The Effect of Artificial Intelligence on the Profitability of First-Degree Price Discrimination

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Abstract

As artificial intelligence and consumer information become increasingly accessible to companies, it will become easier to price discriminate, or offer different prices for different consumers. As use of price discrimination becomes widespread, it is important to determine the effect on the prices paid by consumers and the profits gained by companies. This paper attempts to determine the effect that price discrimination has on profitability, as well as the behavior that two competing stores will exhibit when given the option to price discriminate.

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Background

The increasing popularity of artificial intelligence and dynamic pricing tools has changed the relationship between consumers, sellers, and pricing [1]. The airline and hospitality industries have been using dynamic pricing for years as a method for extracting consumer surplus, as different individuals are willing to pay different amounts for the same flight or hotel room [2]. Major online retailers such as Amazon have developed artificial intelligence-based tools for market design that have allowed for rapid price changes [3] [4].

Price discrimination can be profitable for sellers, but increasingly personalized pricing comes at the tradeoff of decreasing privacy for consumers and increased complexity of pricing tools [5]. Although price discrimination offers the possibility of increased profits, it must be balanced against the effects of increased competition between organizations. If each company uses price discrimination, there will be more direct competition for each consumer, driving prices down.

This paper will examine the effect that price discrimination will have on companies and consumers. Furthermore, a simulation will be performed to determine if it is profitable for companies to price discriminate. The goal of the simulation is to determine in which situations first degree price discrimination can be profitable for a store, and to what degree consumer preferences affect the profitability of price discrimination.

Definition of Terms

Price Discrimination is offering the same or similar products at different prices to different individuals or groups of people. It is considered valuable for sellers as it allows them to obtain extra revenue when some people are willing to pay more for a product than others [6]. It is often split into three categories:

1. First degree -The same product is offered at a different price for each person. The price is set differently for each person, often at the maximum amount they are willing to pay.
2. Second degree -Different prices are offered for similar products based on consumer preference. For example, different classes on airplanes are offering the same service (transportation), but secondary benefits allow airlines to target different groups of people for first class, business, and economy. Another example of second degree price discrimination is offering discounts for buying in bulk. This pricing strategy takes advantage of differences in consumer preferences.
3. Third degree -The same product is offered at different prices to different groups of people. For example, many businesses offer discounts to students or seniors. Discrimination based on age and location is legal, but discrimination based on race, religion, nationality, and gender is illegal in the United States.

Literature Review

"Artificial Intelligence and Economic Theories" [1] examines economic theories such as supply and demand, rational expectation, and prospect theory and how they will be affected by advances in artificial intelligence. The paper predicts that rather than pricing being determined by the aggregate supply and demand of an entire population, AI will allow for individual supply and demand curves. The paper does not address the ethical issues associated with this, nor does it examine the potential profits and losses associated with price discrimination.

"Electronic Commerce and Competitive First-Degree Price Discrimination" [7] provides an algebraic analysis of the profitability of Price Discrimination. The paper concludes that in the case of two stores, the profitability of price discrimination is dependent on how sharply transportation costs increase. This can be interpreted as two stores being a fixed distance apart with consumers distributed uniformly between them. The transportation cost is defined by how much value consumers associate with needing to travel a certain distance. If the transport cost is linear (cost increases at a rate of $\$1/\text{unit distance}$), then price discrimination is not profitable for stores. If transport cost is exponential (cost increases at a rate $\$1/(\text{unit distance})^2$), then price discrimination is profitable for stores. The paper only considers a single parameter for consumer preference, and only a uniform distribution of that preference. Furthermore, the paper only considers the profitability of price discrimination for two stores where each consumer must decide to buy from one of the stores. We will attempt to validate the algebraic findings in this paper with numerical methods, as well as more accurately model the consumer decision making process by allowing consumers the option to not buy from either store based on their level of wealth.

"How Artificial Intelligence and Machine Learning Can Impact Market Design" [3] shows that market design is becoming an increasingly complicated process. For example, in online advertising, "ads are allocated to advertisers using real-time auctions". Dynamic markets with this level of complexity are beyond the scope of human understanding. Use of artificial intelligence to set prices and design the structure of auctions can improve market efficiency. Artificial intelligence will become increasingly necessary as the markets in various industries continue to grow more complex.

