# Buy it Now: An Analysis of the Effects of Buy Prices in Auction Listings

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## Abstract

The rise of online auction platforms in the past decade has presented a wealth of new data and puzzling effects to researchers. New listing strategies and parameters created to give both sellers and bidder flexibility have also led the way for new types of listings. This paper explores the potential behavioral effects of simultaneously listing an auction with a fixed price option using data from eBay. It looks specifically at how the fixed price option—known as the Buy it Now (BIN) option on eBay—affects bidder behavior and how this translates into seller outcomes. It looks at (1) whether or not the BIN price has an effect on the final sale price of an auction, and (2) whether this effect can be attributed to anchoring. Two main results arise from this study. The first is that BIN prices have a positive effect on expected seller revenue, especially when the BIN price is more persistent and when the item is more unique. In the case of the former, this is caused by the higher probability of BIN exercise and in the later, this is caused in part by the pure existence of the BIN price. Second, bids anchor to the BIN price, which can help explain the mechanism through which final sale prices rise with the BIN price. This result is significant because in contrast to previous literature, it suggests that sellers might still benefit by setting a BIN option with effectively zero probability of exercise.

*Keywords:* Internet auctions, online markets, anchoring, bidder behavior

# 1. Introduction

In the first quarter of the 2015 fiscal year, online marketplace eBay helped transact roughly $20.2 billion in gross merchandise volume, part of which came from 800 million listings worldwide (eBay 10-Q 2015). Since introducing fixed price sales in 2002 (Wolverton 2002), eBay has steadily made moves emphasizing the fixed price format over its traditional auction listings (Flynn 2008) and there has been growing evidence that sellers have reacted to this, favoring the fixed price alternative to eBay's traditional auction listings (Einav, Farronato, Levin, and Sundaresan 2013). Of the 800 million listings, roughly 160 million were some type of auction listing with the remaining 640 million making up fixed price sales (eBay 10-Q 2015).

Despite the shift towards fixed price listings, eBay has consistently allowed its sellers additional layers of flexibility with the introduction of different listing strategies and parameters. One such parameter is the "Buy it Now" (BIN) option.[1] The BIN option allows sellers to create an auction and fixed price hybrid listing and list an item as an auction, while simultaneously posting a fixed price. This option allows potential bidders to forego participating in the auction and, instead, purchase the item outright as if it were a fixed price sale. While the BIN price itself is equivalent to a fixed price listing, the focus of this paper will be on the effect of the BIN price in auction plus BIN hybrid listings. In most cases of the auction plus BIN listing, once a valid bid has been submitted, the BIN option disappears and the listing becomes a pure auction listing. The exception to this behavior occurs in certain categories where eBay has implemented a longer-lasting BIN option that persists until bidding has reached 50 percent of the BIN

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[1] While there are many names for this type of option and BIN is an eBay-specific term, for simplicity, this paper will refer to buy prices in general as BIN options.

price.[2] Of the nearly 2.4 billion auction listings posted on eBay in the year 2014, roughly 19.7 percent were auction plus BIN hybrid listings.

What is interesting about the auction plus BIN listing is that, where a bidder in a pure auction listing faces only one decision, his bid amount, the bidder in a hybrid auction listing that currently has no bids must now weigh two related decisions: (1) whether or not he should purchase the item at the BIN price and if not, (2) what he should bid on the item. The existence of the hybrid BIN listing may thus affect bidder decisions in ways that differ from a standard pure auction listing. Intuitively, we might hypothesize that if the seller sets a BIN price higher than the average sale price of an item, he may increase his expected revenue if bidders exercise the BIN price. In fact, it has been shown both theoretically (Budish and Takeyama 2001; Mathews and Katzman 2006) and empirically (Ackerberg, Hirano, and Shahriar 2006) that setting a high BIN price leads to higher expected seller revenues. The mechanism through which this occurs is the exercise of the BIN option by risk averse or impatient bidders who may decide that, instead of taking an uncertain outcome by bidding in the auction, they would prefer to own the item with certainty by taking the BIN price.

There are, however, two major dimensions to the BIN option: (1) whether or not it exists, and (2) whether or not it is exercised. My goal in this paper is to explore whether the existence of the BIN price and by extension, its magnitude, has an effect on bidder behavior independent of its exercise and if so, how it does this. I focus specifically on the effect of the BIN option in auction listings. In addition, I explore the effect of the BIN price in various subgroups of listings on eBay. I look specifically at a subgroup of listings that have a more persistent BIN option and a subgroup of listings where the items are

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[2] See http://www2.ebay.com/aw/core/200710161010352.html

more unique and may not have an established or consistent market value and compare the effects of the BIN option in these groups to a baseline group of listings that have the standard BIN rules and more comparable items. To this end, I define three subgroups within my data that contain: (1) listings in eBay-defined categories with a longer-lasting BIN option, (2) listings in categories that have more unique and thus less comparable items, such as antiques and collectibles, and (3) a baseline group that includes all listings not in any of the other two categories. To clarify, groups (2) and (3) have the standard BIN listing rules and (1) has a more persistent BIN. Groups (1) and (2) tend to have more comparable and ubiquitous items and group (3) has more unique items. Thus there are two dimensions of variation among my groups: BIN duration and item comparability.

The empirical strategy I take advantage of follows the matched listings approach developed by Elfenbein, Fisman, and McManus (2012) and modified by Einav, Kuchler, Levin, and Sundaresan (2015). This particular strategy allows me to compare identical listings by the same seller that have variation in the listing parameters. In particular, I focus on variation in the BIN parameter, looking at its effects on bidding behavior and by extension, its effect on seller outcomes. The key link that I attempt to establish in this paper is one between the BIN price and the final sale price. In particular, I attempt to show that the BIN option affects the final sale price and that the relationship is positive, whereby setting a higher BIN price can results in higher expected seller revenue. More specifically, I aim to identify an existence effect of the BIN price separate from its exercise effect. To do this, I split my analysis into three major steps.

In the first step of my analysis, I explore the effect of the BIN option on the final price while including the effect of sales completed via BIN exercise. I find that at the

highest quartile, setting a BIN option can increase final prices anywhere from 7-13 percent depending on the group the listing is in, where the final prices of items with a more persistent BIN price and with more unique characteristics are affected more substantially by a high BIN price. When I isolate the existence effect of the BIN by excluding listings where the item is sold via the BIN option, I find that this positive effect persists and is consistently significant when the BIN is set in the highest quartile, where the effect ranges from 3-10 percent. I find that the effect is strongest when the item has an uncertain value. Comparing the two regressions, I confirm that the BIN price affects final prices through both its exercise and its existence. The overall effect of the BIN price is greater when the BIN is more persistent and when the underlying value of the item is more uncertain. However, in the more persistent BIN category, BIN exercise contributes more to the effect of the BIN price on the final sales price due to the increased duration of BIN availability. In the listings of items with uncertain values, it is the existence effect of the BIN price that contributes more significantly to the higher final sales price due in part to behavioral anchoring to the BIN option. Thus, while the overall effect of the BIN price on final prices is similarly high in the longer BIN and more unique item groups compared to the base group, the composition of the effect differs: in the longer BIN category, the exercise effect of the BIN price dominates and in the uncertain value category, the existence effect of the BIN price dominates.

Next, I explore the channels through which the effect of the BIN option might manifest by looking at its effect on first and second bids. I find evidence that the first bid anchors to the BIN price, but only consistently in the highest quartile. The effect ranges from 11-21 percent depending on the group. I find that the anchoring effect is highest in

the group of items with uncertain values. I find, surprisingly, that second bids also rise with the BIN price. The effect on the second bid ranges from 11-21 percent and the effect is similarly largest in listings that I define as having uncertain values. This suggests that while the BIN price disappears after the first bid in certain categories, it could be that all or most of the bidders in the auction are affected by the BIN price and that while a valid bid can make the BIN option disappear, it's anchoring effect is not substantially diminished because most subsequent bidders were aware of the BIN option prior to its removal. It also provides some justification for how the existence of the BIN price could affect final sale prices through the anchoring of bids. I also look at the potential effect of the BIN price on the number of bids submitted as a proxy for bidder interest or aggression. I find significant positive effects in the base group and significant negative effects in the longer BIN group with no significant effect in the uncertain value group. The effect of the BIN price on the number of bids is overall not very conclusive.

Finally, I run a set of regressions to show the effect of the first bid and the bid count on the final price. I find that this effect is highly significant across all three groups. From these results, I draw the conclusion that part of the existence effect of the BIN price on the final sale price occurs through an anchoring effect. While the bid count does have a significant effect on the final price, the BIN price only has a significant effect on bid count in the base group.

The rest of this paper will proceed as follows. Section 2 will give some background information about eBay and review some relevant literature. Section 3 will outline the source of the data, the filtering process used in this paper, and the matched listing strategy. Section 4 will cover the empirical strategy I rely on and address some

important issues of endogeneity and selection. Section 5 will present the results and

discuss them in context of previous literature. Section 6 will conclude with a summary

and synthesis of the results and attempt to offer some practical advice for sellers as well

as some potential directions for future study motivated by the results obtained.

## 2. Background & Literature Review

In general, there has been a substantial amount of literature on eBay auctions,[3] perhaps

because of the wealth of data and insights eBay offers to researchers. I will begin by

giving a quick overview of the bidding process on eBay. Next, I will summarize some of

the main results of previous studies as they pertain to buyer behavior in eBay auctions. I

will then discuss studies and research that has looked specifically at the effects of the

BIN option. I will also cover some preliminary research that has looked at behavioral

influences in auctions. Finally, I will give a brief overview of the contributions this paper

attempts to make to the existing literature and knowledge base.

Ebay operates its auctions via a mechanism called proxy bidding. Bidders are

asked to input their maximum willingness-to-pay (WTP) and the proxy bidder software

will bid automatically for the user up to their stated WTP. If the current bidder is not the

highest bidder, the proxy bidder will look at the current price and will continue to bid the

current price plus some small bid increment[4] so long as this total amount is below the

user's WTP. The user's stated WTP is never revealed but the bid that the proxy bidder

places on his behalf is. Note that this is effectively a second-price sealed-bid auction. The

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[3] For a comprehensive summary on research on eBay auctions and online auctions in general, readers are directed to Lucking-Reilly (2000), Hasker and Sickles (2001), and Bajari and Hortaçsu (2004).
[4] This amount is a function of the current high price and ranges from $0.05 to $100.

winner of the auction wins when any other bidder cannot match his bid. The final price of the auction is thus equivalent to the second-highest stated WTP plus the bid increment. Figure 1 gives an example of a typical auction listing with a BIN price. Note that if the BIN option does exist, the price is highly visible to current bidders and the option to exercise it mirrors the option to place a bid.

**2.1 General Determinants of Bidder Behavior and Seller Revenue on eBay**

Because eBay offers sellers many options to customize their listings, there are a large variety of listing types a given bidder can expect to run into while shopping on eBay. The first decision sellers must make is the broad choice of listing format, but even after that, sellers are given the choice of setting reserve prices, secret reserves, and shipping prices. Additionally, certain seller characteristics that are visible on listing pages such as seller reputation may also influence bidder behavior.

