Bargaining vs. Fixed Prices: Sellers' use of eBay Best Offer

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Abstract

eBay Best Offer listings differ from both standard auction listings and fixed price listings, allowing for back-and-forth negotiation between sellers and their potential buyers. Using data collected in 2013 and 2016, I study a seller's choice Best Offer listings vs. fixed price listings. Results indicate that sellers with weaker bargaining power (i.e. lower patience, fewer outside options, and/or higher seller competition) are more likely to bargain. This corroborates the findings of Chen et al. (2016), that sellers with lower bargaining power are more likely to use Best Offer, consistent with a theoretical prediction in Bester (1993). I also find that seller patience, a form of higher bargaining power, is weakened by higher seller competition (more outside options for buyers), causing even the more patient sellers to choose bargaining over fixed prices when competition is high.

I then examine the impact of a seller's choice of markup, choice of Best Offer, and the interaction of these two choices on the seller's profitability (measured by a car's likelihood of selling, wait time until a car sells, and the transaction price). I find that using Best Offer increases the selling likelihood and the transaction price for cars with sufficiently high markups, but decreases the selling likelihood and the transaction price for cars with lower markups. In addition, I find that while a higher markup reduces the likelihood of selling, it also yields a higher transaction price by 40.3%. This highlights an important indirect impact of using best offer (not evident in the approach used in Chen et al. (2016)): using best offer reduces the negative impact of a high markup on sales. That is, combining a high markup with the use of best offer allows sellers to reap the benefits of a high markup on transaction price, while mitigating its harmful impact on sales.

Keywords: bargaining, posted price, eBay, best offer, eBay Motors, seller patience, time cost

1 Introduction

Bargaining has been previously associated with high transaction costs, leading to predictions that its use would decline (Terwiesch et al., 2005). However, e-commerce has reduced transaction costs, allowing the re-emergence of platforms for negotiating prices. For instance, Priceline.com started the Name-Your-Own-Price (NYOP) system for selling travel tickets and hotel rooms in 1998 (Huang et al., 2013), and eBay introduced the "Best Offer (BO)" feature in 2005 (Toklu, 2014). As online retail sales grow rapidly (Anderson et al., 2004), such platforms may initiate a structural shift in retail markets. The re-emergence of bargaining mechanisms, in the context of e-commerce, is important to study.

There have been few empirical tests of how bargaining is carried out. That is not because of a lack of theoretical models to test. Such models have been around for years and yield insights, but remain unconfirmed empirically. Empirical analyses could highlight which theories are more relevant in a given context.

However, studying bargaining empirically is not so straightforward. Bargaining has typically been popular in informal markets, such as in bazaars or stores in developing countries (Bing, 2009), complicating data collection. Written records or available data of transactions, prices, and agents' behavior is seldom available. Surveys are also infrequent, perhaps because a bargaining scenario is complex (with many variables as theoretical candidates for impacting the bargaining outcome). What are the key variables? Surveys are even harder to design for cases in which agents have incentives to hide information, such as their reservation values.

The advent of bargaining platforms emerging on the internet offers some relief for these concerns. The data collection problem has become simple, just as questions regarding bargaining markets have also become more pressing. At the same time, eBay's introduction of the "Best Offer" feature inspires the question of why bargaining is re-emerging on the e-commerce platform, it also provides data. eBay offers an option in which sellers can list items with posted prices but allow potential buyers to make their best offers. The "Best Offer" listing format on eBay mimics a sequential-move alternating offers bargaining game. These Best Offer listings differ from standard auction listings, allowing for back-and-forth negotiation between a seller and his potential buyers (similar to an in-person negotiation) by entering offer amounts online. Only a handful of studies to date have exploited the opportunity for studying bargaining using eBay Best Offer. Therefore, this paper examines the determinants and the outcomes of bargaining (the Best Offer feature) on eBay, by studying sellers' choices between using Best Offer listings vs. fixed price listings. Although the eBay market structure differs from the relevant theoretical models (to be discussed later), this paper is able to test insights of the theoretical literature.

The paper divides the question of why sellers choose bargaining vs. posted prices into two parts: 1) What exogenous factors (including car, seller, and market characteristics) incline a seller to prefer bargaining? and 2) What is the mechanism through which bargaining affects profits?

For the first question, I study the impact of seller patience and market competition using a reduced-form approach and a fractional logit model. According to theoretical models, patience increases a seller's bargaining power, while competition reduces it. However, the net effect of seller patience interacted with high market competition on a seller's choice to bargain is unknown. Hence, I study the interaction of individual-level patience and external competitive pressures. I study this question using data I have collected from 2013 and from 2016. This helps identify which determinants of seller choice are robust over time, and sheds light on the intermediate-term evolution of bargaining on eBay. Previous literature seems to lack strong empirical evidence about individual-level patience (in general, and in the context of bargaining) about bargaining in competitive environments, and about the long-term dynamics of bargaining.

For the first question of this paper, I find in 2013 that at high levels of competition (whether by car make or by city), higher patience inclines a seller to choose bargaining, whereas at lower levels of competition higher patience deters a seller from choosing bargaining. Therefore, seller patience, known to confer bargaining power, is offset by seller competition (because there are more outside options for buyers), leading even the more patient sellers to choose bargaining over fixed prices.Thus, using different variables than Chen et al. (2016), I confirm that it is sellers with lower bargaining power that adopt Best Offer (consistent with the insights of Bester (1993)). This result has strong implications for several other cases in economics where individual-level patience is dominated by external competitive pressures, and therefore deserves further attention. For 2016, I find that seller patience deters a seller from using Best Offer. However, the competition variables are not statistically significant in the 2016 data, and I discuss some reasons why this might hold. Furthermore, across both years, I find that as a seller's experience increases, he is less likely to bargain.

For the second question, I study the impact of using BO on the profit outcomes for a seller.

According to Chen et al. (2016), using BO increases the probability of selling, but does not increase the transaction price of a car. This indicates that although there are some benefits to using BO, there is not sufficient evidence (nor sufficient studies) regarding other expected channels through which BO impacts seller profitability. Furthermore, given that sellers revise their listings away from using BO as they learn more, using BO might also have some negative aspects, but there is no evidence yet of the negative effects of BO for sellers. The absence of such findings point to the need to explore more channels through which BO might benefit sellers. I study three direct channels through which BO could benefit sellers: by increasing sales, by leading to quicker sales, or by raising the transaction price. Finally, I also explore a fourth,less direct channel: I take into account the interaction of a seller's choice of markup and his choice of BO when studying seller's profit outcomes because the pricing and selling decisions can be linked.

The results of this analysis show the importance of this indirect fourth channel, that is, of incorporating the interaction of a seller's choice of markup and choice of using BO. Contrary to Chen et al. (2016), I do not find that BO always increases the likelihood of sale. Instead, I find that BO increases the likelihood of sale only for cars with sufficiently high markups, and that BO *decreases* the likelihood of sale for cars with lower markups. This result provides a more complete picture of both the pros *and cons* of using BO. Results also show that a high markup can be beneficial for sellers because it increases the final transaction price by 40% for cars that do sell. However, a higher markup also reduces the likelihood of a car selling. Here, using BO can provide an advantage for the seller. That is, while a higher markup on a fixed price listing reduces the selling likelihood by 62.7%, a higher markup on a BO listing reduces selling likelihood by only 33.7%. Hence, using BO can recover 29% of the sales that sellers lose if they were to charge a higher markup. This is an indirect benefit of using BO; allowing sellers to reap the benefits of a positive impact of a higher markup on transaction price, while mitigating the negative impact of using a higher markup on the likelihood of selling. This result might have been overlooked by Chen et al. (2016) because they do not include the interaction term of BO choice and markup choice. Finally, I find that BO increases the wait time until a car sells for almost all reasonable levels of markup. This result, combined with the few other negative effects of using BO (mentioned above regarding cars with lower markups), helps explain why seller learning through item-specific revisions disinclines sellers from using BO.

2 eBay Motors and eBay Best Offer

eBay Motors deals exclusively with automobiles, and has been named one of the "most successful companies of the internet era (Adams et al., 2006)." As is typical with other categories on eBay, eBay motors consists of four types of sale formats: 1) fixed price listings called Buy-It-Now (BIN) listings, 2) (since 2005 onwards) fixed price listings[1] with "Best Offer (BO)" features on the listings [2], auctions without BIN prices [3], and auctions with BIN prices. More than 50% of eBay Motors listings under the category of "Cars and Trucks" are auctions, about 20% are BO listings, and less than 10% are (non-BO) fixed price listings (Huang et al., 2013). In terms of selling success of

[1]Sellers can list their item for 3, 5, 7, 10 or 21 days under the fixed price format (this includes BO listings)Toklu (2014).

[2]"Classified Ads" also allow for the BO option, and under "Classified Ads", buyers and sellers communicate privately, and the transaction takes place off eBay Toklu (2014).

[3]Auction listings are not included in this study. Auctions are also subject to different rules and listing fees on eBay than fixed price listings (including both BO and non-BO listings), making the comparison between auctions and fixed price listings more complicated. I assume the independence of irrelevant alternatives applies (IIA) here, and that that the availability of auctions does not affect sellers' choice between posted prices and BO.

Toyota Camry cars, Huang et al. (2013) find that auction listings have a success rate of 33% and BO listings, 18%, coming second to auction listings. Non-BO fixed price listings have the lowest success rate, 5% (Toklu, 2014). Apart from the automobiles category, there is evidence that fixed price listings (BO listings and non-BO listings combined) have surpassed auction listings on eBay, in general (Einav et al., 2013). Furthermore, the BO feature "has been growing in popularity and bargained transactions currently account for nearly 10 percent of total transaction value in the marketplace (Backus et al., 2015)." However, despite the growing importance of the Best Offer feature on eBay, there have been very few studies on eBay Best Offer, and not much is known about this feature.

eBay's introduction of the Best Offer may "mimic" the non-internet bargaining process (Chen et al., 2016). It operates in the following manner: if a seller chooses to bargain using the Best Offer feature, he enables the Best Offer feature on the fixed price listing (BIN listing) by checking a box. [4] BIN listings cost the same with or without the BO feature enabled. This checking of the box by a seller changes the format of a listing from being a BIN listing (posted price mechanism) to a BO listing (bargaining mechanism). However, even for a BO listing, a seller must list an initial asking price. That is, he must post a BIN price, and the buyer can opt to purchase at the BIN price. Buyers can click the "Make Offer" button on a listing page, which allows the buyer to enter a numerical value of his offer amount. This sends an email to the seller who then has 48 hours to respond. Once the seller receives an offer, he can either accept it, reject it and counteroffer if he wants to, or let the offer expire after 48 hours. Sellers can automate the process to some extent by entering private reservation prices in the system so that a certain range of offers is accepted and a certain range of offers is automatically rejected (Toklu, 2014). The buyer is also notified of the seller's response, giving the buyer the option to accept and checkout, or to make a counter-offer (Backus et al., 2015). Under the BO listing format, one seller can receive offers from several buyers, and there can be many negotiation threads running simultaneously for one seller for one given item. Buyers can also opt to make the purchase at the BIN price for a BO listing, in order to circumvent any bargaining (Toklu, 2014). A transaction occurs when the buyer and the seller mutually agree on the offer price or if the buyer opts to purchase at the BIN price (similar to the case of non-BO BIN listing). Sellers and buyers can go on back and forth (as they would generally do in an in-person negotiation) for a maximum number of stages set by eBay. eBay Motors allows the buyer and the seller to make ten offers each and ten counteroffers each.

Buyers have access to some additional information during the transaction, while sellers have a lot more information during the active listing period. By clicking a link to access the offers page, buyers can see the offer history of a given variable, although buyer IDs are not fully displayed on this offer page. That is, all characters of the buyer ID, except the first and the last, are masked with asterisks. Buyers' feedback scores are also displayed alongside the partial IDs. Using this information, buyers can know the number of other buyers competing with them for the same item. Buyers can also see the status of all offers (whether pending, expired or declined) on a given listing, including the date and time of the offers. Offer amounts are displayed on eBay only when the listing ends (regardless of whether the item sold or did not sell). In contrast, each seller has all of

[4] I do not find that the deferred decision principle from Tversky and Shafir (1992) applies here directly, but perhaps indirectly. That is, I do not find evidence that since non-BO is the default option for sellers when listing an item that sellers use non-BO (posted prices) more often. Instead, I find that BO is used more often than non-BO (posted prices). However, perhaps an extension of the insights from Tversky and Shafir (1992), where the "default" option is based on the social norm is indeed applicable. With this respect, the "default" option on eBay Motors seems to be BO, and not posted prices, since most eBay Motors sellers tend to use BO (vs posted prices) for the fixed-price listing format. Hence, it is possible that sellers' use of BO is aligned with using the social default or the social norm. Regardless, this paper offers additional reasons that impact a seller's choice to use BO.

this information throughout the active listing period Toklu (2014) for all his listings.

It can be helpful to compare BO listings to the more commonly known auction listings on eBay. While sellers are committed to selling/accepting the highest bid under the auction mechanism, under the BO mechanism, they can reject any offer. Nevertheless, a BO listing requires that sellers respond to offers within a 48 hour time period; otherwise the offer expires, whereas they do not need to respond to bids on an auction listing. Furthermore, for an auction listing, buyers can observe the bid prices, but they cannot observe the offer amounts for BO listings. Therefore, the BO mechanism gives less information to buyers about other buyers' offer amounts compared to the information given to a buyer regarding other buyers under an auction listing.

Finally, it might help to consider similarities between the BO mechanism and the first price sealed bid auction. In both mechanisms, sellers can observe the offers buyers submit, and buyers cannot observe each others' offers. However, the duration for the submission differs. In the BO mechanism, the period for submission is different for each potential buyer, and is chosen by that buyer; the negotiation period begins from the time of the buyer's first offer. In a first price sealed bid auction format, all buyers are subject to the same time period, *and* buyers are also committed to their offers till the end of the period (vs. only 48 hours in a BO listing). Therefore, first price sealed bid auction formats can be seen as a special case of the BO format: if in the BO listing, all buyers come in at the last 48 hours of the listing period, then the BO mechanism works exactly like the first price sealed bid auction with a BIN price (Toklu, 2014).

3 Literature Review

3.1 Theoretical Literature on Bargaining vs. Posted Prices

In this section, I review theoretical studies that offer insights into sellers' choices between bargaining vs. posted prices. Model assumptions are discussed and are later compared with the market structure of eBay. Although these theoretical models do not match the eBay environment perfectly, they are the sources of insights regarding eBay Best Offer. The predictions of these models provide my primary hypotheses and inform my variable construction.

While Riley and Zeckhauser (1983), Perry (1986), Wang (1995) and Bing (2009) model the interaction between one seller and one buyer, Bester (1993) models the interaction between many sellers and one buyer. This distinguishes the Bester (1993) model as being more applicable to the context of eBay, as Chen et al. (2016) have also pointed out, because typically, there are many sellers in the eBay context. However, the other models also allow for more buyers, unlike Bester (1993), and eBay also typically has many buyers. Therefore, there is not one model that fits eBay perfectly in terms of the market structure, and insights from all models offer valuable insight. In the spirit of Chen et al. (2016), this paper helps distinguish between these theoretical insights, and emphasizes which models are more relevant for the context of eBay Best Offer.

Note that perhaps because most theoretical economic models studying bargaining vs. posted prices assume that the seller is a monopolist (that is, the models only consist of one seller)(Bing, 2009; Perry, 1986; Wang, 1995), their predictions differ from that of Bester (1993), which allows for seller competition. That is, most models suggest that sellers with high bargaining power are more likely to use bargaining, whereas, (Bester, 1993) suggests that bargaining is more likely when sellers have *low* bargaining power. The reversal of prediction, perhaps due to this modeling difference, motivates this paper's focus on studying the effects of seller competition on the seller's choice to bargain.

As Chen et al. (2016) points out, Wang (1995) and Bester (1993) both use Nash bargaining to arrive at the bargaining solution, but there is no reserve price set by the seller in Bester (1993), and there are many sellers in this model compared to the one-seller model in Wang (1995). If a buyer has an outside option, but has low bargaining power, then he would opt for the outside option instead of bargaining. This leads to sellers choosing bargaining only when sellers have relatively weaker bargaining power, allowing buyers to have sufficient bargaining power to want to engage with a bargaining seller at all. Therefore, according to both Bester (1993) and Wang (1995), the seller *wants* to adopt bargaining when he has higher bargaining power, but the modeling differences lead to differing *conclusions* about when bargaining actually occurs. In Wang (1995), a seller having high bargaining power adopts bargaining, while in Bester (1993), a seller having *low* bargaining power chooses bargaining. Bester (1993) emphasizes quality uncertainty as key for this result. He posits that if the quality of a product is determined after observing the item, then there are some moral hazard concerns regarding the quality of the product that play a role in buyers decision-making. Bargaining is preferred by buyers in some cases because under bargaining, the price is determined *ex-post*, so sellers have an incentive to control the quality of the product, which reduces concerns of moral hazard behavior by sellers. Whereas, under posted prices, prices are set ex-ante, and therefore sellers do not have a similar incentive to control the quality of the product (Bester, 1993). Nevertheless, while bargaining may resolve some moral hazard concerns for the buyer, if the seller has *too much* bargaining power, and buyers face switching costs in going from one seller to another, they would prefer not to get locked-in with a seller with high bargaining power. Therefore, if buyers have an outside option, they would only choose to go to a bargaining seller if their relative power is sufficiently high. That is, if the seller has too much bargaining power, buyers would choose not to approach a bargaining seller and would opt instead for their outside option. In such a case, sellers would be better off choosing a posted price method instead of bargaining in the interest of attracting more buyers. This leads to the seemingly counter-intuitive conclusion (one that seems at odds with all of the other literature mentioned) that sellers adopt bargaining when they have *lower* bargaining power. It seems thus that quality uncertainty might be a concern for buyers transacting on eBay Motors, and I discuss this quality uncertainty, or the "lemons problem" that might be present in the automobile market (Akerlof, 1995). Because I am not able to assess the quality of cars directly, I discuss the outcomes that could occur when there is quality uncertainty specific to the use of Best Offer by sellers. I infer some equilibria for sellers' behavior based on the four primary signals that the seller can send to buyers using a combination of markup and BO. These equilibria are explained in Table 2 and Table 3. These tables indicate the likely combinations of seller's optimal strategies for choosing markup and BO depending on whether a seller is patient (or impatient enough to choose bargaining or "very impatient" such that he is willing to accept a price lower than his true valuation), whether he is informed regarding the value and quality of his product, and whether the product itself is of higher quality. While Table 2 indicates some possible strategies for the seller when the buyers are well-informed, Table 3 indicates possible strategies for the seller when buyers are not well informed, and sellers might therefore benefit from engaging in cheap talk [5]. Italicized text in the tables show cases in which sellers charge a higher markup either as a means of misleading buyers regarding the quality of the product due to buyers' lack of information or cases in which the seller does not know the quality of his product but attempts to charge a higher price for it nonetheless. These cases are the cases where the seller may try to con consumers and lower their consumer surplus due to lack of information and to quality uncertainty in the market. The empirical results of this paper then help rule out some of these theoretically plausible cases, allowing for comments on the quality uncertainty in the eBay Motors market.