"Privacy, economics, and price discrimination on the Internet" [5] looks at the trend of decreasing consumer privacy and its effect on the economy. For example, Dell has successfully used price discrimination to increase revenue by 10%. Price discrimination is valuable for businesses as it increases market efficiency, but price discrimination on a large scale requires large amounts of consumer data. Despite large public concern over protecting consumer privacy, this has had little effect on the rising popularity of price discrimination because, "it is often disguised to avoid negative public reactions".

Companies will continue to expand their price discrimination programs (further decreasing consumer privacy) as the required technology becomes widely available and increasing competition demands more dynamic pricing.

Methods

Single Store

We begin by examining the profitability of price discrimination in the case of one store. Assuming that this store offers all members of the population a fixed price A, and that demand is elastic (an increase in price will decrease demand for a product and vice versa), some members of the population will be willing to pay more than A, and some members of the population would be willing to buy from the company if they were offered a price less than A. This potential revenue is called consumer surplus, and when a company is only able to offer a single price to all members of a population, there will often be some amount of consumer surplus [7].

By offering multiple prices that target the consumers willing to pay more and those who are only willing to pay less, a company can convert consumer surplus to profit. In the case of first degree price discrimination or perfect price discrimination, all consumer surplus is converted into profit [2]. This assumes that it is possible to prevent reselling or consumers buying at the lower price and selling to others at a higher price. We will assume that demand is elastic, and that reselling is impossible throughout the rest of this paper.

Multiple Stores

It is profitable for a single store to use price discrimination, but it is unclear whether it is profitable for multiple competing stores to price discriminate. This is no longer a binary decisions problem (price discriminating or not price discriminating) because there are multiple decision makers. Each store must decide whether to price discriminate, as well as how their decision will affect the other store. This creates 4 possible outcomes as shown in the payoff matrix in Table 1. Because we must consider the decisions of multiple rational agents and how decisions affect opponents, we will analyze this problem using game theory.

Prisoner's dilemma payoff matrix

B A	**B stays silent**	**B betrays**
A stays silent	-1 -1	0 -3
A betrays	-3 0	-2 -2

Table 1: Example payoff matrix for the Prisoner's Dilemma

Game Theory

A popular problem in game theory is the prisoner's dilemma. It is a game that can be imagined as two people being interrogated in separate rooms. Both prisoners must decide whether to stay silent or betray their partner and receive different sentences dependent on their decisions. An example of the possible decisions and payoffs for the prisoner's dilemma is shown in Table 1. In this case, if player A decides to stay silent and player B betrays, then player A will receive 3 years in jail and B will receive 0.

The dilemma is that when playing this game, rational players will choose to betray each other every time, despite the potential benefit of mutual silence. The reason for this is that mutual betrayal is the only equilibrium solution, or the Nash equilibrium. An equilibrium solution is one in which neither player can benefit by changing their own decision (assuming the opponent's decision remains fixed).

If both players choose to stay silent, then both can personally benefit by switching their decision to betray their partner. If one player chooses to betray and the other chooses to stay silent, the second player could benefit by also choosing to betray. But, if both players are betraying, neither could possibly benefit by changing their own strategy. For this reason, rational players will adopt the strategy of mutual betrayal despite the potential benefit of cooperation.

Mutual cooperation is considered the pareto optimal solution, or the solution that maximizes payoff for all players involved, while mutual defection is considered the Nash equilibrium solution, or the strategy that rational players will adopt [8]. This game is a dilemma because the equilibrium solution is not the pareto optimal solution.

The payoff matrix from the prisoner's dilemma can be generalized with the weights represented by unknown constants as shown in Table 2. In the classic prisoner's dilemma, $B > A > D > C$. The Nash equilibrium and pareto optimal solution are entirely dependent on the weights in the matrix. A different set of weights may produce a different equilibrium solution, and there is guaranteed to be at least one equilibrium solution [8]. The goal of this research is to run a simulation to determine what these weights are for the game of two stores deciding whether to use price discrimination.

Store 2 / **Store 1**	No Store 2 PD	Store 2 PD
No Store 1 PD	A / A	B / C
Store 1 PD	C / B	D / D

Table 2: Payoff matrix for a two player non-cooperative game

The simulation will be divided into three scenarios:

1. Neither store price discriminating to determine the value of A
2. One store price discriminating to determine the values of B and C
3. Both stores price discriminating to determine the value of D

Creation of Data

A major drawback of this research is the lack of real-world consumer data. This means it will be impossible to generalize these results to specific industries. Nevertheless, creating synthetic data will mean the results of the three simulations will be self-consistent, and still allow for meaningful comparison between the results.