Ariely and Simonson (2003) study auction entry decisions through auctions for Rose Bowl tickets and find that the final price of an auction is significantly and positively influenced by the start price, total number of bids, and total number of bidders. Using eBay data on coin auctions, Bajari and Hortaçsu (2003) explore the effects and interactions of both public and private reserve prices.[5] They find that higher public reserve prices are correlated negatively with the total number of bidders who bid in an auction. They also find that in auctions with at least two bidders, an additional bidder increases auction revenue by 5.5 percent on average. Conditional on bidder entry, they find that higher public reserve prices lead to higher seller revenue in auctions with more

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[5] In general, as it relates to eBay auctions, the terms minimum bid, starting price, and public reserve are interchangeable. All three can be seen as the seller's own bid that is public and starts off the auction. The private reserve is the same except it is never made public to bidders.

than two bidders. They find that setting a private reserve price negatively impacts seller revenue by nearly 13 percent across all auctions.

Katkar and Lucking-Reilly (2000) carry out a field experiment by auctioning off Pokémon cards in matched pairs, with one listing including a public reserve and another including a secret reserve at the same level. They find that setting a private reserve price decreases the probability of sale significantly. In addition, they note that setting a private reserve price decreases the number of bidders and setting a public reserve price in place of a private reserve price of the same magnitude results in higher seller revenue by roughly 90 percent.

Lucking-Reilly, Bryan, Prasad, and Reeves (2007) collect data on eBay auctions of collectible US pennies and find that seller reputation, reserve prices, and auction duration have a significant effect on auction outcomes and prices. They find that a 1 percent increase in positive feedback scores for sellers corresponds to a 0.03 percent increase in seller revenue and that the same decrease in seller feedback corresponds to a 0.11 percent decrease in seller revenue. In addition, they find that setting an auction duration of seven days raises revenue by 24 percent on average compared to a duration of three days and setting a ten-day auction duration raises revenue by 42 percent on average. They also find that setting a public reserve price or a private reserve price increase seller revenue but that the increase from a public reserve price is not significant whereas setting a private reserve price increases seller revenue by 15 percent on average.

Hossain and Morgan (2006) auction music CDs and Xbox games and find that in the case of Xbox games and while holding constant the total cost, lower public reserve prices and higher shipping costs yielded higher revenues than higher public reserve prices

and lower shipping costs. They explain this effect as either a combination of loss aversion and mental accounting on the part of the bidder, or disregard for shipping costs when bidding. Einav et al. (2015) also look at shipping costs and find that a $1 increase in shipping fees corresponds to a $0.82 decrease in the final sale price, suggesting that bidders do not fully take the shipping fee into account.

## 2.2 BIN Prices and eBay Auctions

There has additionally been a fairly substantial amount of literature on the BIN option and its effect on bidder behavior and in the following subsection, I split a sample of the existing literature into theoretical discussions of the BIN option and empirical studies that have been conducted on BIN options which have generally supported the theoretical framework.

Budish and Takeymama (2001) look specifically at permanent BIN options and show that, in a two-bidder model, it may be theoretically sound for a seller to set a BIN price despite the fact that it is functionally an upper limit on the amount of revenue a seller can obtain. In particular, they note that if bidders a risk averse, they may see the BIN price as a form of insurance and thus, setting a buy price may allow sellers to increase expected revenue. Reynolds and Wooders (2009) further extend this result to instances with temporary BIN prices—consistent with the BIN format on eBay—and find that, while both temporary and permanent BIN prices lead to higher expected revenues compared to a pure auction listing, permanent BIN prices are more effective relative to temporary BIN prices. Matthews and Katzman (2006) consider the opposite case where bidders are risk neutral and sellers are risk averse and find that sellers will still choose a

BIN price with a positive probability of exercise. Hidvégi, Wang, and Whinston (2006) find that setting a BIN option can increase expected utility for both buyers and sellers when either are risk averse but that the temporary BIN price is less effective than the permanent BIN price.

Mathews (2004) additionally makes the case for impatience on the side of the bidders and shows that sellers who face impatient bidders will choose a BIN price that will be exercised with positive probability. Bose and Daripa (2009) also propose an alternative explanation for the success of BIN options and determine that the optimal sales mechanism for a seller constitutes some combination of a fixed price option and an auction listing, which allows the seller an additional dimension of price discrimination. They additionally show that a temporary BIN option corresponds with the optimal selling mechanism while a permanent BIN option does not.

In addition to theoretical interest in the BIN option, there have been a number of empirical studies that have explored the effects of the BIN option on bidder behavior and seller outcomes. Durham, Roelofs, and Standifird (2004) study the interaction between eBay's BIN option and seller reputation through the use of controlled auctions with BIN variation posted by the authors themselves and through listed auctions with BIN variation posted by sellers on eBay. They find that the BIN option tends to be used more frequently by high reputation sellers and that the probability of a BIN price exercise increases with the reputation of the seller and with the decrease in BIN price. Anderson, Friedman, Milam, and Singh (2008) find additional evidence to support the positive effect of reputation on the probability of BIN price exercise. They also find that while the choice of a BIN option does not have statistically significant effect on the final sale price,

conditional on having a BIN option, the final sale price increases with the BIN price regardless of whether or not the BIN price is exercised.

Ackerberg, Hirano, and Shahriar (2006) collect information from eBay on auctions of Dell laptops and find that, without controlling for the level of the BIN price, having a BIN price contributes to an average increase in expected revenue for the seller of roughly $29. Regressing expected revenue on the BIN price, they find that revenues increase by roughly $0.07 per dollar increase in the BIN price. These regressions do not control for whether the sale is a BIN sale or an auction sale however and capture the combined revenue effect of the both the pure existence of the BIN price and its exercise.

Shahriar and Wooders (2011) conduct an experiment on the effect of temporary BIN prices in cases where bidders have private values and common values and finds that, consistent with theory, with private values, seller revenue is significantly higher in auctions with a temporary BIN price and in fact, that the lowest revenue achieved with the BIN option was greater than the highest revenue achieved without the BIN option. In the case of common values, they find results contrary to the theory; namely, that setting a BIN price does not hurt expected seller revenue. They account for this inconsistent finding with a behavioral model of naïve bidding.

Einav et al. (2015) study a wide variety of parameters and their effects, but in the context of BIN prices, they find that setting a high BIN price relative to the reference price of a particular item leads to higher seller revenue for the seller. They also test for the effect of the BIN price if it is not exercised by looking at how different levels of the BIN price affect the probability of sale. They find virtually no difference in the probability of sale at different sale prices with different levels of the BIN price.

**2.3 Some Evidence of Anchoring in Auctions**

While the result that sellers can increase expected revenues by setting BIN prices and the mechanism through which this occurs—exercise of the BIN option—has been robustly established in theory and in practice, there has been a relatively small amount of literature that has explored potential behavioral effects in auctions. These studies suggest an alternative effect of BIN price through some form of anchoring.

Beggs and Graddy (2009) give evidence of an anchoring effect in a non-lab setting and focus on art auctions. They use data from art auctions of Impressionist art sold in London and New York and find that a 10 percent increase in the previous sale price and the predicted sale price leads to a 6.2 to 8.5 percent increase in the actual sale price. Hong, Kremer, Kubik, Mei, and Moses (2015) study the effects of the ordering in sequential auctions, focusing of art auctions of Impressionist and Modern art held by Sotheby's and Christie's. They find that in weeks where more expensive items are auctioned early in the week, the weekly sale premium is 21 percent higher than the average sale premium. Both of these studies suggest that final sales prices might be susceptible to anchoring onto other established prices.

There has also been limited research on the effect of anchoring as it related to BIN prices. Dodonova and Khoroshilov (2004) provide some evidence of anchoring in online auctions. Using auction listings from Bidz.com, they take advantage of the same seller posting multiple listings with different BIN prices. They find that variance in the BIN price significantly affects the final sale price in a positive direction. Their study, however, focuses on the use of a permanent BIN price and it is unclear whether they control for exercise of the BIN price or not. In addition, while their results are interesting

and greatly motivate further study of the potential anchoring effects of the BIN option, the small sample size they use—an average of roughly 27 observations across all three items—makes it difficult to draw any broad conclusions.

**2.4 Contribution to Existing Literature**

Thus in conducting this analysis, I attempt to add to the existing literature in three ways. First, I use a rich dataset on auction listings and parameters collected from eBay. Some previous studies that have looked at eBay auction behavior have obtained data by scraping data or conducting experimenter listings and are generally limited by the completeness of the data used and the sample size of observations. The second way I attempt to add to the literature is by additionally exploring the behavioral effect of the BIN option and by looking at how this effect changes in different groups. I define these groups to test specifically for the differential effects of the BIN price when there is variation in the duration of the BIN price and when items become more unique and less comparable. Finally, I apply the strategy of matched listings used in Einav et al. (2015) to studying the effects of BIN listings across a broader range of products and categories, where previous papers have focused on specific categories or products, making broader and comparative conclusions more difficult.

# 3. Data

What follows is a brief description of the general steps I take to create my final dataset. The steps are then described in more detail in the following paragraphs. I first impose a group of limits on the initial collection to manage the size of my dataset as well as control

for the potential confounding effects of different listing parameters outlined above in the discussion of previous literature (Table 1.1). I then construct matched sets from this group of listings by matching those with the same seller, category, and listing title. After this, I normalize the BIN prices by a reference price for comparability and drop those listings without a reference price (Table 1.2). Next, I drop all matched sets that do not have variation in the BIN option or BIN price (Table 1.3). Finally, I trim this intermediate dataset by dropping all outliers. This ultimately gets me to my baseline data set (Table 1.4). What follows is a brief justification of each step in my data narrowing process.

### 3.1 Collecting Auction Listings

In collecting the initial set auction listings, I focus on listings in the year 2014 and I limit the auctions I collect to those whose start- and end-dates fall within the date range, January 1, 2014 to December 31, 2014 to ensure that I am not cutting any auctions short. I exclude eBay Motors and Real Estate listings as those categories contain their own unique listing rules that aren't consistent with rule in the other categories. I limit my data collection to only single-quantity listings to control for situations in which there may be substitutability or complementarity among multiple units (Milgrom and Weber 2004). In addition, I limit the listings I collect to those on the US eBay website and those listed in US dollars in order to control for any exchange rate issues and pass-through effects. In light of the effects outlined above in the discussion of previous literature, I also limit my sample to listings with no reserve price and free shipping. In addition to allowing me to control for the effects of reserve prices and shipping fees, this limitation also helps control the size of my dataset. In order to ensure that start prices are not affecting bidding

behavior or otherwise influencing the level of first bids, I further limit my initial data collection to listings with start prices that are equal to or under $1. I also limit my results to listings of new items to ensure that bidders are not responding to the condition of an item. I collect all first bids on listings as well as second bids if they exist. The initial collection results in a sample of roughly 45.4 million listings of which 42.8 million are unique.[6] Summary statistics for this first pass are included in Table 1.1.

