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Teaching Auction Theory Using Simulations: Some Empirical Evidence

Many instructors find it challenging to teach auction theory in a traditional way due to the highly technical and abstract nature of the topic.Therefore, this paper shows a new approach where the fundamentals are presented to students using Monte-Carlo simulations. Several basic theorems of auction theory are introduced via simulations to help students understand the inner workings of the models. Moreover, many possible exercises are proposed so that students may reinforce their understanding of the material. Data is presented to show evidence of the efficacy of simulations versus a more traditional approach.

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1. Introduction

Teaching auction theory to undergraduates within a game theory course has shown that students frequently struggle to fully comprehend these topics. Several factors contribute to this difficulty. Many undergraduate economics programs do not require calculus or a Mathematical Economics Methods course as prerequisites for upper-level economics courses. Consequently, while students may grasp the intuition behind the models, they are often ill-prepared to follow the mathematical derivations. Prior coursework may have prioritized intuition over mathematical rigor, which, although valuable for building foundational understanding and a 'feel' for strategic situations, leaves students ill-equipped for the technical demands of auction theory. Furthermore, the game theory course is likely the students' initial exposure to complex strategic interactions, necessitating a significant adjustment in their analytical approach. This adjustment requires time and practice. Additionally, students typically lack prior experience with computational modeling techniques, which can significantly enhance familiarity with these models. Finally, many undergraduate economics students experience math anxiety, exhibiting negative emotional responses such as anxiety, nervousness, and even panic when confronted with mathematical tasks.

The application of numerical methods in economics for pedagogical purposes, using programs such as Excel or Mathematica, has a rich history and is well-established. Barreto (2015) reviews the history of the use of technology, particularly spreasheets, in the economic classroom and explores the current environment. He shows how they improve learning outcomes in different fiels of economics.

The list of articles that show how instructors can use software to teach economic concepts is too long to include here. However, some notable contributions related to game theory and microeconomics are Nguyen and Gilbert (2019), where they use simulations to teach quantity and price competition in oligopoly models. Similarly, Gorry and Gilbert (2015) present a series of numerical simulation models that can be used to explore properties of various models of strategic competition in quantities and their economic implications. Also, Pezzino (2016) uses Mathematica to study the properties of strategic competition models and shows how students can modify the models and analyze their implications. Kuroki (2021) is a recent contribution that introduces the open source and widely accesible programmig language Python and Google Colab to teach microeconomic principles to undergraduate students, such as profit and utility maximization. The application of simulations is not restricted to microeconomics, the teaching of other fields such as international trade or macroeconomics also benefit from the use of technology. See Findley (2014) and Gilbert and Oladi (2011). Briand and Hill (2013) utilize Monte Carlo methods in the context of econometric theory. A classic reference in game theory is Gibbons (1992), who provides a rich collection of applications, such as Cournot and Bertrand competition and games with incomplete information, which can also be analyzed using this methodology.

This paper presents the code used for Monte Carlo simulations, covering fundamental topics in auction theory, including equilibrium behavior in first and second-price auctions, seller's revenue with risk-averse buyers, the revenue equivalence theorem, and reserve prices. These topics are suitable for instruction at the conclusion of an upper-level game theory course or the commencement of an auction theory course. To the author's knowledge, this is the first article to present a basic treatment of Monte Carlo simulations as a teaching aid for auction theory. Moreover, this paper presents some empirical evidence showing the effectiveness of this approach. The programs are written in MATLAB (and are compatible with the open-source MATLAB clone Octave) but can be readily adapted for use in Python, Fortran, Julia, Scilab, or other programming languages. The code's complexity is minimal, allowing students to grasp the fundamentals of the language within a single class session or through an instructor-provided handout. For instructors interested in MATLAB, Hanselman and Littlefield (2004) is a valuable resource.

