Buyer Behavior under Best Offer Mechanism: A Theoretical Model and Empirical Evidence from eBay Motors*

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Abstract

We use data from eBay Best Offer listings to analyze haggling over prices in transactions with one seller and a series of potential buyers for a limited-supply product. We characterize this transaction mechanism as a sequential-move game to investigate buyer behavior. Our model suggests that a buyer's offer price increases in relations to the number of buyers who have previously made an offer on the item and the Buy-It-Now price chosen by the seller. On the other hand, the offer price decreases for items which have been listed on eBay for a longer period of time. We empirically test our theoretical predictions using data on the sales of Toyota Camry cars on eBay Motors. The empirical evidence is consistent with our model.

Keywords: eBay, Best Offer, haggling, e-commerce

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1 Introduction

Haggling over prices is a widespread mode of doing business throughout the world. For example, when buying a house or a car, it is a common practice for the buyer and the seller to negotiate a price. As Kuo, Ahn, and Aydın (2011) indicate, there are some recent news reports about bargaining for a discount in major U.S. retail stores such as BestBuy, Sunglass Hut, and Home Depot. Nonetheless, because haggling usually incurs substantial transaction costs in the negotiation process, it becomes less prevalent in the modern economy (Terwiesch, Savin, and Hann, 2005). In the past decade, the development of the Internet commerce drastically reduced the transaction costs, and many Internet platforms developed innovative ways for buyers and sellers to haggle over prices on the Internet. For example, Priceline.com pioneered the Name-Your-Own-Price (NYOP) system for sales of travel tickets and hotel rooms since 1998. In 2005, eBay introduced the Best Offer format for buyers to negotiate a price with the seller for products listed on the website.

In this paper, we propose a theoretical model to characterize the main features of the eBay Best Offer format and use a unique data set to empirically analyze the determinants of a buyer's offer price. This transaction mechanism works as follows. A seller can choose to use the Best Offer format when listing a product for sale on eBay.[1] Choosing this format incurs no additional listing fee. When initiating the listing, the seller needs to announce a Buy-It-Now (BIN) price for the product. If a buyer is willing to pay the BIN price, he/she can buy the product immediately at the BIN price. Otherwise, a buyer can make up to ten offers for each product listed under the Best Offer format.[2] Once a buyer makes an offer, the seller can either accept the offer, reject the offer, make a counteroffer, or simply ignore the offer. An offer or a counteroffer is valid only if it is responded to within 48 hours. When the seller accepts a buyer's offer or a buyer accepts the seller's counteroffer, the transaction is completed. The transaction price is the accepted offer price or the accepted counteroffer

[1]As will be explained in more detail in Section 2, in addition to the Best Offer format, a seller can also choose to sell a product by an auction or by a fixed take-it-or-leave-it price.

[2]A maximum of ten offers is allowed for vehicles and three offers for other products.

price.

Our study focuses on a buyer's first offer for the listings of Toyota Camry cars on eBay Motors. There are two primary reasons for focusing only on a buyer's first offer during the listing period. First, our data reveal that most buyers (78%) only make a single offer on a listing. Secondly, most of the accepted offers (89%) are actually a buyer's first offer. We propose a sequential-move game between a seller and a series of buyers to characterize their behavior under the eBay Best Offer mechanism. Each buyer chooses the BIN option or makes an offer based on the disclosed information. Our model shows that a buyer's offer price is affected by the BIN price, the number of rejected offers revealed on the website, and the remaining time of a listings. These theoretical predictions are consistent with the empirical evidence of our collected data.

The literature on Internet haggling is relatively sparse. Most of the previous research analyzes Priceline's NYOP system and similar mechanisms used by other websites (such as Germanwings.com and Ashampoo.com). All these variants of the NYOP mechanism allow a potential buyer to propose a price to purchase a standardized product. The product is sold to the buyer at the proposed price if it is higher than the seller's secret reserve price. Previous research on the Priceline-type NYOP mechanisms usually focus on interactions between one seller and one potential buyer. For example, Fay (2009) and Chen (2012) propose theoretical models to investigate the specific designs of the NYOP mechanism. Wang, Gal-Or, and Chatterjee (2009), Fay and Laran (2009), and Shapiro (2011) focus on the tradeoff between NYOP and fixed-price sales. Shapiro and Zillante (2009), Amaldoss and Jain (2008), and Fay and Laran (2009) use laboratory experiments to test the theoretical predictions. Besides, there are also some empirical studies using the field data to analyze consumer behavior (Hann and Terwiesch, 2003; Terwiesch et al., 2005; Spann and Tellis, 2006). Different from the above studies, Hinz and Spann (2008, 2010) account for the interactions between potential buyers. In both studies, they investigate the diffusion of information on transaction prices among buyers under the NYOP mechanism.

To the best of our knowledge there has still been no other academic research focusing on eBay's Best Offer mechanism. Although eBay's Best Offer mechanism is similar to the Priceline-type NYOP mechanisms for Internet haggling, there are several important differences, and the primary contribution of our paper is to explicitly account for these differences. Firstly, products listed on eBay usually have very few units for sale even though some sellers may use multiple listings to sell several similar items. This is particularly true in our empirical study of used cars. Because used cars are not a standardized product, each listed car is unique to the potential buyers. In contrast, products sold on the Priceline-type NYOP mechanisms generally have multiple units of a standardized product (such as the flight tickets on a specific day for a particular route) for sale. Consequently, an item is usually sold to one buyer exclusively under the eBay Best Offer mechanism, but not under the Priceline NYOP mechanism. It is important to account for the supply constraints when analyzing the eBay Best Offer mechanism since the supply for each specific product is often fixed at one. Secondly, Priceline-type NYOP mechanisms do not disclose the transaction history of one buyer to another buyer,[3] but eBay does display certain information of previous offers on the website. Specifically, the disclosed information includes how many buyers who have made an offer on the item up to now, when these previous offers were made, and the status of these previous offers. This information can have an important impact on a buyer's behavior. In fact, our empirical analysis shows that buyers do use the disclosed information to make their offer decisions.

Our study is also related to previous research on bargaining. There has been a rich literature on bargaining. (For example, see Ausubel, Cramton, and Deneckere (2002) for a review.) Most research considers the interaction between one seller and *one* buyer. However, in many real-world bargainings, such as the sales of used cars or houses, there might be more than one potential buyer when selling one unit of a product. In this paper, we use the data collected from eBay to analyze the interaction between one seller and *many* potential buyers under limited supply. Our results can help us to understand such bargaining situations.

[3]Potential buyers may attempt to obtain such information through some online forums, but not the official website. See Hinz and Spann (2008, 2010) for more discussions.

Our theoretical model is closest to Kuo et al. (2011). They also study the transactions between a single seller and a series of potential buyers under limited supply. In their context, however, the seller can adjust the BIN price in every period, and whether a buyer choose the BIN option or to bargain with the seller is exogenously determined. Besides, their is no information updating from observing the past history in their model. On the contrary, we develop our model to capture the main features of eBay's Best Offer mechanism.

The rest of the paper is organized as follows. In the next section, we describe our unique data collected from eBay Motors on sales of Toyota Camry cars and show the stylized facts of the Best Offer mechanism. These stylized facts motivate our theoretical model in Section 3. The model characterizes the interactions between a seller and a series of potential buyers in a sequential-move game. Each potential buyer makes his/her offer and BIN decisions based on the disclosed information. In particular, the decisions are affected by other buyers' behavior as revealed in the "offer history". Our empirical study in Section 4 tests our theoretical hypotheses. The estimation results are consistent with our theoretical predictions, suggesting that buyers are rational in using the available information to make an offer. Concluding remarks are in the final section.

2 Overview of the Best Offer Mechanism

In this section, we first introduce the data that we collect from eBay for our analysis. We then summarize the main features of the Best Offer mechanism used in eBay and show the stylized facts found in the data.

2.1 Data

We collect all transactions of Toyota Camry cars listed on eBay Motors during a nine-month period from June 18, 2008 to March 6, 2009. To collect the data, we use a computer program to search for all listings under the category of Toyota Camry cars every day. The program downloads all relevant information shown on the web page (such as the characteristics of the

Table 1: Transaction Results for different selling formats of Toyota Camry on eBay Motors

Format	Auction w/o BIN	Auction w/ BIN	Fixed Price w/o Best Offer	Fixed Price w/ Best Offer
Number of Listings	2,065	1,462	170	650
Percentage of Successful Listings	32.93%	4.86%	4.71%	18.31%
Avg. BIN Price among All Listings	na	13,478	16,475	13,876
Avg. BIN Price of Successful Listings	na	9,747	6,003	10,825
Avg. Transaction Prices	5,100	9,558	6,003	10,182

Notes: The data include all sales of Toyota Camry cars listed on eBay Motors between June 18, 2008 and March 6, 2009. A successful listing means a listing which results in a transaction.

car and of the seller, the bidding history, the transaction result, ...). The data consist of 4,347 listings. This section provides an overview of the selling formats on eBay by using all of these listings. Our main research focus is the Best Offer mechanism. There are 650 listings in our data using this selling format. Section 4 studies the determinants of the offer prices observed in these 650 Best Offer listings.

2.2 The Selling Formats on eBay

There are basically two primary categories of selling formats on eBay: an auction-style format and a fixed-price format. For an auction-style listing, a seller can optionally add a BIN price. For a fixed-price format listing, a seller can optionally add the Best Offer feature. Based on our collected data, Table 1 summarizes the transaction results for each of the four selling formats on eBay. The first format, auction without BIN, is basically an ascending auction with or without a secret reserve price. It allows a seller to list a product for a specific duration. During the listing period, a buyer can submit one or more bids for the product. At the end of the listing period, the product is sold to the buyer with the highest bid at a price equal to the second highest bid as long as the bid is higher than the secret reserve price.[4] Under the second format in Table 1, an auction with a BIN price, a buyer can either submit an

[4] To be more accurate, it is a proxy-bidding mechanism. A buyer enters the maximum amount of his/her willingness to bid on the eBay website, and the eBay computer will bid for him/her by adding a small increment to the current standing price until the standing price exceeds the maximum amount entered by the buyer.

auction bid or purchase the product at the BIN price immediately. As for the third format, a listing under the fixed-price format without using Best Offer, a seller posts a BIN price for the product. During the listing period, any buyer who agrees to pay the BIN price can get the product immediately at that price. The last format, fixed-price with Best Offer, was introduced in 2005. When a seller chooses this format, a buyer can purchase the product at the BIN price at any time during the listing period. Alternatively, the buyer can negotiate with the seller for a price. A transaction occurs when the buyer and the seller mutually agree on the offer price. The focus here is on the last format and we use the term "Best Offer" to refer to this format.

Several features in Table 1 motivate the importance of studying the Best Offer mechanism. First, the Best Offer mechanism makes up 15.0% of all listings. This is not a trivial proportion. Second, 18.31% of listings under the Best Offer format result in a successful transaction. This percentage is the second highest among the four formats. Third, the Best Offer format has the highest average transaction price among the successful transactions.[5]

At first glance, one may think our research is related to Internet auctions, especially because eBay is well known for its auction mechanism and there is rich literature on Internet auctions.[6] However, the Best Offer mechanism is quite different from the auction mechanism. In particular, while a seller is obliged to accept the highest *bid* under the auction mechanism, he/she can reject any *offer* under the Best Offer mechanism. A seller has to decide whether to accept or reject an offer within a 48-hour window under the Best Offer mechanism, but a seller does not need to respond to a bid under the auction mechanism. Moreover, a buyer can observe previous *bids* in the eBay auction mechanism, but no information about other buyer's *offer price* is revealed during the listing period with the Best Offer mechanism.[7] As a result, under the Best Offer mechanism, a buyer cannot learn any information about others'

[5]Note that Table 1 simply shows the summary statistics in the data, but does not account for the heterogeneity of format selection. A formal analysis to compare these formats needs to consider the heterogeneity, but it is beyond the scope of the current paper.