Furthermore, while Bester (1993) does not consider the time cost of bargaining, other theoretical models do. Several bargaining models suggest that bargaining power stems from the patience of

[5] For a detailed explanation of the development of these two tables, see my dissertation, Gujral (2016).

a seller (Osborne and Rubinstein, 1990). However, on the whole, models that consider time costs of bargaining (Bing, 2009; Perry, 1986) yield mixed predictions regarding the specific question of a seller's choice between bargaining and posted prices. That is, while according to Bing (2009), a relatively more patient seller is likely to choose bargaining over posted prices, according to Perry (1986), bargaining will not occur in equilibrium, regardless of time cost. Empirical studies can thus help resolve some of the inconclusiveness of the role of seller patience in a seller's choice between bargaining and posted prices. However, there are very few studies that empirically test seller patience in the bargaining context. In fact, there are very few empirical studies testing patience of an agent, even outside the field of Economics. A recent study, Backus et al. (2015), has initiated the attempt to start filling in this gap between theoretical and empirical work, using the context of eBay bargaining or eBay Best Offer. However, Backus et al. (2015) do not specifically examine a seller's choice of bargaining vs. posted prices. I study the impact of seller patience (characterized by a different variable than the round number listings suggested by Backus et al. (2015)) specifically for examining a seller's choice of the bargaining selling method.

Wang (1995) offers several testable predictions for this paper. Their model has one seller (as previously mentioned) with buyers arriving according to a poisson process, whose valuations are drawn randomly. Sellers, assumed to be risk-neutral, incur a discount in payoff while they wait for buyers to arrive. The seller has the choice of posting a price or of bargaining with the buyers that arrive. Bargaining incurs an additional cost, compared to the posted price method. For the bargaining game, the seller sets a reserve price, and the Nash bargaining solution offers the final transaction price. If the bargaining solution is higher than the sellers reserve price, the item is sold. For the posted price case, in this model, if a buyers randomly drawn valuation exceeds the posted price, the item is sold. As mentioned earlier, this model predicts that a seller chooses to bargain if he has higher bargaining power. Another testable prediction that emerges from this paper is that if a seller has many objects to sell and there are many potential buyers, the seller faces a higher bargaining cost, and therefore prefers the posted price mechanism. Finally, this paper also shows that items which are difficult to value, expensive or costly to display are more likely to be sold through bargaining. The conclusions of this paper form the basis for the variables included in the analysis for this paper.

Other testable predictions come from Perry (1986), whose model suggested that bargaining would not occur in equilibrium. However, bargaining markets persist despite this theory. Though Perry's assumptions do not result in a bargaining equilibrium, perhaps relaxation of one or more of his assumptions could lead to bargaining. Perry shows that if reservation prices are the only unknowns but the distributions of the buyers and sellers valuations are common knowledge, then there is nothing to be learned, and therefore there is no bargaining. Thus, I take into account seller learning as an important factor that determines a seller's choice to use bargaining. I also test the following hypotheses, which emerge from relaxing some of Perry's assumptions:

Bargaining is more likely to occur if no one else knows:

1. A seller's valuation
2. A buyer's valuation
3. A seller's time cost
4. A buyer's time cost

Finally, a seller's reputation has been said to affect his choice to bargain. According to Riley and Zeckhauser (1983), whenever commitment to a price is possible, the seller should choose to post a fixed price. Having a high reputation is one way that a seller can commit. When sellers cannot commit because reputations are difficult to establish or market encounters are highly occasional, sellers would choose to bargain. Therefore, I expect that a seller with higher reputation is less likely to choose bargaining, and I test this empirically in this paper.

Table 1 presents the summarized hypotheses from this literature concerning the question of which sellers are likely to choose bargaining vs. posted prices.

3.2 Previous Studies on eBay Best Offer

Despite extensive literature on eBay Motors and eBay auction listings, in general, there are very few studies on eBay Best Offer. A working paper,Chen et al. (2016), relates most closely to this paper compared with the few other eBay Best Offer studies to be discussed later. Chen et al. (2016) also study bargaining vs. posted prices (BO listings vs. non-BO fixed price listings, respectively), and look at the impact of BO on the probability of selling and on transaction prices to determine the benefits of BO vs non-BO fixed price listings. They find that while BO increases the probability of selling, it has no impact on the transaction price of a car. They also claim that if a car is listed as a BO listing, it has a higher listed price or BIN price (consistent with their expectation). Using a different dataset and different empirical techniques and variables, I find some contrary results to Chen et al. (2016). I do not find that BO alone increases the likelihood of selling or has any impact on the transaction price; I do find that the interaction of markup and BO can both increase the probability of sale and can increase the transaction price of a car, conditioned on the car being sold *and being listed at a sufficiently high markup.* Simultaneously, however, this interaction can also *decrease* the probability of selling for cars with lower markups. Chen et al. (2016) do not include the interaction term of a seller's BO choice and markup choice in their analysis. Furthermore, while it is out of the scope of this paper, in my dissertation, Gujral (2016), I develop evidence that sellers that use BO typically charge a *lower* average markup across all of their listings, which is contradictory to the claim in Chen et al. (2016) that bargaining sellers charge a higher price. I do so by accounting for the endogeneity of a sellers choice of price and of selling mechanism.

Apart from offering different methodologies and variables than Chen et al. (2016), I also extend the literature by studying a few other aspects of bargaining vs. posted prices. In studying the outcomes for a seller, Chen et al. (2016) do not study the time that a car takes to sell. I include in my study of seller outcomes the time that a car takes to sell because I find that this is an important channel through which BO can benefit or harm sellers, affecting their choice to use bargaining or Best Offer. Furthermore, in addition to studying the outcomes of BO, as Chen et al. (2016) do, I extend the literature by also studying the question which sellers adopt BO in the first place. While Backus et al. (2015) "conjecture that sellers use BO as a "demand discovery mechanism," it is worth exploring and confirming empirically what exactly leads to the emergence of bargaining as a market. Therefore, I use theoretically predicted insights regarding what factors are likely to influence a seller's choice to bargain, and test these variables empirically in the first part of this paper.

Two of these studies(Huang et al., 2013; Toklu, 2014) have previously analyzed buyer and seller behavior, respectively, on eBay Best Offer, confirming that both buyers and sellers use eBay Best Offer strategically, in alignment with some insights of bargaining theory. Furthermore, these previous papers also offer insights into which variables are relevant to use when studying bargaining on eBay [6]. Using data on Toyota Camrys from 2008, Huang et al. (2013) focus on analyzing buyer behavior, and confirm that buyers use the information available on an eBay listing when making their first offers for BO listings. They find that the main predictors of buyers' first offers are: 1) the

[6]This paper borrows from and contributes to insights regarding variable construction for this emerging literature on eBay Best Offer, and the variables used in this paper will be explained later on.

length of time since the start of the listing until time of the first offer and 2) the number of other buyers that made an offer prior. The authors conclude that buyers act strategically when using the Best Offer, postulating that buyers with higher reservation values make offers earlier, while other buyers wait towards the end of the listing, when sellers have lower negotiating power because of the threat of the negotiation ending. Their findings are consistent with theoretical insights on bargaining, where the two main drivers of strategic bargaining models are time delay and the threat of negotiation ending without agreement (Osborne and Rubinstein, 1990). With respect to seller behavior on eBay Motors Best Offer, Toklu (2014) concludes that sellers on eBay Motors also act strategically on BO listings and play hard bargaining strategies, using a 2011 dataset of Ford Mustangs. Toklu (2014) estimates buyers' private valuations and proposes a distribution. Then, using counter-factual simulations, he concludes that sellers' behavior in the market is consistent with revenue maximization. Therefore, these two studies provide evidence that buyers and sellers act strategically on eBay Motors BO listings, and that eBay Best Offer seems appropriate for studying predictions of economic bargaining literature.

In addition to confirming predictions from economic bargaining theories and shedding light on the eBay theoretical framework, these studies also offer insight into the variables on eBay that are statistically significant in buyer and seller behavior on eBay Motors Best Offer, and thus guide the selection of variables for this paper. For instance, these studies use the Kelly Blue Book (KBB) price to control for heterogeneity in car values based on observable characteristics such as age, mileage, and mechanical condition (Chen et al., 2009; Huang et al., 2013; Toklu, 2014). In other words, the KBB value is used as an approximation of the actual value of the car (Toklu, 2014). The markup variable used in this paper (to be discussed later) is constructed similarly as the price premium variable used by Chen et al. (2009). The predictors of the price premium were factors such as a seller's feedback score, whether a seller is a dealer or not, the time when an offer was placed, whether the offer was on a weekend or in the morning, the offering buyer's feedback score, if the offer is the first one on the listing, the number of buyers who made an offer prior, whether the title of the listing is clear, and if there is a warranty on the car(Huang et al., 2013). Therefore, I use similar variables as predictors of the markup variable in this paper.

Another recent study on eBay Best Offer, Backus et al. (2015), uses a non-parametric analysis and finds a phenomenon in the data that they classify *post-hoc*, using economic theory. That is, they find that sellers that list prices on eBay Best Offer using round numbers (or multiples of 10s and 100s) can be classified as impatient sellers that are willing to sell their item for a lower price than sellers who list prices as precise numbers. They use a dataset of millions of observations on the eBay collectibles category. Their main contribution is this classification of the signaling equilibrium: buyers and sellers both understand this signaling or "cheap talk" mechanism, and therefore, listings that have round-number pricing receive lower offers, sell faster, and sell for a lower price than listings that have precise-number pricing. They confirm similar patterns using off eBay data in the real estate market (Backus et al., 2015). This study thus also highlights the need for exploring and experimenting empirically with the data available on eBay Best Offer. Given the newness of online bargaining platforms, more empirical testing is needed to understand the available data and online behavior to see which aspect of economic theory does this data/behavior actually represent. In this paper, although I do not classify variables under a certain theoretical concept based on a non-parametric approach, I do use some new variables (not previously used in any eBay study) to represent a theoretical concepts of interest for my analyses. I also use a different variable to measure seller patience than the one classified by Backus et al. (2015), and complement their work on measuring seller patience on eBay. This is important because empirical work on seller patience is rare yet extremely crucial for studying bargaining, according to theoretical literature.

Finally, previous eBay Best Offer literature also helps set some theoretical context and point out some important considerations for studying bargaining on eBay. For instance, Huang et al. (2013) and Toklu (2014) follow the models used for Priceline.com's feature Name-Your-Own-Price(NYOP), but with some variations. Huang et al. (2013) point out that eBay products tend to be less standardized and more restricted in supply than Priceline's products. That is, while there can be multiple units of the same standardized flight ticket being sold on Priceline.com, eBay, and especially eBay Motors, tends to sell fewer units of a good, especially if it is a used item or used car. In this manner, Huang et al. (2013) argue that for the automobile market on eBay, a limited supply model is more appropriate. Furthermore, Huang et al. (2013) emphasize that NYOP models do not typically account for disclosed information, because Priceline.com does not provide information to buyers regarding other buyers' offers as eBay does. In general, eBay discloses considerably more information regarding the buyer and the seller than Priceline.com does, and Huang et al. (2013) confirm that buyers base their behavior on this available information. Toklu (2014) differs from Huang et al. (2013) because it does not allow for the dynamic updating of information by the buyers similar to Huang et al. (2013). Toklu (2014) also uses a finite number of sellers and buyers in the model, whereas Huang et al. (2013) use a one-seller (and many potential buyers) model. Lastly, Backus et al. (2015) use a stylistic model that consists of two types of sellers (one impatient type and one patient type) and many potential buyers to model bargaining using eBay Best Offer. Note that Chen et al. (2016) do not use a specific theoretical model, and they instead emphasize that their empirical work is capable of distinguishing between theoretical models. In doing so, they find evidence consistent with Wang (1995) and Bester (1993), that the higher time cost of bargaining and the multiple-seller model are key features for the context of eBay. Similarly, this paper also does not use any one specific theoretical model, but aims to test insights of theoretical models, while keeping in mind key differences inherent in the eBay context.

4 Data

This paper uses completed listings from eBay Motors Cars and Trucks category, collected in 2013 and 2016. Since the 2013 sample is much smaller than the 2016 data and fewer variables were collected, I make more use of the 2016 data in this paper.

4.1 2013 Data Collection

The data was collected from eBay Motors completed BIN listings using the Web Content Extraction Software Version 6.3, from www.newprosoft.com. Since completed listings are only on eBay Motors for some months after their completion. I sorted listings by "Date listed: Oldest First", in order to get as old listings as possible, because this also enlarges my overall sample. The extractor ran from November 15th through November 18th, and the start dates of the listings in my sample range from Jul 29th 2013 through Nov 11th 2013. The range of end dates of the listings in my sample is Aug 18 2013 through Nov 16 2013. The data set thus represents a cross sectional snapshot of completed BIN listings on eBay Motors Cars and Trucks market for 3.5 months from Jul 29th 2013 to Nov 16th, 2013.

During the three days of data extraction, the software would stop running at times. In order to collect the listings in the time period as completely as possible, the extractor was re-run a couple pages before the page where the extractor had stopped. This is because as new listings got completed, the previous listings became older and could now only be found on previous pages. Data extraction was stopped when over 3000 listings were collected.

Since the main objective of this paper is to study the seller's choice of selling method, the item/car/listing-level data was aggregated at the seller-level, and a seller-level dataset was constructed. The seller sample was determined by the randomly selected cars in the sample. Using all the eBay seller usernames (which appear on the listing page of an item) associated with the over 3000 listings extracted, extractions were run for each seller's profile page on eBay, collecting publicly available information on the eBay seller.

To assemble a rich data set, I needed to get data from a few other webpages and merge the dataset. I collected the Vehicle Identification Numbers (VINs) for each car entered by the sellers on the eBay listing/item pages, and used these VIN numbers to extract information from CarGurus.com, namely the Instant Market Value (IMV) for each car. The following variables were also needed for each listing: duration of a listing, revision history of a listing, and whether or not the listing has the BO feature enabled on it. The revision history variables have never been collected in any eBay study prior to this one. The revision history of a listing is publicly available on eBay on pages, linked to the listing page. The extractor therefore needed to run separately for the revision page data collection. Data regarding the duration of a listing and the enabling of the BO feature also needed to be extracted from a different link to pages that are only available on the eBay API platforms (often only used by software developers). The data collection from the API platform was not as clean as data collection from the eBay pages because of the difference in scraping from an HTML page vs. from a text page. An observation was dropped if it did not extract correctly or if it was missing key variables. The empirical methodology (to be outlined below) required fixed effects dummies for the Make of the car, and this would only work well with more observations per car Make. Hence, observations were dropped if the Make of the car (Honda, Acura, for example) had less than 10 listings in the sample I extracted. If a VIN car occurred multiple times in the data (that is, it had ended multiple times within the 3-4 month period), it was dropped. This is because these few observations that have the same car VIN listed multiple times under different eBay IDs were either representing cars listed and removed due to errors made by the seller, or these represent cars with much longer duration than usual, indicating that these cars might be particularly less likely to sell. Since there were only a handful of such observations, I do not expect their exclusion to impact my results. I also discuss these observations later in the context of left-censoring. Furthermore, if the VIN could not be verified on CarGurus.com, the listing was dropped from the sample. Once all the item-level/listing-level variables were merged in one data set, all of these variables were aggregated and constructed at the seller-level and matched with the seller usernames to complete the seller-level data set required. The final sample, at the item-level, consists of 1107 cars, and this translates to 450 seller-level observations.

4.2 2016 Data Collection

In 2016, the sample selection method differed slightly from that in 2013. Data was collected from March 3rd, 2016 to March 31st, 2016, and consists of listings with start dates ranging from December 11th, 2015 to March 16th, 2016, and with end dates ranging from Dec 9th, 2015 to May 27th, 2016.

I collected data on the same car models as the ones randomly selected into the 2013 data. Therefore, while the item selection in 2013 was completely random, it was not the case in 2016, because it was linked to the randomness of the items available on eBay in 2013. However, despite choosing the same models, the extractor was programmed to collect the first 50-200 results for each model. This implies that the *number* of each type of model was still random. In some cases, despite my attempts to have repeat observations on the same model from the 2013 sample, there was no data to be collected in 2016 for that particular car model. The data set thus represents a cross sectional snapshot of completed BIN listings in 2016 for certain chosen car models on eBay Motors Cars and Trucks market for 3.5 months from Jul 29th 2013 to Nov 16th, 2013.

The extractor was programmed to extract the oldest listings first using the sorting "Date Listed: Oldest First", as was the case in 2013. However, in 2016, I had an additional hurdle: at times, the extractor had errors that caused the filtering mechanism to automatically change to "nearest first" with an embedded zipcode of my hometown, "33063", which I could not hide from eBay, despite changing stealth settings on my computer. This problem had not occurred in 2013 because eBay could not read zip-codes as easily then. Therefore, the 2016 data is not as perfect a representation of the eBay market in terms of geography of the car market and make of the cars as it was in 2013.

Although the entire data collection process originally collected over 30,000 listings, many of those listings were repeat listings because I used two different computers, and this led to repeated items. This repeat collection ensured a higher likelihood of obtaining a richer data set with more variables to overcome random glitches of software extraction in one computer, by using a hopefully better copy of that item on the other computer. That is, this was one method of working around the glitches of my extraction software. I later cleaned the data sets and merged information/variables on these repeat items, and kept the copies of the items that allowed for more key variables being collected. I dropped the accidental auctions that sneaked into the dataset through extraction glitches. Because of some of these data extraction limitations, it was difficult to plan out ex-ante the number of observations that would be in the sample set; therefore, I focused on collecting observations until I reached a large number like 30,000.

As was the case in 2013, listings with duplicate VINs, listings that did not have a valid VIN, listings that did not include the BO variable or price variable, and International listings were all dropped. Therefore, including a variable that does not have a lot of observations (because it was more difficult to collect technically, and at times, it was a variable not entered by the seller enough times) can reduce the number of observations in the regression.

Seller Sample Selection was determined by the item selection, and the seller-level dataset was assembled by aggregating the item-level variables at the seller level, as was the case in 2013.

The final item-level dataset consists of 2497 observations or cars in the sample. At the seller-level, this translates to 1861 sellers. The sample for sold cars contains 305 observations.

5 Variables

This section defines all the variables used throughout the paper. I separate the variables by item-level variables and seller-level variables. Where appropriate, I discuss the relationship I expect the variable to have with bargaining or BO[7].

5.1 Item-Level Variables

- BO is a dummy variable that takes on a value of 1 if the listing has Best Offer enabled on it, and a value of 0 otherwise.

- sold is a dummy variable that takes on a value of 1 if the listing was sold, and a value of 0 otherwise.

- durationdays is a measure of the number of days that a listing lasted. This measure, when the item is sold, represents the number of days it took for an item to sell. However, if the item did not sell, this variable represents the number of days that the seller intended for the listing to last.

[7] Where equations are present, i indexes an item, while j indexes a seller.

- discountratio is a measure of the number discount rate provided on an item that was sold under BO. It is measured as follows:

$$\frac{transactprice_i - BIN_i}{BIN_i}$$

- lntransact is a variable that take a transformation of the transaction price of a car. That is,

$$lntransact = ln(transactprice_i)$$

- priceprem is the markup of a seller can be defined as the excess in the seller's asking price from the average benchmark price divided by the average benchmark price for that car. The markup measure assesses the seller's asking price for a car on eBay against the standard estimate suggested by CarGurus.com. This "Instant Market Value (IMV)" estimate was derived by CarGurus.com using the Vehicle Identification Number (VIN) on the eBay listing of the car. According to CarGurus.com, "the Instant Market Value (IMV) of a vehicle is CarGurus estimated fair retail price for a vehicle based on a detailed analysis of comparable current and previously sold car listings in [the] local market. [The] analysis takes into account details including make, model, trim, year, mileage, options and vehicle history." Therefore, the IMV can be written as the following:

$$\begin{gathered} IMV_i = G(Make_i, Model_i, Trim_i, Year_i, Mileage_i, Options_i, \\ VehicleHistory_i, ComparablePrices_i, LocalCarMarket_i) \end{gathered}$$

  ,

  where G is an unknown function that CarGurus.com uses to estimate the retail price based on the variables listed in parentheses.