**3.2 Constructing Matched Listings and Finding Reference Prices**

After the initial collection, I rely on the same matched listings strategy employed by Einav et al. (2015) and I group listings by seller ID, category, and auction title. This strategy is preferable to regressing over the entire set of listings as it allows for finer control over the regression and takes advantage of the fact that sellers may experiment by listing the same item with variations in different parameters. It also allows me to control for the effects of seller characteristics and potentially different bidding behavior depending on the specific item being listed. Unlike Einav et al. (2015), however, I do not match on listing subtitles. Given that I eventually drop all matched listing sets that do not have any variation in the BIN price, I end up losing a sizeable amount of the data I have collected. Thus, I attempt to maintain the largest baseline sample while also keeping the matched listings accurate. While there may be variation in subtitles even when seller ID, category, and auction title are matched, I make the assumption that this variation does not significantly affect bidding behavior.

Because assessing the magnitude of a BIN price does not make sense unless

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[6] The duplication of observations occurs because I also collect second bids. The fact that less than half of the observations are duplicates is the result of not all listings having second bids. In particular, a standard auction plus BIN listing that ends via BIN exercise will not have a second bid.

compared against some reference price for a given item—for example, a $10 BIN price

on an item that usually sells for $1 is very different from a $10 BIN price on an item that

usually sells for $10—I follow Einav et al. (2015) and normalize BIN amounts by a

reference price for each matched set. In order to develop an estimate of the reference

price for a particular matched set, I use the average of all successful fixed price sales of a

particular item in the year 2014 as a proxy. To construct this average, I collect additional

data from eBay on fixed price sales conditional on success and construct matched listings

with the same method as I use for the auction data. Within these matched listings, I

average the sale price and collapse the sets into a single record that maps a unique

combination of seller ID, category, and auction title to an average fixed price[7]—the

reference price. Finally, I merge this mapping onto the auction data obtained earlier and

define normalized amounts as amounts divided by the average fixed price associated with

each set of matched listings. Because not all sets have corresponding fixed price sales, I

drop those matched sets that do not have any fixed price sales. See Table 1.2 for

summary statistics.

**3.3 Isolating Matched Sets with BIN Variation**

Once I obtain these sets of matched listings, I drop those sets in which there is

only one listing as the point of constructing the sets in the first place is to look at

variation within the sets. I also drop all sets with no BIN variation. BIN variation can

refer to changes in the existence of the BIN price or changes in the level of the BIN price

conditional on existence. I qualify both of these as BIN variation and drop sets in which

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[7] While I refer to this as the average fixed price of an item, note that because I also generate matched sets for the fixed price sales, this amount is really the average fixed price of a particular item listed in a particular category and being sold by a particular seller.

there is no BIN variation at all. Results after listings with no BIN variation are dropped

are shown in Table 1.3.

**3.4 Final Baseline Dataset and Discussion**

Finally, I cut out all outliers, which I define to be the top and bottom 1 percent of

observations by normalized final sales price—the final sales price divided by the average

fixed price of an item. The reason I classify outliers by the normalized sale price is that it

allows me to simultaneously consider outlier data in the fixed price listings and outlier

data in the auction price listings; large deviations between the two would result in either

abnormally large or abnormally small normalized final sale prices depending on the

direction of deviation. This gives me the final baseline dataset, which consists of 174,983

listings that make up 10,460 matched sets (see Table 1.4). By virtue of the restrictions I

place on my dataset, all of the listings in my baseline dataset happen to result in

successful sales. The only variation in the sales then is whether the sale is completed via

auction or via BIN exercise.

Each of the matched sets has an average of 16.73 listings with a minimum of two

and a maximum of 953 listings[8] which gives me some confidence that there are enough

listings within each matched set to make within-set comparisons. The two most popular

categories by far are Jewelry & Watches and Cell Phones & Accessories, respectively

representing 37.9 and 24.5 percent of the sample, followed far behind by Clothing, Shoes,

& Accessories, which makes up 6.9 percent of the listings. In the construction of the

baseline dataset, I also define three subgroups. The first subgroup is defined by eBay and

includes categories in which the BIN price persists until the current price reaches 50

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[8] This particular seller was selling screen protectors for the iPhone 5 / 5S.

percent of the BIN price. I define these listings to be in the "Longer BIN" subgroup. The second group is the "Uncertain Value" group and is less rigorously defined. The motivation behind the creation of this group is to explore the hypothesis that bidders on items that have less-established market values may be more susceptible to external suggestions and anchors such as the BIN price. The categories I include within this subgroup are: Antiques; Collectibles; Art; Stamps; Coins & Paper Money; Entertainment Memorabilia; Sports Memorabilia, Cards & Fan Shop. While this category could be constructed in a more thorough manner,[9] the included categories seem fairly reasonable. Summary statistics by group are shown in Table 2.

Note that by definition, when I construct matched sets, I necessarily drop items that tend to be more unique, those that may not have any fixed price sales, and those that may have very few listings and variation within those listings. The top panel in Figure 2 shows the breakdown of listings into the three groups that I define and as expected, the Uncertain Value group has significantly less listings than the first two groups. While this is an unfortunate tradeoff of using the matched listings approach, the Uncertain Value group does still does have a fairly large number of listings in absolute terms.

The bottom panel in Figure 2 shows the breakdown in BIN exercise by group. As we might expect, there is a significantly higher percentage of listings where the BIN price is exercised in the Longer BIN group. Intuitively, the longer the BIN price is available, the higher the chance that a bidder will come along who is willing to purchase the item outright at the BIN price. In the Base and Uncertain Value groups, the proportion of BIN

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[9] Ideally, I would define "unique" items as those with a number of auction and fixed price listings below a certain threshold instead of broadly defining them via category. This would also require that I define such items before the filtering process as I pre-select for items with a trivial (<$1) start price and no reserve price; it could be that certain items are more likely to have higher start prices or reserve prices.

exercise is relatively consistent.

# 4. Methodology & Empirical Strategy

The data that I collect is organized into matched sets that have within-set variation in the BIN option. This particular organization lends itself easily to fixed-effects regressions. These regressions are ideal in that they allow me to control for effects that are invariant across listings within the same set. Translated into the specific context of my data, this allows me to control for any effects that may result from listings by a particular seller of a particular item in a particular category.

To begin to motivate the regressions I run and to ensure that there is an effect to study in the first place, I start by breaking the BIN price into four quartiles. I construct the quartiles on the normalized BIN price, which I define as the absolute BIN price divided by the average fixed price of the item. This lends itself to easier interpretation and comparability of the BIN price. We can thus view a normalized BIN price of 1 to be a fairly priced BIN, a normalized BIN price less than 1 to be an underpriced BIN, and a normalized BIN price above 1 to be an overpriced BIN. The reason I create indicators for the BIN price by quartile instead of regressing on the absolute price is that the interpretation of any anchoring effect may make more sense by quartile. While we might not expect a $1 change in BIN price to affect bidder behavior on the same item, a BIN price set two times greater than the reference value may very well cause a change in bidding behavior. The specific cut points are outlined in Table 3. As in Einav et al. (2015), I find that, regressing the probability of BIN exercise on an indicator of the BIN price in each quartile, the probability of a sale via the BIN option decreases with the level

of the normalized BIN price (Figure 3). The result is intuitive and we can imagine that it is possible for the seller to set a BIN price that is so high that no one would exercise it.

In order to better understand the dynamics this effect, I define an indicator variable that equals 1 if the bidder "overpays" for an item and 0 otherwise. I define overpaying as a sale where the normalized final sale price is greater than 1. This corresponds with a final price that is greater than the average fixed price of the item. I then regress the probability of overpaying on the BIN price both including BIN exercise sales and excluding BIN exercise sales (Figure 3). The results are rather surprising as, while the probability of BIN exercise decreases with higher BIN price levels, the probability of overpaying rises with the BIN price level. When we include BIN sales, this effect seems readily explainable if there are still enough BIN sales at higher BIN prices to increase the average expected seller revenue. However, operating under the assumption that the BIN exercise is the only channel through which the BIN price has an effect on the final sale price, we would expect that by excluding BIN exercise sales, the probability of overpaying should be relatively constant across each BIN quartile. The fact that this is not what I observe seems to indicate that the BIN exercise is not the only mechanism through which expected seller revenue increases with the addition of the BIN option. This is the motivation behind exploring the potential anchoring effects of the BIN option that operate through BIN existence as opposed to exercise.

**4.1 Empirical Strategy**

To further develop this idea, I proceed by regressing the final sale price on the existence of the BIN option broken down into quartiles in the form:

$$log(Y_{it}) = \alpha_i + \beta \boldsymbol{X}_{it} + \varepsilon_{it} \qquad (1)$$

In the above specification, $\alpha_i$ represents the fixed effect of being in a particular matched

set and $\boldsymbol{X}_{it}$ is a vector of indicator variables for the BIN option in each quartile. The

omitted indicator is an indicator for listings without a BIN option and hence the estimated

effects are relative to listings with no BIN option. I run this regression twice. The first

time is the unconditioned run where I allow for the effect of BIN exercise. Running the

regression a second time, I exclude all listings that sold via the BIN option exercise. This

allows me to compare the overall effect of the BIN option including BIN exercise with

the residual effect of the BIN option that cannot be explained through BIN exercise. The

interpretation of the $\beta$ coefficient is thus the existence and exercise effect of the BIN

price in the first set of regressions and captures the existence effect of the BIN price in

the second set of regressions. It may not be proper to take the $\beta$ in the regression as the

pure existence effect. While this issue is discussed in more detail in section 4.2, the core

issue is that the BIN option is likely to be exercised with higher probability at lower BIN

prices. Hence, exclusion of BIN sales creates a less-balanced sample, which could

overstate the effect of the BIN price on bids. For purposes of interpretation, I also look at

the above regression and replace $\boldsymbol{X}_{it}$ with the log of the BIN amount. This allows me to

interpret the effect of a percentage increase of the BIN amount on the final sale price.

This regression unfortunately also suffers from the same type of selection bias. When the

BIN option is not exercised, we can think of the group of subsequent bidders as a

subsample of the full group of bidders whose valuations are capped at the BIN price.[10]

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[10] This idea is connected to the two-step decision process described in the introduction. The general
assumption is if the bidder is bidding on the item as opposed to exercising the BIN price, his WTP for the
item is by definition under the BIN price or else he would have taken the BIN price.

Thus, at higher BIN prices, the distribution of first bidders on auction listings will necessarily include bidders with higher valuations.