[6]For instance, see Ockenfels, Reiley, and Sadrieh (2007) and Hasker and Sickles (2010) for surveys of recent works.

[7]Offer prices are disclosed at the end of a listing. We use the disclosed prices in our empirical analysis, but buyers cannot observe the prices when they are making their offering decisions.

Table 2: Transaction Results of Toyota Camry sales listed under the Best Offer Format

Result	Ended by an Accepted Offer	Ended by BIN Option	Ended without Transaction	Total
Number of Listings	68	51	531	650
Avg. BIN Price	10,795	10,864	14,560	13,876
Avg. Transaction Prices	9,670	10,864	na	10,182

offer prices on which to decide his/her own offer price.

2.3 Stylized Facts about Best Offer Listings

This paper focuses on buyers' behavior under the Best Offer mechanism. There are 650 listings under this format in our data. Table 2 summarizes these listings according to the transaction results. Roughly 10.5% of the listings ended with an accepted offer while 7.8% ended with a BIN purchase. The remaining 81.7% ended without a successful transaction. Even though we do not control for heterogeneities among listings in this table, listings with a successful transaction tend to have a lower BIN price. In addition, the average transaction price is slightly lower for listing ended by an accepted offer than those ended by a BIN purchase.

The "offer history" on the eBay website discloses information regarding each buyer's offers. In general, the disclosed information includes the buyer's username, the offer price, the offering time, and the results of the offer. Although most of the information is publicly observed by everyone during the listing period, the *offer price* is observed *only by the seller* during the listing period. Because offer prices become publicly observable only after the end of the listing period, we can use them in our empirical analysis. Nonetheless, a seller can choose to list an item on eBay *privately*. For a private listing, the buyer's username and/or the offer price is hidden in the offer history even after the end of the listing period. When the buyer's username is hidden, we cannot tell whether two offers are made by the same buyer using the disclosed information. As a result, we cannot study each buyer's individual

Table 3: Frequency of the Number of Offers Made by a Buyer in a Listing

	Buyers who do not choose BIN.			Buyers who use BIN.
Number of Offers Made by the Buyer	Total Frequency	Frequency of Buyers Whose Last Offer Is Accepted	Frequency of Buyers Whose Last Offer Is Rejected	Frequency
0	-	-	-	10
1	759	34	725	0
2	135	3	132	0
3	53	0	53	0
4	17	0	17	0
5	9	2	7	0
6	4	0	4	0
7	0	0	0	0
8	0	0	0	0
9	1	0	1	0
Total Number of Buyers	978	39	939	10

behavior in these private listings. Similarly, when the offer price is hidden in a private listing, we cannot analyze the choice of offer prices.

Among the 650 Best Offer listings, buyer's usernames are observed in 326 listings. We can observe the number of offers made by each buyer in these 326 listings. Table 3 shows the frequency of offers made by each individual buyer. The second column displays the frequency distribution of the number of offers for buyers who do not purchase with the BIN option. There are 978 buyers in these listings.[8] Although eBay allows a buyer to make up to ten offers in a vehicle listing, most buyers make very few offers. Roughly 78% (759/978) of the buyers make only one offer in a listing. The third and the fourth columns decompose the observations in the second column into two cases, based on whether the buyer's last offer is accepted or rejected. From the third column, we find that 87% (34/39) of the accept offers occurs in a buyer's first offer. The last column shows the number of offers by buyers who end

[8]The same username making offers in different listings are treated as separate buyers. We do not consider the interaction among listings which have overlapping durations in this paper.

up using the BIN option to purchase. As the table indicates, ten buyers purchase with the BIN option, but none of them make any offer before choosing the BIN option.

Table 3 indicates that the first offers are the most important phenomenon in this market. Therefore, our remaining analysis focuses on a buyer's first decision (either making an offer or choosing the BIN option) in a listing. Because we cannot observe offer prices listed as "private", the data of buyers' first decisions consist of 899 observations, including 892 offers and 7 BIN choices.[9] We use these observations in our regression analysis in Section 4.

3 Theoretical Model

In this section we set up a sequential-move game to investigate the determinants of a buyer's offer and BIN decisions under the eBay Best Offer mechanism. We restrict our attention to a sequential equilibrium in which the seller's outside choice value θ is fully revealed after setting the BIN price at period zero. Based on the model analysis, we propose empirical predictions on the determinants of a buyer' offer price. We discuss our model specifications and their implications at the end of this section. Proofs for the propositions and lemmas are relegated to Appendix A.

3.1 The Game Structure

A seller has one unit of a product for sale. The listing of the product lasts for a duration of T periods. At period $t = 0$, the seller publicly announces a BIN price $\bar{p}$. For each period $t = 1, 2, \ldots, T$, a buyer arrives with an arrival probability $\boldsymbol{\lambda}$, and no buyer arrives with probability $1 - \boldsymbol{\lambda}$.[10] The arrival probability $\boldsymbol{\lambda}$ reflects the demand for the product. Assume the value of $\boldsymbol{\lambda}$ is constant over time but unobserved. Both the seller and the buyers have a

[9] If a buyer chooses the BIN option before making any offer, we treat the BIN decision as an observation with an offer price equal to the BIN price.

[10] When the length of a period converges to zero, this arrival process converges to a Poisson process.

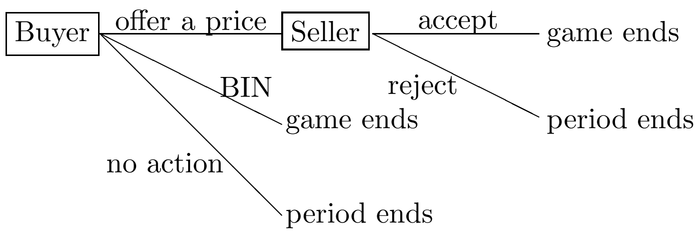

Figure 1: Game Structure in a Period with Buyer Arrival

common belief on its distribution,[11]

$$\boldsymbol{\lambda} = \begin{cases} \lambda_H, & \text{with probability } \mu_H; \\ \lambda_L, & \text{with probability } \mu_L, \end{cases}$$

for some $0 < \lambda_L < \lambda_H < 1$, $\mu_H \geq 0$, $\mu_L \geq 0$, and $\mu_H + \mu_L = 1$. The information revealed in the offer history allows both the seller and buyers to form posterior beliefs of $\boldsymbol{\lambda}$, which in turn affect their decisions.

If no buyer arrives in period t, no one can make any action in the period. If a buyer arrives in period t, he/she can attempt to purchase the product either by choosing the BIN option or by making an offer. Alternatively, the buyer can choose to do nothing and not obtain the product at all. We assume that a buyer can make decisions only at the moment of arrival, and the seller always respond immediately when facing an offer. Whether or not a buyer purchases the product at the moment of arrival, he/she exits the game and never returns.[12] Figure 1 shows the game tree of events when a buyer arrives in period t. If the buyer chooses the BIN option, the product is sold to the buyer at the BIN price $\bar{p}$ and the game ends. If the buyer does not do anything, he/she exits and the period ends. If the buyer chooses to make an offer, the seller can decide either to accept or reject the offer. If an offer is accepted, the product is sold to the buyer at the offer price, and the game ends. If an

[11] We can generalize the distribution of $\boldsymbol{\lambda}$ to any distribution. The model analysis would be essentially identical, but the notations are more complicated.

[12] We rule out the possibility of waiting until a later period to attempt a purchase.

offer is rejected, the buyer gets nothing and leaves, and the period ends. In the basic model presented in this section, we rule out the possibility of multiple offers from the same buyer. This simplification seems reasonable for our empirical study since more than three quarters of buyers make only one offer and 87% of the accepted offers are a buyer's first offer (Table 3). Our model also does not allow a buyer to choose rules the BIN option after a rejected offer. This is consistent with the data shown in Table 3. We discuss how to relax these assumptions in Subsection 3.4

When a buyer submits an offer, all future participants can observe the offering time t. However, the offer price is only observed by the seller, but not by other buyers.[13] In addition, all future participants can also observe the outcome of an offer. The outcome can be either *accepted* or *rejected*.[14] Observing an accepted offer means the product has been sold and the game has finished. Hence, for future buyers, the relevant information revealed by the "offer history" on the website is whether an offer was submitted and rejected in each of the previous period. We denote the history at period t as $\Omega_t \equiv (\omega_1, \omega_2, \ldots, \omega_t) \in \{0,1\}^t$. The s-th element of Ω_t, ω_s, is one if an offer was submitted and rejected in period s and zero if no offer was submitted in period s. The null history in period zero is denoted as $\emptyset$. In addition, we use Ω_{t-1}^+ to denote the history of observing a rejected offer in period t after a history of Ω_{t-1} in period $t-1$. Similarly, use Ω_{t-1}^- to denote the history of not observing an offer in period t after a history of Ω_{t-1}. Moreover, if history Ω_{t_2} occurs after the history Ω_{t_1} for some $t_2 > t_1$, we denote $\Omega_{t_1} \subset \Omega_{t_2}$.

Each buyer independently draws a private value v_t of the product from a commonly known distribution F_v. The value is private information. Besides, submitting an offer involves a fixed cost $c \geq 0$ but choosing the BIN option incurs no cost. The cost can be thought of the mental cost of calculating the buyer's optimal offer price.[15] A buyer's payoff equals the value v_t minus the transaction price when he/she successfully buys the product and zero otherwise.

[13]The eBay website reveals offer prices only after a listing has ended.

[14]Since a seller can reject an offer by simply waiting for expiration, we do not distinguish between a rejected offer and an expired one in our analysis.

[15]Since there is no monetary cost of submitting an offer, we are interested in cases with small submission costs.

In addition, if the buyer makes an offer, the submission cost c has to be subtracted from the buyer's payoff, regardless the offer is accepted or rejected.

When a listing results in a sale, the seller's payoff is the transaction price minus a period-specific cost shifter, denoted as η_t. This cost shifter is the seller's private information. It is the seller's perceived cost shift of doing business with the specific buyer who arrives in period t. For example, if the buyer has bad reputation, the seller might expect a higher probability of having a dispute with the buyer over a transaction. As a result, the seller faces a higher value of η_t.[16] We assume that the distribution of η_t is common knowledge and independent over t. Without loss of generality, normalize its mean to zero and denote the distribution function as F_η and the density function as f_η. We assume that $F_\eta(\eta)/f_\eta(\eta)$ is an increasing function of η.[17] Additionally, the seller has a value on the outside option. For example, the seller can sell the product on another platform or simply retain the product for his/her own use. Denote the seller's outside choice value as θ, which is the seller's private information with a publicly known distribution.[18] When the item is unsold at the end of the game, the seller's payoff is θ.

