submitting a lower bid entails a greater probability of winning but a lower profit if winning, whereas submitting a higher bid entails a greater profit potential but lower probability of gaining the profit (Ding et al. 2005).

In this section, we first introduce the auction variables and discuss their implications for bidding competitiveness. Second, we introduce the pre-game setup screens the students see before the game begins. Third, we explain the main interface of the game. Fourth, we provide a guide and recommendations for successfully conducting the game in a classroom setting. Finally, we address the game limitations.

2.1. Auction Variables

Inspired by Klotz and Chatterjee (1995), we incorporate the following key auction variables known to have a significant effect on the competitiveness of the RA bidding process in the BucknellAuto game.

2.1.1. Number of Invited Sellers (N). The number of potential competitors N in the RA positively correlates to the RA bidding competitiveness. Intuitively, the more participating sellers, the greater pressure the sellers would feel when competing for the buyer's demand. That is, students' average bidding prices tend to drop as N increases. For simplicity, N in the BucknellAuto game is set to three or five, including the student player(s).

2.1.2. Competitor Risk Attitude (β). The more risk-averse the other sellers are, the less attractive entering the auction is to the competitors. In the BucknellAuto game, β denotes how the profit gain is perceived by the automated competitors. More specifically, $\beta < 1$, $\beta = 1$, and $\beta > 1$ represent risk-averse, risk-neutral, and risk-seeking sellers, respectively. For example, the same amount of profit gain would give the seller with $\beta = 0.6$ a smaller utility than it does to the seller with $\beta = 1.0$. Klotz and Chatterjee (1995) indicate that the more risk-averse the sellers are, the lower the price they will bid (but no less than the true cost) due to the worry of not winning.

2.1.3. Manufacturing Cost (C_i). The subscript i is the seller index, where $i \in N$. We assume the manufacturing cost per unit for every auction item is less than or equal to \$1. Rather than bidding on one unit of every auction item, we arbitrarily scale the buyer's demand quantity for each auction item to 100 units to make the auction more realistic. As a result, the total manufacturing cost per auction (C_i) is less than or equal to \$100. To impart idiosyncratic seller expertise on manufacturing different auction items to the BucknellAuto game, we randomize every seller's total manufacturing cost on the same auction item so that C_i uniformly distributes between \$0 and \$100.

2.1.4. Bidding Price (b_i). With the price of b_i, the seller i is willing to supply the 100 units of the auction item. Thus, b_i is essentially the seller i's revenue for a given auction. Note that the BucknellAuto game is significantly simplified such that for each auction, b_i is the only input variable the students need to contemplate: If $b > 0$, the student enters the auction; if $b = 0$, the student does not enter the auction. In the meantime, the automated artifical intelligence (AI) sellers use some bidding prices according to Klotz and Chatterjee (1995). See Appendix A for details. Consider the practical concept of the buyer's *reserve price*, i.e., the price at which the buyer is willing to buy from some other source in the marketplace (Emiliani and Stec 2002). We restrict b_i to be no greater than \$100.

2.1.5. Dual Sourcing (α). In an RA, the buyer can decide whether to split the demand quantity to be awarded to the two lowest sellers. Under a dual-sourcing scenario, the buyer awards a primary demand portion $\alpha \geq 50\%$ to the seller with the lowest price, and the remainder, or $1 - \alpha$, to the seller with the second lowest price. If $\alpha = 100\%$, then the buyer does not split the demand quantity. Prior research shows that the buyer's decision on splitting the demand quantity, or so-called *dual sourcing*, can affect every seller's bidding behaviors. Intuitively, dual sourcing encourages the sellers' participation as it reduces the chance that the participating sellers end up winning nothing. Furthermore, in the second-price (dual-sourcing) game C_i and b_i are always based on the batch size of 100 units but will be automatically adjusted (scaled) when the profit is populated. See Appendix B for more details. Note that under the dual-sourcing setting, the bidder that gets the primary award (α) receives the second lowest price, and the bidder that gets the secondary award ($1-\alpha$) receives the third lowest price. If only one (two) bidder(s) participated in the auction, the buyer pays the reserve price ($100) to the first (second) bidder.

2.1.6. Administrative Cost (K). In practice, providing a seller's quote according to the buyer's specifications takes time and effort and depends on the bid requirements (presentations, prototypes, etc.). In the BucknellAuto game, we account for this and other overhead cost factors with the administrative cost per auction, K. Not entering the auction is the only way to avoid the administrative cost. Intuitively, a high administrative cost may discourage a seller from participating in the RA as it reduces the auction profit margin. Thus, K can be negatively correlated with the propensity of the sellers' participation in the RA. For simplicity, K is invariant with α and stays constant across all participants as well as all the auction items. Note that we do not disallow the total costs ($K + C_i$) to exceed the upper-bound of bidding price ($100); in this case we hope students would make a sensible decision and not enter such an auction.

2.1.7. Seed (s). The seed is to control the random number generator in Excel. We allow users to synchronize the seed value to enable fair comparison of the performance between the students, especially those in the same groups/class.