Based on the challenges mentioned in the first paragraph of the introduction, finding alternatives to the way auction theory is taught could be beneficial. Specifically, professors might find it useful to shift the focus from mathematical derivations to the use of computer simulations for introducing key theorems. The advantage of employing numerical methods is that students can observe the internal processes that generate theoretical results, processes that, while familiar to experienced theorists, may be opaque to beginners. Moreover, students can easily manipulate the code to explore diverse scenarios, such as varying the number of bidders or utilizing different distributions of private values—analyses that are often challenging or impossible to perform analytically. The implementation of this approach is straightforward. First, the auction setting is introduced: for example, a second-price, two-bidder auction with independent values uniformly distributed in the interval [0,1], and later the winning conditions and payoffs for different value realizations are explained. This process is replicated for other standard auction formats taught in introductory courses, such as the sealed first-price auction. Subsequently, bidder payoffs are calculated for various bids and values across multiple realizations of the other bidder's values. Finally, analytical results are derived and compared with the simulation outcomes.

Unlike the standard analytical approach, extending the basic auction model to incorporate reserve prices, non-uniform distributions, or additional bidders becomes straightforward using simulations. Another advantage of this pedagogical approach is its minimal cost to the instructor and students. The code provided herein can be implemented using open-source software such as Octave (a MATLAB clone) or, with minor modifications, Python. Regarding assessment, students are not expected to code independently or make substantial alterations to the provided programs. They are employed solely as instructional tools.

2. Basic Model

All auctions considered in this paper are independent private values (IPV), featuring two bidders with values distributed uniformly and independently within the interval [0,1], and, unless otherwise specified, risk-neutral players. For a more comprehensive understanding of these concepts, readers may consult Krishna (2002) and Wolfstetter (1996).

Computations are performed using Monte Carlo methods. For illustrative purposes, the first example, SPA.m (second-price auction), from the subsequent section is employed. This function accepts the object value and bid of a player as inputs and returns her expected payoff in a second-price auction. A substantial number of random values (represented by the variable x_2) are generated for the other bidder. Subsequently, a large number (M=100,000)) of auctions are simulated, assuming the other bidder utilizes her weakly dominant strategy (bidding her own value), and the average payoff (represented by the variable EP) is computed. This process is repeated 50 times, and the final average is returned as the result (represented by the variable y).

3. Programs

A. Second-Price Auction

The function SPA.m takes the value of the object (x1) and bid (b1) as arguments and returns the expected payoff (the identity of the bidder is irrelevant since this auction is symmetric) assuming that the other player bids her value $\beta(x)=x$.

```
function y = SPA(x1,b1)

rep = 50; M = 100000;

EP = zeros(rep,1);

for i=1:rep x2 = rand(M,1);

[~,I] = max([b1*ones(M,1) x2],[],2);

EP(i) = (x1*ones(M,1) - x2)'*(I==1)/M;

end

y = mean(EP);
```

The variable x_2 represents the value of bidder 2. The vector I records who wins each individual auction. It takes the value 1 if bidder 1 wins and 2 if bidder 2 wins. The variable EP(i) computes the expected payoff of bidder 1 in iteration i. Notice that payoffs for bidder 1 in case of winning are given by her value minus the bid of the other player (x_2). The payoff is zero in case of losing. This program can be used to show students how expected payoff changes with the bid for a given object value. Moreover, they can see that the optimal bid equals the value of the object even if there are more than two bidders. For the first exercise notice that expected payoff for bidder 1 is her value minus the expected value of the other bidder conditional on winning. Define Y as the highest value among the remainder bidders (in this case there are only two bidders) making $Y=X_2$, expected payoffs are:

1.
$$EP_1(x_1,b_1) = P(b_1 > y)(x_1 - E(Y|b_1 > y)) \\ = b_1\left(x_1 - \int_0^{b_1} yf(y|b_1 > y)\,\mathrm{d}\,y\right) = b_1\left(x_1 - \frac{b_1}{2}\right)$$

Where the conditional density is $f(y|b_1 > y) = 1/b_1$. The function above has a unique maximizer at $b_1 = x_1$.