  According to CarGurus.com, the function for estimating the IMV has remained the same from 2013 to 2016, and therefore can be used consistently for analysis in this paper. The IMV therefore serves as an average benchmark price. This measure of the price premium or markup is similar to the ones used in previous literature (Andrews and Benzing, 2007) using KelleyBlueBook.com as the average benchmark price for a given car[8].

[8] Note though that while the *Markup* variable represents the valuation of a given car by the seller, there might be some measurement error in this variable. Note that the true value of a car, denoted below by $TrueValue$, may be different than the CarGurus.com retail estimate for the car. This implies that there might be some measurement error in the *Markup* variable, which might make standard errors larger for the analyses conducted in this paper. This is outlined here as follows:

$$TrueValue = IMV + \sigma$$

Then, the true markup of a car, denoted below by $TrueMarkup$ is different than the $Markup$ variable, as follows:

$$TrueMarkup = \frac{\mathrm{BIN}_i - \mathrm{IMV}_i - \sigma}{\mathrm{IMV}_i + \sigma}$$

Therefore, the observable variable *Markup* is measured with some error, z, such that:

$$TrueMarkup = Markup + z = \frac{\mathrm{BIN}_i - \mathrm{IMV}_i - \sigma}{\mathrm{IMV}_i + \sigma}$$

where $z = \frac{\sigma * BIN}{IMV(IMV+\sigma)}$.

$$\frac{\text{BIN}_i - \text{IMV}_i}{\text{IMV}_i}$$

- transactprice is a variable that captures the transaction price dollar amount of a car for cars that sold.
- InstantMarketValue is the CarGurus.com retail estimate for each car, based on characteristics of the particular vehicle. In addition to Mileage, Year, Make, and Model of the car, InstantMarketValue helps control for any remaining car characteristics that I did not directly observe in the data. CarGurus.com can read these variables based on the Vehicle Identification Number(VIN) of each car, which I obtained from the seller's data entry on the eBay listing page. I expect that cars of a higher price are more likely to be bargained over.
- Mileage is the marked mileage on a given car. I expect that the higher the mileage, the more likely for it to be sold through Best Offer.
- Year is the year the car model was introduced. I expect that the older the car is by year, the more likely it is to be listed as BO.
- No. of BIN revisions (unscaled) is the total number of BIN revisions on a listing (among the most recent revisions on the listing). BIN revisions imply that the seller has learned new information about pricing, and has therefore chosen to revise it. Not all BIN revisions by the seller can be observed through this revision variable, because the seller can choose to relist an item under a completely new item number with a revised price, and it would not be captured under my data collection as a relisted item or as a revised item. This means that this measure underestimates the number of the seller's BIN revisions.
- No. of BIN revisions (scaled) is the same as the variable, No. of BIN revisions (unscale), except that it has been scaled by the number of observations collected on revisions in each year. That is, in 2013, 12 recent revisions were collected for each listing, whereas in 2016, only 4 recent revisions were collected. Therefore, in the the 2013 dataset, No. of BIN revisions (unscale) is divided by 12 to get No. of BIN revisions (scale), whereas in 2016, No. of BIN revisions (unscale) is divided by 4.
- BO revisions (unscaled) is the total number of most recent BO revisions collected for a listing, similar to the variable, BIN revisions (unscaled). This indicates that the seller has learned new information on how to use Best Offer, and has therefore chosen to revise it.
- BO revisions (scaled) is the same as BO revisions (unscaled) variable, but is scaled similar to BIN revisions (unscaled).
- revised is a dummy variable that takes on a value of 1 if the listing has been revised at least once, and a value of 0 otherwise. A revision implies that there was learning and implementation of that learning with regard to that listing or item. Therefore, as revision or learning increases, I expect that BO usage will be reduced.
- relist is a dummy variable that takes on a value of 1 if the item has been relisted by the seller.
- unavailable is a dummy variable that takes on a value of 1 if the item was made unavailable by the seller, and 0 otherwise. I do not have an expected sign for this variable.

- deposit is a categorical dummy that takes on different values for the time period the seller requires a deposit payment in. Values are 24 hours, 48 hours, 72 hours, immediately, and none mentioned. This variable, never before used in an eBay study, represents the seller's signal to the buyer regarding his time seriousness. I do not predict a sign for this variable, but include it as a potential control.

- itemcountstateyr is the number of cars in the dataset that are from the same state. I expect that as the competition by state increases, it is likely to decrease the likelihood of BO.

- itemcountmakeeyr is the number of cars in the dataset for a given year that are of the same Make. I expect that as the competition by Make increases, it is likely to decrease the likelihood of BO.

- ModelavgIMVby1000 is the average IMV for a particular model in the car. It helps control for the expensiveness of a given model, and other unobserved chracteristics of a particular model. As mentioned earlier, I expect that if a car model is relatively more expensive, it is likely to be bargained over. That is, I expect a positive sign on this variable.

- State Dummy is a dummy variable for each state, which allows for controlling for unobserved market/demand characteristics, specific to a state.

- Make Dummy is a dummy variable for each car make, which allows for controlling for unobserved market/demand characteristics, specific to a state.

5.2 Seller-Level Variables

Several of the following seller-level variables are constructed by aggregating item-level variables at the seller level.

- BOperlisting is the fraction of a seller's listings in the sample that are listed as Best Offer.

- Selleravgpriceprem is the average item-level markup/priceprem (explained above) across all of the seller's listings in the sample.

- Patience
  There is not much literature where patience is studied empirically, even outside the field of Economics. Nonetheless, because time may play a key role in bargaining, it becomes crucial to consider the impact of the patience of a seller. This paper uses a variable for patience that has never been tested before, where patience is conceptualized using previous empirical literature on patience. The infrequent times when patience has been noted in research, patience has often been conceptualized as the absence of impatience. Blount and Janicik (2001) consider what constitutes patience (rather than impatience) directly; they claim that there are two primary delay triggers, postponement, and tolerance, to which subjects respond and exhibit patience (Dudley, 2003). Researchers find that self-reported measures of patience are less reliable than measures of patience derived from behavioral observation (Berensky, 2004; Fowler and Kam, 2006). Therefore, this paper measures an individual seller's patience through behavioral observation, rather than using seller self-reports of patience (as is the case in previous empirical studies on patience).

  - Selleravgrelist, the average relisting behavior of a seller across all his items in the sample, measures the patience/tolerance of a seller in two ways. Firstly, sellers are known to automatically relist items. That is, a seller exhibits tolerance for selling the car on eBay in his initial format of listing, without ability to change the duration of the listing. Hence, a seller that uses automatic relisting intends to tolerate the wait till the item sells on eBay. The willingness to wait and tolerate the consequences of listing until the item sells signals that the seller is a more patient seller.

Secondly, sellers can also manually relist their items by a one-click mechanism on eBay for relisting the item. A seller who manually relists an item in this manner exhibits patience, tolerance, and persistence for selling the item on eBay, instead of searching for off-eBay options for selling. Controlling for other indicators of seller's outside options (as I do), even if a seller clicks to relist manually, he shows persistence in selling his items.

$$Selleravgrelist = \frac{\#ofCarsRelisted_j}{\#ofSellerListings_j}$$

- Competition in the eBay Motors market is defined along two dimensions - the Make of the car and the geographic location of the car. Since this data set ended up having fewer of the same models, the market of a particular car *model* is more difficult to analyze than the market of a given car's *make*. In terms of geographic competition, the city-level data was the most disaggregated data available on eBay.
  - countmakeSeller is a variable that measures the competition that a seller faces on eBay from sellers of the same car make (but not necessarily the same model). The variable was constructed by counting up the number of sellers on eBay selling the car of the same Make as a given seller. The higher this number, the more market competition the seller is exposed to.
  - countcitySeller is a variable that measures the competition that a seller faces on eBay from sellers of the same city. The variable was constructed by counting up the number of sellers on eBay selling a car on eBay in the same city as a given seller. The higher this number, the more geographic market competition the seller is exposed to.
- Patience*Competition is the interaction of seller patience with competition variables. I do this because it seems that higher competition can change the relative bargaining power dynamics between sellers and buyers. That is, according to Bester (1993), buyers have higher bargaining power when there is higher seller competition in the market, compared to when there are fewer sellers in the market. Since Bester (1993) presents differing results than other previous models regarding sellers' choices between bargaining and posted prices, I find it worth studying the impact of seller's bargaining power, in the form of patience, in the context of higher seller competition.
  - competitcity*relist is an interaction term variable, where the geographical competition faced by the seller is interacted with seller patience. It is constructed as follows:

$$competitcity * relist = countcitySeller * Selleravgrelist$$

  - competitmake*relist is an interaction term variable, where the competition by car make faced by the seller is interacted with seller patience. It is constructed as follows:

$$competitmake * relist = countmakeSeller * Selleravgrelist$$

- Seller's Outside Options
  - Selleravgunavailable is a listing characteristic variable that measures the average number of a seller's listings that are ended by the seller, claiming that the item was either sold prior, was no longer available or was ended due to an error in a listing. I use this variable to measure how often the seller has an outside option that makes an item unavailable on eBay. Although the item having been "sold prior" was an option used by sellers in 2013, I did not find any usage of this option in 2016. I use the general unavailability of the item, in this case, a car, to mean that the seller chose to end the listing car for an outside option, regardless of the reason he selected on eBay. On the one hand, the seller may exercise his bargaining power by setting a higher posted price. On the other hand, he may choose to bargain due to higher bargaining power. So, I do not predict a sign for this variable.
  - Similar to the case of bargaining power stemming from seller patience, I also interact the seller's bargaining power that stems from his outside options with the seller competition he faces. That is, I also study the following variables:

$$competitcity * unavailable = countcitySeller * Selleravgunavailable$$

$$competitmake * unavailable = countmakeSeller * Selleravgunavailable$$

    I do not predict a sign for the impact of these variables on the seller's use of BO.

- Seller's Communication
  - SelleravgQA is a listing characteristic variable that measures the average number of a seller's listings that had at least one question or more by the buyer along with the seller's answer (or answers) posted on the listing.

- Seller Reputation
  I expect that a seller's reputation will make him less likely to use bargaining, as would be consistent with Riley and Zeckhauser (1983); Bing (2009).
  - I use a seller's Positive Feedback Percent, listed on his profile page, as well as on each of his item listing pages as the reputation variable, where

$$PositiveFeedbackPercent_j = \frac{\#ofPositiveFeedbackPoints_j}{\#ofPositiveFeedbackPoints_j + \#ofNegativeFeedbackPoints_j}$$

  I expect that a the higher a PositiveFeedbackPercent is, the less likely he will be to use bargaining.

- Seller Knowledge/Experience/Learning
  - Feedbackscoreby1000 is the variable used to represent a seller's experience on eBay. According to Chen et al. (2009), feedback score of a seller is generally used as a reputation measure in eBay auctions literature, along with variables that measure positive feedback, but it can instead serve as a variable representing experience of an eBay user (Huang et al., 2013). This is because feedback can only be provided on eBay from a buyer to a seller or from a seller to a buyer after there is a completed transaction between the

two agents. Moreover, one buyer-seller pair can provide feedback for each other only one time. This variable thus indicates the number of new threads of transactions an eBay user has completed. I use feedback score to represent a seller's knowledge and experience, and therefore I expect that the coefficient on this variable will be negative in sign.

- selleravgrevisions is a listing characteristic variable that measures the average number of revisions for each seller across all his listings. In 2013, for each item by a seller, the data collection extracted 12 most recent revisions. However, in 2016, the data collection extracted only 4 most recent revisions. Therefore, at the item-level, I scaled the revisions by the number of observations collected on them. That is, the scaled versions of the revision variables for 2013 divided the total number of revisions on an item by 12, and by 4 in 2016. I use the scaled versions of the revision variables in the analysis, unless otherwise mentioned. I expect the sign on the coefficient for this variable to be negative. That is, I expect that increase in seller's knowledge indicated by his increase in learning/revisions is likely to lead him to choose against bargaining.

$$\frac{\#ofRevisions_j}{\#ofSellerListings_j}$$

I also use variables that concern seller learning specific to pricing and seller learning specific to the BO feature, measured by variables SelleravgBINrevsunscale and Seller-avgBOrevsunscale, respecitvely.

Note:

$$SelleravgBINrevsunscale = \frac{\#ofBINrevisions_j}{\#ofSellerListings_j}$$

and

$$SelleravgBOrevsunscale = \frac{\#ofBOrevisions_j}{\#ofSellerListings_j}$$

- sellerprivate is a dummy variable that takes on a value of 1 if the seller is a private seller, and 0 if the seller is a dealer. If a seller is a private seller, then he is likely to have less outside options than a car dealer, and therefore lower time cost for selling the car on eBay. In addition, a private seller has lower learning and experience of selling and of selling on eBay than a dealer. A private seller's lower time cost, lower experience, and lower knowledge, all point to a private seller being more likely to use BO. Therefore, I expect the coefficient for this variable to have a positive sign with respect to explaining BO.

- Seller's Time Cost
  - sellerlistingsN is the number of total cars with valid VINs by a seller in the sample. If the seller has a higher number of items to sell, and therefore has higher time cost, then according to Wang (1995), the seller is less likely to use bargaining. Chen et al. (2016) also use a similar variable in their empirical analysis on eBay Best Offer.
- Object Valuation

- SelleravgMileage is the average mileage for the cars in the sample by a seller. I expect that old cars are more likely to be sold through bargaining because old cars are harder to value. That is, sellers that sell older cars are more likely to use bargaining as a means of price determination, and therefore I expect the sign on SelleravgMileage to be positive.
- SelleravgYear is the average model year for the cars of a seller in the sample. Old cars are expected to be more likely to be sold through bargaining, as mentioned earlier, therefore I expect SelleravgYear to be negative. These two variables, SelleravgYear and SelleravgMileage together, not only account for whether the car is old or new, but also control for average item characteristics of the seller.
- Seller Make Dummy variables are used to control for the average number of seller listings in a given car make. For example, if a seller's Toyota cars make up 80% of his total listings in the sample, and Honda cars make up 20% of his listings, then SelleravgToyota variable will have a value of .8, and SelleravgHonda will have a value of .2.

6 eBay Motors: Descriptive Statistics

In this section, I describe the data, which includes characteristics of cars, sellers, listings, and the eBay market. The summary statistics are presented in Tables 4-7. More of the analysis in this paper is conducted using the 2016 data because the 2016 data is much larger.

In the 2016 item-level sample (see Table 4), most of the cars in the sample are relatively new in terms of the year, but used and older in terms of mileage. That is, the average Model Year for a car in the sample is 2010, whereas the average car mileage in the sample is 56,046 miles. The average value of a car or IMV, according to CarGurus.com, is $30,263. On average, the markup for a car was -6.9%, which is actually a mark*down* of 6.9%; that is, sellers on eBay list a car at a *lower* price than CarGurus.com's estimate. For the BO listings, the average markup is -5.2%, which is lower in magnitude than the overall average markup.

According to this 2016 item-level sample (see Table 4), 84% of the cars were listed under the BO mechanism. 24% of the cars in the sample are from private sellers, while the rest are from dealers. 12% of the the total listings in the sample resulted in a sale. The average duration for a listing during the data collection period was about 9 days.

For cars that sold (see Table 8 , 81% of them were listed under BO, and for cars that sold, the markup was much lower (or much greater in magnitude), with a value of -40.9% compared to the average markup value in the overall sample of -6.9%. Interestingly, though, among the cars that sold, BO listings had had a markup with a value of -30.9%, which is 10% higher in magnitude than the average overall markup for sold cars (-40.9%). For cars that sold, the average duration of the listing was 5.5 days, the average IMV was $16,659, and the average transaction price was about $14,479.

Most of the cars either required the deposit payment immediately (48.8%) or there is nothing mentioned regarding their deposit time deadline (33.5%). Only about 17.7% of the items have a listed deposit time period on them: of either 24 hours, 48 hours, or 72 hours.

For the seller-level 2016 data (see Table 6, 56.3% of the sellers are private sellers. The mean markup for a seller is actually a mark*down*, equaling -10.7% (lower yet higher in magnitude than the markup at the item-level, of -6.9%). Sellers list 82% of their listings as BO, on average. On average, across all their listings, sellers' revisions on BO equals 0.03, whereas their average number of revisions on BIN equal 0.22. This indicates that sellers revise the price much more than they revise the BO feature. The average number of general revisions (concerning photos, description, payment terms, shipping terms, etc.) for a seller is 0.28. Sellers tend to relist 37.8% of their total listings in the sample. The average positive feedback percent for sellers is 99.2%, and the average feedback score is 439 points. As mentioned earlier, feedback score of a seller measures a seller's experience on eBay, indicating the number of transactions a seller has had with unique buyers. The average number of listings a seller has at a given point of time, according to this sample, is 2.6. 7% of the sellers in this sample are repeat sellers; that is these 2016 sellers were also in the 2013 sample.

In terms of eBay market characteristics, there are about 589 cars, on average, from one state, and about 339 cars for a given car make, on average. Using the seller-level data, I find that there are about 8.7 sellers in a city, whereas there are about 130 sellers in a given car Make.

For the 2013 item-level data (see Table 5), the average car model year was 2006, and the average mileage for a car is 67,333. The average value of a car or IMV, according to CarGurus.com, is $25,501. On average, the markup on a car was 10.4%; that is, sellers on eBay list a car at a higher markup than CarGurus.com's estimate (in contrast with the situation in 2016)[9]. For the BO listings, the average markup is 7.2%; it is lower than the overall average markup, as is consistent with the case of 2016, where the average BO markup is also lower than the overall average markup . 30% of the cars in the sample were from private sellers, slightly higher than the percentage of cars by private sellers in 2016.

Finally, using the 2013 seller-level data presented in Table 7, only 26% of the sellers in 2013 are private sellers (in contrast with the 56.3% in 2016), while the rest are car dealers. With respect to seller-level variables in 2013, I find that a seller's average markup is about -5.4%, which is lower (and also lower in magnitude) than the average item-level markup of 10.4% for 2016. That is, compared to the item-level, sellers tend to price their cars lower, on average, than the CarGurus.com's estimate. Sellers list 82.6% of their listings as BO, similar to the 2016 sample. Sellers tend to relist 19% of their total listings in the sample, which is much lower than the relisting behavior in the 2016 sample. On average, sellers have an average of .14 BIN revisions across all their listings, and .02 BO revisions. Again, note that BIN revisions are much higher than BO revisions, as was the case in 2016. With respect to general revisions, sellers' average number of revisions across their listings is 0.67. [10] The average positive feedback percent for sellers is 94.6%, which is much lower than the positive feedback percent in the 2016 sample, and the average feedback score is 579 feedback points. The average number of listings by one seller is 2.3. In terms of seller-level competition, on average, there are 7.5 sellers in a given city, and 54 sellers of a given car Make.