2.2. Pre-Game Setups

This game was developed using Excel 2013 for the Windows OS. The game was also tested using Excel 2016. The key operational procedure, regardless of which Excel version is used, is the Excel Solver Add-in, which must be enabled before running the simulation. If enabled, "Solver" would appear under the *Data* tab in the Ribbon; if not, then click "File" > "Options" > "Add-Ins" > Manage: Excel Add-ins and "Go" > check the *Solver Add-in* box and "OK."

2.2.1. Game Background. Figure 2 shows the information screen that contextualizes the BucknellAuto game for the students.

2.2.2. Auction Parameters. Figure 3 allows the students to conveniently choose some scenarios using the

Figure 2. Game Background

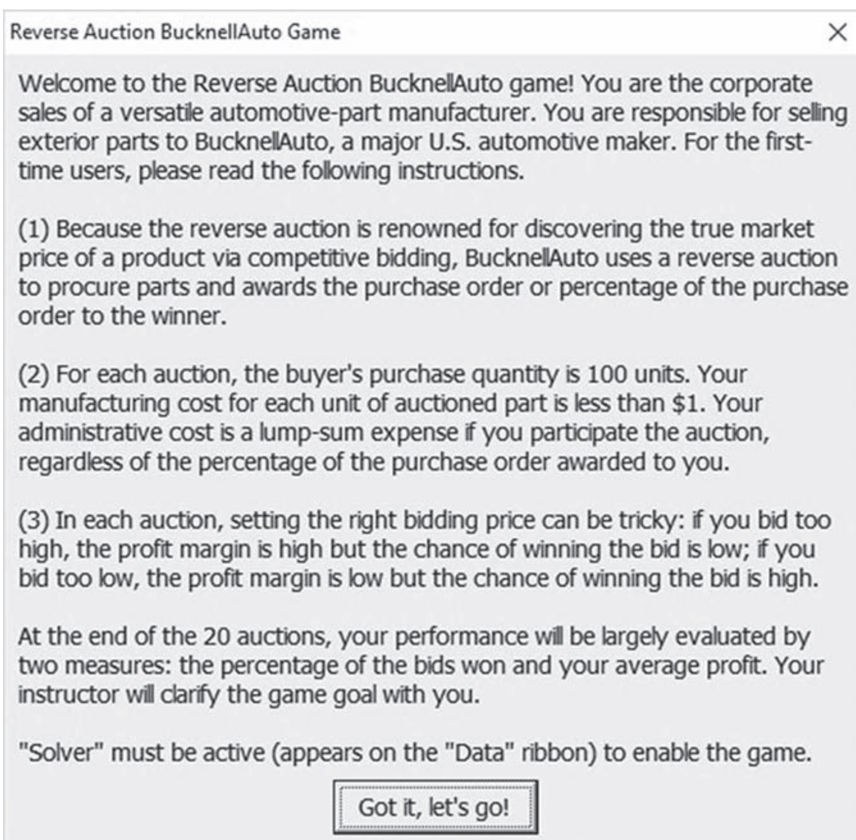


Figure 3. Auction Parameters Using Drop-Down Boxes with Default Values

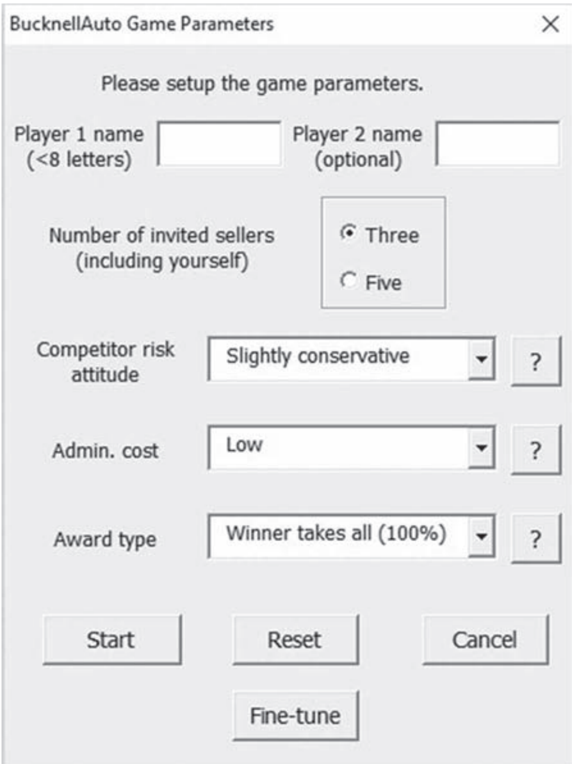
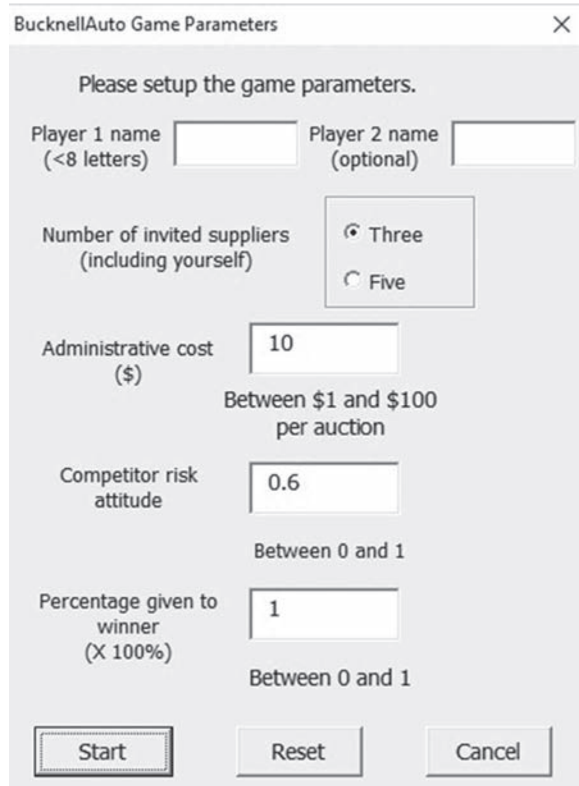