For the second exercise, notice that if there are 3 bidders the distribution of Y is $F(y) = y^2$ and the conditional density is $f(y|b_1 > y) = 2y/(b_1^2)$. Thus, the expression for expected payoffs with 3 bidders is:

2.
$$\mathrm{EP}_1\left(x_1, b_1\right) = {b_1}^2\left(x_1 - \int_0^{b_1} y\frac{2y}{{b_1}^2}\,\mathrm{d}\,y\right) = {b_1}^2\left(x_1 - \frac{2b_1}{3}\right)$$

The previous function is also maximized at b_1=x_1, thus showing that symmetric equilibrium bids are independent of the number of bidders. The code can easily be modified to include another bidder by making the following changes:

```
x3 = rand(M,1);

[~,I] = max([b1*ones(M,1) x2 x3],[],2);
```

```
EP(i) = (x1*ones(M,1) - max([x2 x3],[],2))'*(I==1)/M;
```

The first line creates the values of the third bidder, the second line adds the extra bidder to the auction and the last line shows that, in case bidder 1 wins, the second highest bid is the maximum between the values of the remaining bidders.

As a simple exercise, students could calculate expected payoffs for a given valuation and bid in both two and three player second-price auctions and confirm their answers with the simulated values (assuming the second player bids her value). Additionaly, they can plot the expected payoff as a function of the bid (for a fixed valuation) and compare the graph with the simulated values.

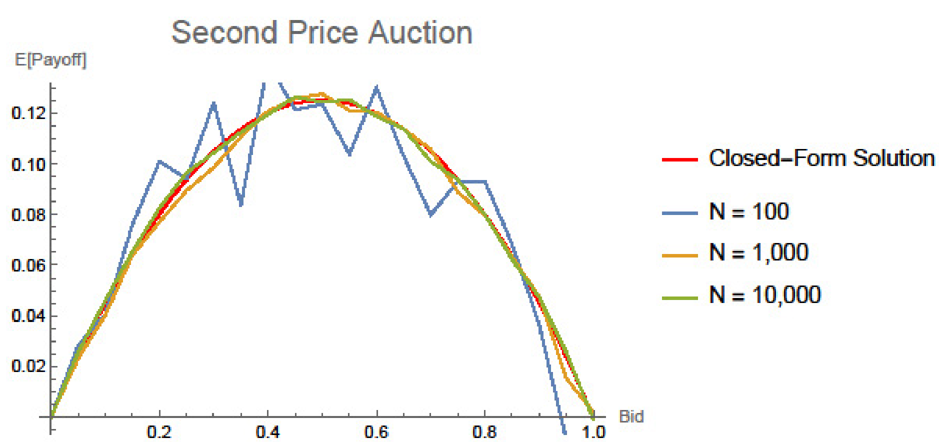
Simulations – Second Price Auction

(Example with N = 10)

Value	Bid	Value Rival	Bid Rival	Winner	Payoff
.5	.3	0.2782	0.2782	1	.2218
.5	.3	0.4261	0.4261	2	0
.5	.3	0.5582	0.5582	2	0
.5	.3	0.1008	0.1008	1	.3992
.5	.3	0.5164	0.5164	2	0
.5	.3	0.1830	0.1830	1	.317
.5	.3	0.7882	0.7882	2	0
.5	.3	0.4788	0.4788	2	0
.5	.3	0.9237	0.9237	2	0
.5	.3	0.4382	0.4382	2	0

$$\text{Expected Payoff} = \frac{.2218 + .3992 + .317}{10} = .0938$$

Expected Payoff (Closed Form) = .105



B. First-Price Auction

Expected payoff in the first price auction, assuming the other bidder uses the equilibrium bid $\beta(x) = x/2$, is given by:

3. $$EP_1(x_1, b_1) = P(b_1 > b_2 = x_2/2)(x_1 - b_1) = 2b_1(x_1 - b_1) for b_1 \leq 1/2$$

If the bid is $b_1 > 1/2$ the probability of winning is 1 and expected payoff is simply $x_1 - b_1$. Notice that the above function is maximized at $b_1 = x_1/2$.

The function FPA.m also takes as inputs the value of the object and bid and returns expected payoff, assuming the other bidder uses the equilibrium bid $b_2 = x_2/2$.

```
function y = FPA(x1,b1)

rep = 50; M = 100000;

EP = zeros(100,1);

for i=1:rep x2 = rand(M,1);

[~,I] = max([b1*ones(M,1) x2/2],[],2);

EP(i) = (x1 - b1)*sum(I==1)/M;

end

y = mean(EP);
```

The only difference between this program and the previous is that in the first price auction the equilibrium bid is half the value of object (as can be seen in line 5 of the code) and the payoff is her value minus her own bid (line 6). The program can easily be modified to account for non-uniform distributions, more than two bidders, non-equilibrium strategies by bidder 2, etc. Like in the second-price auction, students can calculate expected payoffs for a given valuation and bid and compare the results with the simulated ones.

