Cheap Talk, Round Numbers, and the Economics of Negotiation*

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Abstract

Can sellers credibly signal their private information to reduce frictions in negotiations? Guided by a simple cheap-talk model, we posit that impatient sellers use round numbers to signal their willingness to cut prices in order to sell faster, and test its implications using millions of online bargaining interactions. Items listed at multiples of $100 receive offers that are 5%–8% lower but that arrive 6–11 days sooner than listings at neighboring "precise" values, and are 3%–5% more likely to sell. Similar patterns in real estate transactions suggest that round-number signaling plays a broader role in negotiations. *JEL* classifications: C78, D82, D83, M21.

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1 Introduction

Bargaining is pervasive. We bargain over goods, services, salaries, real estate, territorial boundaries, mergers and acquisitions, household chores, and more. As the Coase Theorem demonstrates, when property rights are well-defined and negotiating parties have perfect information, bargaining leads to efficient outcomes (Coase, 1960). At least since Myerson and Satterthwaite (1983), however, economists have understood the potential for bargaining failure. When the parties' valuations are not commonly known, each has an incentive to overstate the strength of their position in order to extract surplus, resulting in efficiency losses. These losses can manifest in the form of delays, or the complete breakdown of negotiations, with real economic costs. We ask whether these informational frictions can be mitigated with the use of cheap talk, which serves as a framework for modeling negotiation. Namely, are some market participants willing and able to signal a weak bargaining position in order to secure a timely sale at a less advantageous price?

We take this question to a novel dataset of millions of bargaining transactions on the eBay.com "Best Offer" platform, where sellers offer items at a listed price and invite buyers to engage in alternating, sequential-offer bargaining, very much in the spirit of Rubinstein (1982). Guided by a simple model, we show that many sellers find it beneficial to signal bargaining weakness in order to sell their items faster, albeit at lower prices.

We begin by introducing a puzzling pattern in the data. Sellers who post items at "round-number" prices—namely multiples of \$100—obtain first-round offers that are significantly lower than the offers obtained by sellers whose posted prices are not round numbers. This is puzzling because rather than post an item at, say \$200, it seems that a seller would be better off by choosing a lower "precise" number such as \$198. And yet, such round-number listings are very common in our setting, even among experienced sellers. How can this be consistent with equilibrium behavior in a well-functioning marketplace with millions of participants?

We develop a stylized model in which round numbers, such as multiples of \$100, are chosen strategically as a cheap-talk signal by impatient sellers who are willing to take a price cut in order to sell faster. The intuition is quite simple: if round numbers are a credible cheap-talk signal of eager (impatient) sellers, then by signaling weakness, a seller will attract buyers faster who rationally anticipate the better deal. In equilibrium, patient sellers prefer to hold out for a higher price, and hence have no incentive to signal weakness, so they choose precise-number listings.

Our model yields a set of testable hypotheses that we take to the eBay data. First, round-number listings not only attract lower offers, but sell at prices that are $5\% - 8\%$ lower on average than nearby precise-number listings. Second, round-number listings receive offers much sooner, approximately 6 to 11 days sooner on average than precise-number listings. Third, round-number listings are $3\% - 5\%$ more likely to sell than precise-number listings. These findings all support the premise of our model, that round numbers are a cheap-talk signal used by impatient sellers. We also find that sellers who use precise listing prices are less likely to accept similar offers than those using round listing prices, and conditional on countering, they make more aggressive counter-offers. This is consistent with a connection between a seller's eagerness to sell—or, formally, their private type—and their propensity to list at round numbers.

A concern with the basic empirical findings may be that, for round-number listings, there are unobservable differences in the seller attributes or in the products themselves, resulting in lower offers and lower prices. There are several plausible reasons this could be the case, and such unaccounted-for heterogeneity—observable to bidders but not to us as econometricians—can bias our estimates. We address this possibility by taking advantage of the fact that items listed on eBay's site in the United Kingdom (ebay.co.uk) will sometimes appear in search results for user queries on the U.S. site (ebay.com). A feature of the platform is that U.S. buyers who see items listed by U.K. sellers will observe prices that are automatically converted into dollars at the contemporaneous exchange rate. Hence, some items will be listed at round numbers in the U.K., while at the same time appear to be precise-number listings in the U.S. Assuming that U.S. buyers perceive that same unobserved heterogeneity as their U.K. counterparts, we can compare their behavior to difference out the bias and demonstrate the existence of a causal effect of roundness.