7 Methodology

7.1 Methodology: Who chooses Best Offer?

Given the paucity of literature on bargaining and an intriguing re-emergence of bargaining markets, I explore what induces sellers to adopt bargaining. I test empirically which factors, alluded to in theory, incline a seller to enter into a bargaining or Best Offer market vs. entering a posted price only market. Best Offer usage by a seller, the dependent variable of interest, is measured by the variable, *BOperlisting*, is the proportion of a seller's listings in the sample that are listed as BO. This is a fractional response dependent variable (outcomes take on values [0,1]), and therefore, I

[9] CarGurus.com's method for calculation over this three-year span (2013-2016) has not changed. Therefore, the change can be attributed to market-level, seller-level, or sample changes over the years rather than a measurement difference for the IMV in 2013 vs. the IMV in 2016.

[10] Note that this is the unscaled version of the revision variable. I collected 12 observations on sellers' most recent revisions, whereas in 2016, I collected only 4 observations; therefore it is not easy to compare the unscaled versions of these variables for the two years.

use the following fractional logit regression model for analysis:

$$\begin{aligned} E[BO|X] = G(&\lambda_0 + \lambda_1 \bar{X}_j + \lambda_2 S_j + \lambda_3 \bar{L}_j + \lambda_4 \bar{M}_j + \lambda_5 Patience_j \\ &+ \lambda_6 Competition_j + \lambda_7 Patience * Competition_j) \end{aligned} \tag{1}$$

where $G(.)$ is the logistic function, known to satisfy $0 < G(z) < 1$ for any real number z.

Note that most of the independent variables in the above equation are denoted with bars (except S_j, which denotes seller characteristics). These bars represent that the variable is an aggregate variable at the seller level; that is, item-level characteristics have been aggregated for each seller across all of the seller's items in the sample. BO represents the seller's choice of Best Offer vs. non-Best Offer fixed price listing, measured by the $BOperlisting$. $\bar{X}_j$ are average item characteristics for the seller, $\bar{L}_j$ are average listing characteristics, and $\bar{M}_j$ are average market characteristics for all of the seller's items. For instance,BO_{ij} denotes the seller's best offer usage at the item-level, which is a binary variable, X_{ij} denotes item/car characteristics, L_{ij} are listing characteristics, and M_{ij} are market characteristics at the item-level. These variables are used to calculate the following averages at the seller level: $\bar{BO}$, $\bar{X}_j$, $\bar{L}_j$,$\bar{M}_j$, respectively are used for the primary analysis.

As mentioned earlier, the main predictors of interest in this paper are market competition, patience-level, and the interaction between these two variables. These variables seem to be important game-changers when it comes to the results for a seller's choice to use bargaining vs. posted prices, as mentioned earlier. Therefore, I focus more on these variables, and the parameters of interest are λ_5,λ_6, and λ_7. Other variables suggested in economic theory are also used as control variables and are discussed.

For this paper, I do not intend to obtain structural estimates; rather, I obtain reduced form estimates for the impact of these variables on the seller's use of Best Offer. Note that I do not include the price or markup variable on the right-hand side of the equation because a seller's pricing strategy can be simultaneous with the seller's choice of bargaining. Therefore, including this variable would bias the estimates of the model. I address the issue of this possible simultaneity in my dissertation, Gujral (2016). For the purpose of this chapter, instead of studying a simultaneous system of both equations (one explaining markup and one explaining BO usage), I estimate the reduced form estimates for variables that impact a seller's choice of Best Offer only. [11]

For the sake of robustness, I drop sellers that were selling relatively rare cars on eBay. Car models that made up less than 0.5% of the sample in either 2013 or in 2016 are the ones classified as "rare". Furthermore, I also used an alternate specification of the model, which included the seller revision variable on the BO feature (to be discussed more later), along with the general revision variable to ensure that the impact of seller revisions on BO specifically has a more robust impact on BO than general revisions.

7.2 Methodology: Effects of Best Offer on Profits

7.2.1 Does BO increase the likelihood of selling?

To study the impact of Best Offer and Markup on the likelihood of selling, I use the Probit model for the binary variable $sold_i$, which takes on a value of 1 if the item is sold at the end of the listing, and 0 if it is not sold by the end of the listing. Given the possible simultaneity of Markup and BO explored more closely in my dissertation, Gujral (2016), I am particularly interested in studying

[11] Where multicollinearity between variables was suspected, an OLS regression between the variables was run to ensure that the R between the two variables did not exceed .5.

the impact of the interaction of the two variables on the likelihood of sale. The equations below represents the probit model of interest:

$$\begin{aligned} sold_i = \alpha_0 + \alpha_1 Markup * BO_i + \alpha_2 Markup_i + \alpha_3 BO_i + \alpha_4 X_i \\ + \alpha_5 S_i + \alpha_6 L_i + \alpha_7 M_i + \alpha_7 Make_i \end{aligned} \tag{2}$$

where $Markup * BO_i$ represents the interaction term between BO and Markup variables, $Markup_i$ is the markup on a given car, BO_i is a binary variable for whether an item is listed as BO or not, X_i denotes item characteristics, S_i denotes seller characteristics, L_i comprises of listing characteristics, $Make_i$ represents make dummies, and where M_i represents market characteristics.

Due to a lack of model thickness in my data, I use make dummies along with the Instant Market Value(IMV)(the CarGurus.com's estimate for each car). Controlling for mileage, year, and some other car characteristics individually, including car make and IMV sufficiently control for car model type. I do include model dummies in some specifications for robustness checks.

7.2.2 Does BO lead to quicker sales?

On the one hand, bargaining is said to be time consuming, and is therefore known to have higher transaction costs. On the other hand, it can increase the rate of selling according to Wang (1995), implying that bargaining can lead to quicker selling, consistent with Chen et al. (2016)'s prediction and finding. Therefore, I test the impact of BO, markup, and the interaction of markup and BO on the time that it takes for cars to sell.

$$\begin{aligned} durat_{ij} = \beta_0 + \beta_1 Markup * BO_{ij} + \beta_2 Markup_{ij} + \beta_3 BO_{ij} + \beta_4 X_{ij} \\ + \beta_5 S_j + \beta_6 L_{ij} + M_{ij} + Make_{ij} \end{aligned} \tag{3}$$

where $durat_{ij}$ represents the time it takes for a car to sell. In my dataset, the duration of a listing is available at the level of seconds, and I convert this to days. Therefore, in this paper, the measure used for duration is duration days. However, this variable is only captured completely for cars that sold during the observation (or data collection) time period. For cars whose listings merely "ended," but were not "sold," duration data is right censored, assuming that these cars will eventually sell, although I do not observe their selling date, and thereby their duration. Therefore, I use survival analysis to study the impact of Best Offer and Markup on the time it takes to sell.

To the extent that cars observed in this data do not differ fundamentally or distributionally in their likelihood of sale, and rather differ more along the lines of *duration* to sale, survival analysis is appropriate to use. To avoid bias in survival analysis, censoring must be "random and non-informative(Despa, 2010)". Part of the censoring in the data occurs due to my choice of data collection time period, which is a randomly chosen date appropriate for my time of graduation. Since I collected only ended listings and dropped any car that happened to be listed multiple times in the ended listings (that is, it must have ended twice within the time period of my data), it is as if I followed a listing throughout its first occurrence on eBay. I do not observe listings that have not yet ended, and it is possible that these un-ended listings might consist of cars that have much longer duration. The analysis in this paper will not be able to comment on such listings with possibly long durations, though perhaps if such a listing *ended* at the time of my data collection, this listing would be in the dataset. Overall though, I do not expect that listings that sold vs. listings that did not sell to have vastly different distributions. Furthermore, I use some insights from the model in this paper that studies the probability of selling for a car. This model and its results gives some signals regarding what distinguishes a car that is more likely to sell than one that is less likely to sell. For example, a higher mileage makes a car less likely to sell. Using Kaplan Meier curves, I explore whether there appears to be a *distributional* difference between high-mileage and low-mileage cars, and I do not find this to be the case. I look at other similar variables that are determinants of selling likelihood to see if the survival probabilities vary vastly along these variables. These results are presented later in the Duration model section, and there is no indication that cars more likely to sell follow a different distribution from cars less likely to sell. It seems reasonable then that perhaps it is mostly a matter of time till a car does sell. Therefore, it is also more relevant in some sense to ask how long a car takes to sell than looking only at whether or not it sells in the time period of observation.

Survival analysis requires specifying a distribution for $durat_i$. Since I generally assume that cars that have sold are not distributionally different than the cars that have sold in my data, I expect that it is perhaps only a matter of time till a car sells. Therefore, I expect that if a car has been on the market for a long time, $durat_i$ would have negative duration dependency. That is, if a car has been on the market for a long time, it may be closer to being sold. However, it is also possible that there is no duration dependency at all. In either case, the Weibull distribution seems appropriate, since it allows for monotonic duration dependency, so it does allow for negative dependency or no duration dependency. Non-parametric estimation using the Kaplan Meier curve, shown in Figure 1, confirms that $durat_i$ has a negative duration dependency, meaning that survival probabilities decreases as time goes on. This is confirmed later in the results presented, when the shape parameter, p, is estimated to be greater than 1 (as will be explained later).

Finally, it must be noted that the data might also left-censored to some degree: if the car was listed prior to the time of data collection as a separate listing than the one observed in the data, then the duration might be longer than what is observed. I drop the few observations that have the same car VIN listed multiple times under different eBay IDs. These observations were either erroneous, or cars more likely to be left-censored, or they could be cars with much longer duration than usual because perhaps they are just not likely to sell. This should not bias my results because these cars may be significantly different than other cars, perhaps even distributionally, making survival analysis less appropriate for these cars. However, despite dropping these observations, I cannot assure that the cars I observed have never been listed prior to their occurrence in the data. Nevertheless, left-censoring of this sort might be random across all the observations in the data, and I do not expect my choice of date for data collection to be systematically causing a left-censoring that biases my data. Therefore, for the purpose of this paper, I do not account for the left-censoring. I focus more on correcting for the right-censoring, because this sort can more easily be observed and is known to be frequent in the data, and can cause systematic bias in studying duration if unaccounted for.

7.2.3 How does BO affect the transaction price?

Best Offer may be impacting the transaction price of a car. According to Chen et al. (2016) Best Offer does not have any impact on the transaction price, but it does increase the likelihood of sale. However, Chen et al. (2016) do not study the impact of the interaction term of markup and BO on either transaction price or likelihood of sale. Previously, I mentioned that it is important to study the impact of the markup and BO together (i.e. of the interaction term) on studying likelihood of selling. I propose studying the impact of this interaction term between markup and BO on the transaction price and the log of transaction price, $ln(transact)$ (for ease of interpretation of the results).

However, before the transaction price can occur, the item (or car, in this case) must pass the hurdle of resulting in trade or in a sale. A car's characteristics, its seller's characteristics, and its listing and market characteristics determine whether or not the item is likely to sell. Whereas, the transaction price of a car is more likely to be determined primarily by the car characteristics and the pricing strategy of the car, while the market characteristics and seller characteristics are still likely to have some impact. The pricing strategy is of interest in this paper. However, not accounting for the impact that pricing strategy (which includes whether or not BO was used, in this case) has on the likelihood of sale can confound the true impact of the pricing strategy on the transaction price. However, the transaction price of a car is only available in the data if the car sold. We can say then that the transaction price is censored from below for cars that have not yet sold. Consider therefore the two steps before a transaction price can occur: 1) an occurrence of a sale, and 2) the transaction price for that sale.

This can be expressed in the following way:

$$\mathrm{d}_i = \begin{cases} 1, & \text{if } d_i > 0 \\ 0, & \text{if } d_i \leq 0 \end{cases} \tag{4}$$

and

$$\mathrm{transact}_i = \begin{cases} transact_i^*, & \text{if } {d_i}^* > 0 \\ 0, & \text{if } {d_i}^* \leq 0 \end{cases} \tag{5}$$

where $transact_i$ is the observed transaction price for a car, $transact_i^*$ is the latent variable, for the true transaction price of a car, and d_i is a dummy variable for whether a car sold or not. There are some hurdles to consider that make an item more likely or less likely to sell. We can think of this hurdle further; consider:

$$\mathrm{transact}_i = \begin{cases} {transact^*}_i, & \text{if } u_c - \bar{c} > 0 \\ 0, & \text{if } u_c - \bar{c} < 0 \end{cases} \tag{6}$$

where u_c is a utility from a item i, and $\bar{c}$ is some threshold utility needed for the car to be sold or selling-worthy. Assume $\bar{c}$ is equal for all cars across all buyers.

Consider the following model of interest:

$$\begin{aligned} transact_i^* = \gamma_0 + \gamma_1 Markup * BO_i + \gamma_2 Markup_i + \gamma_3 BO_i + \gamma_4 X_i \\ + \gamma_5 S_i j + \gamma_6 L_i + \gamma_7 M_i + \varepsilon_i \end{aligned} \tag{7}$$

where BO_{ij} denotes the seller's best offer usage, which is a binary variable, and $Markup_{ij}$ is the seller's markup over a price estimate, or Instant Market Value (IMV) for the car, obtained from CarGurus.com:

$$Markup_{ij} = \frac{BIN_{ij} - IMV_{ij}}{IMV} \tag{8}$$

X_{ij} denotes item/car characteristics, S_{ij} denotes seller characteristics (years of experience on eBay, behavioral indication of patience, seller reputation), L_{ij} are listing characteristics, and M_{ij} are market characteristics. For ease of notation, assume that vector $\mathbf{X}$ is comprised of all of these independent variables in the model of interest.

Having noted the above model and the censoring problems that need to be accounted for, the Tobit model might seem like a reasonable choice. However, the Tobit model turns out to be restrictive in a way that is unappealing to entangle the different parts of the process, as will be explained below. The Cragg two-step model, also known as the hurdle model, is a more general form of the Tobit model. The first step of the model predicts the likelihood of sale using a probit model , and the second part uses a truncated normal regression for studying the transaction price, conditioned on selling.

The Cragg model studies two equations:

$$d_i{}^* = \alpha x_{1i} + \mu_i \tag{9}$$

$$transact_i{}^* = \beta x_{2i} + \varepsilon_i \tag{10}$$

where μ_i and ε_i are random and independently distributed, ε_i $N(0,1)$ and μ_i $N(0,\sigma_\varepsilon{}^2)$ Kiyingi et al. (2016).

Using the Cragg model, the probit part of the model helps predict the following probabilities:

$$P(transact_i = 0|x_{1i}) = 1 - \Phi(x_{1i}\alpha) \tag{11}$$

$$P(transact_i > 0|x_{1i}) = \Phi(x_{1i}\alpha) \tag{12}$$

For the truncated regression part of the model, the following expected value of *transact*, conditional on a car being sold, is being predicted:

$$E(transact_i|transact_i > 0, x_{2i}) = x_{2i}\beta + \sigma * \mu(x_{2i}\frac{\beta}{\sigma}) \tag{13}$$

where $\mu(z)$ is the inverse Mills ratio (IMR), $\mu(z) = \frac{\phi(c)}{\Phi(c)}$, where ϕ is the standard normal probability distribution function. The inverse Mills ratio (IMR) from the truncated normal regression accounts for possible selection bias due to the truncated sample.

The primary distinguishing feature between the Cragg model and the Tobit model is that the Cragg model allows for differing factors (and differing coefficients) in the two steps of the analysis. Note that the vector of independent variables of interest, $\mathbf{X}$, is allowed to be different in the two steps: x_1 and x_2 are not the same sets of variables, and the coefficients, α and β are also allowed to be different. Due to this flexibility, this model is sometimes preferred to the Tobit model. I therefore use the Cragg model so that the variables that determine the likelihood of selling are allowed to be different with respect to their impact on the transaction price (Wooldridge, 2010) (Krupka and Croson, 2016). Furthermore, even when the impact of a variable is in the same direction, it is important to allow the variable to affect the selling likelihood of a car differently than its transaction price. For instance, it is possible that BO leads to *lower* sales than posted prices would because buyers generally do not like to negotiate, and that BO reduces the transaction price due to the negotiation process. In such a case, when the impact of BO is in the same direction (negative) for both selling likelihood and transaction price, distinguishing between these parts allows for the magnitudes of the same variable's impact to vary across these two aspects of selling.

A statistical test can also help in the choice of Cragg model vs. the Tobit model. We can estimate independently the log likelihood ratios for a probit, a truncated regression, and a Tobit model using the same set of variables. We can then compute the following likelihood ratio statistic (Katchova and Miranda, 2004):

$$\hat{\lambda} = 2(lnL_{probit} + lnL_{truncreg} - lnL_{Tobit})$$

where $\hat{\lambda}$ follows a chi-square distribution with R degrees of freedom, where R is the number of independent variables, including a constant. If $\hat{\lambda}$ exceeds the chi-square critical value, then we can reject the more restrictive Tobit model in favor of the Cragg model (Katchova and Miranda, 2004). I conduct this test for the preferred specification for transaction price (explained below), and I get $\hat{\lambda} = 1900.39$ for 66 degrees of freedom. This is well above the critical value, and therefore, I reject the Tobit model in favor of the Cragg model for analyzing transaction price.

8 Results

8.1 Results: Who chooses Best Offer?

Table 7 and Table 6 present summary statistics for 2013 and 2016 data, respectively. Table 11 presents the main results for both 2013 and 2016, explaining the dependent variable, *BOperlisting*, the fraction of a seller's listings in the sample that are listed as BO at the end of the listing.

As mentioned earlier, the primary independent variables of interest are seller competition, seller patience, and the interaction of these two variables. Using 2013 data, I find that an increase in seller patience, measured by a one standard deviation increase in *Selleravgrelist*, or a seller's relisting behavior, increases the log odds of adopting BO by 0.02 points (computed at the mean level of seller competition). However, at the lowest level of seller competition (in terms of both car make and city), the effect of patience is negative, where seller patience *decreases* the log odds of adopting BO by 1.25 points. At the highest level of competition (both in terms of Make and in terms of city), the effect of patience is to *increase* the odds of adopting bargaining by 8.51 points. This holds true even when considering the impact of one type of competition at a time. That is, if competition by city is at its minimum while competition by make is at its average level, the effect of seller patience is to decrease the the log odds of adopting BO by 1.2 points. If competition by make is at its minimum while competition by city is at its average level, the effect of seller patience is to decrease log odds of adopting BO by 0.62 points. Whereas, if competition by make is at its maximum while competition by city is at its average level, the effect of seller patience is to increase log odds of adopting BO by 1.26 points. If competition by city is at its maximum while competition by make is at its average level, the effect of seller patience is to increase the the log odds of adopting BO by 7.31 points. Therefore, at increased levels of competition, seller patience inclines the seller to adopt BO, whereas at lower levels of competition, seller patience disinclines the seller to adopt BO. Using 2016 data, I do not find the competition variables or the interaction terms between seller patience and competition to be statistically significant. I do find though that an increase in seller patience *decreases* the log odds of adopting BO by 0.28 points. This is consistent with the result in 2013, indicating a negative effect of seller patience on the adoption of BO when competition is not an important factor. Therefore, the result on seller patience is robust across both years: when a seller is more patient (and therefore is expected to have high bargaining power), he is less likely to choose to use BO. This is consistent with Chen et al. (2016) and Bester (1993), which suggest that bargaining occurs when sellers have lower bargaining power. Furthermore, the results from the 2013 data show that the rationale provided in Chen et al. (2016) and Bester (1993) for this insight also holds empirically. That is, Bester (1993) differs from other theoretical models on bargaining vs. posted prices, which do not consider seller competition. It is perhaps due to this modeling difference that their model is at odds with other models which had predicted that sellers with *higher bargaining power* would be more likely to choose bargaining over posted prices. I demonstrate, using 2013 data, that power of seller competition is indeed strong enough to weaken the bargaining power of sellers, and substantially so. I show that as competition (either by car make or by city)increases, even a patient seller (who typically does not choose BO) becomes inclined to choosing BO, perhaps due to his weakened bargaining position. [12] However, this latter result could not be confirmed using the 2016 data because the competition variables were not statistically significant for the 2016 analysis. Nevertheless, given the paucity of empirical literature on seller patience, this finding can have important implications for other topics in (and

[12] Apart from seller patience, this weakening of bargaining power, due to outside options occurs also in the case of a seller's outside options (discussed more later), which are also another source of high bargaining power, similar to seller patience.

outside of) Economics, and thus deserves more exploration.