Simulations – First Price Auction

(Example with N = 10)

Value	Bid	Value Rival	Bid Rival	Winner	Payoff
.7	.4	0.647	0.324	1	.3
.7	.4	0.631	0.316	1	.3
.7	.4	0.460	0.230	1	.3
.7	.4	0.822	0.411	2	0
.7	.4	0.799	0.399	1	.3
.7	.4	0.406	0.203	1	.3
.7	.4	0.114	0.057	1	.3
.7	.4	0.462	0.231	1	.3
.7	.4	0.676	0.338	1	.3
.7	.4	0.709	0.354	1	.3

Expected Payoff (Simulation) = 9 (.3) / 10 = .27
Expected Payoff (Closed-form) = 2 (.4) (.7 - .4) = .24

Students can also see how as the number of simulated auctions increase the difference between the analytical and simulated results decreases.

C. Risk Aversion

This subsection analyzes the expected revenue of the seller when bidders are risk averse. In particular, bidders have utility functions with constant relative risk aversion $u(x) = x^{\alpha}$ in which the coefficient of risk aversion is $1 - \alpha$. It is known, see for example Krishna (2002), that equilibrium bids in this case are given by:

4. $$\beta\left(x\right) = \frac{1}{F\alpha(x)} \int_0^x y f\alpha(y)\,\mathrm{d}\,y$$

Where $F_{\alpha}(x) = x^{(}1/\alpha)$.

Evaluating the integral and simplifying yields:

5. $$\beta(x) = x/(1+\alpha)$$

Expected revenue for the seller is 2 times (since there are two players) expected bidder payment:

6. $$E\left[R\left(\alpha\right)\right] = 2\int_0^1 P(\mathrm{win})\beta(x)f(x)\,\mathrm{d}\,x = 2\int_0^1 x\frac{x}{1+\alpha}\,\mathrm{d}\,x = \frac{2}{3(1+\alpha)}$$

The following function (FPARA.m) calculates expected revenue for the seller assuming that both bidders use the equilibrium bid $\beta(x) = x/(1+\alpha)$. This function creates 100000 random values for the players' valuations and compute equilibrium bids ($b1$ and $b2$) for each auction. Then it computes the maximum of those two and the vector ERS keeps track of the winning bid in each auction. Finally, a simple average is taken over all auctions.

function y = FPARA(alpha)

rep = 50;

```
M = 100000;
ERS = zeros(rep,1);
for i=1:rep
x = rand(M,2);
b1 = x(:,1)/(1+alpha);
b2 = x(:,2)/(1+alpha);
[~,I] = max([b1 b2],[],2);
ERS(i) = ((I==1)'*b1 + (I==2)'*b2)/M;
end
y = mean(ERS);
```

Students can change the value of alpha and analyze how expected revenue is affected, noting also that $\alpha = 1$ reduces to the risk neutral case. Several interesting extensions can be analyzed here such as increasing the number of bidders, changing the original distribution, etc. It is illuminating to try to carry out these extensions both analytically and numerically and cross check the results.

D. Reserve Prices

We can also study the effect of reserve prices on the seller's expected revenue.

This function calculates the seller's expected revenue in a first price auction as a function of the reserve price. Both bidders use equilibrium bids $\beta(x) = x/2 + r^2/2x$ for$x > r$ and zero otherwise. Expected revenue is:

7. $$E\left[R\left(r\right)\right] = 2\int_r^1 P(\text{win})\beta(x)f(x)\,\mathrm{d}\,x = 2\int_r^1 \left(\frac{x}{2} + \frac{r^2}{2x}\right)\mathrm{d}\,x = \frac{1}{3} + r^2 - \frac{4}{3}r^3$$