Figure 4. Auction Parameters Using Text Boxes with Default Values



drop-down boxes on the pre-determined values of the BucknellAuto game parameters. Figure 4 alternatively allows the student to design any desired scenarios by entering the parameter values after clicking the [Fine-tune] button in Figure 3.

2.2.3. Game Tutorial. Figure 5 shows the Bucknell-Auto game instruction, the last screen before the game begins.

2.2.4. Game Interface. Figure 6 shows the main game interface. To prevent user errors, we protect the cells of the worksheet except cell C11 where the individual student enters a bidding price between 0 and $100. For further customization or edits, instructors can remove the protection from the spreadsheet by clicking the "Unprotected sheet" under the *Review* tab. A copy of the BucknellAuto game can be obtained from the authors or from the Institute of Transportation Engineers (ITE) website.

- *Second-price option* (*Area A2*:*B2*). The users can play the game in the second-price auctions by checking the box in A2 which would cause B2 to show "TRUE." To switch back to the first-price auctions, the users uncheck the box so B2 shows "FALSE." The users can do this change at any time, but it is recommended to stick with one setting for a round of 20 auctions.
- *Game parameters* (*Area A3*:*B8*). The users can change the values of the BucknellAuto game variables at any time by clicking the [Reset AI Sellers] button.
- *Game steps* (*Area C6*:*C13*). In each auction, the student must complete the following steps: (i) Click [Prepare auction] button to clear any data generated from the previous auction. (ii) Click [Mfg. cost] button to randomly draw a manufacturing cost for producing 100 units of the auction item. (iii) In cell C11, enter 0 to not participate in the auction or a value less than or equal to $100 to place a bid. (iv) Click [Auction results] button to reveal the auction results. Note that