There exist two values to describe each consumer. The "personal preference" represents a consumer's preference for store 1 or store 2. The "wealth" represents a consumer's aversion to high prices. Each consumer is offered a certain price by both stores and use the four values to determine their "choice". Consumers can make the decision to not buy anything (0), buy from store 1 (1), and buy from store 2 (2). A sample of five consumers is shown in Table 3.

	Personal_Preference	Wealth	Store1_Price	Store2_Price	Choice
0	0.537907	0.798120	6.228195	1.166556	2
1	0.530161	0.819176	7.009743	7.597064	0
2	0.791286	0.951025	0.949492	4.530833	1
3	0.930428	0.693050	3.272404	5.231559	2
4	0.471790	0.464606	1.161018	5.775775	0

Table 3: A sample of the synthetic consumer data used in the simulations

The values for the four features are random values from various probability distributions. Personal preference is represented with a beta distribution, usually with the parameters $\alpha = \beta = 2$, but in scenario 1 the parameters are changed to examine the effects that kurtosis has on profitability. A beta distribution was chosen as it is simple to represent preference between stores. The distribution is positive only on the interval $[0,1]$, and values less than 0.5 represent a preference for store 1 while values greater than 0.5 represent a preference for store 2. Values at the extremes represent a stronger preference than values close to 0.5. Wealth is represented with a normal distribution with the parameters $\mu = 1,\ \sigma = 0.25$. Store price for the training data was represented with a uniform distribution on the interval $[0,10]$, but when running the simulations, the store price was set using alternative methods.

Neural Network Classifier

To create the simulation, it was necessary to create a classifier, or a method for predicting consumer behavior based on changes in inputs. A densely connected neural network classifier was chosen due to their high accuracy, ability to handle large amounts of data (both in sample size and number of features), and nonlinearity (to represent complex interactions between features). Alternatives considered include linear classifiers, SVMs, decision tree classifiers, and clustering algorithms such as KNN. Each of these was considered inferior to a neural network classifier due to lower classification accuracy, slower prediction speed, or higher difficulty to implement.

The neural network classifier and simulation were created in Python using TensorFlow. The network includes 4 input neurons representing personal preference, wealth, the price offered by store 1, and the price offered by store 2. There are 3 output neurons representing the three choices each consumer has (buying nothing, buying from store 1, and buying from store 2). The neural network can easily be modified to add more inputs such as weather, distance consumer is from each store, etc., as well as more outputs such as increasing the number of stores or products that the consumer can choose between.

The neural network was trained using supervised learning using 35,000 samples and accuracy was evaluated using 15,000 samples. Based on experimentation, two hidden layers with 15 neurons each, a batch size of 20, and 5000 steps was the ideal balance between training time and accuracy. When evaluated, the neural network was able to classify consumer behavior with 96% - 98% accuracy.

The neural network classifier was used in scenario 2 and 3 to determine the maximum price a consumer is willing to pay while considering their preferences and the prices offered by both stores.

Results

Scenario 1

In scenario 1, neither store used price discrimination. This led to both stores setting the same price for every consumer in the population. The goal was to determine the equilibrium price where both stores maximize their profit. By testing various prices with a population of 50,000 consumers, the optimal price was determined to be $2.80. This will be used as a benchmark for comparison with the results from the following scenarios.

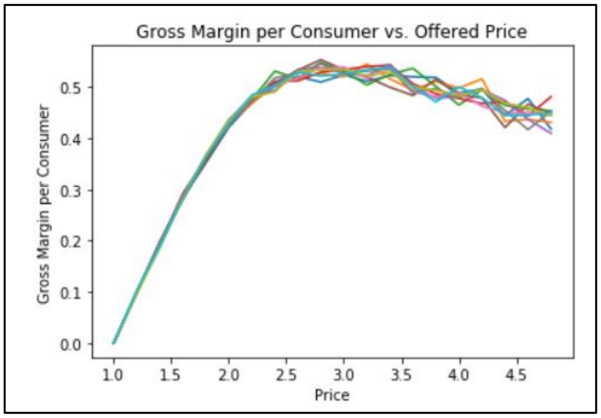

Figure 1: Plot of the results of scenario 1. Optimal price and profit per consumer is found to be invariant to changes in the beta parameter represented by the different colors

The chosen performance metric was gross margin per consumer or $\frac{(\text{revenue} - \text{cost})}{number\ of\ consumers}$ (cost was set at a constant $1 per sale). This metric was chosen because each of the simulations was ran with a different number of consumers in the population to either increase accuracy or decrease runtime as needed, and this metric is invariant with changes in population size. This allows for meaningful comparison between the results of the simulations.