Next, I explore whether the BIN price has an effect on submitted bids. I focus in particular on the first bid because in most categories, the BIN price disappears after the first bid. This regression is an attempt to narrow down the channel through which the BIN price affects the final sale price. With this in mind, the set of regressions that I run are similar in form to the first set:

$$log(Y_{it}) = \alpha_i + \beta \boldsymbol{X}_{it} + \varepsilon_{it} \qquad\qquad (2)$$

Here, I regress the log of the first bid on the level of the BIN price. I condition the above regression on listings where the BIN price is not exercised, as including listings that are ended via BIN exercise would bias my results upwards due to the fact that in the non-longer BIN categories, the first bid must equal the BIN price if the BIN is exercised. Because I also collect data on second bids, I also run the same regressions on the second bids in order to better understand the effect of the BIN price on bids. This allows me to test whether the BIN only affects the first bid or whether the effect carries over to bids that come after. In listings where the BIN price disappears after the first bid, the only difference in the listing page that the first and second bidders see is the existence of the BIN option. To see why this is, recall that eBay runs auctions listings as second-price sealed-bid auctions, meaning the current price that is displayed on the listing page is the second highest bid. When the first bid is received, the BIN price disappears and the first bidder is automatically the highest bidder so long as he beats the starting price. By extension, the starting price is automatically the second-highest bid. Thus, while the second bidder can see that there has been one bid placed on the item, the current price

will remain the same and he will only see that the first bidder bid the current price and will not be able to get a sense of the first bidder's WTP. Note that we should still be cognizant of the possible selection bias in this case, which may muddle the interpretation of the $\beta$ coefficient.

I also consider the possibility that the number of bids received might positively affect that sale price of an item at auction. In this case, I take the bid count to be some proxy of bidder interest or bidding aggression. Holding the item and first bid constant, it could be that a greater amount of interest or more aggressive bidding might lead to higher final sales prices. This idea is confirmed by Ariely and Simonson (2003). With this in mind, I test to see if the BIN price has an effect on the number of bids submitted on a given listing. To begin, I assume that the bid count on a given item is given by a Poisson distribution. I run the following regression:

$$log(E(Y_{it})) = \alpha_i + \beta \boldsymbol{X}_{it} + \varepsilon_{it} \tag{3}$$

Here, I regress the log count of bids[11] received on an indicator for the level of the BIN price. Hence the predicted mean of the bid count is given by the following relationship: $E(Y_{it}) = e^{\alpha}e^{\beta x}$. Given that my explanatory variables are indicators, the interpretation of the regression would be that a BIN price in a given quartile would result in a bid count $e^{\beta}$-times the bid count in the omitted category—listings with no BIN option.

The final set of regressions I run attempt to make the connection between the level of the first bid and the number of bids and the final sale price. To test this relationship, I run the following regression:

$$log(Y_{it}) = \alpha_i + \beta_1 log(x_{it}) + \beta_2 log(z_{it}) + \varepsilon_{it} \tag{4}$$

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[11] It is important to note here that by the number of bids received, I count the absolute number of bids received and not the unique number of bids received. This would include bids made by the same bidder.

Here, I regress the log of the final sale price on the log of the level of the first bid and the

log of the number of bids received. The motivation behind this regression is to establish a

link between the first bid and the number of bids and the final sale price. In particular, if

the BIN option does affect first bids and bid counts and the first bid and bid counts affect

the final sale price, this allows me to consider first bids and the number of bids as

possible channels through which the existence of the BIN option might affect the final

sale price.

**4.2 Addressing Endogeneity and Selection Bias**

An important caveat to consider is that the matched sets I create are drawn from

the entire year. In particular, I do not cluster my matched sets so that all listings are from

the same month. The issue with this is that I cannot control for items that may be more

prone to seasonal variation in demand. Take, for example, a Thomas Kinkade "Christmas

on Main Street" tapestry—an item in one particular matched set. This item was listed and

sold in both June and October. We might expect that because this is a seasonal item,

increased demand in the months leading up to the Christmas season may cause the item

to sell for more and in fact, in my data, the item sold in October sold for 18 percent more

than the exact same item sold for in June. While this is not a perfect example, it illustrates

a potential source of endogeneity in my model. To help address this concern, I look at

variation in listing month within the matched sets and the results show that the average

variation is around one month. This gives me a sense that most of the listings in my

matched sets are not too widely dispersed. Even then, there is some evidence that the

effect of clustering listings may not change the results significantly.[12] However, to properly interpret the results, we must take these concerns into consideration.

A more concerning issue is the potential selection bias that arises from comparing bids at varying levels of the BIN price and conditioning on listings that do not sell via BIN exercise. To see this, consider the following example of a particular matched set, $A$, with two listings $A_1$ and $A_2$, where both listings have a BIN option but the BIN option in $A_1$ is set at $10 and the BIN option in $A_2$ is set at $20. Let us consider a three-bidder model where the distribution of bidder valuations is $\{b_1, b_2, b_3\} = \{\$5, \$15, \$25\}$ and where the distribution of values is more-or-less the same between the two listings. Consider the two following scenarios:

1. $A_1$: BIN = $10. The BIN will be exercised if bidders 2 or 3 are first to the listing (~66% of the time). The BIN will disappear if bidder 1 is first to the listing and the first bid recorded will be $5 (~33% of the time).

2. $A_2$: BIN = $20. The BIN will be exercised if bidder 3 is first to the listing (~33% of the time). The BIN will disappear if bidder 1 or 2 is first to the listing and the first bid recorded will be $5 or $15 (~66% of the time).

Because the probability of BIN exercise decreases with the level of the BIN price, by conditioning on listings that do not sell via BIN exercise, the bids, bid numbers, and final sale prices that remain in the sample are disproportionately representative of those listings with higher BIN prices. Thus, this selection issue could overstate the effect of the BIN price. Note here also that because the bidders with higher valuations exercise the

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[12] Einav et al. (2015) report experimenting with more stringent matched listings conditions that restrict listings by time and find that their results are not significantly different.

lower BIN price, the distribution of possible first bidders if the BIN is not exercised is necessarily truncated, with an upper limit at the BIN price.[13] By extension, at higher BIN prices, we see that the distribution of possible first bids is extended with every increase in the BIN price. If we assume that each bidder has some positive probability of being the first to arrive at a given listing, a higher BIN will also lead to a higher first bid on average. When interpreting the results, this selection bias must be taken into account. In light of this, however, we also might not expect the selection bias to be substantially different among different samples given that it is present across the entire baseline dataset. So while it is necessary to take the results of any given conditioned regression with a grain of salt, it may still be valid to compare the relative strength of effects among different samples and attribute that difference to differences in the relative strength of the BIN existence effect.

## 5. Results & Discussion

### 5.1. Effect of the BIN Option on Seller Revenue

The first set of regressions I run attempt to determine the relationship between the BIN option and the final sale price. I first regress the log final sale price on an indicator for having the BIN price, uncontrolled for the quartile of the BIN price. The results of this regression on all three groups are shown in Table 4. I find that in all three groups, there is a positive relationship between setting a BIN option at any level and expected seller revenue. This is not a particularly surprising outcome given the theoretical literature and various empirical studies that have backed this finding up.

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[13] Note that this represents the extreme case where every subsequent bidder has seen the BIN price. In reality, we might expect some of the bidders arrive late and never see the BIN price.

It is interesting to note, however, that the point estimates on the coefficient of interest—the effect of having a BIN option on expected seller revenue—varies across groups. The effect of the BIN price is almost double in the Longer BIN group and while it is statistically significant at the 1 percent level in both the Base and Longer BIN groups, it is only significant at the 10 percent level in the Uncertain Value group. The higher point estimate in the Longer BIN group may be explained by the fact that, because the BIN price persists longer, it is more likely to be exercised. This intuition is backed up by the knowledge that there are significantly more BIN sales in the Longer BIN group compared to the other two groups (Figure 2). The lack of significance in the Uncertain Value group is puzzling but might be easier to interpret by re-specifying the model and making it more flexible to different levels of the BIN price.

I run the next set of regressions on the effect of BIN prices broken down by quartiles. This regression is unconditioned and reflects the overall effect of the BIN price on the final sale price, including the effect of BIN exercise. The results are shown in Table 5.1 and are fairly consistent with the previous results. In both the Base and Longer BIN categories, I find that setting a BIN price at any level leads to a positive effect on average seller revenue. In particular, setting a BIN price in the highest quartile increases expected seller revenue by 7.0 percent on average in the Base category. In the Longer BIN category, this increase is almost twice that of the Base category at 13.4 percent and in the Uncertain Value category, the increase is roughly 13.7 percent. In order to establish the effect of BIN prices independent of BIN exercise, I run the next set of regression conditional on listings that do not sell via BIN exercise.

The results of the conditioned regression are given in Table 5.2. I find that setting a BIN in the fourth quartile leads to a 3.73 percent increase in the final sales price in the Base group, a 3.16 percent increase in the final sales price in the Longer BIN group, and a 10.23 percent increase in the final sales price in the Uncertain Value group. Comparing these results to the unconditioned regression, I find that at the highest quartile, the effect of the BIN price is almost halved in the Base group when excluding the BIN exercise effect. In the Longer BIN group, the effect is only a quarter of the size of the effect in the unconditioned regression. And in the Uncertain Value group, the conditioned effect is three-fourths of the effect in the unconditioned regression.

By comparing the effects in both regressions, I get a rough picture of the magnitude of the behavioral existence effect of the BIN option in relation to the BIN exercise effect. In particular, while there is still a significant existence effect in the Base group, half of the positive effect on final sale prices can be accounted for by BIN exercise. In the Longer BIN group, the existence effect is roughly in line with the effect in the Base group although it is almost twice that in the unconditioned regression. This result is intuitive because while we might expect a more persistent BIN to increase the change of BIN exercise, holding the level of the BIN price constant, a longer-lasting BIN should not amplify the existence effect of the BIN price in a meaningful way. In the Uncertain Value group, in contrast with the first two groups, the effect of the BIN does not diminish greatly in the conditioned regression. This points to the fact that the existence effect of the BIN price seems to make up a large portion of its overall effect as opposed to BIN exercise. A possible explanation for this may be that bidders are more averse to exercising the BIN price on listings of items that have an uncertain value

because they may see it as blindly taking the seller's suggestion of the item's worth. It is interesting, thus, to note that even without exercising the BIN option, bidders are still being influenced by the existence of the BIN price.

I also explore regressing the log final sale price on the log BIN price to obtain a marginal effect of the BIN price. The results of this regression are given in Table 5.3. I find that conditional on having a BIN option where it is not exercised, a 10 percent increase in the BIN price results in a 1.1 percent increase in the final sale price in the Base group, a 2.4 percent increase in final sale price in the Longer BIN group, and a 6.2 percent increase in final sale price in the Uncertain Value group. As in the previous regressions, I find a stronger existence effect in the Uncertain Value group. In order to explore the mechanism for the residual effects of the BIN price better, I turn to the remaining results.

## 5.2. Effect of the BIN Option on Bids

I look next at the effect of the BIN price on first bids. I condition the sample on only those listings that do not sell via the BIN in order to drop instances where the first bid might equal the BIN if it was exercised. I find that there is variance in the results across all three groups but that in general, setting a BIN price at the highest quartile results in a positive effect on the first bid, which is significant in the Base and Longer BIN groups at the 1 percent level and in the Uncertain Value group at the 5 percent level. Specifically, setting a BIN in the final quartile in the Base group leads to an average increase in the first bid by 13.2 percent. In the Longer BIN group, the effect is an 11.4 percent increase, and in the Uncertain Value group there is a 21.7 percent increase. While

the effect in both the Base and Longer BIN groups are fairly similar, the effect is almost doubled in the Uncertain Value group. This difference could potentially be explained by the fact that bidders may be more susceptible to exogenous price anchors such as the BIN price when they have uncertainty about the value of an item. This effect is another entry in the growing list of results that show that the existence effect of the BIN price is higher in the Uncertain Value category.