Figure 5. Game Tutorial

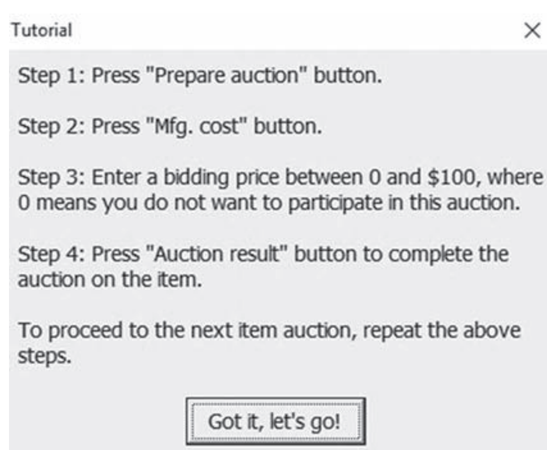
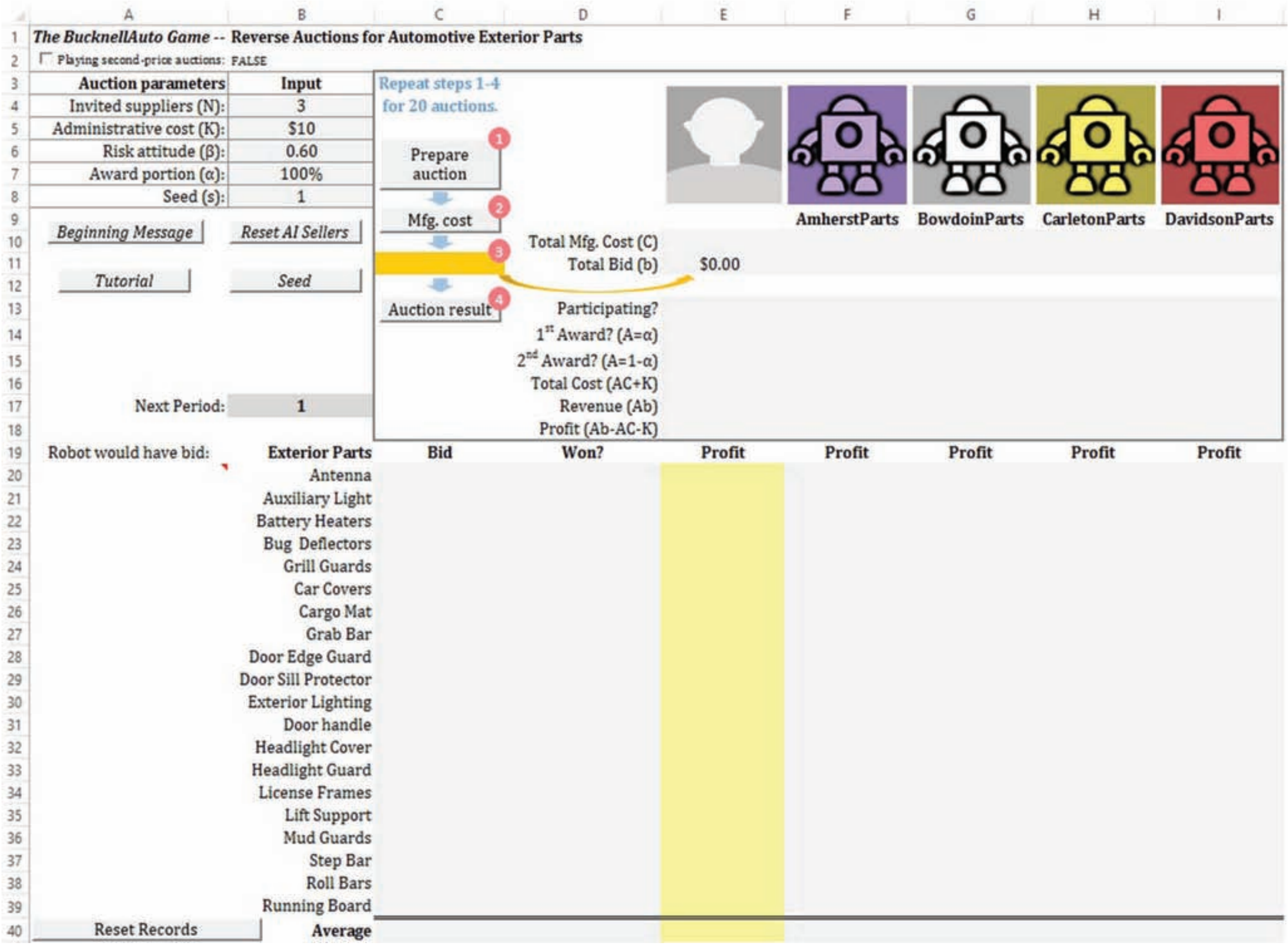


Figure 6. Screen-Shot of the Reverse Auction Bidding Game



this instruction is available by clicking the [Tutorial] button.

• *Current results* (*Area E*10:*I*18). This displays the seller's profit. It is equal to the revenue minus the total cost which is the sum of the administrative cost and the manufacturing cost. The details of calculating the profit given α are provided in Appendix B.

• *Past results* (*Area A*19:*I*40). The competitive aspect of classroom games can be a significant motivating factor for keeping the students engaged (Miyaoka 2005). To allow the students to compare their performances to those of all the AI sellers throughout the BucknellAuto game, the bidding history appears in C20:I40. The cells below A19 show what the AI sellers would have bid given the student's total cost. The [Reset records] button clears any historical data thus far. Figure 7 shows the game results at the end of the 20 auctions.

We offer a two-player game for the instructor who wants to assign the students in pairs to compete with each other. No additional software or hardware would be needed compared to the single-player game because the two players will be sharing the same computer screen. Figure 8 shows the game interface when choosing to play the game in the two-player mode. This interface functions almost identically to the single-player game interface. The only procedural difference is that the students take turns entering the bids while the other student is looking away. Because the two players would have the same total manufacturing cost, a sealed-bid setting makes sellers' collusion less likely.

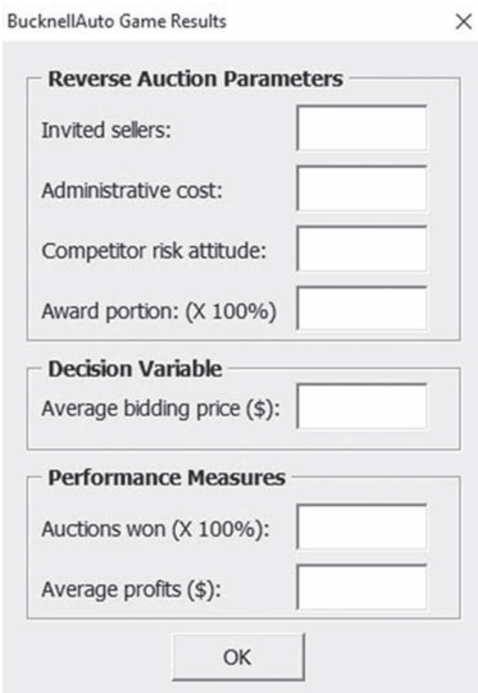
Next, we provide a guide and recommendations for using the BucknellAuto game in the classroom.