With respect to the impact of competition, using 2013 data, I find that a one standard deviation increase in competition by city increases the log odds of adopting BO increase by 0.15 points, and a similar increase in competition by make decreases the log odds of adopting BO 0.57 points (computed at the average level of patience and outside options). Note that geographic competition and product competition have differing impacts on the adoption of Best Offer. This might be because the increase in competition by Make might be exhibiting the impact of higher information in a competitive market. That is, as the number of cars of a given car make increases, there is higher information in the eBay market for cars of that make, disinclining sellers to use BO for such makes. Whereas, in the case of geographic competition of cars, it seems that the information line of reasoning (applicable for competition by Make) is less relevant than the theoretical insight regarding sellers' need to enhance their chances for buyer arrival (Wang, 1995). Furthermore, this result on geographic competition is also consistent again with Bester (1993); Chen et al. (2016) in that higher competition weakens a seller's bargaining power, leading him to bargain. Therefore, it is important to distinguish the varying effects of competition along both dimensions: product market and geographic market. As mentioned earlier, using the 2016 data, I do not find that competition variables are statistically significant.

With respect to control variables, using 2013 data, I find that if a seller has more outside options, measured by a one standard deviation increase in *Selleravgunavailable*, then the log odds of adopting BO are decreased by 0.33 points (computed at the average level of competition by car Make). That is, if the seller has higher bargaining power, in the form of higher outside options, he is *less* likely to choose bargaining. This result is again consistent with the theoretical insights of Bester (1993) and empirical findings of Chen et al. (2016) that bargaining is more likely to occur when sellers have lower bargaining power. This result is further emphasized when looking at the interaction term between the seller's outside options and the competition faced by the seller in terms of car make, measured by *competitmake*unavailable*, which is statistically significant and has a positive sign. At the lowest level of competition by car make, I find that an increase in seller's outside options decreases log odds by 0.63 points. Whereas, at the highest level of competition by car make, an increase in seller's outside options inclines him to use bargaining. This implies that a seller's bargaining power (due to higher outside options) is weakened due to higher seller competition by car make (i.e., when the buyer has relatively more outside options). This makes a seller more likely to use Best Offer vs. posted prices, as was the case with the seller patience variable (and as is consistent with (Bester, 1993)).

The results regarding seller reputation are somewhat ambiguous. I find that if a seller has a higher positive feedback percent by one standard deviation, then the log odds of adopting BO are lower by 2.32 points. This is in contradiction with the expected result for this variable. Whereas, using the 2016 data, I find that an increase in a seller's positive reputation, measured by a one standard deviation increase in *PositiveFeedbackPercent*, reduces the log odds of adopting BO by 0.16 points (consistent with theoretical insight of Riley and Zeckhauser (1983) and empirical evidence of Chen et al. (2016)). There are two things to be noted here: the surprising result in the 2013 data, and the inconsistency of the results across the two years of study. A reason for this surprising result in the 2013 data is that perhaps using positive feedback percent alone is not the best variable for measuring a seller's reputation on eBay. Some previous eBay studies have suggested that using *net* positive feedback percent (subtracting neutral and negative feedback points from positive feedback points) might be a less ambiguous measure of seller reputation (Cabral and Hortacsu, 2004; Andrews and Benzing, 2007), suggesting that eBay reputation variables still need further exploration.

I also studied the impact of seller learning, knowledge, and experience of the cars and of the market. Using 2013 data, I find that if a seller has higher feedback score, measured by a one standard deviation increase in *Feedbackscoreby1000*, then the log odds of adopting BO are lower by 0.22 points. This is consistent with the expectation that a seller with higher experience would be less likely to adopt BO. Also consistent with expectation is the finding that if a seller sells newer cars in terms of Model Year(implying that buyers and sellers all have more information regarding the valuation of those cars), the log odds of adopting BO are lower by 0.09 points. While using the 2016 data, the variables of statistical significance than those in 2013, seller learning and knowledge are important in 2016. I find that a seller's increased learning on his listings, measured by a one standard deviation increase in *selleravgrevisionstotal*, decreases the log odds of adopting BO by 0.17 points. In addition, if a seller is a private seller (vs. being a car dealer), the log odds of adopting BO are higher by 0.32 points. This is consistent with expectations becuase a private seller is typically expected to have lower time cost, lower knowledge and lower experience, inclining him to choose BO over posted prices. These findings regarding seller learning, experience, and knowledge across both years of data are aligned with the expectation that relaxing some of the assumptions inPerry (1986) might lead to the occurrence of bargaining in equilibrium. That is, lack of knowledge regarding the market and/or regarding the valuations of other agents in the market were expected to incline a seller to use BO, and the results of the paper confirm this to be true empirically.

8.2 Results: Effects of Best Offer on Profits

As mentioned earlier, the second part of the paper focuses on understanding the channels through which the use of BO might benefit or harm the seller. Using the 2016 data, I was able to observe the relevant outcomes for examining the sellers' benefits: whether or not a car sold, the transaction price of a car, and the time duration of the listings. These outcomes serve as the dependent variables for this second part of the paper. Whereas, the primary independent variables of interest are the listed markup of a car, whether or not BO is enabled for this listing, and the interaction term of these two variables. The results for this part of the paper are presented in Table 14. This table presents the results for the three dependent variables for this part of the paper. That is, the first column presents the results of the probit model which explains the likelihood of selling and the second column presents results for the model explaining the time needed for selling a car. The third column studies the impact of the markup and BO on the transaction price ($ln(transact)$. to be exact). The summary statistics for the model predicting the likelihood of selling, the duration of the listings, and the transaction price are presented in Table 8, Table 9, and Table 10, respectively.

8.2.1 Results: Likelihood of Selling

The approach I use for studying the impact of using BO on the likelihood of a car sale is different than the approach used in Chen et al. (2016). The primary difference is that I study the impact of a seller's choice of BO *interacted* with the seller's choice of markup, because I hypothesize that these two choices of the seller are closely linked. I find that at the average level of markup, using BO *reduces* the likelihood of selling a car by 10.2%, shown in the results of Table 14. However, it turns out that for cars with higher markups, the use of BO *increases* the likelihood of selling. The turning point of the effect of using BO occurs at about a markup of 10.8%. That is, I find that at a markup value of 0.108 or 10.8%, the impact of BO on the likelihood of selling changes from negative to positive. Put another way, if a seller asks for a BIN price which is at least 10.8% higher than the CarGurus.com's estimate for the car, then using BO increases the chances of the car being sold. Whereas, for cars with listed markups lower than 10.8%, using BO *decreases* the probability of selling the car. [13] This result is very important, because no previous study has documented empirically that eBay Best Offer can have a negative impact. However, without this insight, there is not much explanation for why sellers would revise their listings and choose against using Best Offer, as discussed earlier in the Part One results. Previous work has not offered any negative impacts of using Best Offer, and therefore does not provide any reasons for why sellers would choose against using Best Offer, when the eBay fees for listing a car through either mechanism is exactly the same. This effect could not have been seen in my work if I had not accounted for the interaction term. In alternate specifications where I do not include the interaction term, as can be seen in Table 16, I find that the BO variable alone *is* statistically significant with a negative sign, but is not statistically significant when the interaction term of markup and BO is included in the specification. Therefore, without the inclusion of the interaction term, my data would have yielded an opposite and misleading result than that of Chen et al. (2016), who suggest that the use of BO increases the likelihood of selling. However, my approach offers an explanation for why opposing results may be seen in papers studying this topic with different datasets: not accounting the interaction of the choice of markup and the choice of using BO.

With more clarity and completeness regarding the nature and direction of the impact of BO, we can discuss more closely the theoretical underpinnings for the signaling that might be occurring in the market due to the interaction of markup and BO. As can be seen in Table 2 and in Table 3, sellers that use low markups might be either impatient, very impatient, uninformed regarding the quality of their product, or they might have a low quality product. Note that among the total 21 cases listed completely, i.e. without the symbol"?", in these two tables, the combination of a low markup and BO use occurs 10 times (48% of the complete cases listed). However, each of these cases 10 cases, where the markup is lower and the seller is using BO, there is some quality uncertainty present. That is, either the car is indeed of a lower quality, or the car is of high quality, but the seller is uncertain about the quality or the valuation of his car. With this framework in mind, it is thus not surprising that cars with lower markups listed under a BO listing lead to a lower likelihood of sale. That is, the framework presented shows that these particular cases pose some quality concerns for the buyers.

While the above-mentioned results explain a relatively more direct impact of using Best Offer on car sales, Best Offer usage also offers an indirect benefit to car sellers. This indirect impact of BO is best understood by first considering the impact of a higher markup on the likelihood of selling. As shown in Table 14, a one standard deviation increase in the markup of a car *decreases* the probability of selling by 0.38 points (computed at the average BO usage), as can be expected. Nevertheless, note that while at the minimum value of the BO variable (when BO=0), i.e., when there is no BO used, and the method of selling is the posted price method, an increase in markup reduces the probability of selling by 62.7%. Whereas, when BO is used, an increase in markup reduces the probability of selling by a substantially lower percentage: 33.7%. Therefore, using BO (vs. using posted prices) reduces the negative impact of a high markup on the likelihood of sale by 29.0%. While this result alone reveals a benefit of using BO, the importance of this result of this indirect channel of BO's impact can be fully grasped only when the positive impact of a high markup strategy on transaction price is also unearthed (as will be explained later).

Apart from the primary independent variables of interest of this part of the paper, results regarding control variables also offer insight into what impacts the selling of a car on eBay. I find that a relatively more expensive car, measured by an increase in the variable *lnIMVby100*, is less likely to sell. An older car, in terms of higher mileage, is also less likely to sell. These results are

[13] At the lowest value of markup in the 2016 data, using BO reduces the likelihood of sale by 300%, while at the highest value of the markup, BO increases the likelihood of selling, by 56.7%.

consistent with expectation because I would expect older and more expensive cars to have lower quantity demanded. Surprisingly though, a newer car, in terms of the year of the model, is less likely to sell. I expected that older cars, in general, will be less in demand and therefore less likely to sell, but perhaps there is higher availability of newer cars off-eBay, and therefore newer models are less likely to sell on eBay. Interestingly, I also find that a seller's listed deposit time deadline (for once a car has been sold) can also impact the likelihood of selling. That is, if sellers indicate that they require a deposit immediately (vs. in 24 hours) or if they do not mention any time deadline for a deposit ((vs. mentioning 24 hours), the car is less likely to sell. This variable has never been tested before in any eBay study, and it represents the seller's indication of his seriousness with respect to his time. These results show that if the seller is either too strict or too lax in terms of the time-seriousness he indicates for a given car, the car will be less likely to sell.

8.2.2 Results: Duration

An important channel for understanding seller benefits and costs due to bargaining is the time it takes for cars to sell under posted prices vs. the time it takes for cars to sell under bargaining (or through Best Offer in this case). I use survival analysis to study the time that a car takes to sell, or the wait time that the seller must undergo before a car sells. Similar to the previous section where I studied the likelihood of selling for a car, the independent variables of primary interest for this duration analysis are a seller's choice to use BO, the markup listed for that car, and the interaction of these two variables.

In order to use survival analysis, some general distributional assumptions must be made given the context of the data. In the data, the time period for which these cars are observed is a limited time period. That is, cars may get relisted later or the seller may sell them off-eBay, without the car being *observably* sold according to the data. However, I reason that most of these cars will eventually sell even if their selling is not directly observed or marked in this data. Therefore, I choose the Weibull distribution, which allows for monotonic duration dependency, allowing sufficient flexibility for this scenario. This implies that the duration distribution will either have positive duration dependency throughout, or negative duration dependency throughout. Either of these cases also allow for there being no duration dependency, in which case the Weibull distribution reduces to the exponential distribution. Note that positive duration dependency, in this case, would mean that perhaps cars are more likely to sell (i.e., probability of "hazard" increases) as the time period in which it did not sell increases and constant or no duration dependency implies that the probability of a car selling at any point is independent of how much time the car has already spent in the unsold state, i.e. duration is independent of the time that has already passed. The shape parameter, p, reported in Table 14 is greater than 1, and this confirms positive duration dependency, although since p is not drastically greater than 1, the data exhibits more signs of constant duration dependency. Therefore, the use of the Weibull distribution for the survival rate analysis seems appropriate, because Weibull allows for monotonic duration dependency, and the special case of Weibull is the constant duration dependency or the exponential distribution. I confirm the expected duration dependency and thereby the legitimacy of the use of the Weibull distribution using the non parametric estimation using the Kaplan Meier Curve in Figure 1[14].

[14] In addition, I use the Kaplan Meier graphs to address to some extent any distributional concerns that might arise for using the duration model in my analysis. That is, since the use of the duration model implicitly assumes that the censored and uncensored observations follow the same distribution, and the censoring in this data occurs based on whether or not a car sold, it is worth noticing the distribution patterns for cars that sold vs. for cars that did not sell. This cannot be observed in a straightforward manner because we only observe explicitly and completely the selling time duration for the cars that sol, and not for the cars that did not sell. Therefore, I instead study two categorical variables *known* to impact the probability of selling (according to the results of the previous section, presented in the

The results for the duration model are presented in the second column of Table 14. Note that for the duration analysis, the reported coefficients indicate whether a given independent variable increases the probability of hazard or failure (which in this case, is defined as the selling of a car), or decreases the probability of failure. That is, if the coefficient is positive, then the variable increases the probability of selling; meaning that the car is likely to sell faster. If the coefficient is negative, then the variable decreases the speed of reaching the hazard event, or, in this case, decreases the speed of selling.

When looking at the direct impact of BO, I find that at the average level of markup, using BO increases the time for selling a car by 7.4%. At the highest value for markup, I find that using BO increases the time for selling by 48.7%. At the lowest level of markup, using BO can reduce the time for selling by 167%. This indicates that in this given data, BO is negatively affecting the time taken for a car to sell. That is, using BO slows down the time for selling for the entire range of car markups in this data[15]. Using BO can only expedite the time needed for selling if the value of the markup is -0.262 or lower. That is, using BO can decrease the time for selling if the car is listed at a price that is 26.2% lower than the CarGuru's estimate, which could then be beneficial for the seller. Even if there existed cars in the data with such low markups (which is not the case in this given data), there would be yet another problem: its likelihood of selling would be lower, as shown in the previous section regarding low markup cars. Therefore, it seems that sellers are definitely not gaining any benefit from BO in terms of reduced duration for selling. Instead, they are incurring much higher wait time or time until a car sells due to their use of BO.

Furthermore, the results in Table 14 also allow for seeing some indirect channels of negative impact that BO can have. In order to understand the negative impact of BO, first consider the negative impact of a high markup on duration. That is, I find that a one standard deviation increase in the markup of a car leads to 36.7% longer time ((-0.476+(.84)*-.386)*.458) for selling the car (computed at the average level of BO usage). At the minimum value of BO (=0), i.e. if the car is listed under the posted price mechanism, a one standard deviation increase in markup leads to a an increased time for selling, by 21.8%. At the maximum value of BO (=1), i.e. if the car is listed under the BO mechanism, an increase in the markup takes a longer time to sell, by 39.4%. This indicates that using BO can add to the increase in time taken for selling a car with a high markup. Whereas, using a posted price mechanism decreases the time for selling a high markup car, by 17.6% (39.4-21.8=17.6). Note, though, that in either case, whether with BO or without BO, a higher markup increases the wait time or time until a car sells. Therefore, while later on, I will discuss the positive impacts of a high markup on transaction price, it will be important to keep in mind that it also can delay the time needed for sell. Furthermore, using BO makes this negative impact even worse, and this is important for truly understaning seller behavior with respect to BO. That is, while there are some benefits to using BO, there may be some harmful effects as well.

first column of Table 14, such as the mileage (high or low) of a car and whether a seller is a private seller. The idea here is to study whether these factors, known to impact the likelihood of selling, have differing distributions when it comes to duration for selling. If the distributions for the values of each of these variables differ, then there is clearly a different distribution for cars that sold and cars that did not sell, making survival analysis inappropriate for this analysis. As can be seen in Figure 3 and Figure 4, that while higher mileage increases the time for selling a car, and a private seller sells a car faster than a car dealer, the duration distributions do not differ along the values that these two variables take on. This alleviates some concerns that might arise regarding sold vs. unsold cars following vastly different distributions and the possible violation of the assumptions that make survival analysis appropriate for this paper.

[15] Figure 2 presents the non-parametric estimation using the Kaplan-Meier curve, whhich also confirms that the red graph (which represents BO listings) has higher probabilities of "survival," than the blue graph(which represents posted price listings). In this case, high probabilities of "survival" imply longer time in the market without being sold. Therefore, it can be seen using the non-parametric estimation as well that the time for selling a car increases when sellers use BO

As previously noted, there is no other study that has found any negative impact of BO on sellers. This result also complements the result from Part One of this paper, which shows that some sellers choose not to use Best Offer as they learn more. Perhaps they experience longer wait times for selling a car under BO than they would under posted prices, and therefore choose not to use BO.

The results for control variables for the duration analysis are similar to the results of the model that explains the selling likelihood of a car. That is, I find that a more expensive car, measured by *lnIMVby1000*, takes longer time to sell, a car with higher mileage takes longer time to sell, and a newer car model (in terms of model year) also takes longer time to sell. I also find that if a seller is too lax about the deposit time deadline, or if he mentions nothing with this regard, his car takes longer to sell. Perhaps this seller is actually in no rush to sell or perhaps buyers do not perceive him to be very serious, and therefore it takes longer time to sell this seller's car. These results are consistent with expectations, because these factors that slow down the selling of a car are also the ones that are likely to decrease demand for the cars. Therefore, as mentioned in the previous section, these factors make the car less likely to sell, and also slower to sell, as shown by the duration analysis. In addition, I find that a private seller's car sells much quicker than a dealer's car. This may be because a private seller has lower time cost than a dealer, and is therefore able to invest more time into selling the car quicker. Finally, I find that if a car is listed by a seller who is relatively more patient, measured by his relisting behavior or *Selleravgrelist*, then the car is likely to take a longer time to sell. This is consistent with the expectation that a patient seller is willing to wait for longer to sell his car, and therefore his car takes longer to sell.