Whenever a buyer chooses the BIN option, the game terminates. Alternatively, whenever an offer is accepted by the seller, the game also terminates. We are going to analyze each participant's optimal behavior at any possible non-terminal history.

3.2 Equilibrium after Period Zero

In this subsection, we assume that the seller's choice of the BIN price $\bar{p}$ in period zero is higher than the outside choice value θ and is a monotonic function of θ. Because of the monotonicity, θ is fully revealed after observing the BIN price $\bar{p}$. Denote the inferred value

[16] Although the buyer knows his/her own reputation, he/she does not know with certainty how the reputation affects the seller's perceived cost shift of doing business with him/her. Consequently, the cost shifter η_t is assumed to be the seller's private information.

[17] There is one important reason for including such a shock in the model. When the submission cost is positive, rejection of an offer would never occur in equilibrium without such a shock. This would be inconsistent with the observed data.

[18] We do not specify the distribution of θ in the model because buyers would infer the true value of θ in equilibrium and the distribution is irrelevant for the analysis.

as $\hat{\theta}$. In any sequential equilibrium, all buyers believe $\theta = \hat{\theta}$ with probability one.

3.2.1 Seller Decisions

Whether an offer is accepted depends on the seller's expected surplus of rejecting it. Let $\pi_t(\theta, \hat{\theta}, \bar{p}, \Omega_t)$ denote the seller's expected payoff of not selling the product at the end of period t after observing the history Ω_t. Since the values of θ, $\hat{\theta}$, and $\bar{p}$ are fixed after period zero, we will suppress these three arguments in $\pi_t(\cdot)$ for simplicity when no confusion arises.

The seller is willing to accept an offer x if and only if the payoff of acceptance, $x - \eta_t$, is greater than the expected payoff of rejection, $\pi_t(\Omega_t)$. The condition for accepting an offer can be expressed as

$$x - \pi_t(\Omega_t) > \eta_t.$$

3.2.2 Buyer Decisions

First, consider a buyer's optimal offer price if he/she wants to make an offer. Since the cost-shifter η_t is the seller's private information, the buyer has to take expectation over η_t. Given the seller's expected payoff π, the choice of the optimal offer price for a buyer with value v is to maximize the expected surplus:

$$\max_x F_\eta(x - \pi)(v - x). \tag{1}$$

Denote the optimal offer price as

$$x(v, \pi).$$

The following proposition shows that $x(v, \pi)$ is a well-defined function with positive partial derivatives in both arguments:

Proposition 1. *There is a unique solution in a buyer's choice of the offer price. Moreover,*

$$0 < \frac{\partial x(v, \pi)}{\partial v} < 1 \qquad \textit{and} \qquad 0 < \frac{\partial x(v, \pi)}{\partial \pi} < 1.$$

Note that the inferred value of the seller's outside option $\hat{\theta}$ equals its true value θ. Therefore, the optimal offer price of the buyer who arrives in period t can be expressed as $x(v_t, \pi_t(\hat{\theta}, \hat{\theta}, \bar{p}, \Omega_t))$ in a sequential equilibrium.

Since a buyer can choose from the BIN option, making an offer, or doing nothing, we need to compare the expected payoff of these three options. Conditional on the seller's expected payoff π, a buyer's expected payoff from making the optimal offer $x(v, \pi)$ is

$$F_\eta(x(v,\pi) - \pi)[v - x(v,\pi)] - c. \tag{2}$$

The payoff from making the BIN purchase is

$$v - \bar{p}. \tag{3}$$

The payoff of doing nothing is zero. Hence, the buyer faces the following maximization problem.

$$\max\{v - \bar{p}, \quad F_\eta(x(v,\pi) - \pi)[v - x(v,\pi)] - c, \quad 0\}.$$

By the envelope theorem, the slope of the expected payoff from making the best offer in (2) with respect to v is $F_\eta(x(v,\pi) - \pi) \in (0,1)$. The slope of the payoff from BIN in (3) is one. Comparison of the payoffs in these two options makes it clear that the choice of the BIN option versus making an offer follows a cutoff rule. Given the information $(\hat{\theta}, \bar{p}, \Omega_t)$, BIN is better than making an offer if and only if $v_t \geq B_t(\Omega_t)$, where the cutoff point $B_t(\Omega_t)$ is implicitly defined by the following equation:

$$F_\eta\Big(x\big(B_t(\Omega_t), \pi_t(\Omega_t)\big) - \pi_t(\Omega_t)\Big)\big[B_t(\Omega_t) - x\big(B_t(\Omega_t), \pi_t(\Omega_t)\big)\big] - c = B_t(\Omega_t) - \bar{p}. \tag{4}$$

It is also obvious that a submitted offer $x(v, \pi)$ must be less than the BIN price $\bar{p}$.

Similarly, the decision to do nothing also follows a cut-off rule. Do nothing is better than making an offer if and only if $v_t \leq N_t(\Omega_t)$, where the cutoff point $N_t(\Omega_t)$ is implicitly defined by the following equation:[19]

$$F_\eta\Big(x\big(N_t(\Omega_t),\pi_t(\Omega_t)\big)-\pi_t(\Omega_t)\Big)\big[N_t(\Omega_t)-x\big(N_t(\Omega_t),\pi_t(\Omega_t)\big)\big]-c=0. \tag{5}$$

When the cost of submitting an offer c is large enough, $N_t(\Omega_t) > B_t(\Omega_t)$, and the buyer does not want to making an offer regardless his/her value v. Since our research interest is on the decision of making an offer, our analysis focuses on the case with small cost on submitting an offer such that $N_t(\Omega_t) < B_t(\Omega_t)$.

3.2.3 Bayesian Updating of the Arrival Probability

The belief of the arrival probability $\boldsymbol{\lambda}$ is updated according to the Bayes' rule. When a buyer arrivals in period t (i.e. $\Omega_t = \Omega_{t-1}^+$), the probability of observing a rejected offer is

$$\Pr[N_t(\Omega_t) \le v_t \le B_t(\Omega_t), x(v,\pi_t(\Omega_t)) - \eta_t < \pi_t(\Omega_t)].$$

Since the buyer's valuation v_t and the cost shifter η_t are independent of the arrival probability $\boldsymbol{\lambda}$, the posterior belief after observing a rejected offer in period t only depend on the observed history Ω_{t-1}, but not v_t and η_t:[20]

$$\begin{aligned}
&\Pr[\boldsymbol{\lambda}=\lambda_0|\Omega_{t-1}^+]\\
=&\frac{\Pr[\boldsymbol{\lambda}=\lambda_0|\Omega_{t-1}]\lambda_0\Pr[N_t(\Omega_{t-1}^+)\le v_t\le B_t(\Omega_{t-1}^+),x(v,\pi_t(\Omega_{t-1}^+))-\eta_t<\pi_t(\Omega_{t-1}^+)]}{\sum_{\lambda=\lambda_H,\lambda_L}\Pr[\boldsymbol{\lambda}=\lambda|\Omega_{t-1}]\lambda\Pr[N_t(\Omega_{t-1}^+)\le v_t\le B_t(\Omega_{t-1}^+),x(v,\pi_t(\Omega_{t-1}^+))-\eta_t<\pi_t(\Omega_{t-1}^+)]}\\
=&\frac{\Pr[\boldsymbol{\lambda}=\lambda_0|\Omega_{t-1}]\lambda_0}{\sum_{\lambda=\lambda_H,\lambda_L}\Pr[\boldsymbol{\lambda}=\lambda|\Omega_{t-1}]\lambda}
\end{aligned} \tag{6}$$

for $\lambda_0 = \lambda_H, \lambda_L$. When no offer is observed in period t, there are two possibilities: either no buyer arrives or the arriving buyer does not want to take any action. The posterior belief

[19] Both of the cutoff points, $B_t(\Omega_t)$ and $N_t(\Omega_t)$, also depend on $\hat{\theta}$ and $\bar{p}$ through the buyer's offer price $x(v,\pi_t(\hat{\theta},\hat{\theta},\bar{p},\Omega_t))$. We suppress $\hat{\theta}$ and $\bar{p}$ to simplify the notation.

[20] The posterior belief also depends on the inferred value of the seller's outside choice $\hat{\theta}$ and the BIN price $\bar{p}$. We suppress these two variables for simplicity.

after observing no offer in period t is

$$\Pr[\boldsymbol{\lambda} = \lambda_0 | \Omega_{t-1}^-] = \frac{\Pr\left[\boldsymbol{\lambda} = \lambda_0 | \Omega_{t-1}\right] \left\{(1-\lambda_0) + \lambda_0 \Pr\left[v_t \le N_t(\Omega_{t-1}^+)\right]\right\}}{\sum_{\lambda=\lambda_H,\lambda_L} \Pr\left[\boldsymbol{\lambda} = \lambda | \Omega_{t-1}\right] \left\{(1-\lambda) + \lambda \Pr\left[v_t \le N_t(\Omega_{t-1}^+)\right]\right\}}, \tag{7}$$

for $\lambda_0 = \lambda_H, \lambda_L$.

3.2.4 Seller's Expected Surplus of Continuation

The next step is to compute the seller's expected surplus $\pi_t(\Omega_t)$ at each given history Ω_t. Obviously, the expected surplus of not having sold the product at the end of the final period equals the outside choice value,

$$\pi_T(\Omega_T) = \theta \text{ for any } \Omega_T \in \{0,1\}^T.$$

For period $t < T$, the expected surplus can be computed recursively from the possible histories in the next period. Given the buyer's decision functions in the next period, $B_{t+1}(\Omega_{t+1})$, $N_{t+1}(\Omega_{t+1})$, and $x_{t+1}(v, \pi_{t+1})$, the expected surplus of not having sold the product at the history Ω_t in period t is

$$\begin{aligned}
\pi_t(\Omega_t) = \sum_{\lambda=\lambda_H,\lambda_L} & \Pr(\boldsymbol{\lambda} = \lambda | \Omega_t) \times \\
& \Big\{\lambda \Pr\left[v_{t+1} \ge B_{t+1}(\Omega_t^+)\right] \bar{p} \\
& +\lambda \Pr\left[N_{t+1}(\Omega_t^+) < v_{t+1} < B_{t+1}(\Omega_t^+)\right] \times \\
& \quad E\left[\max\left\{\pi_{t+1}(\Omega_t^+), x(v_{t+1}, \pi_{t+1}(\Omega_t^+)) - \eta_{t+1}\right\} \middle| N_{t+1}(\Omega_t^+) < v_{t+1} < B_{t+1}(\Omega_t)\right] \\
& + \left[(1-\lambda) + \lambda \Pr(v_{t+1} \le N_{t+1}(\Omega_t^+))\right] \pi_{t+1}(\Omega_t^-)\Big\},
\end{aligned} \tag{8}$$

where the first term inside the bracket is the surplus for selling by BIN in the next period; the second term is the surplus for receiving an offer in the next period; the last term is the surplus for no offer arriving in the next period.