2.3. Game Development

The BucknellAuto game can be conducted in four phases.

2.3.1. Phase 1. Before the game begins, the students gain understanding of the RA by relating it to the well known forward auction, Sotheby's, since the auction participants' roles and responsibilities in the two types of auction are completely opposite. The instructor may spend some time educating the students about the core concepts of the first-price auction type used by the game. The goal of this session is to familiarize the

Figure 7. Reverse Auction Results



students with the general structure of the RA. In our experience, this may take about 15 minutes.

2.3.2. Phase 2. After the introduction, students should freely play a few auctions to familiarize themselves with the game operations (the Excel Solver Add-in must be enabled when opening the spreadsheet file, otherwise the game will not function). The instructor should remind the students of three things: (i) The total cost to their company is the random manufacturing cost less than $100 plus the administrative cost. (ii) Bidding $0 signifies they want to drop out of the current auction. (iii) The objective is to *maximize the average profit and win at least three auctions*. Essentially, the two implicit objectives, i.e., average profit and percent of the auctions won, require different bidding strategies. If time permits, the instructor may single out one objective or adjust the required number of actions won to let students discover the appropriate bidding strategy during game play. We think the fun of the game can be augmented if different objectives and different bidding strategies are tried. This session may take about ten minutes. Students should then be ready to play the game. At the end, every student should click the [Reset Records] button to clear all the trial results thus far before proceeding to the next phase.

2.3.3. Phase 3. Before the competition officially starts, the instructor announces the auction parameter values and initiates the BucknellAuto game. To effectively use class time, the instructor focuses on highlighting some, but not all, of the auction parameters. For example, the default beginning auction parameter setting is three sellers, low administrative cost, slightly conservative risk attitude, and winner takes all auction ($N = 3$, $K = \$10$, $\beta = 0.6$, and $\alpha = 100\%$, respectively). At the end of the 20 auctions, the instructor can list the students' average profits and the percentage of auctions won on the blackboard, and the students themselves can compare their results to the AI sellers' results. If time permits, the instructor should let the students play a second round using $N = 5$. At the end of this round, the students can compare their average profits and the percentage of auctions won between the two rounds. We recommend students play at least two rounds of the BucknellAuto game using different parameter values to experience how the game variables can affect the bidding intensity. In our experience, each round takes about seven minutes to complete.

2.3.4. Phase 4. After the game, the instructor should facilitate discussion to augment the students' learning experience. Sample questions are as follows:

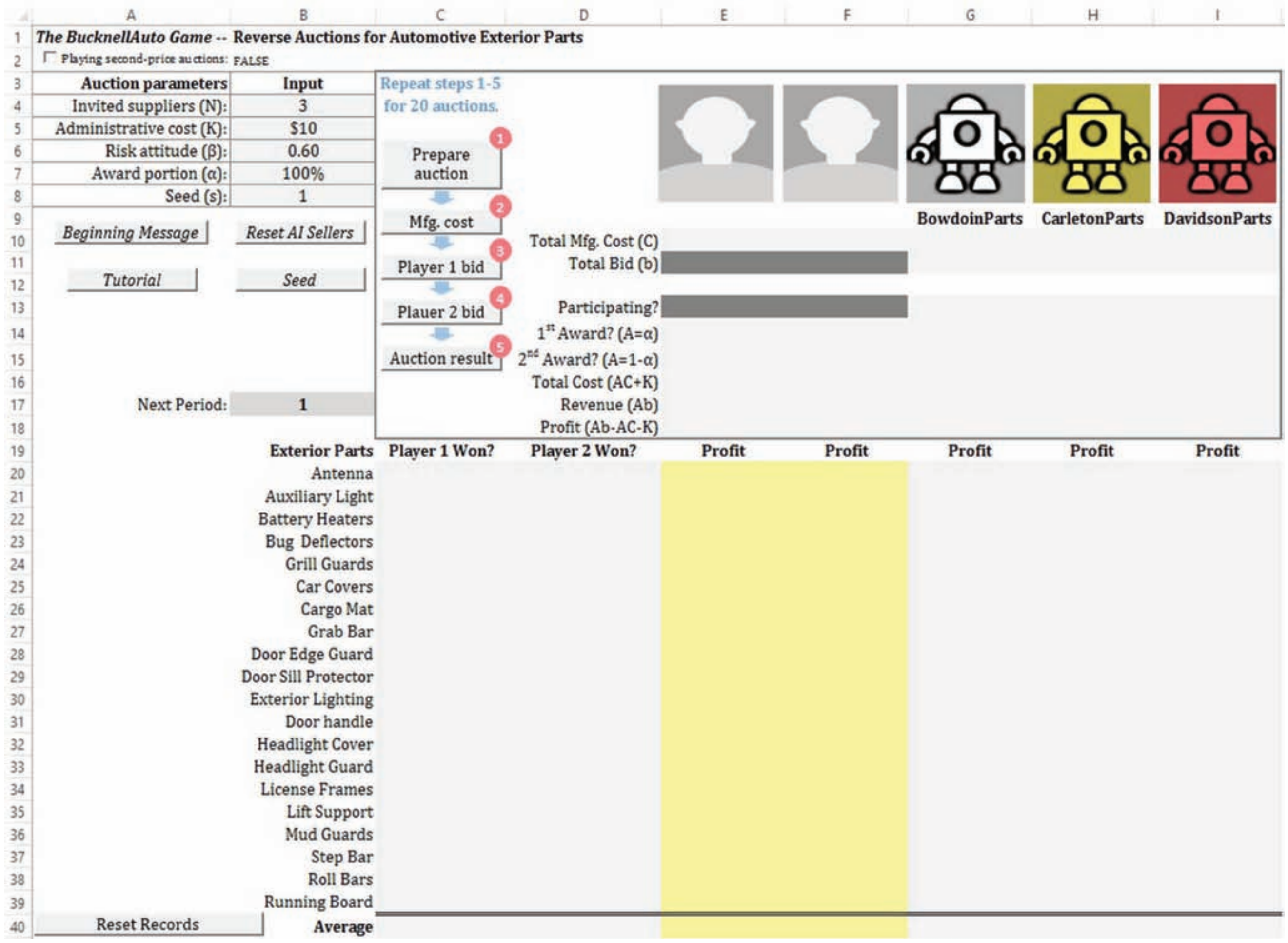
1. In general, how do you feel about bidding in an RA as a seller?
2. Did your bidding strategies differ between the two rounds of auctions? If so, how did the parameter values affect your bidding behavior?
3. How could using an RA affect the buyer-seller relationship? How much do you agree that RA is an effective tool for discovering the true market value of the item?