Another concern may be that what we find is an artifact special to the eBay bargaining environment. We obtain data from the Illinois real estate market that has been used by Levitt and Syverson (2008) where we observe both the original listing price and the final sale price. The data does not let us perform the vast number of tests of we can for eBay's large data set, but we do find evidence that homes that were listed at round numbers sell for less than those listed at precise numbers.

Our theoretical framework is closely related to Farrell and Gibbons (1989) and Cabral and Sákovics (1995), who show that cheap talk may influence bargaining with asymmetric information. Single crossing in their model comes from the differential cost of bargaining breakdown for high- and low-valuation parties.[1] Our single-crossing comes from differences in patience, and we discus this and other possible mechanisms in Section 3 and 6.

Our primary contribution is empirical: we document a signaling equilibrium in the spirit of Spence (1973) and Nelson (1974). This is challenging because the essential components of signaling equilibria — beliefs, private information, and signaling costs — are usually unobservable to the econometrician. The oldest thread in this literature concerns "sheepskin effects," or the effect of education credentials on employment outcomes (Layard and Psacharopoulos, 1974; Hungerford and Solon, 1987). Regression discontinuity has become the state of the art for estimating these effects following Tyler et al. (2000), who use state-by-state variation in the pass threshold of the GED examination to identify the effect on wages for young white men on the margin of success. By holding attributes such as latent ability or educational inputs constant, they isolate the value of the GED certification itself, i.e. the pure signaling content, rather than its correlates. We complement this literature by identifying not only the effect of the signal, but also the equilibrium trade-off that makes separating equilibrium possible in a cheap-talk setting. In this sense our detailed data allows us to go further in proving the empirical relevance of signaling models. Additionally, there is a small literature in empirical IO studying costly signaling games in a variety of settings e.g. limit pricing in Gedge et al. (2013) and borrowing in Kawai et al. (2013), as well as a growing literature on the empirics of bargaining and negotiation (Ambrus et al., 2014; Bagwell et al., 2014; Grennan, 2013, 2014; Larsen, 2014; Shelegia and Sherman, 2015).

Our work is also related to a literature on numerosity and cognition; in particular, how nominal features of the action space of a game might affect outcomes. Recent work in consumer psychology and marketing has studied the use of round numbers in bargaining (Janiszewski and Uy, 2008; Loschelder et al., 2013; Mason et al., 2013). These papers argue from experimental and observational evidence that using round numbers in bargaining

[1] Intuitively, high-valuation buyers (or low-valuation sellers) have more to lose from bargaining breakdown, and therefore may be willing to sacrifice some bargaining advantage to increase the likelihood of transacting. Our approach is similar in that we use the probability of transacting to obtain single crossing, but different in that we do so by modeling the matching process of buyers to sellers. This approach is related to a more recent literature on directed search (Menzio, 2007; Kim, 2012; Kim and Kircher, 2013) but unlike papers in that literature we do not employ a matching function.

leads to "worse" outcomes (i.e. lower prices). By way of explanation they offer an array of biases, from anchoring to linguistic norms, and come to the brusque conclusion that round numbers are to be avoided by the skillful negotiator.[2] This literature leaves unanswered the question of why, then, as we demonstrate below, round numbers are so pervasive in bargaining, even among experienced sellers. We reconcile these facts with an alternative hypothesis: that round numbers are an informative signal, sometimes used to sellers' advantage *despite* the negative signal they send about one's own bargaining strength.

2 Online Bargaining and Negotiations

The eBay marketplace became famous for its use of simple auctions to facilitate trade. In recent years, however, the share of auctions on eBay's platform has been surpassed by fixed-price listings, many listed by businesses (Einav et al., 2013). For fixed-price listings, eBay's platform offers sellers the opportunity to sell their items using a bilateral bargaining procedure with a feature called "Best Offer". We conjecture that, like auctions, Best Offer serves as a demand discovery mechanism for sellers.