To compute $\pi_t(\Omega_t)$ for a given history Ω_t in period t, we need to know the expected payoffs of the two possible histories in the next period, Ω_t^+ and Ω_t^-, and the posterior belief $\Pr(\boldsymbol{\lambda}|\Omega_t)$ at the current history. On the other hand, when using equation (7) to compute the posterior belief $\Pr(\boldsymbol{\lambda}|\Omega_t)$, we need to know the probability that a buyer does not want to do anything, $\Pr[v_{t+1} < N_{t+1}(\Omega_t^+)]$, which in turn depends on the seller's expected payoff at that history, $\pi_{t+1}(\Omega_t^+)$. Consequently, the recursive formulae to compute the two series, $\{\pi_t(\Omega_t)\}$ and $\{\Pr(\boldsymbol{\lambda}|\Omega_t)\}$, are intertwined. The following proposition shows that we can compute the expected payoffs and posterior beliefs for given θ, $\hat{\theta}$ and $\bar{p}$ at all possible histories in the game.

Proposition 2. *The seller's expected payoff* $\pi_t(\Omega_t)$ *and posterior belief* $\Pr(\boldsymbol{\lambda}|\Omega_t)$ *for any history* $\Omega_t \in \{0,1\}^t$ *for any* $t = 0, 1, \ldots, T$ *are well-defined.*

3.2.5 Equilibrium Properties

In this subsection, we show how the seller's expected surplus changes with the offer history and over time.

We say history $\Omega_t \equiv (\omega_1, \omega_2, \ldots, \omega_t) \in \{0,1\}^t$ has more rejected offers than history $\Omega_t' \equiv (\omega_1', \omega_2', \ldots, \omega_t') \in \{0,1\}^t$ if $\omega_s \geq \omega_s'$ for any $s = 1, 2, \ldots, t$. Denote the relationship as $\Omega_t \geq \Omega_t'$.

Lemma 1. *For any given period* t, $\Pr(\boldsymbol{\lambda} = \lambda_H|\Omega_t) \geq \Pr(\boldsymbol{\lambda} = \lambda_H|\Omega_t')$ *if* $\Omega_t \geq \Omega_t'$.

Proposition 3. *For any given period* t*, if the cost of submitting an offer* c *is low enough,* $\pi_t(\Omega_t) \geq \pi_t(\Omega_t')$ *if* $\Omega_t \geq \Omega_t'$

This proposition shows that if c is small, the seller's expected payoff $\pi_t(\theta, \hat{\theta}, \bar{p}, \Omega_t)$ is higher when more rejected offers are revealed in the history. Intuitively, more rejected offers in the history indicate higher arrival probability $\boldsymbol{\lambda}$. As a result, the seller has a higher chance of selling the product to a future buyer. However, when the submission cost is too high, it is possible that observing more rejected offers reduces the seller's expected payoff.[21]

The following proposition shows that, conditional on the information of any given history Ω_t, the seller's expected surplus $\pi_t(\Omega_t)$ decreases over time.

[21] When the submitting cost c is large, there is a negative effect on the current period expected payoff π_t from a higher next period expected payoff π_{t+1}. This is because a higher π_{t+1} is more likely to discourage a buyer from making an offer. Under certain distributions of buyer valuations, it is possible that this negative effect dominates other positive effects.

Proposition 4. *For any give Ω_t and $t_2 \geq t_1 \geq t$,*

$$E_{\Omega_{t_1}}[\pi_{t_1}(\Omega_{t_1})|\Omega_t] \geq E_{\Omega_{t_2}}[\pi_{t_2}(\Omega_{t_2})|\Omega_t] \tag{9}$$

where the first expectation is taken over all Ω_{t_1} in period t_1 with $\Omega_t \subset \Omega_{t_1}$ and the second expectation is taken over all Ω_{t_2} in period t_2 with $\Omega_t \subset \Omega_{t_2}$.

Proposition 1 shows that a buyer's offer price increases in the seller's expected surplus. Combining this result with Propositions 3 and 4, we have the following two corollaries on a buyer's offer price.

Corollary 1. *For any given period t, a buyer's offer price increases in the number of rejected offers observed in the history Ω_t when the submission cost c is small enough.*

Corollary 2. *A buyer's offer price is expected to be lower if the buyer arrives in a later period.*

3.3 Choice of the Buy-It-Now Price in Period Zero

In period zero, the seller needs to decide upon the BIN price $\bar{p}$. Since the seller is guaranteed to obtain the outside choice value θ by rejecting all offers, the optimal BIN price $\bar{p}$ must be more than the outside choice value θ. While slightly abusing the notation, let $\bar{p}(\theta)$ denote the seller's optimal BIN price when the outside option value is θ and denote its inverse function as $\hat{\theta}(\bar{p})$.

The seller's expected surplus in period zero is $\pi_0(\theta, \hat{\theta}(\bar{p}), \bar{p}, \emptyset)$. The choice of the BIN price $\bar{p}$ has both a direct effect and a strategic effect on the seller's expected surplus. The direct effect of a higher BIN price is twofold. On the one hand, it reduces the probability of selling by the BIN option. On the other hand, it raises the revenue from selling by BIN. There is a tradeoff between these two impacts. Moreover, since buyers will infer the seller's outside choice value θ from the observed BIN price $\bar{p}$, the buyer's choice of the BIN price is affected by a strategic effect. The strategic effect leads buyers to infer a higher outside choice value

$\hat{\theta}$ from observing a higher BIN price, which in turn increases their offer prices and increases the probability of choosing the BIN price. Hence, the seller has an incentive to choose a higher BIN price. The optimal BIN price for any given θ is the solution to the maximization problem:

$$\max_{\bar{p}} \pi_0(\theta, \hat{\theta}(\bar{p}), \bar{p}, \emptyset). \tag{10}$$

In a sequential equilibrium, $\hat{\theta}(\bar{p}) = \theta$. As a result, the function $\hat{\theta}(\bar{p})$ satisfies the differential equation[22]

$$\frac{\partial \pi_0(\theta, \theta, \bar{p}, \emptyset)}{\partial \bar{p}} + \frac{\partial \pi_0(\theta, \theta, \bar{p}, \emptyset)}{\partial \hat{\theta}} \frac{d\hat{\theta}(\bar{p})}{d\bar{p}} = 0. \tag{11}$$

The function for the optimal BIN price, $\bar{p}(\theta)$, is the inverse function of $\hat{\theta}(\bar{p})$.

We use the following numerical example to demonstrate the existence of a monotonic function $\bar{p}(\theta)$.

Example 1. *Assume that the distribution of the buyer's valuation, F_v, follows a log-normal distribution. The mean of $\log(v)$ is 3 and the variance is 1. Then the distribution of v has a mean of 33.12, a median of 20.09, and a standard deviation of 43.41. In addition, assume $\lambda_H = 0.3$, $\lambda_L = 0.1$, $c = 0.1$, $T = 5$, and the distribution of η_t is type-I extreme value distribution.*

Figure 2 shows the optimal BIN price as a function of the seller's outside choice value θ in a sequential equilibrium. The graph shows that $\bar{p}(\theta)$ is an increasing function.

The following proposition shows that, when the cost of submitting an offer is small enough, the seller's expected surplus for each possible history increases in the seller's outside choice value θ in the equilibrium path.

Proposition 5. *For any $\theta_1 > \theta_2$, when the submitting cost c is small enough,*

$$\pi_t(\theta_1, \theta_1, \bar{p}(\theta_1), \Omega_t) > \pi_t(\theta_2, \theta_2, \bar{p}(\theta_2), \Omega_t) \tag{12}$$

[22]The partial derivative $\partial \pi_0 / \partial \hat{\theta}$ denotes the partial derivative with respect to the second argument in $\pi_0(\theta, \hat{\theta}, \bar{p}, \emptyset)$.

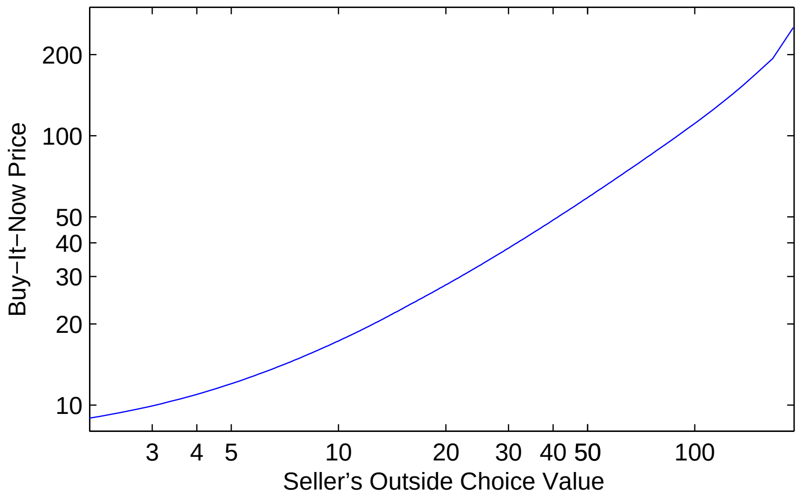

Figure 2: The Seller's Optimal Choice of the BIN Price in Equilibrium

for any $\Omega_t \in \{0,1\}^t$ *for* $t = 0, 1, 2, \ldots, T$.

Since the seller's optimal BIN price $\bar{p}$ increase in θ in equilibrium, Propositions 1 and 5 together imply a buyer's offer price to increase in the BIN price.

Corollary 3. *When the submission cost* c *is small enough, a buyer's offer price increases in the BIN price* $\bar{p}$ *at any given history* $\Omega_t \in \{0,1\}^t$ *for* $t = 1, 2, \ldots, T$.

In summary, our theoretical model predicts three important determinants of the buyer's offer price. Corollaries 1 and 2 predict the offer price to increase in the number of buyers who have made an offer on the listing, but to decrease over time. Moreover, Corollary 3 shows the offer price to be positively correlated with the BIN price. In the next section, we will use the data collected from eBay to verify these empirical predictions.

3.4 Discussions

Before moving on to the empirical analysis, we briefly discuss some of our model specifications and their effects on our empirical predictions.[23]

[23]We would like to thank an anonymous referee for many suggestions on our model specifications.

First, to keep our focus on the competition among buyers, we abstract away the bargaining game between a given buyer and the seller within a period. Our theoretical model restricts each buyer to make at most one offer or a BIN purchase. It seems a restrictive assumption. Nonetheless, if the game structure is more complicated, our empirical predictions remain true as long as the buyer's offer price increases in the seller's expected surplus of rejecting the current offer (i.e. $x(v, \pi)$ increases in π). This result holds in many more general bargaining games. For example, Appendix B presents an extended model in which a buyer can make two offers. Proposition 6 for the extended model indicates that the offer price increases in the seller's expected surplus.[24] Besides, the extended model also shows that the buyer's expected additional gain from making two offers is very small relative to the expected surplus of making a single offer. Therefore, if the submission cost of making the second offer is greater than the additional gain, the buyer would choose to make only a single offer in equilibrium. This result suggests that the assumption of making only one offer is not too restrictive.

Second, as we explained in Footnote 17, we introduce a period-specific shock η_t in the model so that rejecting an offer may occur in the equilibrium path. We interpret the shock η_t as a buyer-specific cost shifter. Nonetheless, there are other possible interpretations of this shock. For example, η_t can be viewed as the seller's update on his/her outside choice value using the new information observed in that period (such as receiving an offer outside the eBay platform). The crucial assumption here is that the buyer has some uncertainty of the seller's acceptance decision. Besides, we assume η_t to have an identical and independent distribution in every period only to simplify the exposition. If the distribution varies over time, the model analysis is essential the same. We merely need to replace the identical distribution function F_η by a period-specific distribution $F_{\eta,t}$ in each period. If the distribution is not independent over time, the seller's private information on previous η_t's would affect his/her expectation about future η_t's. We need to account for this information when computing the seller's expected surplus $\pi_t(\Omega_t)$.