8.2.3 Results: Transaction Price

I now discuss the impact of a seller's choice of BO, choice of markup, and the interaction of these two variables on the final transaction price of a car. The third column of Table 14 presents the results for explaining the impact of BO and markup on the transaction price. In particular, though, this column only presents the results for the tier 2 (Truncated Regression part) of the Cragg model. That is, the tier 1 (Probit part) of the Cragg model has been suppressed in the presentation of the results, because it does not differ much from the results presented in first column of Table 14. This is so because note that this first column of Table 14 is exactly the probit model that is run for the Cragg model tier 1, intended for explaining the probability of a car selling. Note that whether or not a car sold is the basis for identifying which observations are censored. Also, recall from the methodology section that the tier 2 results, the Truncated Regression that is, presents coefficients, which should be interpreted as effects that hold true, *conditioned* on a car being sold.

As can be seen in the third column of Table 14, I find that using BO *decreases* the transaction price by 5% (computed at the average level of markup), which may be a benefit to consumers, but can be considered to be a negative impact of using BO for sellers. At the highest value of markup, using BO increases the transaction price of a car by 5.3%, and at the lowest value of markup, using BO decreases the transaction price by 44% [16]. Furthermore note that a car's markup needs to be at least 0.13 or 13% in order for the use of BO to *increase* the transaction price of a car and prove beneficial for a seller.

The third column of Table 14 also shows that a one standard deviation increase in the markup of a car increases the transaction price of a car by 40.3%, conditioned on the car being sold (computed at the average value of BO in the sample). At the minimum value of BO (=0), i.e. when the car

[16] Note thus that BO decreases the transaction price of cars *more* for cars that have lower markups. This suggests that either sellers with higher markups might lose some bargaining power due to a low markup or that these cars have a much lower quality, where quality is the real determinant of lower bargaining power. This will be discussed more later.

is listed under the posted price mechanism, I find that a one standard deviation increase in the markup of a car leads to a higher transaction price by 33.9%. At the maximum value of BO(=1), i.e. when the car is listed under BO, an increase in markup leads to a 41.9% higher transaction price. This implies that using BO can increase the positive impact of the markup on transaction price, by 8% (41.9-33.9=8). That is, if a car is listed under BO, then conditioned on the car being sold, increasing the markup of that car is likely to increase the transaction price by 8% more than if the car was listed under the posted price mechanism. This represents the indirect channel of benefit that sellers can reap using BO by adding on BO benefits onto the benefits they incur from a higher markup.

With respect to the control variables, I find that as the IMV, the retail estimate of the car from CarGuru.com, increases, the transaction price of the car also increases. The elasticity of transaction price with respect to the IMV is equal to 1.02. Therefore, while somewhat higher on eBay, the transaction price of a car goes hand-in-hand with the CarGuru estimate for the car. I also find that if a car is older, in terms of mileage, then it sells for a lower transaction price. Again, surprisingly, if the car is newer by year, I would expect for it to sell for a higher transaction price, but it instead sells for a lower transaction price, conditioned on being sold. However, it seems that the demand for newer cars might be lower on eBay vs. off-eBay, as would be consistent with other results discussed in this paper regarding the variable that measures the newness of a car in terms of model year. Finally, conditioned on being sold, a car that has no time deadline for the deposit requirement sells for a higher transaction price, conditioned on there being a sale. Interestingly, this result shows that despite the fact that these factors decrease the probability of sale, conditioned on selling, this variable can increase the transaction price [17]. Perhaps these sellers are, in fact, able to extract a higher transaction price because they are more lax or patient regarding the deposit deadline.

9 Robustness Checks

For robustness of the first part of the paper, I drop sellers who were selling rare cars (i.e. cars that made up less than 0.5% of either the 2013 sample or the 2016 sample) to check if the primary results of the paper might be driven by rare/extreme/collectible cars. As can be seen in Table 12, primary results from 2013 and 2016 both remain unaffected when sellers of rare cars are dropped from the sample.

I also run an alternate specification, shown in Table 13, which includes the BO revision variable in the specification, in addition to the general revisions variable used in other specifications. I do this to check if it might be revisions/learning specific to BO (vs. general learning) that impact a seller's choice to adopt BO. I find that general learning/revisions and BO-specific learning/revisions *both* have a negative impact on usage of BO in 2016, and that neither have an impact in 2013. This confirms that sellers that revise more often, and therefore learn more, generally and specifically regarding BO, tend to revise their listings against using BO. This confirms that it is not just that sellers learn more and therefore do not use BO, but that there is something that they learn regarding BO, which makes them not use BO. However, it is not until the evidence provided in the second part of the paper that we learn *why* sellers choose not to use BO.

[17] Note that the advantage of the Cragg model is that it allows for differing impacts of the variables in the two parts of the analysis. For instance, while a higher markup has a negative impact on the probability of selling, its impact on transaction price (conditioned on a non-zero transaction price) is positive. In addition, while a seller's lack of mentioning the deposit time period or asking for the deposit to be submitted immediately decrease the probability of selling, these variables have no impact on the transaction price of a car. These differences for each part of the process, selling and transaction price, would be confounded if the Tobit model were used instead.

I run four main robustness checks for the second part of the paper. Firstly, since the main analysis of this paper is conducted at the item-level, it is possible that errors might be clustered by seller. Furthermore, errors might also be clustered by Make, Model, and state if the likelihood of selling follows similar trends within a particular make, model, and state. Therefore, I run the model for predicting the variable *sold*, presented in the first column of Table 14, with errors clustered by the seller, car make Car Model, and the state that the car is listed in. As can be seen in Table 15, the results are exactly identical to the primary results presented in Table 14, indicating that the model is robust to the clustering.

The next three robustness checks are conducted simultaneously. Since one of the contributions of this paper is to study the specification that includes the interaction term of markup and BO, *Markup*BO*, I run some alternate specifications of the model, in which I exclude either the BO variable or the interaction term in order to see how the results might change. I also include/exclude some other variables to study which specification is more preferred for the primary results. Finally, I run these specifications on a dataset that does not include rare/collectible cars. That is, I drop the cars that made up less than 0.5% of the sample for the data collected in 2013 or in 2016, since these cars might be luxury or collectible cars that might behave differently than all other cars. Running these analyses again on a dataset that does not include these cars would confirm that results are not driven by these rare cars.

As can be seen in Table 16, column(5) (which includes the interaction term in the specification), the primary results are not different than the results presented in Table 14. Therefore, it does not seem to be the case that collectible or rare cars were driving the main results presented in Table 14.

Now consider the specifications in column (1), (2), and (3) of Table 16. While column (1) excludes both the BO variable and the interaction term, column (2) specification includes the BO variable, but excludes the interaction term. Finally column (3) includes all three variables of interest, as is preferred. Note that most of the variables in these three columns have similar coefficients and similar statistical significance as the primary results presented in Table 14. However, the statistical significance of BO fluctuates across these three specifications. Note that inclusion of the BO variable in column (2)'s specification does not change the magnitude for the markup variable much, but it does indicate that BO variable is statistically significant, and has a negative impact on the likelihood of sale. That is, using BO can reduce the probability of selling. The BO variable, however, loses statistical significance when the interaction term for the variable is included in column (3). That is, whenever the interaction term is included in the model, the BO variable becomes statistically insignificant, while the interaction term remains statistically significant with a positive sign. This implies that not including the interaction term in the specification can give incomplete results regarding BO. As discussed earlier with respect to the impact of BO on the likelihood of selling, it is not the case that BO uniformly reduces the likelihood of sale or uniformly increases the likelihood of sale. Instead, for high levels of markup, using BO increases the likelihood of sale, while for lower levels of markup, BO decreases the likelihood of sale. This result would not have been captured if the interaction term between markup and BO was not included in the specification. Therefore, the preferred specification is the specification presented earlier: the one that includes all three variables: markup, BO, and markup*BO.

Finally, since I do not include Car Model fixed effects (model dummies) in this paper, in order to ensure that unobserved model characteristics are not driving the main results regarding the probability of selling, I used the variable *ModelavgIMVby1000*, which is the average IMV in the sample for all cars of the same model. When this variable was not statistically significant in any of the specifications form (1) - (3), I checked to see if dividing this variable along the lines of old and new would make a difference. That is, I used the variable *ModelavgIMVbynewoldby1000*, which inputs a different value for a car of the same model depending on whether the mileage on the car exceeds 500 (old car) or not (new car). As can be seen, replacing *ModelavgIMVby1000* with *ModelavgIMVbynewoldby1000* does not change anything. Thus, it seems that controlling for the value of each unique car specifically (which accounts for the model within it), using the variable *lnIMVby1000*, is sufficient, since *lnIMVby1000* is statistically significant. Therefore, the results of the model explaining the probability of selling are not driven by unobserved model characteristics.

10 Conclusions

I considered two questions in this paper: who chooses to bargain and how bargaining affects seller profits. With respect to the first question, during 2013, increased competition by car make deterred a seller from bargaining, whereas increased competition by city inclined a seller to bargain. This result regarding increased city competition is consistent with the insight from Wang (1995) that bargaining is more likely to be adopted when a seller wants to increase the rate of buyer arrival. It is also consistent with Bester (1993), because higher competition weakens sellers' bargaining power, and according to Bester (1993), sellers are more likely to bargain when they have weaker bargaining power. However, the result regarding competition by car make is not consistent with Bester (1993). It is instead aligned with the expectation that in markets with higher competition, there is greater information regarding the product and its pricing, making price dispersion and bargaining less likely. It is thus important to distinguish between the different types of competition, and empirical work highlights which theory is more relevant for the different cases. With regard to the insight of Bester (1993), it seems that competition by city weakens a seller's bargaining power more than competition by make does, making a seller likely to bargain. This might be because the geographic market takes higher precedence than the market by car make (which does not account for the location of cars) in terms of weakening bargaining power. This might be because sellers and buyers both prefer transacting in their geographical neighborhood (rather than within a given Make) for large transactions, such as in the case of automobiles, making higher *geographic* competition a stronger source of weakening bargaining power for sellers than competition by car make. Unfortunately, the 2016 data does not yield much insight on the impact of competition on bargaining, preventing a robustness check on these results. Using the 2016 data, I find that there is no impact of competition variables on the seller's choice to bargain.[18],[19]. Further empirical work regarding competition of different types in the context of bargaining is desirable for more

[18]It is possible that competition variables are not statistically significant in the 2016 data due to a few differences in data collection between 2013 and 2016. That is, selection of specific makes and the glitches in extraction, that caused the geographic representation of the data to be skewed towards listings closer to Florida, (as mentioned in the data section) may have led to an imperfect representation of the eBay market in terms of the city and make competition, contaminating the competition variables in 2016. However, my dissertation (Gujral, 2016) presents means tests that show that there are indeed other differences between 2013 and 2016, especially related to sellers' revision behavior and markups/pricing behavior, that might also explain the change in results observed from 2013 and 2016. With the rapid pace of change that is possible due to internet and e-commerce, this observable difference from 2013 to 2016 is a finding worth noting.

[19]I also used a variable, competition by Make on eBay Motors (in general); that is, this alternate competition variable did not represent the competition *within* the sample of observations (as is the case with the current competition measure used). Rather, this variable measured the competition by Make on eBay Motors by counting the number of all cars (not just the ones in my sample) for each make that were listed on eBay on a given day. I also did not find any impact of competition using this alternate competition variable. However, this measure was collected about 10 days after the collection of the completed listings used for the sample. So, it is possible that the time period of the listings in the sample did not match this competition variable very well; especially if the eBay car market competition changes very rapidly. Further exploration of competition variables on eBay would enhance the understanding for the 2016 results

conclusive insights. In addition, more long-term empirical studies on eBay Best Offer would help determine how robust these results are[20]. I now discuss the impact of seller patience, a source of high bargaining power, on the adoption of Best Offer by sellers. During the 2013 period, higher patience inclined a seller to choose bargaining when faced with higher competition (both in terms of car make and in terms of city) and disinclined a seller to choose bargaining when faced with lower competition. This is consistent with the theoretical insights of Bester (1993) which suggest that bargaining occurs in equilibrium when sellers have lower bargaining power. This is because when faced with higher competition in the market, a seller's high bargaining power due to patience is weakened; inclining even sellers with high patience to bargain. During the 2016 period as well, higher patience disinclined a seller from choosing bargaining (again consistent with Bester (1993)), and as mentioned earlier, competition variables did not have an impact on sellers' choice of using bargaining at all in 2016. Therefore, the result regarding the negative impact of seller patience on the adoption of Best Offer is robust across both years of study.

Note that these results could be true specifically for "eBay Best Offer" type of bargaining. That is, perhaps weaker sellers bargain through the "Best Offer" signal on eBay, whereas stronger bargainers may be bargaining *off*-eBay and keeping their price/markup high on eBay. Keeping a high markup on eBay may serve as another type of bargaining strategy (for *off*-eBay transactions). That is, a seller might attempt to misrepresent his valuation for a car *on* eBay in order to be a stronger bargainer for a possible off-ebay bargaining game. This is reasonable, especially in the car market setting, because the sellers may have a general understanding that a negotiation (on or off-eBay) may ensue regardless of whether the seller indicates his willingness to negotiate through the Best Offer signal on eBay. That is, the line between bargaining vs. posted prices may not, in its entirety, be determined by a seller's use of Best Offer alone. There might be some sellers that are willing to bargain but do not indicate this using the Best Offer feature. Nevertheless, Best Offer still serves to distinguish the sellers who are in fact *signaling* their willingness to negotiate. A strong bargainer may not openly signal his willingness to bargain vs. those who are not. For instance, a patient seller may be exercising his patience and bargaining power in *not* indicating his willingness to negotiate, and may bargain off-eBay anyway [21]. This notion is supported in my dissertation, Gujral (2016), where I show that a more patient seller also charges a higher markup/price than a less patient seller and is more likely to choose posted prices over bargaining. Furthermore, sellers with higher markups tend to provide *lower* discount rates under bargaining, signaling that high markups increase a seller's bargaining strength. Therefore, while this data only allows for observing on-eBay bargaining, if high markups really do give sellers high bargaining power, then the sellers using the posted prices method on eBay would have even *higher* bargaining power because they also charge higher markups than sellers that use Best Offer. That is, not only do sellers with exogenously high bargaining power choose posted prices, but that they can leverage this strength further by also choosing to list a higher markup and negotiating hard during a possible *off*-eBay bargaining game. Therefore, perhaps the conclusion that higher bargaining power inclines a seller to choose posted prices, while lower bargaining power inclines a seller to choose bargaining is limited to Best Offer-specific bargaining. More bargaining studies that observe both on and off-eBay bargaining behavior would provide more insights into generalizable bargaining behavior.

The results of this paper also highlight the primary determinants of a bargaining platform. Apart from low bargaining power, this paper also finds that if sellers are less experienced or have

[20] When comparing 2013 and 2016 results, there are three primary sources for reconciling differing results: inter-sample individual differences, data collection differences, and behavior changes over time. Further long-term empirical analyses would help disentangle whether behavior changes over time that are causing these differences, and would thus provide more insight into long-term dynamics of bargaining in competitive markets

[21] To know whether this is true off-eBay, more research is needed for off-eBay bargaining.

less knowledge about the valuation of the product or about the valuations of the other agents, bargaining is more likely to occur (consistent with Wang (1995) and Perry (1986)) . Interestingly though, while sellers with more information and more knowledge tend not to choose bargaining, it is not the case that bargaining declines over time, in general, on eBay Motors. This might be because there are continually new entrants in the eBay Motors market, who are unexperiecned and are trying to gather information regarding the market and the valuations of the car(s) they sell. Therefore, bargaining may be more likely to occur in markets that regularly witness new entrants or used goods. While some of these findings were predicted by theoretical insights, this paper helps in identifying which theoretical insights hold more weight in the context of eBay Best Offer and sheds light on the actual dynamics of the market.

With respect to the question, how Best Offer affects profits, I studied the impact of markup, BO, and the interaction of these two on a car's likelihood of selling, on the time it takes for a car to sell, and on the transaction price of the car. I find that using BO increases the likelihood of sale only for cars with sufficiently high markups, and that BO *decreases* the likelihood of sale for cars with lower markups. Similarly (yet at a different threshold of markup), I also find that using BO increases the transaction price for cars with sufficiently high markups, and decreases the transaction price for cars with lower markups. Clearly, a high markup is beneficial for sellers because it can both increase the likelihood of sale and the transaction price of the car. Hence, BO has some additional indirect benefits, which allow sellers to reap the benefits of a high markup. That is, while a high markup is found to increase the transaction price of a car, conditioned on the car selling, it can also *reduce* the likelihood of a car selling. However, comparing the situation of a high markup being used with BO vs. a high markup being used with fixed prices, using BO mitigates the loss in sales due to a higher markup by a substantial 29%. This helps sellers reap the benefits of a high markup on the ultimate transaction price of a car (i.e., an increase of 40.3%), while substantially mitigating the negative impact of a high markup on sales. Furthermore, note that while markup increases the transaction price of a car, regardless of whether the car is listed under BO or under posted price mechanism, this positive effect of markup on the transaction price is even greater for cars listed under BO. That is, a high markup car under BO yields an 8% higher transaction price than a high markup car under the posted price method. While not included in this paper, I also test whether among bargaining sellers, sellers with higher markups exhibit bargaining strength. That is, I study the nature of discount provided by bargaining sellers during a negotiation, and whether a high markup impacts the discount rate for a given transaction. I find that a one standard deviation increase in a car's markup leads to a lower 2.3% lower discount provided by the seller for that car, conditioned on a car being sold, indicating that a higher markup likely gives sellers bargaining power that helps extract a higher transaction price.

A high markup is clearly beneficial for sellers, and thus deserves further examination. As discussed in more detail in my dissertation, Gujral (2016), a seller may charge a higher markup for a variety of reasons. One reason for charging a higher markup is to signal to buyers that the car is of a higher quality , since car quality is not observable merely through an online listing. Or, it could also be that a higher markup may be a form of "cheap talk," where a seller tries to signal that a car is of high value, but it may not really be the case. This "cheap talk" mechanism is similar to the one explained in Croson et al. (2003), which allows for the markup on an item to be conceived as the pie of surplus to be shared between the consumer and the seller. That is, the size of the surplus "pie" in this case is likely known most closely by the seller who lists an asking price for the car, and the buyer would not know the size of the surplus that needs to divided if a bargaining game were to ensue. It is plausible then that sellers that list a higher markup may be lying regarding the implied value of the car. Experimental studies have argued that "cheap talk" of this sort can be advantageous. Another type of "cheap talk" or reason for charging a higher markup is if a seller is truly uninformed about the value of an item and does not want to undervalue it with a low listed markup. Therefore, while a seller may indeed be using a higher markup to signal higher quality, he may also be lying in order to reap the benefits of imperfect information regarding the product (and this is especially true for the case of used cars). The data and analysis of this paper cannot clearly determine if a higher markup on a car indicates a higher quality car or if a higher markup is merely a strategy by the seller to *signal* higher quality, whether this signal is actually true or not. However, buyers' behavior on eBay, indicated by the selling success of high markup cars seems to indicate that buyers might perceive (whether rightfully or wrongly) a car with a higher markup to be of a higher quality than a car with a lower markup. Nevertheless, as discussed earlier using Table 2 and Table 3, it may be that sellers using lower markups with BO might be trying to sell a lower quality car for a higher price, and therefore buyers are perceiving and behaving reasonably. That is, the success of high markup cars on eBay Motors and the negative outcomes of low markup cars, whether being sold under posted prices or under BO, suggests that perhaps buyers are able to understand this quality signal. In my dissertation, Gujral (2016), I explore a seller's markup strategy more closely for traces of possible cheating on the seller's part, and I do not find evidence that low quality cars are being sold as high quality using eBay Best Offer. This is similar to the results of Huston and Spencer (2002), who studied collectibles on eBay, and Adams et al. (2006), who studied Chevrolet Corvettes on eBay Motors, who also do not find a "lemons problem (Akerlof, 1995)" (where low quality cars are being sold for higher prices) on eBay. Nevertheless, the strategic use of markups by sellers in the context of eBay Motors deserves more attention in future work given its substantial impact and interesting dynamics as evidenced by this paper.