A price of $2.80 for both stores leads to a profit of $0.53 per consumer for each store, meaning with a population of 50,000 consumers, each store makes a total of $26,500 in profit.

An important finding is that the optimal price and gross margin per consumer is invariant with changes in the parameters of the beta distribution when $\alpha = \beta$, or when the distribution is symmetric. This corresponds with increasing and decreasing the kurtosis to create either a more uniform or peaked distribution of consumer preferences as shown in Figure 1. Figure 2 shows the plot of gross margin per consumer vs. the price offered by both stores to every consumer with different colors representing different values of α and β. The maximum gross margin per consumer is ~0.53 in all cases with an equilibrium price of $2.80.

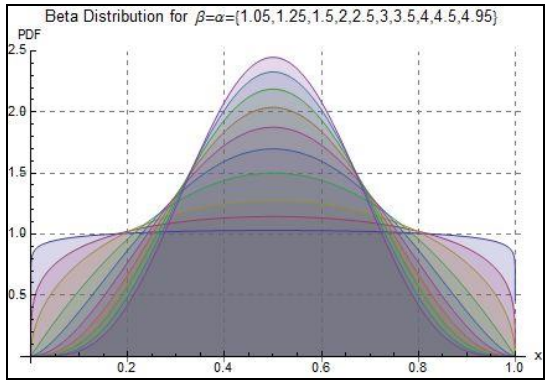

Figure 2: Probability density function of the beta distribution for various values of the parameters

Scenario 2

In scenario 2, store 1 uses first degree price discrimination while store 2 sets a constant price for all consumers. The simulation was also tested with store 2 price discriminating and store 1 maintaining a fixed price and the results were the same, as expected. Figure 3 shows the results of this simulation with the red lines representing the benchmark from scenario 1.

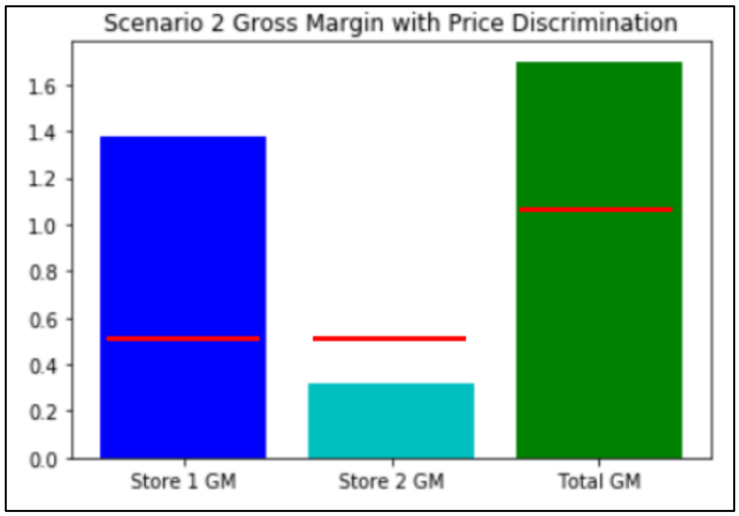

Figure 3: Results of scenario 2 with red lines representing the benchmarks from scenario 1

Store 1 is much more profitable with $1.34 in profit per consumer up from $0.53. Store 2 is slightly less profitable with $0.34 down from $0.53. The total profit, or the combined profits of store 1 and store 2 increased from $1.06 in scenario 1 to $1.68 in scenario 2.

This increase in total profit is significant, as it means price discrimination is not a zero-sum game. Profit gained by store 1 doesn't necessarily mean an equal loss in profit for store 2. This means that store 1 can gain additional revenue by converting previously undecided consumers. In scenario 1, approximately 40% of all consumers chose not to buy from either store because they were not willing to pay $2.80 and it was not profitable for stores to lower the price for all other consumers to gain the additional undecided consumers.

In scenario 2, store 1 can set a lower price for certain consumers, thereby decreasing the number of undecided consumers to approximately 12%. Consumers who bought from store 1 payed an average of $2.64 with 68% of them paying less than $2.80. Lower prices for the majority come at the price of higher prices for the wealthy minority, with those who paid over $2.80 paying an average of $4.88.