[24]Besides, Rubinstein (1982) shows that, in an alternating offering game under full information, the buyer's first offer is $(\delta v + \pi)/(1 + \delta)$ where $\delta \in (0, 1)$ is the discount factor. The offer price also increases in π.

Third, the submission cost c in our model can be either positive or zero. When the cost is zero, some of our model analysis can be simplified. In particular, $c = 0$ implies $N_t(\Omega_t) = -\infty$ for all Ω_t, which means that making an offer is always better than doing nothing. Therefore, the Bayesian updating in (7) would depend only on the past history Ω_{t-1}, but not on the seller's future surplus $\pi_t(\Omega_{t-1}^{+})$. As a result, Proposition 2 is trivially true because the calculation of the posterior beliefs $\{\Pr(\lambda|\Omega_t)\}$ is not intertwined with that of the expected surpluses $\{\pi_t(\Omega_t)\}$. Actually, in some of our proofs, we only focus on the case with $c = 0$ and use continuity to extend our result to positive submission costs. Nonetheless, Table 3 indicates that most buyers only make one or two offers, suggesting that the submission cost is likely positive. Consequently, we explicitly allow the submission cost to be positive in our model.

Fourth, we assume that both the seller and the buyers are uncertain about the value of the arrival probability $\boldsymbol{\lambda}$. This assumption is the driving force behind our prediction that a buyer's offer price increases in the number of the buyers who have made an offer to the listing. If we simplify this specification by assuming that the arrival probability $\boldsymbol{\lambda}$ follows a degenerate distribution, then the arrival probability is no longer stochastic, and its value becomes the players' common knowledge. As a result, the offer history Ω_t would have no effect on a buyer's offer price. Nonetheless, the empirical estimation in the next section indicates that the offer history Ω_t has a significant effect on the offer price. This empirical evidence suggests that the arrival probability is stochastic.

4 Estimation

In this section we propose an empirical model to verify our theoretical predictions about the determinants of a buyer's offer price. Specifically, Corollaries 1 and 2 predict the offer price to increase in the number of buyers who have made on offer on the listing, but to decrease over time. Moreover, Corollary 3 shows the offer price to be positively correlated with the

BIN price.[25] Since the seller's choice of the BIN price is likely to be an endogenous variable, we use exclusive instruments to form moment conditions and estimate the coefficients by the Generalized Method of Moments (GMM).

4.1 Observed Variables

Table 4 presents definitions and descriptive statistics for the variables used in the empirical study. After eliminating listings without the buyer's username and/or offer price, we are left with 899 observations, including 892 offers and 7 BIN purchases. The upper panel of the table shows listing-specific variables, including product characteristics and seller characteristics. These variables are identical for offers within a listing. The variables in the lower panel are offer-specific, such as the offer price, offering time, and buyer characteristics.

The value of a car varies with many observable characteristics, such as age, mileage, and mechanical conditions. The Kelly Blue Book (more commonly known as the "blue book") is a commonly used reference for estimating the value of a used car. Since our focus is the impact of the trading system on the offer price, not the impact of the observed characteristics, the blue book price is used to control for heterogeneities among cars. Specifically, we obtain the blue book price for each car according to its age, mileage, feature, and the zip code of the seller's location. We normalize a price (a seller's listed BIN price or a buyer's offer price) by dividing the price by the blue book price for the listed car. We then take a logarithm of the ratio in the estimation. Therefore, the logarithm of normalized prices can be interpreted as the percentage of deviation from the blue book price. Table 4 indicates the median BIN price to be approximately 14.3% ($\exp(0.134) = 1.143$) higher than the blue book price while the median offer price is 22.3% ($\exp(-0.252) = 0.777$) lower than the blue book price.

Even though we use the blue book price to control for several aspects of quality heterogeneities, car quality may still differ in other aspects. We include two variables to account for additional quality difference. The dummy variable $CLEAR$ takes a value of one if the vehicle

[25] An alternative explanation of the relationship between the BIN price and the offer price is that buyers use the BIN price as a reference point to evaluate the product. See Kamins, Dreže, and Folkes (2004) for a discussion about this effect on eBay auctions.

Table 4: Descriptive Statistics of First Offers

Variable	Definition	Mean	Median	Std. Dev.
Listing characteristics				
BIN	Buy-It-Now price (in \$)	11608	9800	7855
$BLUE$	Kelly Blue Book price (in \$)	10475	8993	6706
$\ln(BIN/BLUE)$	Log of (BIN price/ Kelly Blue Book price)	0.093	0.134	0.332
$CLEAR$	Whether the title is clear	0.789	1	0.408
$WARRANTY$	Whether the vehicle is still under warranty	0.326	0	0.469
$SCORES$	Seller's feedback score on eBay	364	135	1099
$DEALER$	Whether the seller is a dealer	0.482	0	0.500
$DURATION$	Duration of the listing (in days)	11.157	10.000	6.026
$OTHER$	Whether the seller lists other vehicle concurrently	0.560	1	0.497
$\ln(BIN/BLUE)_{other}$	Log of (BIN price/ Kelly Blue Book price) of other vehicles listed by the seller concurrently	0.028	0.036	0.338
Offer characteristics				
$OFFER$	Buyer's first offer price (in \$)	8008	6000	6575
$\ln(OFFER/BLUE)$	Log of (first offer/ Kelly Blue Book price)	-0.452	-0.252	0.848
$PRIOR$	Number of buyers having made an offer	1.942	1	2.347
$FIRST$	Whether the offer is the first one of the listing	0.330	0	0.470
$TIME$	Length of time since the start of the listing (days)	6.226	5.096	4.901
$SCOREB$	Buyer's feedback score on eBay	77	10	211
$WEEKEND$	Whether the offer is made on weekend	0.300	0	0.459
$MORNING$	Whether the offer is made between 6–10 am	0.224	0	0.417

Note: The observation number is 899.

title is clear and zero otherwise. A clear title basically means that there are no outstanding payments to be made on the car. It also means that the car has never been reported as being excessively damaged or stolen. The other dummy variable $WARRANTY$ takes a value of one if the vehicle is still under warranty and zero if its warranty has expired.

Literature on Internet transactions indicates that sellers and buyers can use feedback ratings on the platform to build reputations and overcome problems caused by information asymmetry. (Livingston, 2005; Houser and Wooders, 2006) We include the seller's feedback score on eBay, $SCORES$, as an explanatory variable to determine a buyer's willingness to pay. The higher the feedback score a seller has, the higher the probability that the seller will deliver the subjects as described. Besides, we also include a buyer's feedback score ($SCOREB$) to control for the effects due to a buyer's reputation.

In collecting data on a seller's listing for a Toyota Camry, we use the hyperlinks to follow all of his/her listings on eBay at the same time. The dummy variable $OTHER$ indicates whether the seller has listed any other vehicle with a BIN price on eBay at the same time. When the seller has listed another vehicle, we compute the logarithm of the normalized BIN prices for other vehicle listed by the seller at the same time and denote it as $\ln(BIN/BLUE)_{other}$.[26] We will use these two variables as exclusive instruments in our estimation to control for the endogeneity problem.

4.2 Empirical Specification

Our empirical model is specified as

$$\begin{aligned}\ln(OFFER/BLUE) = \beta_0 + \beta_1 \ln(BIN/BLUE) + \beta_2 FIRST + \beta_3 PRIOR + \beta_4 TIME \\ + \beta_5 CLEAR + \beta_6 WARRANTY + \beta_7 \ln(SCORES) + \beta_8 DEALER \\ + \beta_9 \ln(SCOREB) + \beta_{10} WEEKEND + \beta_{11} MORNING + \varepsilon, \quad (13)\end{aligned}$$

[26]We set the value of this variable to zero when the seller does not list any other vehicle with a BIN price on eBay at the same time. When the seller has listed more than one other vehicle at the same time, we choose the one with the nearest closing time to compute the value of this variable.

where the variables are defined as in Table 4. The error term, ε, represents product characteristics observed by the seller and buyers but unobserved to econometricians. For instance, ε may capture quality information presented by the photos posted by the seller on the webpage. Buyers can use the information to determine their offer prices, but that information is not observed by econometricians. We assume that ε is independent across listings and has a mean of zero. But we allow ε to be correlated for offers within the same listing.

Corollary 3 suggests that a buyer tends to offer a higher price when observing a higher BIN price. Therefore we expect $\beta_1 > 0$. A buyer's offer price will also increase when the demand for the product is believed to be stronger. Corollary 1 shows that the inferred demand is stronger when more buyers have made an offer. We use $FIRST$ and $PRIOR$ to capture this effect and expect $\beta_2 < 0$ and $\beta_3 > 0$. By using these two variables as covariates, we allow the marginal effect of the first buyer in a listing to be different from that of the subsequent buyers. According to Corollary 2, a buyer will decrease the offer price toward the end of the listing period because the seller will have less chance of selling the product to other buyers. The variable $TIME$ captures this effect, and we expect $\beta_4 < 0$.

When a seller has a higher outside value of the listed car, he/she may spend less effort to describe the car on the eBay listing (such as providing fewer photos), resulting a lower value of ε. As a result, the posted BIN price could be correlated with the unobserved characteristics ε. The endogeneity of the BIN price may be a concern for establishing a causal relationship from its estimated coefficient. We overcome the endogeneity problem by using exclusive instruments to form moment conditions in the next subsection.

We estimate the regression equation (13) based on the GMM. Although the equation can be also estimated by performing the two-stage least squares (2SLS) method, the unobserved characteristics ε are assumed to be homoscedastic across listings in the 2SLS. Instead, in our GMM estimation, the standard errors are robust to the presence of arbitrary heteroskedasticity.[27]

[27] We use the user-written command in Stata 'ivreg2' to estimate the regression equation. We estimate the model under the option 'gmm' so that the parameters are estimated using the optimal weighting matrix in the GMM.

4.3 Exclusive Instruments

We propose two variables to control the endogeneity of the BIN price in the regression equation: $OTHER$ and $\ln(BIN/BLUE)_{other}$. The primary intuition for choosing these instruments is that these variables may correlate with a seller's outside option value, but they are probably not to affect the unobserved characteristics ε directly (after controlling for the seller's reputation and observed characteristics).

When a seller has a better outside choice for one car, he/she is likely to have a better outside choice for another one as well. For instance, if the storage cost is lower in a seller's location, the seller has a relatively higher outside choice value for any of the cars listed on eBay. Hence, we expect the BIN price of one car to be correlated with the BIN price of other cars listed by the same seller at the same time. As long as the unobserved characteristic ε of a particular car is uncorrelated with the BIN price of other cars, these two variables are reasonable choices for exclusive instruments.[28]

We assume that the unobserved characteristic ε is uncorrelated with all the explanatory variables in the regression equation (13) except for $\ln(BIN/BLUE)$. We estimate the coefficients using the GMM with the following orthogonality condition:

$$E[\varepsilon \mathbf{z}] = \mathbf{0} \tag{14}$$

where the vector $\mathbf{z}$ includes the two exclusive instruments, $OTHER$ and $\ln(BIN/BLUE)_{other}$, and all the explanatory variables in the regression equation except the endogenous variable, $\ln(BIN/BLUE)$.