References

C. Adams, L. Hosken, and Ya-Ting Newberry, P. Yu. Vettes and lemons on ebay. Social Science Research Network Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=880780, 2006.

George Akerlof. The market for lemons: Quality uncertainty and the market mechanism. In *Essential Readings in Economics*, pages 175–188. Springer, 1995.

Steven T Anderson, Daniel Friedman, Garrett H Milam, and Nirvikar Singh. Buy it now: A hybrid internet market institution. *UC Santa Cruz Economics Working Paper*, (565), 2004.

T. Andrews and C. Benzing. The determinants of price in internet auctions of used cars. *Atlantic Economic Journal*, 35, 2007.

Matthew Backus, Tom Blake, and Steven Tadelis. Cheap talk, round numbers, and the economics of negotiation. Technical report, National Bureau of Economic Research, 2015.

A. J.. Berensky. Can we talk? self-presentation and the survey response. *Political Psychology*, 2004.

Helmut Bester. Bargaining versus price competition in markets with quality uncertainty. *The American Economic Review*, 83(1):278–288, 1993.

Y. Bing. Pricing for bargaining? Toulouse School of Economics, May 21, Summer School 2009, 2009.

S. Blount and G. A. Janicik. When plans change: Examining how people evaluate timing changes in work organizations. *Academy of Management Review*, 2001.

Luis Cabral and Ali Hortacsu. The dynamics of seller reputation: Theory and evidence from ebay. Technical report, National Bureau of Economic Research, 2004.

Jong-Rong Chen, Ching-I Huang, and Chiu-Yu Lee. First offers on ebay motors. *First Offers on Ebay Motors (September 23, 2009)*, 2009.

Kong-Pin Chen, Han Yong, Chia-Ching Lin, and Ya-Ting Yu. Bargaining versus posted-price: Evidence from ebay motors. Social Science Research Network Working Paper, http://ssrn.com/abstract=2758262 or http://dx.doi.org/10.2139/ssrn.2758262, 2016.

Rachel Croson, Terry Boles, and J Keith Murnighan. Cheap talk in bargaining experiments: lying and threats in ultimatum games. *Journal of Economic Behavior & Organization*, 51(2):143–159, 2003.

Simona Despa. What is survival analysis. *Cornell University Statistical Consulting Unit*, 2010.

Kenneth C Dudley. *Empirical development of a scale of patience.* PhD thesis, West Virginia University, 2003.

Liran Einav, Chiara Farronato, Jonathan D Levin, and Neel Sundaresan. Sales mechanisms in online markets: What happened to internet auctions? Technical report, National Bureau of Economic Research, 2013.

James H Fowler and Cindy D Kam. Patience as a political virtue: Delayed gratification and turnout. *Political Behavior*, 28(2):113–128, 2006.

Kritee Gujral. Bargaining vs. posted prices: an analysis using the ebay automobile market. University of Florida Dissertation, http://economics.clas.ufl.edu/people/current-phds/job-market/, 2016.

Ching-I Huang, Jong-Rong Chen, and Chiu-Yu Lee. Buyer behavior under the best offer mechanism: A theoretical model and empirical evidence from ebay motors. *Journal of Economic Behavior & Organization*, 94:11–33, 2013.

John H Huston and Roger W Spencer. Quality, uncertainty and the internet: the market for cyber lemons. *The American Economist*, 46(1):50–60, 2002.

Ani L Katchova and Mario J Miranda. Two-step econometric estimation of farm characteristics affecting marketing contract decisions. *American Journal of Agricultural Economics*, 86(1):88–102, 2004.

I Kiyingi, A Edriss, M Phiri, M Buyinza, and H Agaba. Adoption of on-farm plantation forestry by smallholder farmers in uganda. *Journal of Sustainable Development*, 9(2):153, 2016.

Erin L Krupka and Rachel TA Croson. The differential impact of social norms cues on charitable contributions. *Journal of Economic Behavior & Organization*, 2016.

M. J. Osborne and A. Rubinstein. *Bargaining and Markets.* Academic Press, Inc., 1990.

Motty Perry. An example of price formation in bilateral situations: A bargaining model with incomplete information. *Econometrica: Journal of the Econometric Society*, pages 313–321, 1986.

John Riley and Richard Zeckhauser. Optimal selling strategies: When to haggle, when to hold firm. *The Quarterly Journal of Economics*, pages 267–289, 1983.

Christian Terwiesch, Sergei Savin, and Il-Horn Hann. Online haggling at a name-your-own-price retailer: Theory and application. *Management Science*, 51(3):339–351, 2005.

Kerem Yener Toklu. Structural analysis of the" best offer" mechanism on ebay. 2014.

Amos Tversky and Eldar Shafir. Choice under conflict: The dynamics of deferred decision. *Psychological science*, 3(6):358–361, 1992.

Ruqu Wang. Bargaining versus posted-price selling. *European Economic Review*, 39(9):1747–1764, 1995.

Jeffrey M Wooldridge. *Econometric analysis of cross section and panel data*. MIT press, 2010.

11 Figures and Tables

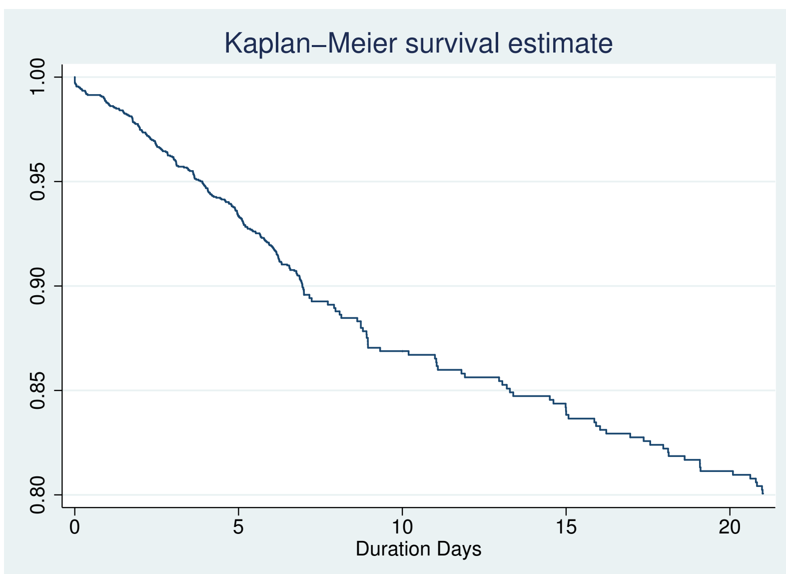

Figure 1: Survival (or not selling) probabilities for all cars

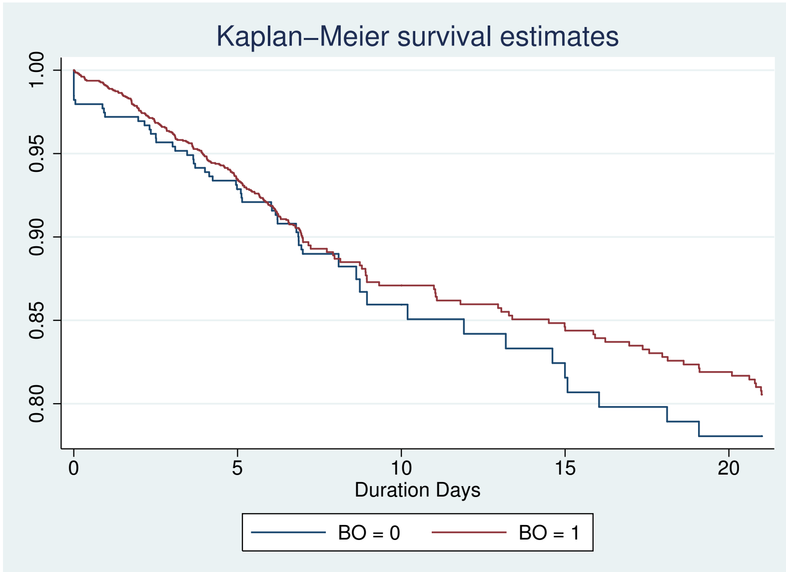

Figure 2: Survival (or not selling) probabilities for BO vs. non-BO cars

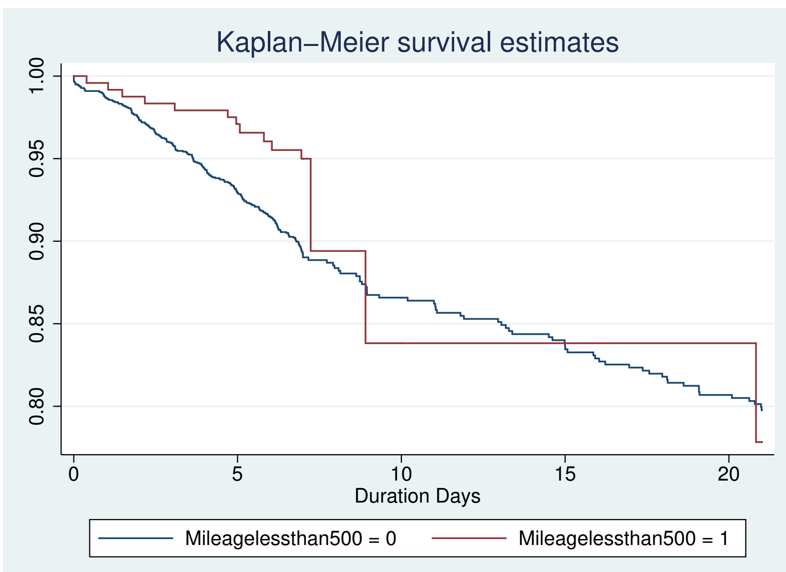

Figure 3: Survival (or not selling) probabilities for new/young cars vs. old cars

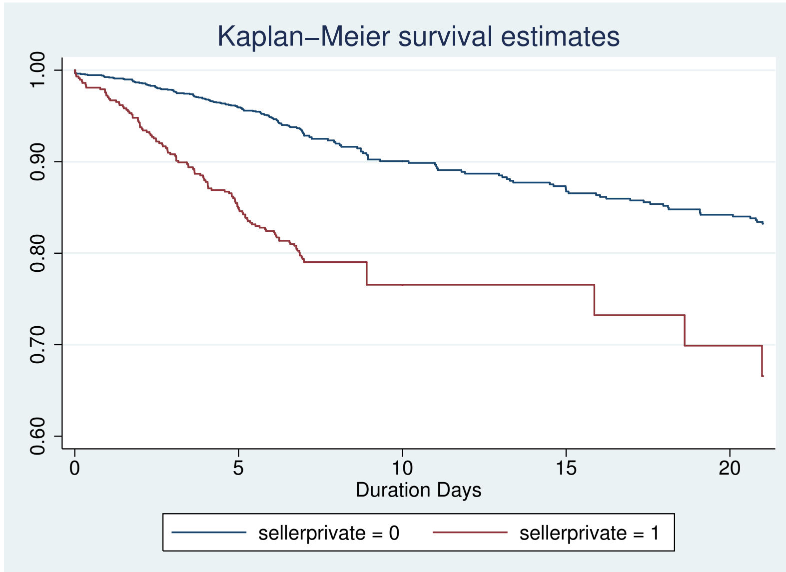

Figure 4: Survival (or not Selling) probabilities for private seller Cars vs. cars by a dealer

Table 1: Hypotheses and Variables

Bargaining vs. Posted Price Theory	**Variable (Expected Sign)**
Seller patience is used for signaling high valuation for an item; lending bargaining power during a negotiation (Bing, 2009), but in equilibrium, it may be sellers with lower bargaining power that choose to bargain (Bester, 1993)	Selleravgrelist (?)
If a seller is patient and faces high competition, then he has higher bargaining power through patience, but relatively lower bargaining power due to higher competition (Bester, 1993).	competitcity*relist (?)
	competitmake*relist (?)
Low time cost for the seller is the real source of bargaining power (Bing, 2009).	sellerprivate(+)
	SelleravgQA(+)
	sellerlistingsN(-)
	Selleravgunavailable(-)
Lack of knowledge regarding buyers' valuations in the market may lead to choice of bargaining (Relaxation of Perry's (1986) assumption).	sellerprivate(+)
	SelleravgMileage(+)
	SelleravgYear(-)
	Selleravgrevisionstotal(-)
	sellerprivate(+)
	countmakeSeller(-)
	countcitySeller(-)
	Feedback Score(-)
Lack of knowledge regarding a seller's time costs in the market may lead to choice of bargaining (Relaxation of Perry (1986)'s assumption).	Selleravgrevisionstotal(-)
	sellerprivate(+)
	countmakeSeller(-)
	countcitySeller(-)
	Feedback Score(-)
Lack of knowledge regarding buyers' time costs in the market may lead to choice of bargaining (Relaxation of Perry (1986)'s assumption).	Selleravgrevisionstotal(-)
	sellerprivate(+)
	countmakeSeller(-)
	countcitySeller(-)
	Feedback Score(-)

Table 1: Hypotheses and Variables (Table Continued)

Bargaining vs. Posted Price Theory	**Variable (Expected Sign)**
Lack of knowledge regarding sellers' valuations in the market may lead to choice of bargaining (Relaxation of Perry (1986)'s assumption).	Selleravgrevisionstotal(-) sellerprivate(+) countmakeSeller(-) countcitySeller(-) Feedback Score(-)
A higher ability to commit (or higher reputation) leads to lower bargaining usage (Riley and Zeckhauser, 1983)	Positive Feedback Percent (-)
Higher number of items to sell leads to choosing posted price over bargaining (Wang, 1995).	sellerlistingsN (-)
If a seller has more outside options, then he has higher bargaining power.	Selleravgunavailable (?)
If a seller has more outside options and faces high competition then he has higher bargaining power.	competitcity*unavailable (?) competitmake*unavailable (?)

Table 2: Possibilities for Seller Markup and BO Strategy when Buyers are Perfectly Informed

Seller believes that buyers are well-informed.			
	Patient	**Impatient**	**Very Impatient**
Informed	High Markup	High Markup	?
	No BO	BO	BO
Uninformed	*High Markup*	Low Markup	Low Markup
	BO	BO	BO
High Quality Product			
	Patient	**Impatient**	**Very Impatient**
Informed	Low Markup	Low Markup	Low Markup
	No BO	BO	BO
Uninformed	*High Markup*	Low Markup	Low Markup
	BO	BO	BO
Low Quality Product			

Each cell indicates the possible choice of markup and BO that a seller will choose given his patience level, knowledge regarding the value of his product, and whether his product is of high or low quality.
The italicized text is indicative of cases in which the seller is likely to misrepresent the value/quality of his product.
The "?" represents ambiguity regarding the action that a seller will take.

Table 3: Possibilities for Seller Markup and BO Strategy when Buyers are Not Well-Informed

	Seller believes that many buyers are not well-informed.		
	Patient	**Impatient**	**Very Impatient**
Informed	High Markup	High Markup	?
	BO	BO	BO
Uninformed	*High Markup*	Low Markup	Low Markup
	BO	BO	BO
		High Quality Product	
	Patient	**Impatient**	**Very Impatient**
Informed	*High Markup*	*High Markup*	?
	No BO	*BO*	BO
Uninformed	*High Markup*	Low Markup	Low Markup
	BO	BO	BO
		Low Quality Product	

Each cell indicates the possible choice of markup and BO that a seller will choose given his patience level, knowledge regarding the value of his product, and whether his product is of high or low quality.
The italicized text is indicative of cases in which the seller is likely to misrepresent the value/quality of his product.
The "?" represents ambiguity regarding the action that a seller will take.

Table 4: Item-Level Summary Statistics for 2016

Variable	**Obs.**	**Mean**	**SD**	**Min**	**Max**
sold	2497	0.123	0.328	0.0	1.0
durationdays	2497	9.266	5.816	0.0	21.0
transactprice	2497	1768.507	7591.415	0.0	159649.0
priceprem	2497	-0.069	0.458	-4.6	1.0
BO	2497	0.839	0.367	0.0	1.0
priceprem*BO	2497	-0.052	0.416	-4.4	1.0
IMVby1000	2497	30.263	29.519	0.2	336.5
Mileageby1000	2497	56.046	50.178	0.0	401.0
Year	2497	2010.274	4.193	1986.0	2016.0
sellerprivate	2497	0.243	0.429	0.0	1.0
deposit=48 hours	2497	0.090	0.286	0.0	1.0
deposit=72 hours	2497	0.004	0.063	0.0	1.0
deposit=immediately	2497	0.485	0.500	0.0	1.0
deposit=none mentioned	2497	0.336	0.472	0.0	1.0
itemcountstateby100	2497	5.893	5.298	0.0	14.0
itemcountmakeby100	2497	3.392	2.734	0.0	8.8

Table 5: Item-Level Summary Statistics for 2013

Variable	Obs.	Mean	SD	Min	Max
priceprem	896	0.104	0.466	-1	4
priceprem*BO	896	0.072	0.377	-1	3
BO	1107	0.824	0.381	0	1
IMVby1000	897	25.501	26.329	4	245
lnIMVby1000	897	2.958	0.705	1	6
Mileageby1000	1105	67.333	56.581	0	369
Year	1105	2006.368	5.978	1983	2014
sellerprivate	1107	0.299	0.458	0	1

Table 6: Seller-Level Summary Statistics for 2016

Variable	Obs.	Mean	SD	Min	Max
Selleravgpriceprem	1853	-0.107	0.540	-5	1
BOperlisting	1861	0.829	0.371	0	1
SelleravgBOrevsunscale	1861	0.029	0.168	0	2
Selleravgrelist	1861	0.378	0.465	0	1
SelleravgBINrevsunscale	1861	0.215	0.510	0	4
Selleravgrevisions	1861	0.278	0.928	0	9
sellerprivate	1665	0.563	0.496	0	1
PositiveFeedbackPercent	1586	99.165	4.386	33	100
Feedbackscoreby1000	1861	0.439	2.620	-0	96
sellerlistingsN	1861	2.585	9.956	1	298
repeatsellertag	1861	0.071	0.258	0	1
countcitySeller	1861	8.662	15.331	1	78
countmakeSeller	1861	129.557	94.954	1	326

Table 7: Seller-Level Summary Statistics for 2013

Variable	Obs.	Mean	SD	Min	Max
Selleravgpriceprem	450	-0.054	0.446	-3	1
BOperlisting	450	0.826	0.370	0	1
SelleravgBOrevsunscale	450	0.017	0.125	0	1
Selleravgrelist	450	0.190	0.357	0	1
SelleravgBINrevsunscale	450	0.139	0.454	0	4
Selleravgrevisions	450	0.679	1.817	0	15
sellerprivate	392	0.260	0.439	0	1
PositiveFeedbackPercent	434	94.648	20.974	0	100
Feedbackscoreby1000	448	0.579	3.202	0	65
sellerlistingsN	450	2.296	4.571	1	85
repeatsellertag	450	0.264	0.442	0	1
countcitySeller	450	7.553	11.093	1	44
countmakeSeller	443	54.271	47.943	5	139