Figure 5: Results of scenario 3 showing the profit of each store after each iteration

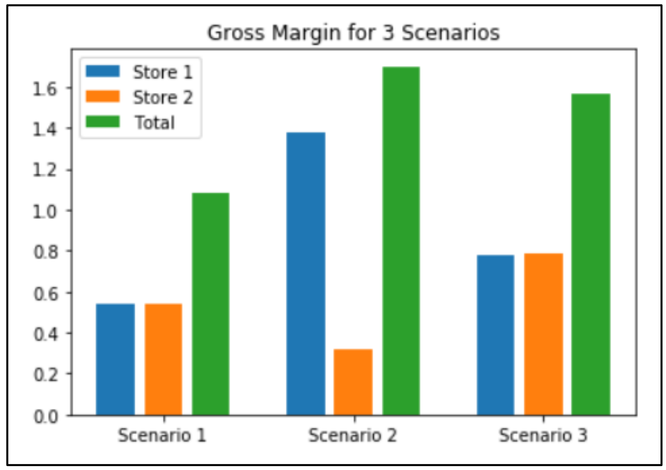

Figure 4: Summary of results for all 3 scenarios

Scenario 3

In scenario 3, both stores used price discrimination, and are directly competing for each individual consumer. An example of the behavior of the stores is shown below:

To begin, both stores would offer a consumer a fixed price of $2.80. Then, store 1 would use the neural network classifier to change the price, possibly raising it to $3.50 if it believes the consumer is willing to pay more. Store 2 would respond by lowering the price to $2.50 to try to get the consumer to switch from buying at store 1 to store 2. Store 1 would lower its price to compensate for this, etc. The stores would go back and forth adjusting their price until both arrived at an equilibrium where neither could benefit by adjusting their price further. This equilibrium price would differ depending on the consumer's preference for one store over another and the consumer's wealth. An equilibrium price was usually reached after 6 iterations of the stores alternating and adjusting their own price.

The results of the simulation are shown in Figure 4. After both stores find an equilibrium price after 6 iterations, each store earns a gross margin of $0.78 per consumer, higher than the $0.53 without price discrimination. On average, consumers who bought from one of the stores paid $7.20 with less than 22% of consumers paying less than $2.80.

Summary of Results

Results of the 3 scenarios are summarized in Figure 5. Both stores earn more profit in scenario 3 than in scenario 1. Another important finding is that the total profit in scenario 3 is less than the total profit in scenario 2 due to increased competition between the stores.

Analysis of Results

To determine the behavior of the stores, the results are placed into a payoff matrix. We start out with both stores not using price discrimination and earning $0.53. Either store can personally benefit by using price discrimination, and if one store is using price discrimination, it is profitable for the other store to do the same.

Store 2 **Store 1**	S2 Doesn't Use PD	S2 Uses PD
S1 Doesn't Use PD	0.53 0.53	1.38 0.32
S1 Uses PD	0.32 1.38	0.78 0.78

Table 4: Payoff matrix incorporating values found from the simulations

We arrive at the same equilibrium solution for this payoff matrix as we did with the prisoner's dilemma, but the pareto optimal solution also happens to be when both stores use price discrimination. In other words, both stores will choose to use price discrimination and it is the most profitable decision for both stores.

Conclusion

Because synthetic data was used to run these simulations, the results are not generalizable to real world companies. Nevertheless, if an industry has consumer preferences that are roughly normally distributed, and wealth is normally distributed, then these results should be valid.

These findings show that stores will have an economic incentive to price discriminate, and that if one competitor uses price discrimination, other stores will make significantly less profit unless also using price discrimination. Mutual price discrimination is ideal for companies as it increases total profits. As technology improves, consumer information becomes more accessible, and price discrimination becomes easier for companies to adopt, price discrimination will become inevitable if a company's only concern is profitability.

There are several things that could prevent widespread adoption of price discrimination. For example, consumers could be opposed to the idea of different people paying different prices. Through protests and boycotts, consumers could make it detrimental for companies to adopt price discrimination. Governments could also intervene on behalf of the consumers by placing regulations on price discrimination. Laws such as the Robinson-Patman act aim to limit the ability of companies to price discriminate, but the many exceptions make its enforcement inconsistent [9].

Further Research

The simulation was created to be highly modular. It is a simple process to adjust the inputs if different data is available and run the simulation again to see the effect on profitability. Further research could include more economic concepts to more accurately model consumer behavior and make the results more robust. For example, consumers may be opposed to the practice of price discrimination, especially if it violates their concept of fairness. Research could determine at what point consumer distrust outweighs the profitability of price discrimination.

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