Before moving on to discuss our estimation results, we show the validity of our exclusive instruments. Table 5 reports the first stage of the two stage least squares (2SLS) estimation. The variables in the upper panel are the exclusive instruments. They are jointly significant

[28] If we simply drop the observations without listing other vehicles on eBay concurrently, we would lose 44% of the observations in the estimation, causing much larger standard errors. Instead, by setting $\ln(BIN/BLUE)_{other} = 0$ for these observations and adding the dummy variable $OTHER$ to the regression equation, we can use all observations in the estimation and the dummy variable $OTHER$ will control for the selection bias resulting from missing values.

Table 5: First Stage of the 2SLS for the Instruments

	Dependent variable
	$\ln(BIN/BLUE)$
$\ln(BIN/BLUE)_{other}$	0.406***
	(0.090)
$OTHER$	-0.049
	(0.045)
Listing characteristics	
$CLEAR$	0.239***
	(0.069)
$WARRANTY$	-0.052
	(0.040)
$\ln SCORES$	-0.004
	(0.013)
$DEALER$	0.138***
	(0.044)
Offer characteristics	
$PRIOR$	-0.013**
	(0.006)
$FIRST$	0.009
	(0.016)
$TIME$	0.007**
	(0.004)
$\ln SCOREB$	0.003
	(0.005)
$WEEKEND$	0.001
	(0.022)
$MORNING$	0.010
	(0.020)
constant	-0.136*
	(0.081)
Number of observations	850
R-squared	0.347
F-statistic	8.10

Notes: Robust standard errors are given in parentheses. Superscripts ***, **, and *represent significance at 1%, 5%, and 10%, respectively.

with a p-value of 0.0001. The F statistic is over eight and the χ^2 statistic for the Anderson-Rubin test is 14.22, which has a p-value of 0.0008. These statistics indicate that these two instruments jointly are relevant to the endogenous variable, $\ln(BIN/BLUE)$.

4.4 Estimation Results

Table 6 compares our preferred specification in the last column with other choices of explanatory variables in other columns. After deleting incomplete samples, we are left with 880 observations.[29] The t-values in Table 6 are computed based on robust standard errors. As has been pointed out in Subsection 4.2, we allow for correlated unobserved characteristics ε for offers within the same listing.

All the estimated coefficients have the expected signs. The results are robust across most of the specifications we tried. Our empirical results are consistent with our theoretical predictions and suggest that buyers are rational in the sense of using the available information to determine the offer price.

Our theoretical model suggests that a higher BIN price means that the seller has a higher outside choice value and is less likely to accept an offer. As a result, we expect to see a positive relationship between the offer price and the BIN price. Under the preferred specification, our estimation indicate that a 1% increase in $\ln(BIN/BLUE)$ is associated with approximately 1.15% increase in the $\ln(OFFER/BLUE)$, which confirms our theoretical prediction.

On average, buyers begin to make offers roughly 6.2 days after a car is listed. The length of time since the start of the listing has a significantly negative effect on the offer price. Other things being equal, the price that a buyer is willing to offer is reduced by 1.5% with every passing day. Our model predicts that a buyer is likely to offer a lower price toward the end of a listing period because the seller is willing to accept a relatively lower offer to avoid no transaction.[30]

[29] We could not obtain a blue book price for some cars, mainly due to unavailability of the owner's ZIP code or vehicle's age.

[30] An alternative explanation for the negative sign is that an individual with a stronger desire to buy tends to make an offer earlier and offer a higher price.

Table 6: Estimated Coefficients with Different Explanatory Variables

	Dependent variable: $\ln(OFFER/BLUE)$			
	Model 1	Model 2	Model 3	Preferred Model
Constant	-0.842***	-0.628***	-0.817***	-0.842***
	(0.123)	(0.073)	(0.155)	(0.152)
Listing characteristics				
$\ln(BIN/BLUE)$	1.102***	1.130***	1.140***	1.147***
	(0.211)	(0.171)	(0.199)	(0.198)
$CLEAR$	0.091		0.043	0.041
	(0.102)		(0.104)	(0.104)
$WARRANTY$	0.135**		0.146***	0.142***
	(0.057)		(0.056)	(0.055)
$\ln SCORES$	0.038**		0.033**	0.034*
	(0.019)		(0.018)	(0.018)
$DEALER$	0.019		0.065	0.054
	(0.057)		(0.054)	(0.054)
Offer characteristics				
$PRIOR$		0.023**	0.022**	0.022**
		(0.011)	(0.011)	(0.011)
$FIRST$		-0.140**	-0.116*	-0.120*
		(0.072)	(0.069)	(0.069)
$TIME$		-0.010	-0.013	-0.015*
		(0.010)	(0.010)	(0.009)
$\ln SCOREB$		0.043***	0.041***	0.041***
		(0.013)	(0.013)	(0.013)
$WEEKEND$		-0.034	-0.031	-0.030
		(0.057)	(0.054)	(0.054)
$MORNING$		0.161***	0.133**	0.135**
		(0.059)	(0.057)	(0.058)
$DURATION$			-0.004	
			(0.005)	
Number of observations	862	880	850	850
R-squared	0.226	0.178	0.256	0.255
Hansen J-statistic	0.402	0.247	0.007	0.001
p-value	0.526	0.619	0.934	0.975

Notes: Robust standard errors are given in parentheses. Superscripts ***, **, and *represent significance at 1%, 5%, and 10%, respectively.

Although the eBay website does not disclose the offer price during the listing period, it reveals the buyer's username for each offer. Hence, a potential buyer can infer the demand for the product in a particular listing by observing the number of buyers who have already made an offer for it beforehand. Our estimation finds that the first buyer to make an offer tends to offer a significantly lower price. The first buyer's offer price is 13.3% ($\exp(-0.120 - 0.023) = 0.867$) lower than the second buyer. Moreover, when more buyers have made an offer, the offer price becomes significantly higher. Each additional buyer increases the offer price by 2.3%. Both indicate that the inferred demand positively affects a buyer's offer price.

In addition to comparing the estimated coefficients with our theoretical model, we can compare them with the literature on Internet transactions. A seller's reputation, as measured by the feedback score, is recognized as an important factor in determining a buyer's willingness to pay in Internet auctions (Melnik and Alm, 2002; Livingston, 2005; Houser and Wooders, 2006). Our analysis of the offer prices shows similar results. The seller's feedback score on eBay has a significantly positive impact on offer prices. Besides, a buyer's feedback score also has a significantly positive effect on the offer price. There are different explanations for the effect of a buyer's feedback score. On the one hand, the score is representative of the buyer's reputation. A buyer with a good reputation can expect the seller to be willing to accept a relatively lower price since he is more likely to honestly complete the transaction process. On the other hand, a buyer who is willing to pay more for a product is likely to have more successful transactions in the past and accumulate a higher score. Our regression suggests the latter explanation is more important than the former one. These findings are different from those for Internet auctions. For instance, Houser and Wooders (2006) show that a buyer's reputation has no effect on price.

Following the finding in Lucking-Reiley, Bryan, Prasad, and Reeves (2007), we also consider the timing effect. Offers made between 6 am to 10 am Pacific Time tend to be significantly higher than those made at other times. Offer prices are also higher on weekdays, although the difference is insignificant. The reason could be that buyers making an offer on weekday mornings have a stronger desire to buy a car.

The J-statistic of the Hansen overidentification test is 0.001 with a p-value of 0.975. Clearly, we cannot reject the hypothesis that the instruments and ε are jointly uncorrelated at any conventional significance level.

4.5 Robustness Checks

Finally, we consider several alternative estimation approaches to check the robustness of the GMM estimation. The first column in Table 7 is our preferred specification using the GMM. In the second column, we ignore the endogeneity problem and estimate the regression equation (13) by the Ordinary Least Squares (OLS) method. Although most estimated coefficients are very similar to our GMM estimation result, the coefficient of $\ln(BIN/BLUE)$ is 8% smaller than that in the GMM estimation. The last column consider the censoring problem in our data. Under the Best Offer mechanism, a buyer can always obtain the product by paying the BIN price. Therefore, a buyer's offer is bounded from above by the BIN price. Our GMM estimation ignores the censoring problem, but there are 7 BIN purchases in our sample. We use the standard Tobit model to account for censoring of the data but ignore the endogeneity of the BIN price. Since less than 1% of the observations are censored, it is unsurprising to find the estimated coefficients do not change much after accounting for censoring.

5 Conclusion

Our study contributes to the understanding of haggling over prices by investigating the Best Offer format on eBay. Different from most previous research, we explicitly consider the competition among potential buyers due to limited supply. Both the theoretical model and the empirical evidence show that a buyer's offer price crucially depends on the information available to them. The length of time when the offer is made after the start of a listing is negatively related to the offer price. Buyers are able to infer the seller's outside choice value from the BIN price, and hence make a higher offer when observing a higher BIN price. Although the values of other buyers' offer prices are unknown, the number of buyers who

Table 7: Robustness Checking with Different Estimation Methods

	Dependent variable: $\ln(OFFER/BLUE)$		
	GMM	OLS	Tobit
Constant	-0.842***	-0.861***	-0.856***
	(0.152)	(0.163)	(0.163)
Listing characteristics			
$\ln(BIN/BLUE)$	1.147***	1.051***	1.040***
	(0.198)	(0.099)	(0.100)
$CLEAR$	0.041	0.070	0.073
	(0.104)	(0.083)	(0.084)
$WARRANTY$	0.142***	0.135**	0.129**
	(0.055)	(0.054)	(0.055)
$\ln SCORES$	0.034*	0.033*	0.032*
	(0.018)	(0.018)	(0.018)
$DEALER$	0.054	0.070	0.068
	(0.054)	(0.052)	(0.052)
Offer characteristics			
$PRIOR$	0.022**	0.021**	0.021**
	(0.011)	(0.010)	(0.010)
$FIRST$	-0.120*	-0.118*	-0.115**
	(0.069)	(0.071)	(0.070)
$TIME$	-0.015*	-0.014	-0.014
	(0.009)	(0.009)	(0.009)
$\ln SCOREB$	0.041***	0.042***	0.042***
	(0.013)	(0.013)	(0.013)
$WEEKEND$	-0.030	-0.031	-0.034
	(0.054)	(0.054)	(0.054)
$MORNING$	0.135**	0.135**	0.137***
	(0.058)	(0.058)	(0.059)
Number of observations	850	850	850
R-squared	0.255	0.256	
Hansen J-statistic	0.001		
p-value	0.975		

Notes: Robust standard errors are given in parentheses. Superscripts ***, **, and *represent significance at 1%, 5%, and 10%, respectively.

have made offers beforehand is an indicator of the demand for the product and affects each potential buyer's offer price.

There are several interesting research questions for future work on related topics. Our data indicate that most buyers make only one offer in a listing. The extended model in Appendix B suggests that this could be caused by the submission costs. Future work can test this hypothesis against other potential explanations. In addition, our model allows a potential buyer to play in the game for only one period. An interesting extension is to allow buyers to play in the game for multiple periods and to consider whether a buyer would strategically wait for some periods before making an offer. Another line of research would be to compare the eBay Best Offer format with the Priceline-type NYOP mechanisms and the fixed-price take-it-or-leave-it mechanism.

A Proofs

This appendix contains our proofs for the propositions in the main text.