Notice that this function is maximzed at $r = 1/2$ generating an expected revenue of 5/12, higher than the expected revenue without reserve price.

```
function y = Exp_seller(r)
rep = 50;
M = 100000;
EPS = zeros(rep,1);
for i=1:rep
x = rand(M,2);
A1 = x(:,1) > r;
```

```
A2 = x(:,2) > r;

b1 = A1.*(x(:,1)/2 + .5*r^2 ./ x(:,1));

b2 = A2.*(x(:,2)/2 + .5*r^2 ./ x(:,2));

[~,I] = max([b1 b2 r*ones(M,1)],[],2);

EPS(i) = ((I==1)'*b1 + (I==2)'*b2 )/M;

end

y = mean(EPS);
```

An interesting exercise for students involves modifying the FPA.m function such that it becomes clear that non-reserve price equilibrium bids are no longer optimal in the case of positive reserve prices.

E. Revenue Equivalence Theorem

This program (RET.m) calculates the expected seller revenue in three different auctions satisfying the assumptions of the revenue equivalence theorem (the person with the highest value gets the object and a bidder with value zero for the good has expected payment of zero). In particular, the program compares expected revenue from first-price auctions, second-price auctions, and all-pay auctions in which all bidders pay independently of who gets the object. The equilibrium bid in this last mechanism is $\beta(x) = x^2/2$.

```
rep = 50;

M = 100000;

EPS1 = zeros(rep,1);

EPS2 = zeros(rep,1);

EPS3 = zeros(rep,1);

for i = 1:rep

X = rand(M,2);

[C1,I1] = max([X(:,1)/2 X(:,2)/2],[],2);

EPS1(i) = ((I1==1)'*X(:,1)/2 + (I1==2)'*X(:,2)/2)/M;

[C2,I2] = max([X(:,1) X(:,2)],[],2);

EPS2(i) = ((I2==1)'*X(:,2) + (I2==2)'*X(:,1))/M;

EPS3(i) = sum(X(:,1).^2/2 + X(:,2).^2/2)/M;

end

EPS = [ mean(EPS1) mean(EPS2) mean(EPS3)];
```

The 100000 × 2 matrix X represents the valuations of the two bidders in all the auctions. In the first price auction the player with the highest bid wins and the vector I1 tracks the identity of the winner. The vector EPS1 determines the revenue of the seller in each auction. A similar procedure is used in the second-price and all-pay auctions and finally the average is taken to calculate expected seller revenues.

6. Conclusion

This paper introduced several programs designed to assist instructors in teaching auction theory to undergraduate or introductory graduate students encountering the material for the first time. In the author's experience teaching auction theory within a game theory course, many students struggle to comprehend the concepts underlying the equations. By implementing programs that explicitly simulate each player's valuations, auction outcomes, bids, and other relevant factors, students can more readily visualize the internal mechanisms of the basic models. For instructors interested in adopting this methodology, minimal prerequisites are needed. Calculus is used only to maximize expected payoffs as shown in Sections 3.1 and 3.2. No prior knowledge of programming is required; however, students can be provided with a summary of fundamental Octave or MATLAB commands and syntax. When ask to extend the models or change assumptions, students have to figure out how to do it but in general the changes are straightforward and in general they should cause no major difficulties. In addition, to serve as a useful tool to learn auction theory more efficiently, the introduction of simulations represents the first time most students are exposed to the use of numerical methods to solve problems, which is valuable in and of itself.

The numerical simulations presented herein have been employed with considerable success at the undergraduate level, and it is the hope that instructors will find them equally valuable in their own courses. It is also noteworthy that the approach outlined in this paper can be extended to other sub-disciplines that utilize auctions, such as industrial organization, finance, and environmental economics. In these fields, students may not be required to master closed-form solutions to basic models; however, developing an intuitive understanding of auction dynamics can significantly enhance their education. The preceding exposition is particularly effective in achieving this objective. Furthermore, empirical evidence is presented in Appendix B demonstrating that the approach described in this article improved mean test scores relative to a traditional instructional method. In a future article, this methodology will be applied to introduce the more complex topic of common value auctions.

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Appendix A

This appendix explores some extensions mentioned in the article. In particular, the first-price auction code is modified to include non-uniform distributions, more than two players and non-equilibrium bidding strategies.