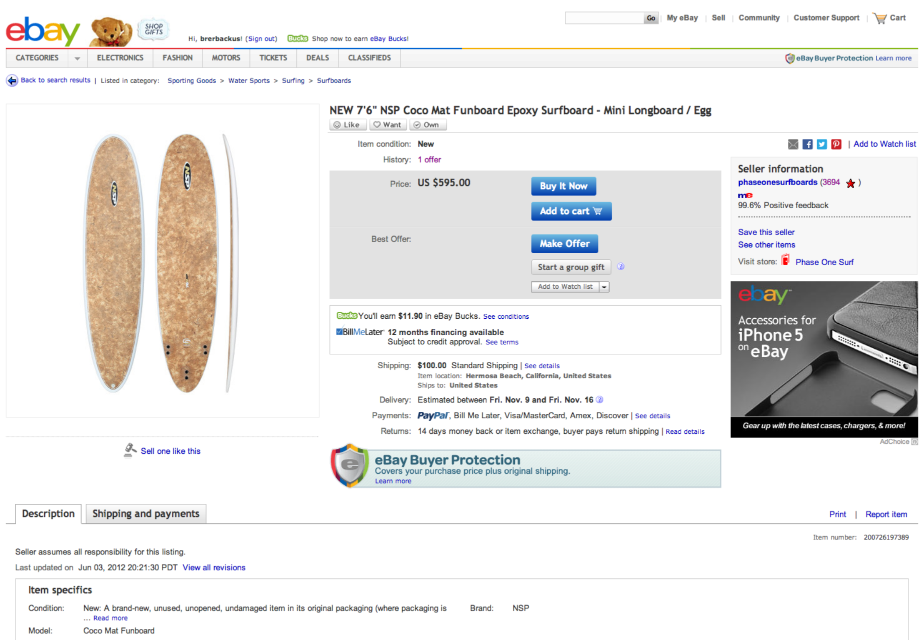
The feature modifies the listing page as demonstrated in Figure 1 by enabling the "Make Offer" button that is shown just below the "Buy It Now" button. Upon clicking the Make Offer button, a prospective buyer is prompted for an offer in a standalone numerical field.[3] Submitting an offer triggers an email to the seller who then has 48 hours to accept, decline, or make a counter-offer. Once the seller responds, the buyer is then sent an email prompting to accept and checkout, make a counter-offer, or move on to other items. This feature has been growing in popularity and bargained transactions currently account for nearly 10 percent of total transaction value in the marketplace.[4]

[2]From NPR (2013), Malia Mason of Mason et al. (2013) NPR interview on *All Things Considered* June 3, 2013: Rob Siegel: "What do you mean don't pick a round number?" Malia Mason: "[...] so if you're negotiating for, lets say, a car– you're buying a used car from someone, [...] don't suggest that you'll pay 5,000 dollars for the car. Say something like: I'll pay you 5,225 dollars for the car, or say 4,885 dollars for the car." Rob Siegel: "Why should that be a more successful tactic for negotiating?" Malia Mason: "It signals that you have more knowledge about the value of the good being negotiated."

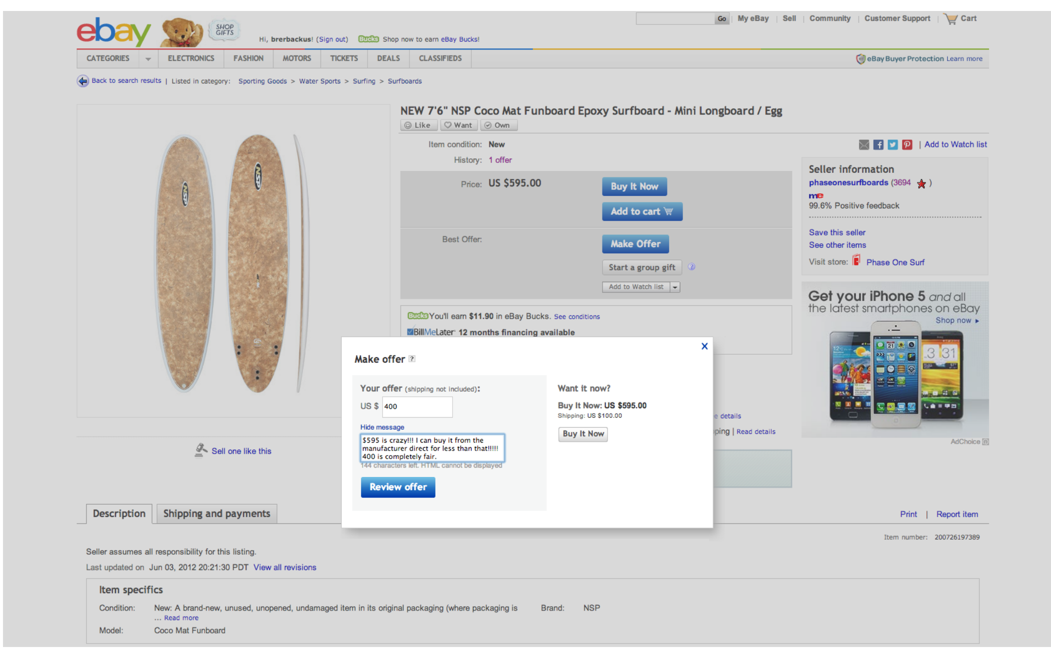
[3]The buyer can also send a message with their offer, as seen in frame (b) of Figure 1. We leave the analysis of those messages, which requires a different approach, for future work.