A.1 Proposition 1

Proof. The first order condition for the maximization problem in (1) is

$$f_\eta(x-\pi)(v-x) - F_\eta(x-\pi) = 0.$$

To show the existence and uniqueness of the maximum, let $z = x - \pi$. The first order condition can be rewritten as

$$v - \pi = z + \frac{F_\eta(z)}{f_\eta(z)}. \tag{15}$$

Because the distribution of η has the property that $F_\eta(z)/f_\eta(z)$ is an increasing function of z, the right hand side of equation (15) strictly increases in z. Therefore, there exists a unique z which satisfies the first order condition (15) for any given value of v and π. This implies that a unique solution x exists for the maximization problem (1).

Next, consider the partial derivative of $x(v, \pi)$ with respect to v. Note that when v increases by an amount δ while holding π fixed, the right hand side of Equation (15) must also increase by δ. Since the slope of the right hand size as a function of z is greater than one, z has to increase by an amount less than δ. This implies that x is an increasing function of v with a slope less than one.

Finally, consider an increase of π by an amount δ while holding v fixed. The right hand side of Equation (15) has to decrease by δ. Consequently, z must go down by an amount less than δ. Since $x = z + \pi$, x increase by an amount less than δ. $\square$

A.2 Proposition 2

Proof. We need to show that, at any history $\Omega_t \in \{0,1\}^t$ for $t = 0, 1, \ldots, T$, both $\pi_t(\Omega_t)$ and $\Pr(\boldsymbol{\lambda}|\Omega_t)$ can be expressed as functions of Ω_t, θ, $\hat{\theta}$, $\bar{p}$, and the initial belief of $\boldsymbol{\lambda}$.

Note that in the last period, $\pi_T(\Omega_T) = \theta$, $\forall \Omega_T \in \{0,1\}^T$. Besides, by definition $\Pr(\boldsymbol{\lambda} = \lambda_H|\emptyset) = \mu_H$ in period zero. Moreover, according to equation (6), in order to compute $\Pr(\boldsymbol{\lambda}|\Omega^+_{t-1})$, the posterior belief after observing a rejected offer in period t, we only need to know the belief in the previous period $\Pr(\boldsymbol{\lambda}|\Omega_{t-1})$ but not the seller's expected payoffs.

We prove the proposition by the induction method on the number of periods T. Suppose there is only one period $T = 1$. By the reasoning in the previous paragraph, we immediately know $\Pr(\boldsymbol{\lambda}|\emptyset)$, $\Pr(\boldsymbol{\lambda}|\{1\})$, $\pi_1(\{1\})$, and $\pi_1(\{0\})$. According to equation (7), the posterior belief at the history $\{0\}$, $\Pr(\boldsymbol{\lambda}|\{0\})$, can be computed from knowing both $\Pr(\boldsymbol{\lambda}|\emptyset)$ and $\pi_1(\{1\})$. (The latter term affects the cutoff point $N_1(\{1\})$ for the choice between no action and making an offer and enters the updating formula (7).) Finally, the initial expected payoff $\pi_0(\emptyset)$ is computed from $\Pr(\boldsymbol{\lambda}|\emptyset)$, $\pi_1(\{1\})$, and $\pi_1(\{0\})$ according to the recursive formula (8). So, we can compute both the seller's expected payoffs and the posterior beliefs on $\boldsymbol{\lambda}$ at all possible histories in a one-period game: $\emptyset, \{0\}, \{1\}$.

Now, suppose we can compute both the seller's expected payoffs and the posterior beliefs on $\boldsymbol{\lambda}$ at all possible histories when a game has $T-1$ periods. Consider a game with T periods. Given the initial belief on the arrival probability $\boldsymbol{\lambda}$, we can compute $\Pr(\boldsymbol{\lambda}|\{1\})$ according to the Bayesian updating rule (6). The subgame from period one to period T after observing a rejected offer in period one can be viewed as a $(T-1)$-period game with the initial belief $\Pr(\boldsymbol{\lambda}|\{1\})$. Therefore, by the induction assumption, we know the seller's expected surplus $\pi_t(\Omega_t)$ and posterior belief $\Pr(\boldsymbol{\lambda}|\Omega_t)$ for any Ω_t satisfying $\{1\} \subset \Omega_t$ for any $t = 1, 2, \ldots, T$. In particular, we know $\pi_1(\{1\})$. Together with the initial belief $\Pr(\boldsymbol{\lambda}|\emptyset)$, we can compute $\Pr(\boldsymbol{\lambda}|\{0\})$ by the Bayesian updating rule (7). Similarly, the subgame from period one to period T after observing no offer in period one can be viewed as a $(T-1)$-period game with the initial belief $\Pr(\boldsymbol{\lambda}|\{0\})$. Again, the induction assumption implies we know the seller's expected surplus $\pi_t(\Omega_t)$ and posterior belief $\Pr(\boldsymbol{\lambda}|\Omega_t)$ for any Ω_t satisfying $\{0\} \subset \Omega_t$ for any $t = 1, 2, \ldots, T$. Since the expected surplus at period zero $\pi_0(\emptyset)$ is derived from the initial belief $\Pr(\boldsymbol{\lambda}|\emptyset)$ and the two possible expected surpluses in period one, $\pi_1(\{1\})$ and $\pi_1(\{0\})$, we can obtain $\pi_0(\emptyset)$. Consequently, for a T-period game, we can obtain both the seller's expected payoffs and the posterior beliefs on $\boldsymbol{\lambda}$ at all possible histories. By induction, we can extend the result for any value of T. $\square$

A.3 Lemma 1

Proof. It suffices to show that the posterior belief of the high arrival probability λ_H becomes more likely after observing a rejected offer but it becomes less likely after observing no offer. By equation (6), $\lambda_H > \lambda_L$ implies

$$\begin{aligned}
\Pr(\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}^+) &= \frac{\Pr[\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}]\lambda_H}{\Pr[\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}]\lambda_H + \Pr[\boldsymbol{\lambda} = \lambda_L|\Omega_{t-1}]\lambda_L} \\
&> \frac{\Pr[\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}]\lambda_H}{\Pr[\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}]\lambda_H + \Pr[\boldsymbol{\lambda} = \lambda_L|\Omega_{t-1}]\lambda_H} \\
&= \Pr[\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}].
\end{aligned}$$

By equation (7), $\lambda_H > \lambda_L$ implies

$$\begin{aligned}\Pr[\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}^-] &= \frac{\Pr\left[\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}\right]\left\{1 - \lambda_H \Pr\left[v > N_t(\Omega_{t-1}^+)\right]\right\}}{\sum_{\lambda=\lambda_H,\lambda_L} \Pr\left[\boldsymbol{\lambda} = \lambda|\Omega_{t-1}\right]\left\{1 - \lambda \Pr\left[v > N_t(\Omega_{t-1}^+)\right]\right\}} \\ &< \frac{\Pr\left[\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}\right]\left\{1 - \lambda_H \Pr\left[v > N_t(\Omega_{t-1}^+)\right]\right\}}{\sum_{\lambda=\lambda_H,\lambda_L} \Pr\left[\boldsymbol{\lambda} = \lambda|\Omega_{t-1}\right]\left\{1 - \lambda_H \Pr\left[v > N_t(\Omega_{t-1}^+)\right]\right\}} \\ &= \Pr\left[\boldsymbol{\lambda} = \lambda_H|\Omega_{t-1}\right].\end{aligned}$$

□

A.4 Proposition 3

Proof. We prove that the statement holds at $c = 0$ by induction on the period number t. In the final period $\pi_T(\Omega_T) = \theta$ for any $\Omega_T \in \{0,1\}^T$. The claim holds trivially.

Now suppose the claim hold at a given period $t+1$ when $c = 0$. Consider $\Omega_t, \Omega'_t \in \{0,1\}^t$ with $\Omega_t \geq \Omega'_t$. Lemma 1 shows that $\Pr(\lambda_H|\Omega_t) \geq \Pr(\lambda_H|\Omega'_t)$. When $c = 0$, making an offer is always better than doing nothing. Hence, $N_{t+1}(\Omega_t^+) = N_{t+1}(\Omega_t'^+) = -\infty$. Because $\Omega_t \geq \Omega'_t$ implies $\Omega_t^+ \geq \Omega_t'^+$ and $\Omega_t^- \geq \Omega_t'^-$, the induction assumption says $\pi_{t+1}(\Omega_t^+) \geq \pi_{t+1}(\Omega_t'^+)$ and $\pi_{t+1}(\Omega_t^-) \geq \pi_{t+1}(\Omega_t'^-)$, which in turn imply $B_{t+1}(\Omega_t^+) \leq B_{t+1}(\Omega_t'^+)$ and $x(v, \pi(\Omega_t^+)) \geq x(v, \pi(\Omega_t'^+))$. Therefore, by equation (8), we know $\pi_t(\Omega_t) \geq \pi_t(\Omega'_t)$. By using induction on t, the statement holds for any period $t = 1, 2, \ldots, T$ when $c = 0$. By continuity, the statement holds for any c close enough to zero. □

A.5 Proposition 4

Proof. Since a buyer never submits an offer higher than the BIN price, the seller's expected payoff $\pi_t(\Omega_t) \leq \bar{p}$ for any history Ω_t for any period t. By equation (8), the seller's expected payoff at the history Ω_t is

$$
\begin{aligned}
&\pi_t(\Omega_t)\\
\geq &E[\lambda|\Omega_t]\Pr\left[v > N_{t+1}(\Omega_t^+)\right]\pi_{t+1}(\Omega_t^+) + \left\{(1-E[\lambda|\Omega_t]) + E[\lambda|\Omega_t]\Pr\left[v \leq N_{t+1}(\Omega_t^+)\right]\right\}\pi_{t+1}(\Omega_t^-)\\
= &E[\pi_{t+1}(\Omega_{t+1})|\Omega_t].
\end{aligned}
$$

Then, the inequality (9) holds by applying induction and the law of iterated expectations to the above inequality. □

A.6 Proposition 5

Proof. We prove the proposition by induction on the period number t for the case $c = 0$. The result can be generalized to small positive value of c by continuity. In the last period, it is obvious that $\pi_T(\theta_1, \theta_1, \bar{p}(\theta_1), \Omega_T) = \theta_1 > \theta_2 = \pi_T(\theta_2, \theta_2, \bar{p}(\theta_2), \Omega_T)$ for any $\Omega_T \in \{0,1\}^T$. Now, suppose the inequality (12) holds for all histories in period $t+1$. In particular, for any history in period t, $\Omega_t \in \{0,1\}^t$, the induction assumption implies $\pi_{t+1}(\theta_1, \theta_1, \bar{p}(\theta_1), \Omega_t^+) > \pi_{t+1}(\theta_2, \theta_2, \bar{p}(\theta_2), \Omega_t^+)$ and $\pi_{t+1}(\theta_1, \theta_1, \bar{p}(\theta_1), \Omega_t^-) > \pi_{t+1}(\theta_2, \theta_2, \bar{p}(\theta_2), \Omega_t^-)$. These inequalities imply $B_{t+1}(\theta_1, \bar{p}(\theta_1), \Omega_t^+) < B_{t+1}(\theta_2, \bar{p}(\theta_2), \Omega_t^+)$. According to equations (6) and (7), when $c = 0$, posterior beliefs $\Pr(\boldsymbol{\lambda}|\hat{\theta}, \bar{p}, \Omega_t)$ are independent of θ and $\bar{p}$. Besides, when $c = 0$, $N_{t+1}(\theta_1, \bar{p}(\theta_1), \Omega_t^+) = N_{t+1}(\theta_2, \bar{p}(\theta_2), \Omega_t^+) = -\infty$. Therefore, equation (8) implies $\pi_t(\theta_1, \theta_1, \bar{p}(\theta_1), \Omega_t) > \pi_t(\theta_2, \theta_2, \bar{p}(\theta_2), \Omega_t)$. By induction, the proposition holds for any $t = 0, 1, 2, \ldots, T$. □

B An Extended Model

In this appendix, we extend the original model to allow a buyer to have two rounds of opportunities to make an offer or make a BIN purchase. We show that the buyer's offer price in each round would still increase in the seller's expected surplus of rejecting this buyer's offer(s). As a result, our predictions for the empirical tests remain true in the extended model.