In addition, I find that setting a BIN price under the average fixed price can actually lead to a decrease in the level of the first bid by roughly 22.0 percent in the Uncertain Value group. This effect is significant at the 5 percent level. Recall that the positive effect on the first bid of the BIN price in the Uncertain Value group was also larger in magnitude. This may again reinforce the idea that bidders are more susceptible to an anchoring effect when they bid on items with no established fixed price or few comparable items and it demonstrates they may actually bid lower when the BIN price is set lower than the average fixed price of the item. This negative effect is absent in the other two groups and may reflect the absence of strong anchoring.

Another noteworthy result is that the point estimates in the Longer BIN group are all positive, whereas there are instances of negative effects in the other two groups. This may be caused by the fact that in the other two groups—where the BIN price disappears after the first bid—bidders may bid low on purpose[14] in order to get rid of the BIN price so that more risk averse or impatient bidders cannot come along and purchase the item outright. In contrast, in the Longer BIN category, first bidders do not have this same incentive to bid at the minimum level because the BIN option persist until bidding

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[14] Note that first bidders are only required to beat the starting price and because I've limited the starting prices to $1 or less, first bidders are free to bid at very low levels.

reaches 50 percent of the BIN price. In fact, if first bidders do bid in order to take away the BIN option in the Longer BIN category, they may have an incentive to bid higher in hopes that the current price reaches 50 percent of the BIN faster and the BIN option disappears.

Thus, it might be the case that in normal BIN categories, first bidders will bid the absolute minimum amount in order to take away the BIN option when it is set at a lower or more reasonable range. Because I have filtered by listings with low starting prices, this could result in a lot of first bids at the $1 range and in fact, the median first bid in listings with a BIN option in my baseline dataset is $1. This behavior could bias my results downwards. However, if we accept that this explanation is true, we might expect bidders to only bid to get rid of the BIN option at the lower quartiles of the BIN price, where it is more likely that another bidder might come along and exercise it. Thus, while we may have to take the estimated results on lower BIN quartiles with a grain of salt, there may not be as big of a concern in interpreting the results in the higher BIN quartiles, where it is unlikely that a bidder will exercise the BIN.

I run the same regression on second bids and find that across all groups, the effect of the BIN price is similar to the effect of the BIN price on first bids. In particular, a BIN price set in the highest quartile results in an 11.2 percent increase in second bid in the Base group, an 11.5 percent increase in the second bid in the Longer BIN group, and 21.4 percent increase in the second bid in the Uncertain Value group. Again, I observe that the effect is greater in the Uncertain Value group. These results are important because they show that the existence effect of the BIN option may be the result of anchoring on first and subsequent bids. They also point to the possibility that second bidders are anchoring

to the BIN price as well, meaning that either the effects of the higher BIN carry over to subsequent bids, or that first bidders may not be the only bidders who view the BIN price and that it could be that—in the extreme case—all bidders on a particular listing may have seen the BIN price before bidding.[15]

This finding may also give us an intuition as to how final prices might also anchor to the BIN price.[16] Looking at listings with a BIN option, roughly 14.8 percent are won by the first bidder. In light of the above results, this gives us an idea of why final prices might be higher. In addition, controlling for quartile, the percent of listings where the first bidder wins increases substantially when moving from listings with no BIN option to having a BIN option in higher quartiles.

### 5.3. Effect of the BIN Option on the Number of Bids

I also explore the possibility that the BIN price can affect the number of bids submitted by regressing the log number of bids on the BIN price. The results of this regression are shown in Table 7. I find a significant positive effect of the BIN option across all levels in the Base group, a significant negative effect of the BIN option across all levels in the Longer BIN group, and no significant effect of the BIN option on bids in the Uncertain Value group. Unfortunately, without knowing how many of the bids are distinct bidders, it is difficult to draw any concrete conclusions from the results.

In the Base group, we might expect that the BIN option can affect bids in two ways: (1) it causes entry of more bidders, and (2) it causes bidders, conditional upon entry, to bid more often. In the first case, it might be that when users search for items on

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[15] Note that the key distinction here is that the BIN price disappears on the first bid and not the first view.
[16] Recall that the final sale price in an eBay auction listing is simply the second highest bid plus the bid increment.

eBay, they are more likely to filter by listings with a BIN option. This is supported by the statistics on fixed price sales that we find across the eBay platform. Thus, having an auction with a BIN price might attract more bidders in general. The second explanation could be that some form of sunk cost fallacy or reference dependence induces the bidder, having bid on an item, to consider it his and to keep on raising his bid as he is outbid. This effect has been observed in penny auctions (Augenblick 2015) and there is also some evidence of incremental bidding on eBay, either due to a fundamental misunderstanding of the auction mechanics or due to strategic concerns (Roth and Ockenfels 2002).

In the Longer BIN group, the consistently negative point estimates are a little difficult to interpret. Recall that the regression is conditioned on listings that sell via auction. Thus, there could be additional issues of selection bias whereby listings with less interest tend not to sell via the BIN option. This is not a problem in the Base and Uncertain Value groups because the BIN option disappears after the first bid. On the other hand, because the BIN option in the Longer BIN group persists, those listings with a BIN option that do not sell via the BIN option could disproportionally be listings that have less bidder interest and thus have a lower number of bids.

In the Uncertain Value group, the lack of significant coefficients could simply be a result of the comparatively smaller sample size. It could also reflect the fact that users who purchase more unique items do not necessarily look for BIN listings as often as users who purchase more typical items because they trust seller-defined fixed prices less. All in all, it is rather difficult to draw any robust conclusions regarding the effect of BIN prices on bidder entry and the number of bids submitted.

**5.4. Effect of First Bids and Bid Count on Final Price**

Finally, I regress the log of the final sale price on the log of the first bid and number of bids. Having established that the BIN price affects first bids partially via anchoring and to a limited extent, the number of bids, I test to see if this effect can be linked to higher final sale prices. The results of this regression are given in Table 8. I find that there is a significant effect of first bids on the final sale price across all three categories. There is also evidence that the bid count affects the final sales price positively in all three groups. This result allows me to reasonably conclude that one channel through which the BIN price can affect the final sale price is through the first bid. And in particular, it also allows me to conclude that part of the residual effect of the BIN price on the final sale price, excluding the effect of BIN exercise, can be explained via bid anchoring.

# 6. Conclusion

To conclude, I find that the BIN price has a significant effect on the final sale price in auction listings. In particular, the overall effect of the BIN price is stronger in categories with a more persistent BIN price because this increases the probability that the BIN price will be exercised. I also find, however, that this effect is robust even when I exclude the possibility of BIN exercise. In other words, I show that there is an unaccounted for behavioral effect of the BIN price on seller revenue that does not depend on the bidder exercising the BIN price. This effect is consistently larger in listings where the item's value is difficult to determine. I show that a possible channel for this is via the anchoring of first bids on auction listings with the BIN option but I find unclear evidence that the

BIN price affects bidder entry and the number of bids submitted. Consideration also needs to be given, however, to the potential selection bias in my conditioned regressions and thus, it is impossible to say with certainty that the full effect is due to anchoring although it may be more valid to compare the relative effects of anchoring among different groups.

The implications of these findings are interesting for both bidders and sellers and can perhaps explain the situation in Figure 1. In this particular listing, the seller has set a BIN price of $1,800, corresponding roughly to a normalized BIN price of 4.5 if we take the price of the same item listed on Apple's official online store of $399 to be a reasonable reference price. This is well within the fourth quartile of BIN prices as I've defined it in this paper. Figure 5 shows that the final sale price of this item, $935, is only half of the BIN price but still over two times greater than the reference price. The significance, then, is that sellers may still be able to increase revenue by setting a high BIN price even if they don't expect it to be exercised. This contradicts some of the advice that arises naturally from studies that consider the BIN exercise as the main mechanism through which sellers can increased expected revenue. If we believe that the only affect of the BIN price on the final sale price is through BIN exercise, it would be wise for the seller to set a BIN price at some optimal level where there is still some positive probability of exercise.

The results of this paper suggest that sellers can still benefit from setting a BIN price, even where the probability of BIN exercise is effectively zero. The reason why a seller might do this would be to take advantage of the potential anchoring effect of the BIN price. My results also suggest that this effect is stronger if the item is more unique

and less comparable. Thus, if a seller is attempting to sell an item, he might benefit by stressing the uniqueness of his item and setting a high BIN price. In fact, he would do better to err on the side of setting a BIN price that is too high as it is possible to actually limit his potential earnings if he sets the BIN price too low.

If the seller were selling a less unique item, my results would suggest that he attempt to list it in a category with a more persistent BIN price. A practical example of how this might be achieved is by taking advantage of potential overlap in the different categories. While looking up listings for the Apple Watch, I found it being listed in both the Jewelry & Watches category and in the Cell Phones & Accessories category. The significance here is that while the Jewelry & Watches category has a normal BIN option that disappears after the first bid, the Cell Phones & Accessories category has a persistent BIN option. Thus, in light of my results, I would recommend that the seller list his item under the Cell Phones & Accessories category to take full advantage of the stronger effects of the BIN price on seller revenue in the categories with a longer-lasting BIN option. Of course, this strategy would only work if the seller had an item that could reasonably be classified into a longer BIN category, as eBay actively removes misclassified listings and punishes sellers who deliberately misclassify their listings.

While it is interesting to note the anchoring effect of BIN prices on eBay, this idea has been floating around in the live auction business for quite some time. Brandley (2015) gives an example of its use in oral auctions: "Folks, look at this nice Civil War Sword and I'd like $500 for it … well, somebody give me $100? $50?" This example is a nice one because it cleanly encapsulates two of the main results I find in this paper: (1) it shows that giving bidders a high price anchor—even a price that the seller does not

expect anyone to take—can ultimately increase the final sale price, and (2) it suggests that this strategy might be more effective in auctions where bidders do not have an accurate way of assessing the true value of an item. This study reveals some very interesting results in bidding behavior and seller outcomes on eBay and there are a wealth of extensions that could help better tease out the causes of this behavior.

The first would be to add the additional dimension of visibility and attention. In particular, it might be more interesting to know if there is a difference in bidding behavior between bidders who have seen the BIN price and those who haven't. While I attempt to get at this idea partially by comparing the anchoring effects of the BIN price between the first bidder—who I can be certain has seen he BIN price—and the second bidder, I also note that there is no reason why the second bidder could not have seen the BIN price as well. One way to do this would be to observe page view data by bidder and keep track of individual bids and their associated bidder IDs. This would also help alleviate some of the concerns with potential selection bias in running conditioned regressions. As such, this path seems to be a particularly promising avenue for future consideration and research.

Another possible extension would be to consider whether the anchoring effect of the BIN price is as simple as a shift in bids towards the absolute magnitude of the BIN price or if the mechanism through which the anchoring effect manifests itself is much more complicated. Embedded in the earlier example given by Bradley (2015) is the idea that bidders might anchor to a suggested price and bid higher because they perceive winning the item at a price below the suggested price to be a deal. Bradley (2015) calls this "the 'prospect of a deal'" and this idea is captured in Thaler's (2008) discussion of

transaction utility, whereby a consumer gains utility proportional to the terms of the deal and is positively affected when he perceives that he is getting a good deal on an item.