The first program uses the exponential distribution, which is parameterized by λ, for the valuation of player 2. The function exprnd in Octave is part of the statistics package, which needs to be installed at the beginning of the program.

```
pkg load statistics

function y = FPA_exp(x1,b1)

rep = 50; M = 100000;

EP = zeros(100,1); lambda = .5;

for i=1:rep

x2 = exprnd(lambda,M,1);

[~,I] = max([b1*ones(M,1) x2/2],[],2);

EP(i) = (x1 - b1)*sum(I==1)/M;

end

y = mean(EP);
```

The following program shows how to add another player to the auction and the use of non-equilibrium valuations. I use, again, the uniform distribution, and players use non-equilibrium strategies. Remember that equilibrium strategies are 2/3 of the valuation, but in this case bidders 2 and 3 bid half and a third of their valuations respectively.

```
function y = FPA2(x1,b1)

rep = 50; M = 100000;

EP = zeros(100,1);

for i=1:rep

x2 = rand(M,1); x3 = rand(M,1);

[~,I] = max([b1*ones(M,1) x2/2 x3/3],[],2);

EP(i) = (x1 - b1)*sum(I==1)/M;

end

y = mean(EP);
```

Appendix B

This appendix presents data demonstrating the efficacy of the simulation-based pedagogical approach compared to the traditional (pen-and-paper) method. As a control group, the Spring 2011 course is used, where a traditional teaching method was employed. That semester the author had 18 students enrolled in the course. The treatment group consisted of combined data from two subsequent courses (Fall 2016 and Spring 2020) where the simulation-based changes described in this article were implemented. It was decided to combine the observations from these two courses due to the COVID-19 pandemic and reduced enrollment compared to previous years. The Fall 2016 course had 12 students, and the Spring 2020 course had 9 students. The exam questions in the treatment group were identical across both years but differed slightly from those in the control group. However, it is the author's view that the differences were not substantial enough to introduce significant bias into the results. The overall difficulty level across both groups remained essentially the same. Each exam was graded on a scale from 0 to 100. Table 1 shows the summary statistics and below I perform a two-sample t-test with unequal variances. We can see that the mean score in the control group was lower than the mean score in the treatment group. The difference was 8.2 points.

Table 3: Two sample t-test with unequal variance

Groups	Observations	Mean	Std Deviation	Std Error	95% Lower Bound	95% Upper Bound
Control	18	74.61	11.3	2.66	68.99	80.23
Treatment	21	82.8	10.15	2.21	78.19	87.43
Combined	39	79.03	11.34	1.82	75.35	82.7
Difference		-8.2		3.46	-15.24	-1.16

The null hypothesis of the t-test is that there is no difference in mean test scores between the two groups. The t-statistic is -2.366.

$H_0 : Diff = 0$

$H_(a) : Diff < 0$

p-value = 0.0119

$H_(a) : Diff \neq 0$

p-value = 0.0237

The p-value of the one-sided test is 0.0119, and of the two-sided test is 0.0237. We reject the null hypothesis that there is no difference in mean test scores at the 5% significance.

Table 2 shows the results of the non-parametric two-sample Wilcoxon rank-sum test (Mann-Whitney).

Table 4: Two-sample Wilcoxon rank-sum test (Mann-Whitney)

Group	Observations	Rank Sum	Expected
Control	18	280	360
Treatment	21	500	420
Combined	39	780	780

Unadjusted Variance: 1260

Adjustment for ties: -2.93

Adjusted Variance: 1257.07

$H_0 : Var_c = Var_t$

$H_a : Var_c \neq Var_t$

The test statistic is z = -2.25 and the p-value of the test is 0.024

The mean test score in the treatment is higher than in the control. Both tests reject the null hypothesis that there is no difference in mean test scores at the 95% confidence. Unfortunately, due to the small sample size and the way the data was collected I cannot included other control variables, so the analysis is very primitive. However, this provides some evidence as to the effectiveness of using simulations to improve test scores. Moreover, and this is anecdotal evidence, students have repeteadly told me that they enjoyed the simulations and that it helped them better understand the topic.