Table 8: Summary Statistics: Sold Model

Variable	**Obs.**	**Mean**	**SD**	**Min**	**Max**
sold	2497	0.123	0.328	0.0	1.0
durationdays	2497	9.266	5.816	0.0	21.0
discountratio	2497	0.008	0.034	0.0	0.4
lntransact	2497	1.123	3.026	0.0	12.0
transactprice	2497	1768.507	7591.415	0.0	159649.0
priceprem	2497	-0.069	0.458	-4.6	1.0
BO	2497	0.839	0.367	0.0	1.0
priceprem*BO	2497	-0.052	0.416	-4.4	1.0
Selleravgrevisions	2497	0.182	0.691	0.0	7.0
Selleravgrelist	2455	0.358	0.408	0.0	1.0
IMVby1000	2497	30.263	29.519	0.2	336.5
Mileageby1000	2497	56.046	50.178	0.0	401.0
Year	2497	2010.274	4.193	1986.0	2016.0
sellerprivate	2497	0.243	0.429	0.0	1.0
deposit=48 hours	2497	0.090	0.286	0.0	1.0
deposit=72 hours	2497	0.004	0.063	0.0	1.0
deposit=immediately	2497	0.485	0.500	0.0	1.0
deposit=none mentioned	2497	0.336	0.472	0.0	1.0
itemcountstateby100	2497	5.893	5.298	0.0	14.0
itemcountmakeby100	2497	3.392	2.734	0.0	8.8
PositiveFeedbackPercent	2497	98.940	4.640	33.3	100.0
Feedbackscoreby1000	2497	1.321	5.105	0.0	95.5
ModelavgIMVbnewold1000	2497	30.371	25.098	0.2	336.5

Table 9: Summary Statistics: Duration Model

Variable	**Obs.**	**Mean**	**SD**	**Min**	**Max**
sold	2452.000	0.124	0.329	0.0	1.0
durationdays	2452.000	9.290	5.828	0.0	21.0
discountratio	2452.000	0.008	0.034	0.0	0.4
lntransact	2452.000	1.132	3.035	0.0	12.0
transactprice	2452.000	1777.440	7629.596	0.0	159649.0
priceprem	2452.000	-0.069	0.458	-4.6	1.0
BO	2452.000	0.840	0.367	0.0	1.0
priceprem*BO	2452.000	-0.052	0.416	-4.4	1.0
Selleravgrevisions	2452.000	0.182	0.692	0.0	7.0
Selleravgrelist	2452.000	0.357	0.408	0.0	1.0
IMVby1000	2452.000	30.478	29.684	0.2	336.5
Mileageby1000	2452.000	55.830	50.224	0.0	401.0
Year	2452.000	2010.306	4.182	1986.0	2016.0
sellerprivate	2452.000	0.235	0.424	0.0	1.0
deposit=48 hours	2452.000	0.088	0.283	0.0	1.0
deposit=72 hours	2452.000	0.004	0.064	0.0	1.0
deposit=immediately	2452.000	0.488	0.500	0.0	1.0
deposit=none mentioned	2452.000	0.335	0.472	0.0	1.0
itemcountstateby100	2452.000	5.927	5.298	0.0	14.0
itemcountmakeby100	2452.000	3.366	2.717	0.0	8.8
PositiveFeedbackPercent	2452.000	98.930	4.671	33.3	100.0
Feedbackscoreby1000	2452.000	1.329	5.140	0.0	95.5
ModelavgIMVnewold1000	2452.000	30.514	25.256	0.2	336.5

Table 10: Summary Statistics: Transaction Price Model, for non-zero Transaction Price

Variable	**Obs.**	**Mean**	**SD**	**Min**	**Max**
sold	305	1.000	0.000	1.0	1.0
durationdays	305	5.529	4.648	0.0	21.0
discountratio	305	0.063	0.076	0.0	0.4
lntransact	305	9.196	0.855	6.8	12.0
transactprice	305	14478.566	16986.478	900.0	159649.0
priceprem	305	-0.409	0.858	-4.6	0.7
BO	305	0.810	0.393	0.0	1.0
priceprem*BO	305	-0.306	0.759	-4.4	0.7
Selleravgrevisions	305	0.280	0.806	0.0	5.0
Selleravgrelist	305	0.135	0.256	0.0	0.9
IMVby1000	305	16.659	16.118	4.7	165.6
Mileageby1000	305	82.996	54.496	0.0	260.0
Year	305	2007.761	4.039	1994.0	2016.0
drivertrain1	245	0.457	0.499	0.0	1.0
drivertrain2	245	0.273	0.447	0.0	1.0
drivertrain3	245	0.269	0.445	0.0	1.0
cylinders	300	6.190	1.692	3.0	12.0
EngineVolumeLiters	292	3.652	1.353	1.0	8.0
sellerprivate	305	0.407	0.492	0.0	1.0
deposit=48 hours	305	0.148	0.355	0.0	1.0
deposit=72 hours	305	0.007	0.081	0.0	1.0
deposit=immediately	305	0.452	0.499	0.0	1.0
deposit=none mentioned	305	0.246	0.431	0.0	1.0
itemcountstateby100	305	4.505	4.223	0.0	14.0
itemcountmakeby100	305	2.436	2.482	0.0	8.8
PositiveFeedbackPercent	305	99.003	3.883	50.0	100.0
Feedbackscoreby1000	305	0.888	2.442	0.0	23.6
ModelavgIMVnewold1000	305	20.131	13.082	4.7	95.7

Table 11: BOperlisting: Fractional Logit

Concept Variable	Variable Measure	2013	2016
Seller Patience	Selleravgrelist	-2.151**	-0.603**
		(0.748)	(0.307)
Patience*Competition	competitcity*relist	0.198*	0.006
		(0.116)	(0.012)
Patience*Competition	competitmake*relist	0.014*	0.003
		(0.008)	(0.002)
Seller City Competition	countcitySeller	-0.023	-0.005
		(0.015)	(0.008)
Seller Make Competition	countmakeSeller	-0.017**	-0.002
		(0.007)	(0.002)
Seller's Outside Options	Selleravgunavailable	-2.446**	-0.082
		(0.774)	(0.420)
Outside Options* Competition	competitcity*unavailable	0.007	0.025
		(0.063)	(0.020)
Outside Options* Competition	competitmake*unavailable	0.023*	-0.003
		(0.014)	(0.003)
Seller Reputation	Positive Feedback Percent	0.011**	-0.037**
		(0.006)	(0.017)
Seller Learning	Selleravgrevisionstotal	0.043	-0.180**
		(0.084)	(0.068)
Seller Experience	Feedbackscoreby1000	-0.068**	-0.012
		(0.028)	(0.008)
Seller's Time Cost	sellerlistingsN	-0.001	0.002
		(0.018)	(0.006)
Seller's Time Cost/Knowledge/Experience	sellerprivate		0.320*
			(0.165)
Seller Communication	SelleravgQA	0.400	
		(1.324)	
Object Valuation Difficulty (Information)	SelleravgMileageby1000	-0.001	0.000
		(0.004)	(0.002)
Object Valuation Difficulty (Information)	SelleravgYear	-0.094*	-0.007
		(0.050)	(0.026)
Object Expensiveness	SelleravgIMVby1000	0.017	-0.004
		(0.013)	(0.004)
cons		191.148*	19.913
		(100.549)	(52.210)
N		428.000	1417.000
r2		0.1523	0.0522

* p<0.10, ** p<0.05
Standard Errors are reported in the parentheses.
Seller Make Dummies included.

Table 12: Robustness Check for BOperlisting: Fractional Logit; & Collectible/Rare Cars Dropped

Concept Variable	Variable Measure	2013	2016
Seller Patience	Selleravgrelist	-2.269**	-0.659**
		(0.768)	(0.318)
Patience*Competition	competitcity*relist	0.199*	0.016
		(0.119)	(0.013)
Patience*Competition	competitmake*relist	0.015*	0.003
		(0.008)	(0.002)
Seller's Outside Options	Selleravgunavailable	-2.507**	-0.097
		(0.797)	(0.455)
Outside Options*Competition	competitcity*unavailable	0.011	0.024
		(0.065)	(0.020)
Outside Options*Competition	competitmake*unavailable	0.024*	-0.002
		(0.014)	(0.003)
Seller Learning	Selleravgrevisionstotal	0.040	-0.220**
		(0.084)	(0.068)
Seller Reputation	Positive Feedback Percent	0.012**	-0.039**
		(0.006)	(0.018)
Seller Experience	Feedbackscoreby1000	-0.070**	-0.008
		(0.030)	(0.007)
Seller City Competition	countcitySeller	-0.024	-0.005
		(0.015)	(0.008)
Seller Make Competition	countmakeSeller	-0.019**	-0.002
		(0.007)	(0.002)
Seller Communication	SelleravgQA	0.557	
		(1.469)	
Object Valuation Difficulty (Information)	SelleravgMileageby1000	-0.001	0.000
		(0.004)	(0.002)
Object Expensiveness	SelleravgIMVby1000	0.016	-0.004
		(0.012)	(0.004)
Object Valuation Difficulty (Information)	SelleravgYear	-0.094*	-0.010
		(0.052)	(0.026)
Seller's Time Cost	sellerlistingsN	-0.003	0.001
		(0.018)	(0.006)
Seller's Time Cost/Knowledge/Experience	sellerprivate		0.334**
			(0.167)
cons		192.351*	26.684
		(105.363)	(53.006)
N		421.000	1347.000
r2		0.1658	0.0465

* p<0.10, ** p<0.05
Standard Errors are reported in the parentheses.
Seller Make Dummies included.

Table 13: Robustness Check for BOperlisting: Fractional Logit; BO Revision Variable Included

Concept Variable	**Variable Measure**	**2013**	**2016**
Seller Patience	Selleravgrelist	-1.111**	-0.333**
		(0.390)	(0.170)
Patience*Competition	competitcity*relist	0.096**	0.002
		(0.046)	(0.006)
Patience*Competition	competitmake*relist	0.007*	0.002
		(0.004)	(0.001)
Seller Competition	countcitySeller	-0.013	-0.003
		(0.008)	(0.004)
Seller Competition	countmakeSeller	-0.009**	-0.001
		(0.003)	(0.001)
Seller's Outside Options	Selleravgunavailable	-1.394**	-0.101
		(0.424)	(0.228)
Outside Options*Competition	competitcity*unavailable	0.002	0.014
		(0.030)	(0.010)
Outside Options*Competition	competitmake*unavailable	0.013*	-0.001
		(0.007)	(0.001)
Seller Reputation	Positive Feedback Percent	0.006**	-0.019**
		(0.003)	(0.009)
Seller Learning (General)	Selleravgrevisions	0.020	-0.071*
		(0.048)	(0.040)
Seller Learning (BO-Specific)	SelleravgBOrevsunscale	-0.023	-0.862**
		(0.539)	(0.236)
Seller Experience	Feedbackscoreby1000	-0.037**	-0.008
		(0.013)	(0.006)
Seller's Time Cost	sellerlistingsN	-0.001	0.001
		(0.012)	(0.003)
Seller's Time Cost/Knowledge/Experience	sellerprivate		0.174*
			(0.090)
Seller Communication	SelleravgQA	0.213	
		(0.690)	
Object Valuation Difficulty (Information)	SelleravgMileageby1000	-0.000	0.000
		(0.002)	(0.001)
Object Valuation Difficulty (Information)	SelleravgYear	-0.050*	-0.011
		(0.026)	(0.014)
Object Expensiveness	SelleravgIMVby1000	0.009	-0.002
		(0.006)	(0.002)
cons		100.858**	24.918
		(51.382)	(28.779)
N		428.000	1417.000
r2		0.1505	0.0666

* p<0.10, ** p<0.05
Standard Errors are reported in the parentheses.
Seller Make Dummies included.

Table 14: Main Results: Probit, Survival Analysis, Cragg Model Tier 2

Concept Variable	**Variable**	**sold**	**duration**	**lntrans.**
Markup	priceprem	-1.371*	-0.476*	0.395*
		(0.24)	(0.13)	(0.03)
Markup*BO	priceprem*BO	0.636*	-0.386*	0.093*
		(0.24)	(0.15)	(0.03)
BO	BO	-0.069	-0.101	-0.012
		(0.11)	(0.17)	(0.03)
Seller Patience	Selleravgrelist		-1.980*	0.034
			(0.21)	(0.05)
Seller Learning	Selleravgrevisions	-0.002	0.039	-0.004
		(0.05)	(0.07)	(0.01)
Seller Reputation	PositiveFeedbackPercent	-0.005	-0.015	0.001
		(0.01)	(0.01)	(0.00)
Seller's Time	deposit=48 hours	-0.069	0.002	0.035
		(0.15)	(0.22)	(0.04)
Seller's Time	deposit=72 hours	0.110	0.490	0.010
		(0.54)	(0.74)	(0.12)
Seller's Time	deposit=immediately	-0.269*	-0.251	0.038
		(0.13)	(0.19)	(0.03)
Seller's Time	deposit=none mentioned	-0.309*	-0.338+	0.075*
		(0.14)	(0.21)	(0.04)
Seller Experience	sellerprivate	0.072	0.309*	-0.015
		(0.10)	(0.15)	(0.02)
Seller Experience	Feedbackscoreby1000	-0.006	0.003	-0.003
		(0.01)	(0.02)	(0.00)
Object Valuation	ModelavgIMVnewold1000	-0.004		-0.001
		(0.00)		(0.00)
Object Valuation	lnIMVby1000	-0.233*	-0.748*	1.017*
		(0.10)	(0.18)	(0.04)
Object Valuation	Mileageby1000	-0.004*	-0.003*	-0.002*
		(0.00)	(0.00)	(0.00)
Object Valuation	Year	-0.071*	-0.057*	-0.017*
		(0.02)	(0.03)	(0.01)
Competition	itemcountstateby100			0.001
				(0.00)
Competition	itemcountmakeby100			-0.031
				(0.09)
cons		142.087*	115.861*	41.762*
		(31.46)	(50.86)	(10.22)
p			1.05	
cons			0.044	
sigma				0.159*
N		2497.000	2452.000	305.000
r2		0.2436		

+ p<0.10, * p<0.05

Note: Standard errors are reported in the parentheses and Make dummies are included.

Table 15: Robustness Check: Sold (Y/N) Probit Model with Clustered Standard Errors

Concept	**Variable**	**(1)**	**(2)**	**(3)**	**(4)**
Markup	priceprem	-1.371**	-1.371**	-1.371**	-1.371**
		(0.222)	(0.247)	(0.249)	(0.239)
Markup*BO	priceprem*BO	0.636**	0.636**	0.636**	0.636**
		(0.245)	(0.277)	(0.272)	(0.255)
BO	BO	-0.069	-0.069	-0.069	-0.069
		(0.188)	(0.098)	(0.102)	(0.075)
Seller Learning	Selleravgrevisions	-0.002	-0.002	-0.002	-0.002
		(0.051)	(0.058)	(0.052)	(0.053)
Seller Reputation	PositiveFeedbackPercent	-0.005	-0.005	-0.005	-0.005
		(0.009)	(0.008)	(0.007)	(0.008)
Seller's Time	deposit=48 hours	-0.069	-0.069	-0.069	-0.069
		(0.161)	(0.206)	(0.169)	(0.201)
Seller's Time	deposit=72 hours	0.110	0.110	0.110	0.110
		(0.429)	(0.430)	(0.436)	(0.416)
Seller's Time	deposit=immediately	-0.269*	-0.269*	-0.269**	-0.269**
		(0.148)	(0.151)	(0.133)	(0.111)
Seller's Time	deposit=none mentioned	-0.309**	-0.309	-0.309**	-0.309*
		(0.153)	(0.192)	(0.145)	(0.179)
Seller Experience	sellerprivate	0.072	0.072	0.072	0.072
		(0.111)	(0.099)	(0.102)	(0.098)
Seller Experience	Feedbackscoreby1000	-0.006	-0.006	-0.006	-0.006
		(0.009)	(0.010)	(0.013)	(0.011)
Object Valuation	lnIMVby1000	-0.233**	-0.233**	-0.233**	-0.233**
		(0.091)	(0.107)	(0.097)	(0.095)
Object Valuation	Mileageby1000	-0.004**	-0.004**	-0.004**	-0.004**
		(0.001)	(0.001)	(0.001)	(0.001)
Object Valuation	Year	-0.071**	-0.071**	-0.071**	-0.071**
		(0.015)	(0.016)	(0.014)	(0.015)
Object Valuation	ModelavgIMVnewold1000	-0.004	-0.004	-0.004	-0.004
		(0.004)	(0.004)	(0.004)	(0.003)
cons		142.087**	142.087**	142.087**	142.087**
		(29.131)	(31.139)	(27.250)	(29.963)
N		2497.000	2497.000	2497.000	2497.000
r2		0.2436	0.2436	0.2436	0.2436
Clus. by Seller		Y	N	N	N
Clus. by Make		N	Y	N	N
Clus. by Model		N	N	Y	N
Clus. by State		N	N	N	Y

* p<0.10, ** p<0.05
Note: Standard errors and clustered standard errors are reported in the parentheses.
Make dummies included.

Table 16: Robustness Check: Sold (Y/N) Probit Model with Alternate Specifications & Collectible/Rare Cars Dropped

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
priceprem	-0.769**	-0.774**	-1.327**	-1.326**	-1.325**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BO		-0.187*	-0.108	-0.103	-0.102
		(0.063)	(0.317)	(0.343)	(0.349)
priceprem*BO			0.606**	0.612**	0.611**
			(0.019)	(0.018)	(0.018)
.003	-0.003				
	(0.870)	(0.979)	(0.963)	(0.952)	(0.957)
PositiveFeedbackPercent	-0.001	-0.002	-0.002	-0.002	-0.002
	(0.957)	(0.862)	(0.868)	(0.843)	(0.844)
deposit=48 hours	-0.042	-0.050	-0.049	-0.049	-0.050
	(0.785)	(0.746)	(0.749)	(0.749)	(0.745)
deposit=72 hours	0.025	0.001	0.074	0.073	0.069
	(0.962)	(0.998)	(0.889)	(0.892)	(0.898)
deposit=immediately	-0.290**	-0.298**	-0.303**	-0.305**	-0.307**
	(0.025)	(0.022)	(0.020)	(0.019)	(0.019)
deposit=none mentioned	-0.321**	-0.335**	-0.327**	-0.323**	-0.323**
	(0.017)	(0.013)	(0.016)	(0.017)	(0.017)
sellerprivate	0.043	0.053	0.060	0.057	0.056
	(0.662)	(0.594)	(0.543)	(0.563)	(0.572)
Feedbackscoreby1000	-0.005	-0.005	-0.005	-0.005	-0.006
	(0.674)	(0.665)	(0.689)	(0.672)	(0.664)
lnIMVby1000	-0.274**	-0.279**	-0.286**	-0.223**	-0.220**
	(0.001)	(0.001)	(0.001)	(0.031)	(0.033)
Mileageby1000	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Year	-0.065**	-0.065**	-0.065**	-0.070**	-0.070**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ModelavgIMVby1000				-0.004	
				(0.291)	
ModelavgIMVnewold1000					-0.005
					(0.281)
cons	129.708**	130.462**	130.841**	140.370**	139.930**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	2371.000	2371.000	2371.000	2371.000	2371.000
r2	0.2287	0.2320	0.2327	0.2327	

* p<0.10, ** p<0.05

Note: Standard errors are reported in the parentheses.

Make dummies included.