Due to the wealth of auction information made possible by the rise of online auction platforms like eBay, it is increasingly possible and fruitful for economists to study the varying effects of auction parameters on bidding behavior and outcomes. In particular, there is still much to be learned about how parameters like the BIN price affect behavior and additional study in this sub-topic would yield useful and applicable results not only for the study of auctions, but also the study of economic behavior.

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# Appendix

**Figure 1.** Screenshot of auction listing with a BIN option



*Notes:* This screenshot was taken on May 7, 2015 on the main eBay US site. This particular listing was selling a new 42mm Space Gray Apple Watch with a Black Sport Band. Note that because it is listed in a longer-lasting BIN category, the BIN option will continue to be available until the current bid meets or exceeds 50 percent of the BIN price. As of May 7, 2015, the exact same item was simultaneously available on the official Apple online store for $399.

**Figure 2.** Breakdown of groups in the baseline dataset
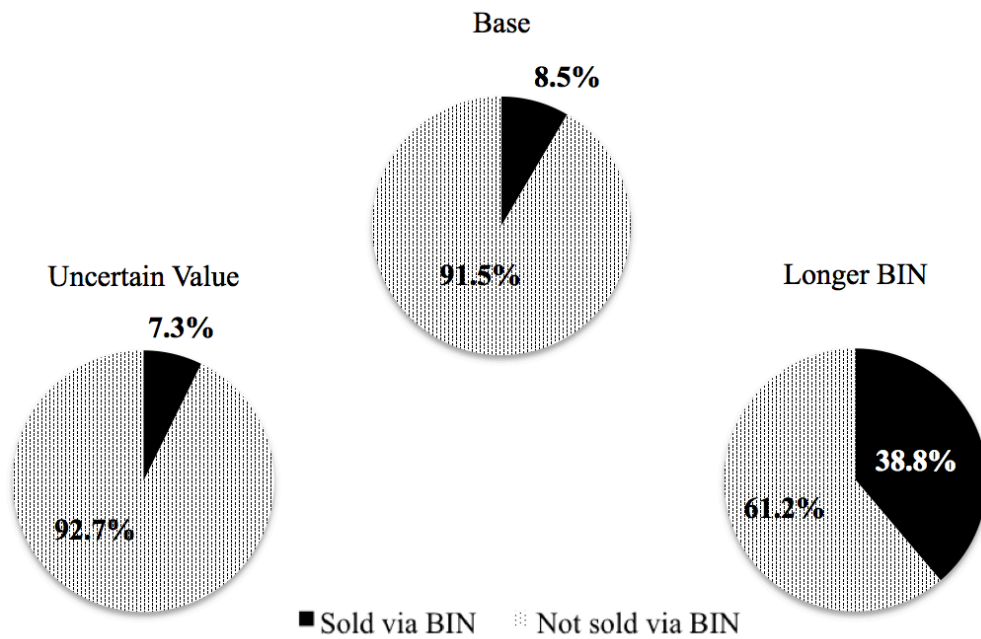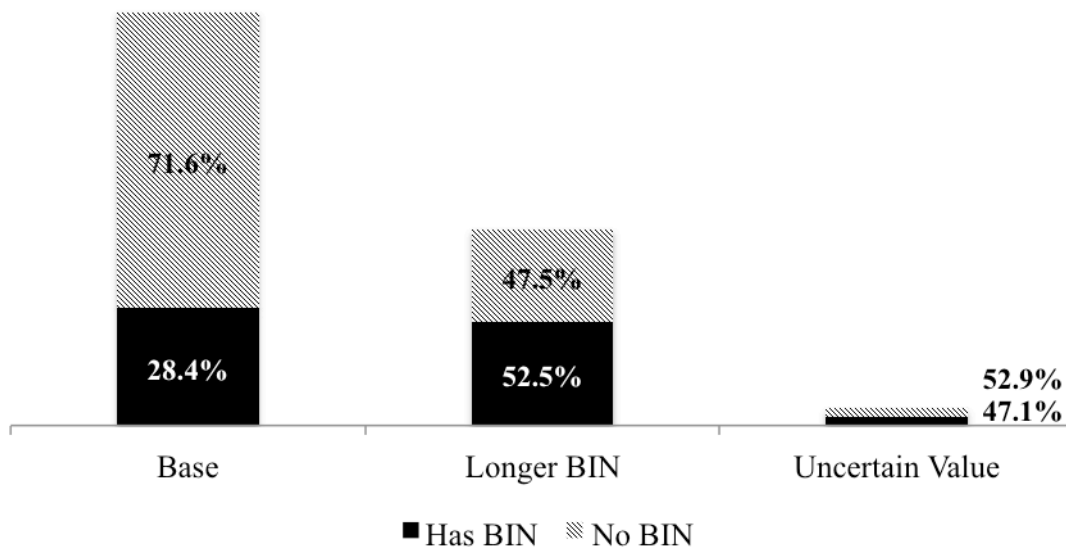


*Notes:* The top panel depicts the baseline dataset, split into three groups. The listings are then divided by whether or not the seller decided to include a BIN option. The bottom panel shows the breakdown of sales in each group by BIN exercise and non-BIN exercise. Because all listings result in a sale in the baseline dataset, if a listing is not sold via BIN, it is sold via auction.

**Figure 3.**  Probability of BIN sale and overpayment by BIN quartile
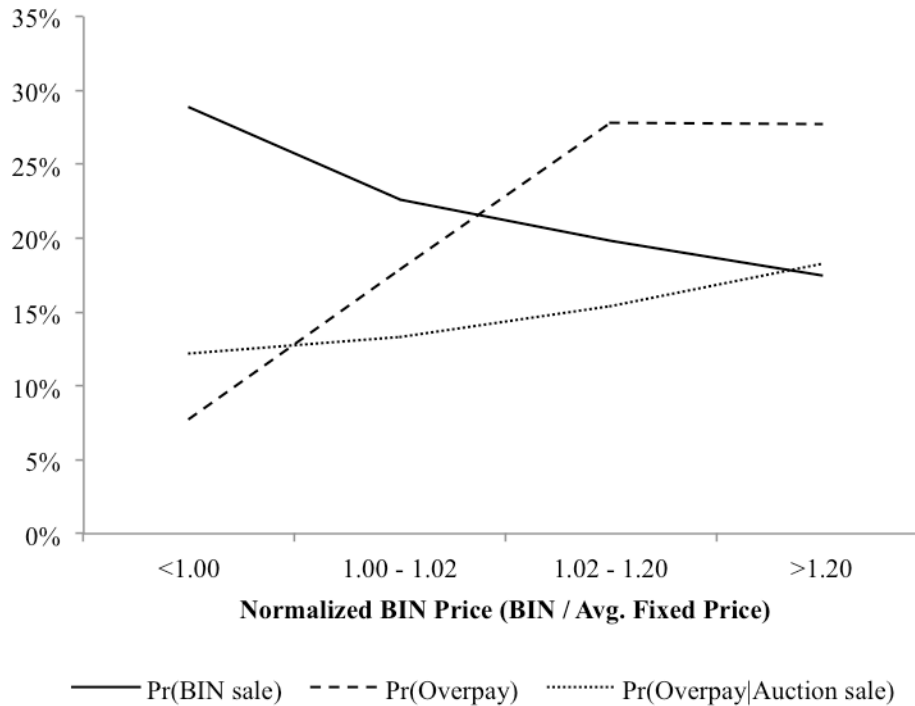


*Notes:*  This figure shows the effect of the BIN price on the probability of a BIN sale in the solid black line. The probability of overpaying, defined as paying more than the average fixed price, is shown in the broken line. The probability of overpaying, excluding BIN sales, is plotted by the dotted line. The four ranges on the bottom correspond to the four quartiles of normalized BIN prices.

**Figure 4.**  Screenshot of auction sale
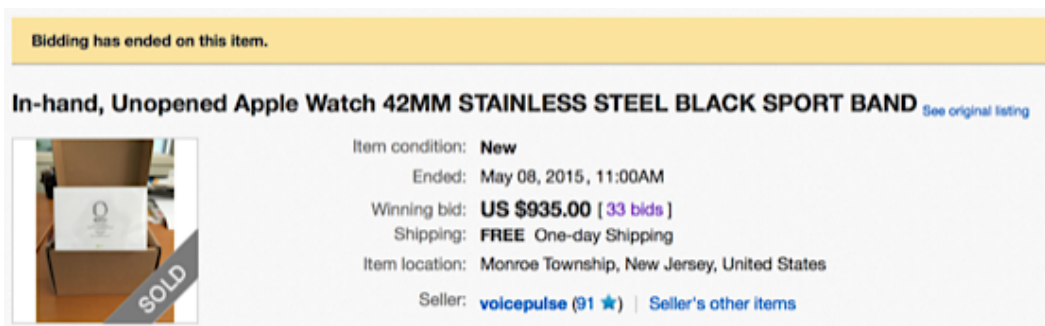


*Notes:*  This screenshot was taken on May 8, 2015. The listing depicted is the same as the listing shown in Figure 1.

**Table 1.1.** Summary statistics for all auction listings collected

|  | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| First bid as fraction of final sale | 45.3 | 1.10 | 814.68 | 0.00 | 4,192,400 |
| Second bid as fraction of final sale | 38.7 | 0.75 | 670.02 | 0.00 | 4,158,759 |
| Final sale price | 45.4 | 6.64 | 61.89 | 0.00 | 70,600 |
| Num. of bids | 45.5 | 7.39 | 6.64 | 0 | 10,342 |
| Indicator: Has BIN option | 45.5 | 0.03 | 0.17 | 0 | 1 |
| Indicator: Sold via BIN | 1.28 | 0.21 | 0.41 | 0 | 1 |
|  |  |  |  |  |  |
| Indicator: In Longer BIN group | 45.5 | 0.16 | 0.37 | 0 | 1 |
| Indicator: In Uncertain Value group | 45.5 | 0.04 | 0.19 | 0 | 1 |
|  |  |  |  |  |  |
| Top three categories: |  |  |  |  |  |
| Jewelry & Watches (49.7%) | 22.6 |  |  |  |  |
| Crafts (14.4%) | 6.5 |  |  |  |  |
| Clothing, Shoes & Accessories (10.3%) | 4.7 |  |  |  |  |
|  |  |  |  |  |  |
| Successful sales (99.8%) | 45.3 |  |  |  |  |

*Notes:* This table contains summary statistics for all auction listings collected. First bid and second bid amounts are normalized by the sale price and are only listed if the sale is successful. Note that due to the limitations placed on the data, almost every listing results in a sale (99.8% of all listings). Observation counts are all listed in millions. This sample constitutes listings that started and ended within the period of January 1, 2015 to December 31, 2014. The dataset is additionally filtered on: first and second bids only; free shipping and no reserve; starting price less than or equal to $1; US listings only listed in USD.