[4]Analyzing sellers' choice of mechanism between auctions, fixed prices, and fixed prices with bargaining, is beyond the scope of this paper. We conjecture that Best Offer and auctions are alternative price discovery mechanisms. The 30-day duration of fixed price listings may be appealing when there are few potential buyers because the 10-day maximum duration of auctions constrains its effectiveness.

Figure 1: Best Offer on eBay



(a) Listing Page



(b) Make an Offer

Notes: Frame (a) depicts a listing with the Best Offer feature enabled, which is why the "Make Offer" button appears underneath the "Buy It Now" and "Add to Cart" buttons. When a user clicks the Make Offer button, a panel appears as in frame (b), prompting an offer and, if desired, an accompanying message.

Table 1: Summary Statistics

Variable	Mean	(Std. Dev.)	N
Listing Price (BIN)	166.478	(118.177)	10472614
Round $100	0.053	(0.225)	10472614
BIN in [99,99.99]	0.114	(0.318)	10472614
Offers / Views	0.027	(0.09)	10395821
Avg First Offer $	95.612	(77.086)	2804521
Avg Offer $	105.875	(1062.989)	2804521
Avg first Offer ratio (Offer/BIN)	0.631	(3.849)	2804521
Avg Counter Offer	148.541	(7896.258)	1087718
Avg Sale $	123.136	(92.438)	2088516
Search Result Hits/Day	212.718	(292.657)	10472614
Views/Day	2.093	(5.941)	10472614
Time to Offer	28.153	(56.047)	2804521
Time to Sale	39.213	(67.230)	2088516
Lowest Offer $	89.107	(74.702)	2804521
Highest Offer	125.06	(7381.022)	2804521
Pr(Offer)	0.268	(0.443)	10472614
Pr(BIN)	0.049	(0.216)	10472614
Pr(Sale)	0.199	(0.4)	10472614
Listing Price Revised	0.570	(0.495)	4045843
# Seller's Prior BO Listings	69974.77	(322691.987)	10472614
# Seller's Prior Listings	87806.748	(387681.096)	10472614
# Seller's Prior BO Threads	2451.256	(5789.343)	2804521

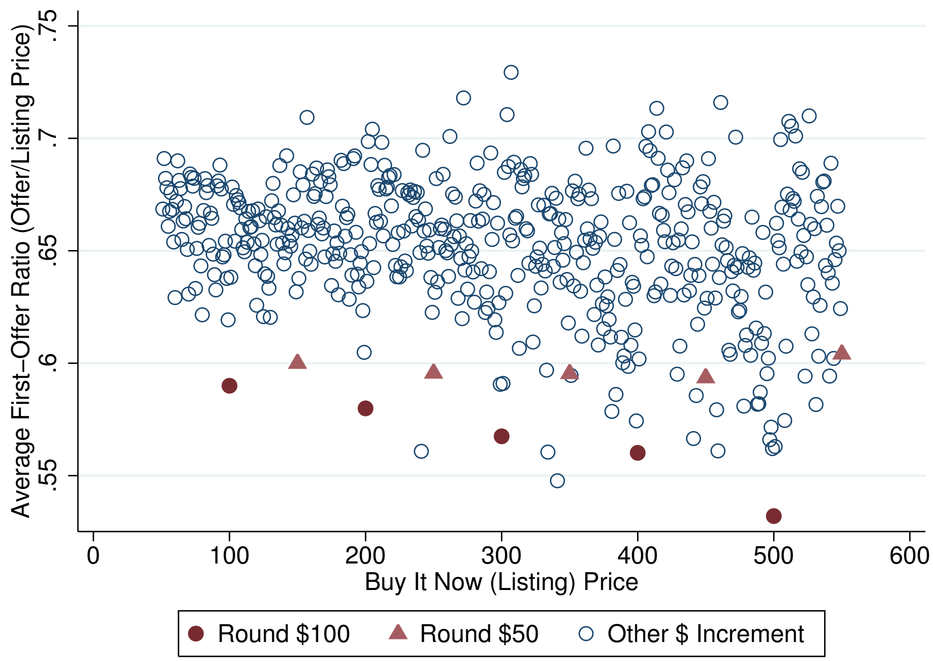
Notes: This table presents summary statistics for the main dataset of BO-enabled collectibles listings created on eBay.com between June 2012 and May 2013 with BIN prices between $50 and $550.