Within the RA construct, it is possible to result in a win-win situation for the buyer and seller. For example, non-incumbent sellers can benefit from the RA in terms of gaining access to new customers, and sellers can examine their competitiveness by benchmarking the bids (Kumar and Maher 2008). Thus, the discussion gives the instructor an opportunity to balance any potentially biased viewpoints. This session may take about ten minutes. On a side note, the instructor may consider awarding the students who have the highest objective values (the average profit and/or the percentage of auctions won) to enhance the competitive aspect of the game.

2.3.5. Extended Discussions. While the primary learning objective of the BucknellAuto game is an introduction to the mechanisms and issues in an RA, the game can also be used for secondary learning objectives such as learning more about auction types and utility theory. Depending on available class time, the instructor may further engage the students with some advanced discussions.

The core concepts of the first-price and second-price auction types and their implications for the bidding rationale could be naturally taught with the BucknellAuto game. The instructor may refer students who are interested in the bidding strategy of first-price or second-price auctions to Kagel and Levin (1993),

Figure 8. Screen-Shot of the Two-Player Reverse Auction Bidding Game



Che (1993), and the listed references. For general understanding, the instructor may show the risk-neutral, equilibrium bid predictions for the *forward auctions* as shown below, where x denotes the seller's private evaluation of the item values (Kagel and Levin 1993):

$$\text{First-price: } x(N-1)/N$$
$$\text{Second-price: } x.$$

Also, Kagel and Levin (1993) provided some interesting statistics: Around 90% of all the bids in the first-price auction experiments fall below the theoretical prediction, whereas only 4% of all the bids in the second-price auction experiments fall below the prediction. We hope playing the game can help students relate these bidding strategies via the first-hand experience.

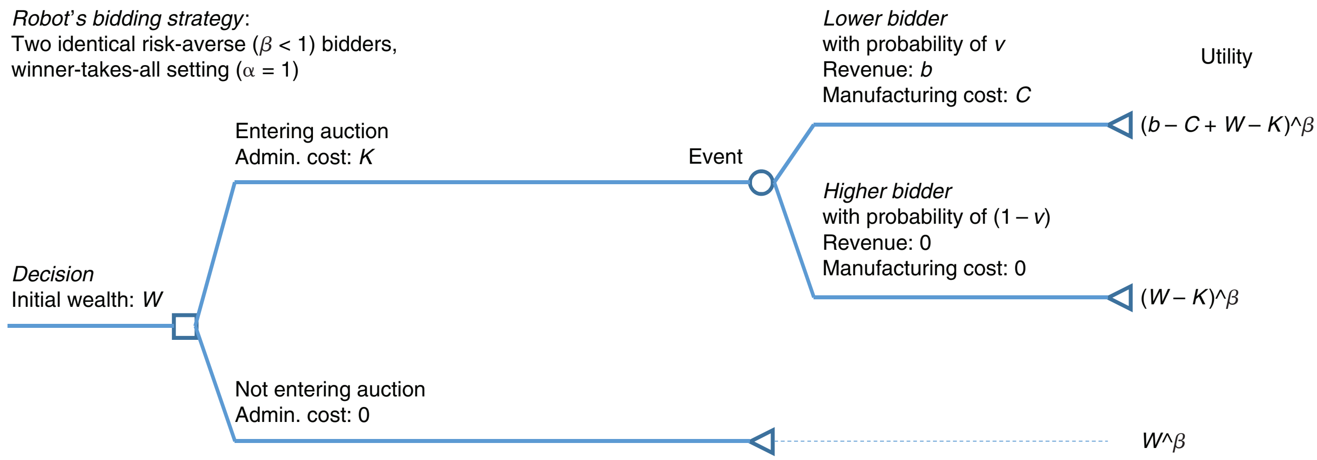
For students who are interested in the robots' bidding rationale, the instructor may construct a decision tree to illustrate the basic idea of the utility theory on which the AI seller bidding rationale is based. Figure 9 shows that the two identical, risk-averse sellers would enter the auction if and only if the expected utility of entering the auction is greater than the expected utility of not entering the auction:

$$v(b-C+W-K)^{\beta}+(1-v)(W-K)^{\beta}>W^{\beta},$$

where v is the probability that the seller is the lower seller than the other, and W is the seller's initial wealth.

A numerical example would also be helpful for the students' understanding. Consider two identical risk-averse sellers ($\beta = 0.6$) that place random bidding prices above the manufacturing cost ($v = 0.5$). The sellers face two options in a reverse auction: To bid or not to bid? Without loss of generality, we assume the sellers have an initial wealth equal to the administrative cost ($W = K$) so that entering the auction is an option. Suppose the total manufacturing costs are \$50 and the administrative costs are \$10 (identical sellers). As a result, the bidding price must be greater than \$81.75 if the sellers decided to enter the auction. If the two sellers are not identical with respect to the distribution of the random bidding prices ($v \neq 0.5$), then the seller who aims at earning \$25 as profit would not bid unless her winning probability v is at least 0.58. Note

Figure 9. Simplified Example of How the AI Seller Decides Whether to Enter the Auction



that the solutions can be easily obtained by the function of "Goal-Seek" in Excel. The instructor may prefer to offer these relatively straightforward utility calculations as assignments, exercises or homework problems after the exercise.

2.4. Game Limitations

To focus on the core factors in an RA for students, we have streamlined the complex RA structure to a simple game that can be played quickly and repeatedly. Inevitably, the BucknellAuto game cannot fully reflect reality due to its limitations. Issues that can be discussed in a wrap-up discussion are:

- *Single bid*: Only a single bid is permitted per auction item per seller, but in practice buyers can operate the bidding process in stages. In this scenario, the buyer manages a series of bids from each seller in the hope of further lowering the accepted price (Emiliani and Stec 2002).
- *Price-only auction*: The BucknellAuto game assumes a price-only auction, but in practice the buyers can consider other seller attributes such as capacity, quality or lead time when determining the auction winners (Talluri and Ragatz 2004, Teich et al. 2005).
- *Seller assessment*: In practice, participating sellers in the RA must quote the auction item based on the same item material and manufacturing specifications requested by the buyer. The buyer would be wary of any abnormally low bidding price in case the seller is gaining a cost advantage over competitors by not adhering to these specifications. In the BucknellAuto game, a very low manufacturing cost would not disqualify the seller from participation.
- *Incumbent seller*: In practice, the buyer may use the incumbent seller to fulfill the demand request if no sellers participate (Kumar and Maher 2008). In the BucknellAuto game, we assume that, if no seller participates, then the buyer will clear the need for the current auction using an external source.

3. Effectiveness Evaluation

To evaluate the BucknellAuto game effectiveness, we have designed a student survey with five quantitative questions and one qualitative question requesting general feedback (Ashenbaum 2010). The undergraduate students from the Quantitative Reasoning for Managers (first- and second-year students) or Global Supply Chain Management (third- and fourth-year students) courses participated to the game. The students answered the questions before and after participating in the game. The following statistics are based on 109 surveys collected.

In the survey, the first three multiple-choice questions were an attempt to reveal the students' explicit understanding of the facts and purposes of reverse auctions. We found that the students have significantly improved their knowledge about reverse auctions after playing our game. The fourth and fifth survey questions focused on the students' overall understanding of reverse auctions and their comfort in explaining a reverse auction to someone else. The survey questions are as follows:

Q1. A reverse auction is typically conducted with the following participants:

(1) Multiple buyers, multiple suppliers.
(2) Multiple buyers, single supplier.
(3) *Single buyer, multiple suppliers.*
(4) Single buyer, single supplier.

Q2. In a reverse auction, the bidding prices tend to

(1) increase, in favor of the suppliers.
(2) increase, in favor of the buyer.
(3) decrease, in favor of the suppliers.
(4) *decrease, in favor of the buyer.*

Q3. A reverse auction is a tool for discovering the true ________ of the auctioned subject.

(1) Quality.
(2) Service.

Table 1. Game Effectiveness Evaluation

Correct rate	Q1 (%)	Q2 (%)	Q3 (%)	Q4	Q5
Before game	76.15	57.80	83.49	1.97	1.93
After game	97.25	91.74	94.50	6.27	6.31

(3) *Market price.*
(4) Delivery time.