**Table 1.2.** Summary statistics for all matched sets with a reference price

|  | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| First bid as fraction of final sale | 5.5 | 0.61 | 24.08 | 0.00 | 15,400 |
| Second bid as fraction of final sale | 5.0 | 0.54 | 13.35 | 0.01 | 10,040.98 |
| Final sale price | 5.5 | 9.51 | 64.64 | 0.01 | 64,999 |
| Num. of bids | 5.6 | 9.12 | 8.61 | 0 | 10,342 |
| Indicator: Has BIN option | 5.6 | 0.02 | 0.15 | 0 | 1 |
|   Normalized BIN price | 0.1 | 1.19 | 4.22 | 0.01 | 555.56 |
|   Indicator: Sold via BIN | 0.1 | 0.24 | 0.43 | 0 | 1 |
|  |  |  |  |  |  |
| Indicator: In Longer BIN group | 5.6 | 0.17 | 0.37 | 0 | 1 |
| Indicator: In Uncertain Value group | 5.6 | 0.07 | 0.26 | 0 | 1 |
|  |  |  |  |  |  |
| Matched sets | 0.3 |  |  |  |  |
|   Num. of Listings | 0.3 | 10.18 | 8.61 | 1 | 131 |
|   Average fixed price | 0.3 | 20.22 | 169.71 | 0.83 | 67,000 |
|  |  |  |  |  |  |
| Top three categories: |  |  |  |  |  |
|   Jewelry & Watches (43.3%) | 2.4 |  |  |  |  |
|   Cell Phones & Accessories (9.0%) | 0.5 |  |  |  |  |
|   Crafts (8.0%) | 0.4 |  |  |  |  |
|  |  |  |  |  |  |
| Successful sales (99.9%) | 5.5 |  |  |  |  |

*Notes:* This table contains summary statistics for an intermediate sample. First bid and second bid amounts are normalized by the sale price and are only listed if the sale is successful. Note that due to the limitations placed on the data, almost every listing results in a sale (99.9% of all listings). Observation counts are all listed in millions. This constitutes listings that started and ended within the period of January 1, 2015 to December 31, 2014. The dataset is additionally filtered on: first and second bids only; free shipping and no reserve; starting price less than or equal to $1; US listings only listed in USD. In addition, I have dropped all listings that do not have a corresponding fixed price sale, which I use as a reference price.

**Table 1.3.** Summary statistics for all matched sets with BIN variation

|  | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| First bid as fraction of final sale | 194,184 | 0.53 | 14.49 | 0.00 | 5,500 |
| Second bid as fraction of final sale | 176,755 | 0.72 | 38.89 | 0.00 | 10,000 |
| Final sale price | 194,184 | 23.87 | 64.64 | 0.01 | 20,300 |
| Num. of bids | 194,726 | 11.57 | 10.79 | 1 | 132 |
| Indicator: Has BIN option | 194,726 | 0.36 | 0.48 | 0 | 1 |
| Normalized BIN price | 70,834 | 1.16 | 1.82 | 0.01 | 303.03 |
| Indicator: Sold via BIN | 70,834 | 0.21 | 0.41 | 0 | 1 |
|  |  |  |  |  |  |
| Indicator: In Longer BIN group | 194,726 | 0.31 | 0.46 | 0 | 1 |
| Indicator: In Uncertain Value group | 194,726 | 0.03 | 0.17 | 0 | 1 |
|  |  |  |  |  |  |
| Matched sets | 10,623 |  |  |  |  |
| Num. of Listings | 10,623 | 13.22 | 11.93 | 1 | 104 |
| Average fixed price | 10,623 | 45.12 | 132.65 | 0.99 | 3,724 |
|  |  |  |  |  |  |
| Top three categories: |  |  |  |  |  |
| Jewelry & Watches (38.3%) | 74,633 |  |  |  |  |
| Cell Phones & Accessories (23.3%) | 45,444 |  |  |  |  |
| Clothing, Shoes & Accessories (7.2%) | 13,967 |  |  |  |  |
|  |  |  |  |  |  |
| Successful sales (99.7%) | 194,183 |  |  |  |  |

*Notes:* This table contains summary statistics for an intermediate sample. First bid and second bid amounts are normalized by the sale price and are only listed if the sale is successful. The BIN price is normalized by the average fixed price. Observation counts are listed in full amounts. Note that due to the limitations placed on the data, almost every listing results in a sale (99.7% of all listings). This constitutes listings that started and ended within the period of January 1, 2015 to December 31, 2014. The dataset is additionally filtered on: first and second bids only; free shipping and no reserve; starting price less than or equal to $1; US listings only listed in USD. In addition, I have dropped all listings that do not have a corresponding fixed price sale, which I use as a reference price. Finally, I have removed all listings with no BIN variation.

**Table 1.4.** Summary statistics for the baseline dataset

|  | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| First bid as fraction of final sale | 174,983 | 0.36 | 0.91 | 0.00 | 128.68 |
| Second bid as fraction of final sale | 162,040 | 0.50 | 11.50 | 0.00 | 3,121.82 |
| Final sale price | 174,983 | 23.82 | 74.02 | 0.04 | 3,950 |
| Num. of bids | 174,983 | 11.54 | 10.82 | 1 | 132 |
| Indicator: Has BIN option | 174,983 | 0.36 | 0.48 | 0 | 1 |
| Normalized BIN price | 63,839 | 1.13 | 0.73 | 0.03 | 100.20 |
| Indicator: Sold via BIN | 63,839 | 0.22 | 0.42 | 0 | 1 |
|  |  |  |  |  |  |
| Indicator: In Longer BIN group | 174,983 | 0.31 | 0.46 | 0 | 1 |
| Indicator: In Uncertain Value group | 174,983 | 0.03 | 0.16 | 0 | 1 |
|  |  |  |  |  |  |
| Matched sets | 10,460 |  |  |  |  |
| Num. of Listings | 10,460 | 16.73 | 36.59 | 2 | 953 |
| Average fixed price | 10,460 | 44.61 | 131.51 | 0.99 | 3,724 |
|  |  |  |  |  |  |
| Top three categories: |  |  |  |  |  |
| Jewelry & Watches (37.9%) | 66,301 |  |  |  |  |
| Cell Phones & Accessories (24.5%) | 42,783 |  |  |  |  |
| Clothing, Shoes & Accessories (6.9%) | 12,012 |  |  |  |  |

*Notes:* This table contains summary statistics for my baseline dataset. Note that in this set, all listings sell. First bids and second bids are normalized by the final sale price. The BIN price is normalized by the average fixed price. This constitutes listings that started and ended within the period of January 1, 2015 to December 31, 2014. The dataset is additionally filtered on: first and second bids only; free shipping and no reserve; starting price less than or equal to $1; US listings only listed in USD. Additionally, I have dropped outliers and matched sets with no BIN variation.

**Table 2.** Summary statistics for baseline dataset by group

| | (1) Base | | | | | (2) Longer BIN | | | | | (3) Uncertain Value | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | Std. Dev. | Min | Max | Obs. | Mean | Std. Dev. | Min | Max | Obs. | Mean | Std. Dev. | Min | Max |
| First bid as fraction of final sale | 115,389 | 0.39 | 1.02 | 0.00 | 128.68 | 54,795 | 0.29 | 0.64 | 0.00 | 70 | 4,799 | 0.35 | 0.59 | 0.00 | 28.08 |
| Second bid as fraction of final | 107,874 | 0.56 | 11.80 | 0.00 | 3,121.82 | 49,736 | 0.38 | 11.34 | 0.00 | 2,450.98 | 4,430 | 0.38 | 0.97 | 0.00 | 37.64 |
| Final sale price | 115,389 | 16.31 | 66.94 | 0.04 | 3,750 | 54,795 | 39.79 | 86.95 | 0.05 | 3,950 | 4,799 | 22.01 | 38.11 | 0.12 | 554 |
| Num. of bids | 115,389 | 9.82 | 8.39 | 1 | 132 | 54,795 | 14.98 | 14.05 | 1 | 119 | 4,799 | 13.59 | 10.73 | 1 | 124 |
| Indicator: Has BIN option | 115,389 | 0.28 | 0.45 | 0 | 1 | 54,795 | 0.53 | 0.50 | 0 | 1 | 4,799 | 0.47 | 0.50 | 0 | 1 |
| Normalized BIN price | 32,797 | 1.12 | 0.85 | 0.04 | 100.20 | 28,781 | 1.13 | 0.57 | 0.03 | 75.75 | 2,261 | 1.24 | 0.72 | 0.20 | 14.21 |
| Indicator: Sold via BIN | 32,797 | 0.08 | 0.28 | 0 | 1 | 28,781 | 0.39 | 0.49 | 0 | 1 | 2,261 | 0.07 | 0.26 | 0 | 1 |
| Indicator: In Longer BIN group | 115,389 | 0 | 0 | 0 | 0 | 54,795 | 1 | 0 | 1 | 1 | 4,799 | 0 | 0 | 0 | 0 |
| Indicator: In Uncertain Value group | 115,389 | 0 | 0 | 0 | 0 | 54,795 | 0 | 0 | 0 | 0 | 4,799 | 1 | 0 | 1 | 1 |
| Matched listings | 6,755 | | | | | 3,156 | | | | | 549 | | | | |
| Num. of Listings | 6,755 | 17.08 | 34.17 | 2 | 885 | 3,156 | 17.36 | 43.59 | 2 | 953 | 549 | 8.74 | 12.46 | 2 | 159 |
| Avg. Fixed Price | 6,755 | 40.61 | 128.11 | 0.99 | 3,724 | 3,156 | 55.22 | 146.34 | 0.99 | 3,500 | 549 | 32.90 | 59.50 | 0.99 | 565.25 |

*Notes:* This table contains summary statistics filtered by group. Note that in this set, all listings sell. First and second bids are normalized by the sale price. BIN prices are normalized by the average fixed price. Observation counts listed in full amounts. The Longer BIN group is defined by eBay. The Uncertain Value group includes: Antiques; Collectibles; Art; Stamps; Coins & Paper Money; Entertainment Memorabilia; Sports Memorabilia, Cards & Fan Shop. The Base group is defined as all other listings not in the other two groups.

**Table 3.** Normalized BIN quartile breakdown

|            | Obs.    | Mean | Std. Dev. | Min  | Max    |
|------------|---------|------|-----------|------|--------|
| No BIN     | 111,144 | 0    | 0         | 0    | 0      |
| Quartile 1 | 15,465  | 0.84 | 0.22      | 0.03 | 0.99   |
| Quartile 2 | 16,324  | 1.00 | 0.01      | 1    | 1.02   |
| Quartile 3 | 15,991  | 1.10 | 0.05      | 1.02 | 1.19   |
| Quartile 4 | 16,059  | 1.57 | 1.34      | 1.19 | 100.20 |
| Total      | 174,983 | 0.41 | 0.70      | 0    | 100.20 |

*Notes:* The above table splits all the observations with a BIN price into quartiles of roughly equal size, ordered by the normalized BIN price. For simplicity, in the paper, I define the quartiles as follows: Quartile 1 corresponds to a normalized BIN under 1.00. Quartile 2 corresponds to a normalized BIN between 1.00 and 1.02. Quartile 3 corresponds to a normalized BIN between 1.02 and 1.20. Quartile 4 corresponds to a normalized BIN greater than 1.20.