B.1 Two Rounds of Making an Offer

In the original model, a buyer has only one opportunity to make an offer. If the offer is rejected, the buyer receives zero surplus and leaves the game. Now, we allow the buyer a second chance to make an offer.

Specifically, each of the periods $t = 1, 2, \ldots, T$ consists of two rounds. The first round is identical to the original model. A buyer may arrive. If a buyer arrives, he can either choose the buy-it-now option, make an offer, or do nothing. When the buyer makes an offer and the offer is rejected by the seller, they enter the second round. In the second round, the buyer can choose again between purchasing with the buy-it-now option, making an offer, and doing nothing. If the second offer is rejected, the buyer leaves the game without a transaction, and the game goes to the next period.

To simplify the notation, we will suppress the subscript for the period, t. Suppose that the seller receives independent cost shocks in each of the two rounds, denoted as $\eta^{(1)}$ and $\eta^{(2)}$, respectively. Denote their distribution functions as $F_\eta^{(1)}$ and $F_\eta^{(2)}$ and their density functions as $f_\eta^{(1)}$ and $f_\eta^{(2)}$. We also assume that both $F_\eta^{(1)}(\eta)/f_\eta^{(1)}(\eta)$ and $F_\eta^{(2)}(\eta)/f_\eta^{(2)}(\eta)$ are increasing functions of η. Denote the cost of submitting an offer in each round as $c^{(1)}$ and $c^{(2)}$. Recall that the seller's expected surplus of not selling the product at the end of the period is $\pi = \pi_t(\Omega_t)$, the buy-it-now price is $\bar{p}$, and the buyer's private valuation on the product is v.

B.2 Decisions in the Second Round

The analysis of the second round is identical to that of the original model with a single round. The buyer's optimal offer price y in the second round is determined by maximizing the expected surplus,

$$\max_y F_\eta^{(2)}(y - \pi)(v - y) - c^{(2)}. \tag{16}$$

Denote the optimal offer price as $y^*(v,\pi)$. Proposition 1 in the main text implies that y^* increases in π.

Similar to the original model, the choice between BIN, an offer, and no action follows a cutoff rule. When $v \geq B^{(2)}(\pi)$, the buyer chooses the buy-it-now option. When $N^{(2)}(\pi) \leq v \leq B^{(2)}(\pi)$, the buyer makes an offer at the price $y^*(v,\pi)$. When $v \leq N^{(2)}(\pi)$, the buyer does nothing. The buyer's expected surplus of entering the second round is

$$V^{(2)}(v,\pi) = \begin{cases} 0, & \text{if } v \leq N^{(2)}(\pi); \\ F_\eta^{(2)}(y^* - \pi)(v - y^*) - c^{(2)}, & \text{if } N^{(2)}(\pi) \leq v \leq B^{(2)}(\pi); \\ v - \bar{p}, & \text{if } v \geq B^{(2)}(\pi). \end{cases} \tag{17}$$

The seller's expected surplus of entering the second round is

$$\Pi^{(2)}(v,\pi) = \begin{cases} \pi, & \text{if } v \leq N^{(2)}(\pi); \\ \mathbb{E}[\max\{\pi, y^*(v,\pi) - \eta^{(2)}\}], & \text{if } N^{(2)}(\pi) \leq v \leq B^{(2)}(\pi); \\ \bar{p}, & \text{if } v \geq B^{(2)}(\pi). \end{cases} \tag{18}$$

B.3 Decisions in the First Round

The buyer's first-round offer price x is determined by maximizing the expected surplus,

$$\max_x F_\eta^{(1)}(x - \Pi^{(2)}(v,\pi))[v - x - V^{(2)}(v,\pi)] + V^{(2)}(v,\pi) - c^{(1)}. \tag{19}$$

Let $x^*(v, V^{(2)}, \Pi^{(2)})$ denote the optimal offer price in the first round. Figure 3 illustrates an example of a buyer's expected surplus in the two rounds under optimal offers when the submission cost is zero in both rounds.[31] Note that the second-round expected surplus is identical to the buyer's expected surplus of making an optimal offer in the single-round model. As the example shows, the additional gain from making two offers is very small relative to the expected surplus of making only one offer. As a result, when the buyer incurs

[31] We choose $\pi = 10$ and assume that $\eta^{(1)}$ and $\eta^{(2)}$ are both distributed as the type-I extreme value distribution in this example.

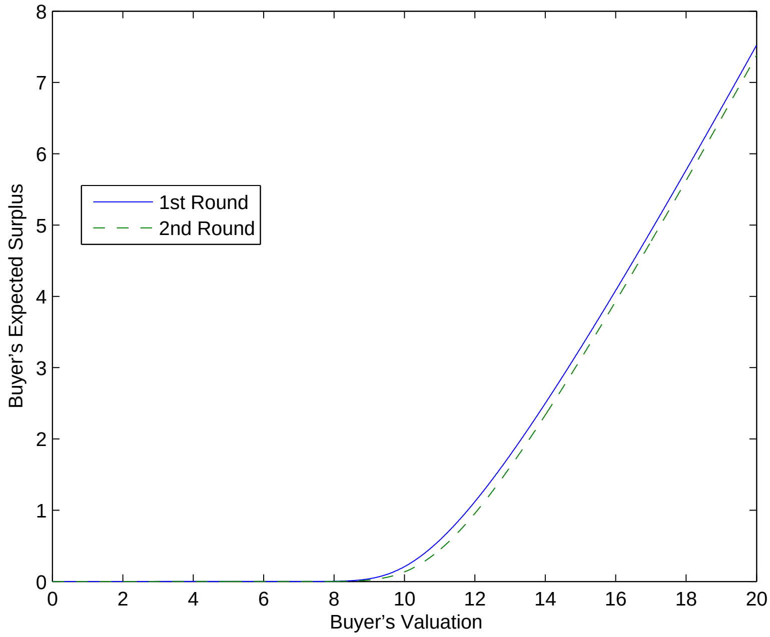

Figure 3: Buyer's Expected Surplus in the Two-Round Model

a positive submission cost to make an offer, the cost might outweigh the additional gain from the second offer. The can explain the fact we found in Table 3 that most buyers make very few offers.

Because the first term in (19) must be positive when the buyer chooses the optimal offer price x^*, it is obvious that the buyer's expected surplus of making an offer in the first round is higher than the expected surplus of entering the second round, $V^{(2)}$, as long as the submitting cost $c^{(1)}$ is small enough (i.e. $c^{(1)} < F_\eta^{(1)}(x^* - \Pi^{(2)})[v - x^* - V^{(2)}]$). Similarly, since making an offer in the first round gives a buyer an additional opportunity to buy the item at a price lower than the BIN price $\bar{p}$, the buyer never use the BIN option in the first round unless the submission cost $c^{(1)}$ is too high.

Lemma 2. *If the submission cost $c^{(1)}$ is small enough, a buyer would never use the BIN option in the first round.*

Proof. It suffices to show that the expected surplus with offering the optimal price x^* in the first round is higher than the surplus of using the BIN option, $v - \bar{p}$. The expected surplus of offering the optimal price x^* in the first round is

$$F_\eta^{(1)}(x^* - \Pi^{(2)})[v - x^* - V^{(2)}] + V^{(2)} - c^{(1)},$$

which is greater than the expected surplus of entering the second round, $V^{(2)}$, when $c^{(1)}$ is small enough. Now, consider the two possible cases. First, if $v \geq B^{(2)}$, then $V^{(2)} = v - \bar{p}$. Second, if $v < B^{(2)}$, then $V^{(2)} > v - \bar{p}$. Therefore, the expected surplus from the optimal first-round offer is higher than using the BIN option in either case as long as $c^{(1)}$ is close to zero. $\square$

Proposition 6. *The optimal offer price in the first round increases in the seller's expected surplus of not selling the item in the current period, π, in the equilibrium path.*

Proof. The first order condition for the maximization problem (19) is

$$f_\eta^{(1)}(x^* - \Pi^{(2)})[v - x^* - V^{(2)}] - F_\eta^{(1)}(x^* - \Pi^{(2)}) = 0.$$

The optimal offer price depends on v, $V^{(2)}$, and $\Pi^{(2)}$. Since $V^{(2)}$ and $\Pi^{(2)}$ are functions of π, the total effect of π on a buyer's optimal first-round offer is

$$\frac{dx^*}{d\pi} = \frac{\partial x^*}{\partial V^{(2)}} \frac{\partial V^{(2)}}{\partial \pi} + \frac{\partial x*}{\partial \Pi^{(2)}} \frac{\partial \Pi^{(2)}}{\partial \pi}.$$

The first order condition can be expressed as

$$v - x^* - V^{(2)} = \frac{F_\eta^{(1)}(x^* - \Pi^{(2)})}{f_\eta^{(1)}(x^* - \Pi^{(2)})} \equiv H(x^* - \Pi^{(2)}),$$

where we define $H \equiv F_\eta^{(1)}/f_\eta^{(1)}$ to simplify the notation. By the implicit function theorem, we have

$$\frac{\partial x^*}{\partial V^{(2)}} = -\frac{1}{1 + H'(x^* - \Pi^{(2)})} \qquad \text{and} \qquad \frac{\partial x^*}{\partial \Pi^{(2)}} = \frac{H'(x^* - \Pi^{(2)})}{1 + H'(x^* - \Pi^{(2)})}.$$

Therefore,

$$\frac{dx^*}{d\pi} = \frac{H'(x^* - \Pi^{(2)})\frac{\partial \Pi^{(2)}}{\partial \pi} - \frac{\partial V^{(2)}}{\partial \pi}}{1 + H'(x^* - \Pi^{(2)})}.$$

In the above equation, $H' > 0$ because H is an increasing function by assumption. By applying the envelope theorem to (17), we know $\partial V^{(2)}(v, \pi)/\partial \pi \leq 0$. From (18), we know $\Pi^{(2)}(v, \pi)$ increases in π for $v < B^{(2)}(\pi)$ and is independent of π for $v > B^{(2)}(\pi)$. Besides, the seller must choose a BIN price $\bar{p}$ high enough so that $\Pi^{(2)}(v, \pi)$ jumps upwards at the discontinuous point $v = B^{(2)}(\pi)$ in the equilibrium path. (Otherwise, the seller can increases his/her expected surplus by setting a higher BIN price in period zero.) Consequently, in the equilibrium path, we must have $\partial \Pi^{(2)}(v, \pi)/\partial \pi \geq 0$ for any given v. Therefore, the buyer's offer price in the first round is an increasing function of π. $\square$

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