For Q4 and Q5, please use a number between 1 and 7, where 1 is strongly disagree and 7 is strongly agree, to answer the questions.

Q4. I feel that I have a big picture understanding of reverse auctions.

Q5. I could describe the basics of how a reverse auction works.

Q6. General comments.

We note that any missing or illegible answers in the collected surveys were treated as incorrect. We found significant statistical evidence showing that the game can effectively achieve its primary purpose. Table 1 shows the pregame and postgame survey statistics. The tests of equal proportions for the first three questions and the tests of equal means for the last two questions rejected the hypotheses that the pregame and postgame results are equal (Q3 results are significant with a p-value = 0.0173; all the other question results are significant with $p < 0.0001$).

Finally, we offered a sample of representative comments from the last survey question:

- *I have learned what a reverse auction is and how competitive it is to be a seller in a reverse auction. The exercise helped me put reverse auctions in a real-life experience to really learn how it works.*
- *From the exercise, I learned that it is difficult to find a balance between bidding low to attract business and bidding high to keep a profit margin. This exercise helped me learn that reverse auctions are very competitive from the seller's point of view.*
- *By doing the game, I experienced first-hand the influence of multiple sellers on my bidding decisions as well as the overall profit flow of the auction. The decision-making skills and thinking that went into the game let me clearly see the advantages and the disadvantages of such an auction.*
- *I really liked this exercise! I learned that it is important in a reverse auction to bid low enough that you will win, but high enough that you will have a profit. It was also interesting to look at the averages at the end!*
- *The simulation was very helpful. It forced you to try to think like the competitors to a point where you had a good idea in what they were going to bid. By adding the additional sellers, you felt increased level of pressure where you were afraid to bid too high and became greedy when your manufacturing cost were low, and it steered you away from bidding when your costs were mid to high.*

Based on our experiences with the BucknellAuto game and the data above, we believe the game efficiently and effectively helps an instructor augment the student's RA learning experience and transform the lecture session into a fun and interactive activity.

4. Conclusion

The prevalence of RAs in academic research and in practice motivated us to introduce RAs to our undergraduate business majors. This paper presents a spreadsheet-based RA bidding game in which students assume the seller role and vie for the buyer's business by bidding against a number of automated AI sellers. The BucknellAuto game allows students to logically think through the practical trade-off between winning the auctions and making profits when bidding. In our experience, this experimental learning game improved the student's understanding of the basis of RA. We believe the BucknellAuto game can help operations research or management science instructors better engage the students in teaching the fundamental concepts of RA, and transforming the conventional RA lecture into a fun and interactive session. While our primary goal was to provide an introduction to and illustration of RAs for undergraduate business majors, the BucknellAuto game could also be used to complement more technical instruction on supply chains including more detailed methodological instruction on topics such as auction design, utility theory, and game theory.

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Appendix A. Seller Bidding Rationale

In the game, the automated sellers' bidding behavior is governed by a bidding function using the auction parameters to generate each seller's bid. See Klotz and Chatterjee (1995) for more details. Here we present only some key points of the AI sellers' bidding rationale.

Basically, the robots will enter the auction if and only if the expected utility associated with entering is at least as large as the expected utility of not entering: (We suppress the subscript i for ease of disposition)

$$\begin{aligned}
&\Pr(C \text{ is lowest})\mathbb{E}[U(\text{winning} \mid C \text{ lowest})]\\
&\quad + \Pr(C \text{ is second lowest})\mathbb{E}[U(\text{winning} \mid C \text{ second lowest})]\\
&\quad + \Pr(C \text{ is greater than second lowest})\\
&\qquad \cdot \mathbb{E}[U(\text{not winning} \mid C \text{ is greater than second lowest})]\\
&\qquad \geq U(\text{not entering the auction at all}).
\end{aligned}$$

Given the auction parameter values, one may solve the drop-out manufacturing cost, e.g., C^*, from this inequality. The robots then use C^* to decide whether to enter the auction.

For example, if the total manufacturing cost for an auction item, C, is greater than the drop-out cost, C^*, then the seller's expected utility of entering the auction would be less than the utility of not entering the auction, prompting the seller to drop out of the auction by bidding zero. If entering the auction, the robots then calculate the equilibrium bidding price which is a function of C, K, N, β, α and involves some integration requiring a separate worksheet in the game file to numerically approximate the results.

Appendix B. Bidding Profit Calculations

For a given auction:

(i) The sellers who decide not to participate by bidding zero incur no profit nor loss.

(ii) The seller with the lowest b calculates the profit using the following formula:

$$\alpha b - \alpha C + K.$$

(iii) The seller with the second lowest b calculates the profit using the following formula:

$$(1-\alpha)b - (1-\alpha)C + K.$$

(iv) The other sellers have the profit as:

$$-K.$$

Note that in a dual-sourcing setting, if there is only one winner, then the winner takes the entire demand quantity instead of α.

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