**Table 4.** The effect of the BIN option on the final sales price

|                          | (1) Base $log$(Final sale price) | (2) Longer BIN $log$(Final sale price) | (3) Uncertain Value $log$(Final sale price) |
|--------------------------|------------------|------------------|---------------------|
| Indicator: Has BIN option | $0.0584^{***}$   | $0.0825^{***}$   | $0.0336^{*}$        |
|                          | (12.99)          | (16.57)          | (1.92)              |
|                          |                  |                  |                     |
| Constant                 | $1.133^{***}$    | $2.325^{***}$    | $2.237^{***}$       |
|                          | (471.60)         | (758.96)         | (210.98)            |
|                          |                  |                  |                     |
| Adjusted $R^2$           | 0.91             | 0.94             | 0.91                |
| Num. of Obs.             | 115,389          | 54,795           | 4,799               |
| Num. of Matched Listings | 6,755            | 3,156            | 549                 |

*Notes:* The dependent variable in the above regression is the log of the final sale price and includes fixed effects. The regression is unconditioned. Standard errors are robust and clustered by matched set.

$t$ statistics in parentheses
$^{*} p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$

**Table 5.1.** The effect of BIN price on final sale prices by quartile, unconditioned

| | (1) Base $log$(Final sale price) | (2) Longer BIN $log$(Final sale price) | (3) Uncertain Value $log$(Final sale price) |
|---|---|---|---|
| Indicator: 1$^{st}$ Quartile | 0.0185 (0.87) | 0.0285$^{*}$ (1.77) | -0.0910 (-1.50) |
| Indicator: 2$^{nd}$ Quartile | 0.0810$^{***}$ (10.59) | 0.0701$^{***}$ (3.06) | -0.0291 (-0.86) |
| Indicator: 3$^{rd}$ Quartile | 0.0276$^{**}$ (2.47) | 0.0791$^{***}$ (5.31) | 0.0505$^{*}$ (1.72) |
| Indicator: 4$^{th}$ Quartile | 0.0679$^{***}$ (5.17) | 0.126$^{***}$ (7.46) | 0.128$^{***}$ (2.80) |
| Constant | 1.135$^{***}$ (460.68) | 2.327$^{***}$ (407.62) | 2.237$^{***}$ (218.19) |
| Adjusted R$^2$ | 0.91 | 0.94 | 0.91 |
| Num. of Obs. | 115,389 | 54,795 | 4,799 |
| Num. of Matched Listings | 6,755 | 3,156 | 549 |

*Notes:* The dependent variable in the above regression is the log of the final sale price and includes fixed effects. The regression is unconditioned. Standard errors are robust and clustered by matched set.

$t$ statistics in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 5.2.** The effect of BIN price on final sale prices by quartile, conditioned

|  | (1) Base | (2) Longer BIN | (3) Uncertain Value |
|---|---|---|---|
|  | $log$(Final sale price) | $log$(Final sale price) | $log$(Final sale price) |
| Indicator: 1st Quartile | -0.0279*** | -0.0829*** | -0.119*** |
|  | (-3.28) | (-8.26) | (-4.02) |
| Indicator: 2nd Quartile | 0.0105* | -0.0491*** | -0.0518 |
|  | (1.71) | (-4.42) | (-1.60) |
| Indicator: 3rd Quartile | -0.00950 | -0.00720 | 0.0340 |
|  | (-1.03) | (-0.90) | (1.26) |
| Indicator: 4th Quartile | 0.0366*** | 0.0311*** | 0.0974*** |
|  | (3.67) | (3.98) | (4.12) |
| Constant | 1.136*** | 2.463*** | 2.265*** |
|  | (595.75) | (883.10) | (230.12) |
| Adjusted $R^2$ | 0.91 | 0.95 | 0.91 |
| Num. of Obs. | 112,602 | 43,622 | 4,634 |
| Num. of Matched Listings | 6,718 | 3,066 | 545 |

*Notes:* The dependent variable in the above regression is the log of the final sale price and includes fixed effects. The regression is conditioned on listings that do not result in a BIN sale. This is to control for the revenue effects of BIN exercise and to isolate the revenue effects of BIN existence. Standard errors are robust and clustered by matched set.

$t$ statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 5.3.** The marginal effect of BIN prices on final sale price, conditioned

|  | (1) Base log(Final sales price) | (2) Longer BIN log(Final sales price) | (3) Uncertain Value log(Final sales price) |
|---|---|---|---|
| log(BIN price) | 0.109*** | 0.236*** | 0.620*** |
|  | (3.46) | (3.20) | (3.89) |
| Constant | 1.600*** | 1.741*** | 0.585 |
|  | (20.39) | (7.86) | (1.22) |
| Adjusted $R^2$ | 0.94 | 0.95 | 0.91 |
| Num. of Obs. | 30,010 | 17,608 | 2,096 |
| Num. of Matched Listings | 6,494 | 2,853 | 532 |

*Notes:* The dependent variable in the above regression is the log of the final sales price and includes fixed effects. The explanatory variable is a continuous variable reflecting the log of the BIN price. The regression is conditioned on listings that have a BIN option and listings that were not sold via the BIN option. Standard errors are robust and clustered by matched set.

*t* statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 6.1.** The effect of BIN prices on first bids

|  | (1) Base $log$(First bid) | (2) Longer BIN $log$(First bid) | (3) Uncertain Value $log$(First bid) |
|---|---|---|---|
| Indicator: 1$^{st}$ Quartile | 0.0656$^{**}$ | 0.0296 | -0.249$^{**}$ |
|  | (2.03) | (0.59) | (-2.10) |
| Indicator: 2$^{nd}$ Quartile | -0.0451$^{*}$ | 0.171$^{***}$ | -0.125 |
|  | (-1.93) | (3.11) | (-0.96) |
| Indicator: 3$^{rd}$ Quartile | -0.0228 | 0.0683$^{*}$ | 0.293$^{***}$ |
|  | (-0.65) | (1.73) | (2.70) |
| Indicator: 4$^{th}$ Quartile | 0.124$^{***}$ | 0.108$^{***}$ | 0.196$^{**}$ |
|  | (3.27) | (2.79) | (2.06) |
| Constant | -1.105$^{***}$ | -0.386$^{***}$ | 0.0563 |
|  | (-152.11) | (-27.92) | (1.43) |
| Adjusted $R^2$ | 0.39 | 0.35 | 0.30 |
| Num. of Obs. | 112,602 | 43,622 | 4,634 |
| Num. of Matched Listings | 6,718 | 3,066 | 545 |

*Notes:* The dependent variable in the above regression is the log of the first bid and includes fixed effects. The regression is conditioned on all listings that did not result in a BIN sale. This is done to isolate the effect of the BIN price on first bids. If BIN sale listings were included, all BIN sales in regression samples (1) and (3) and some of (2) would have first bids equal to the BIN price and would bias my coefficients upwards. Standard errors are robust and clustered by matched set.

$t$ statistics in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 6.2.** The effect of BIN prices on second bids

| | (1) Base $log$(Second bid) | (2) Longer BIN $log$(Second bid) | (3) Uncertain Value $log$(Second bid) |
|---|---|---|---|
| Indicator: $1^{st}$ Quartile | 0.0388 | 0.0400 | 0.0603 |
| | (0.85) | (1.01) | (0.61) |
| Indicator: $2^{nd}$ Quartile | 0.0405$^{**}$ | 0.151$^{**}$ | -0.0354 |
| | (2.46) | (2.31) | (-0.24) |
| Indicator: $3^{rd}$ Quartile | 0.0212 | 0.0984$^{**}$ | 0.108 |
| | (0.61) | (2.13) | (1.02) |
| Indicator: $4^{th}$ Quartile | 0.106$^{***}$ | 0.109$^{**}$ | 0.194$^{**}$ |
| | (3.19) | (2.17) | (2.40) |
| Constant | -0.342$^{***}$ | 0.214$^{***}$ | 0.459$^{***}$ |
| | (-63.71) | (16.86) | (16.29) |
| Adjusted $R^2$ | 0.45 | 0.36 | 0.29 |
| Num. of Obs. | 107,874 | 42,582 | 4,430 |
| Num. of Matched Listings | 6,629 | 3,022 | 520 |

*Notes:* The dependent variable in the above regression is the log of the second bid and includes fixed effects. The regression is conditioned on listings that result in an auction sale as opposed to a BIN sale. Standard errors are robust and clustered by matched set.

$t$ statistics in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 7.** The effect of BIN prices on the number of bids

| | (1) Base $log$(Bid count) | (2) Longer BIN $log$(Bid count) | (3) Uncertain Value $log$(Bid count) |
|---|---|---|---|
| Indicator: 1st Quartile | -0.00859$^*$ | -0.0447$^{***}$ | 0.000117 |
| | (-1.66) | (-6.96) | (0.01) |
| Indicator: 2nd Quartile | 0.0320$^{***}$ | -0.0681$^{***}$ | 0.00496 |
| | (7.20) | (-8.72) | (0.25) |
| Indicator: 3rd Quartile | 0.0136$^{**}$ | 0.000656 | -0.0332$^*$ |
| | (2.56) | (0.14) | (-1.83) |
| Indicator: 4th Quartile | 0.0150$^{**}$ | -0.0173$^{***}$ | -0.00935 |
| | (2.44) | (-3.51) | (-0.53) |
| Num. of Obs. | 112,406 | 43,368 | 4,609 |
| Num. of Matched Listings | 6,718 | 3,066 | 545 |

*Notes:* The dependent variable in the above regression is the log of the expected count of bids conditional on the BIN quartile and includes fixed effects. The regression is conditioned on all listings that did not result in a BIN sale. This is done in order to control for premature curtailment of the bid count due to a BIN sale. The bid count in this case refers to the total number of bids placed and not the total number of unique bids. Standard errors are robust and clustered by matched set.

*t* statistics in parentheses
$^*$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 8.** The effect of the first bid and the number of bids on the final sale price

|  | (1) Base<br>log(Final sale price) | (2) Longer BIN<br>log(Final sale price) | (3) Uncertain Value<br>log(Final sale price) |
|---|---|---|---|
| log(First bid) | 0.0615*** | 0.0231*** | 0.0428*** |
|  | (77.78) | (24.86) | (11.56) |
| log(Bid count) | 0.273*** | 0.0756*** | 0.256*** |
|  | (106.26) | (27.48) | (24.78) |
| Constant | 0.672*** | 2.206*** | 1.666*** |
|  | (132.33) | (350.72) | (69.04) |
| | | | |
| Adjusted $R^2$ | 0.92 | 0.94 | 0.92 |
| Num. of Obs. | 115,389 | 54,795 | 4,799 |
| Num. of Matched Listings | 6,755 | 3,156 | 549 |

*Notes:* The dependent variable in the above regression is the log of the final sale price and includes fixed effects. The explanatory variables are the log of the first bid amount and the log of the number of bids. The regression is unconditioned. Standard errors are robust and clustered by matched set.

*t* statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.02$