We restrict attention to items in eBay's Collectibles marketplace which includes coins, antiques, toys, memorabilia, stamps, art and other like goods. Our results generalize to other categories, but we believe that the signaling mechanism is naturally greatest in collectibles where there is greater heterogeneity in valuations.

Our data records each bargaining offer, counter-offer, and transaction for any Best Offer listing. We have constructed a dataset of all single-unit Best Offer enabled listings (items for sale) that started between June 2012 and May 2013. We then limit to listings with an initial "Buy It Now" (BIN) price between $50 and $550. This drops listings from both sides of our sample: inexpensive listings, in which the costs of bargaining dominate the potential surplus gains, and the right tail of very expensive listings. We are left with 10.5 million listings, of which 2.8 million received an offer and 2.1 million sold.[5] We construct several measures of bargaining outcomes, which are summarized in Table 1.

[5]Note that these figures are not representative of eBay listing performance generally because we have selected a unique set of listings that are suited to bargaining.

Figure 2: Average First Offers by BIN Price

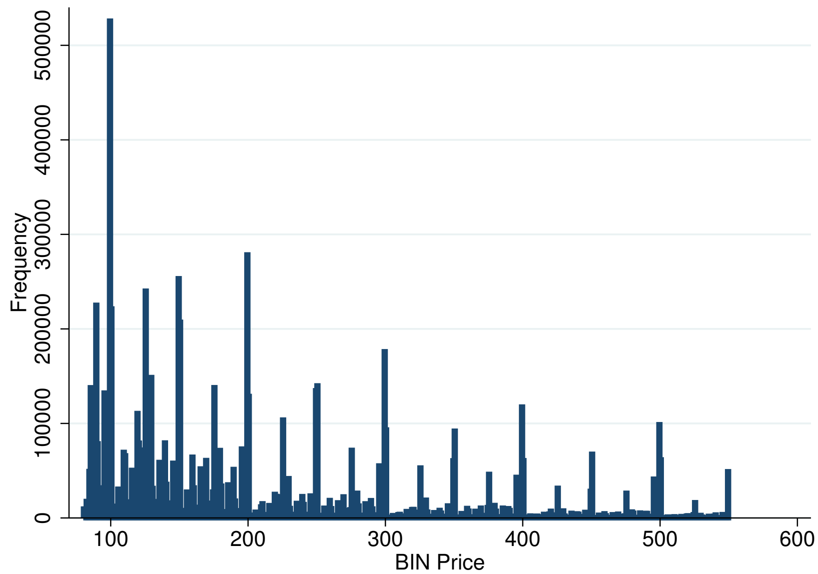


Notes: This scatterplot presents average first offers, normalized by the BIN price to be between zero and one, grouped by unit intervals of the BIN price, defined by $(z-1, z]$. When the BIN price is on an interval rounded to a number ending in "00", it is represented by a red circle; "50" numbers are represented by a red triangle.

Sale prices average near 79 percent of listed prices but vary substantially. Buyers start far more aggressively, with the average starting offer at 63 percent of the posting price. Sellers wait quite a while for (the first) offers to arrive, 28 days on average, and do not sell for 39 days. This would be expected for items in thin markets for which the seller would prefer a price discovery mechanism like bargaining. Finally, we also record the count of each seller's prior listings (with and without Best Offer enabled) as a measure of the sellers' experience level.

To motivate the rest of the analysis, consider the scatterplot in Figure 2. On the horizontal axis is the listing price of the goods listed for sale, and on the vertical axis we have the *average* ratio of the first offer to the listed price. For example, imagine that there were a total of three listed items at a price of $128 that received an offer from some buyer. The first item received an offer of $96, or 75% of $128, the second item received an offer of $80, or 62.5% of $128, and the third received an offer of $64, or 50% of $128. The average

Figure 3: Buy it Now Prices for Best Offer Listings



Notes: This is a histogram of seller's chosen listing prices for our dataset. The bandwidth is one and unit intervals are generated by rounding up to the nearest integer.

of these first offer ratios is $\frac{1}{3}(0.75 + 0.625 + 0.5) = 0.625$. As a result, the corresponding data point on the scatterplot would have $x = 128$ and $y = 0.625$. Because listings can be made at the cent level, we create bins that round up the listing price to the nearest dollar so that each listing is group into the range $(z - 1, z]$ for all integers $z \in [50, 550]$. That is, a listing at \$26.03 will be grouped together with a listing of \$26.95, while a listing of \$24.01 will be grouped together with a listing of \$25. Each point in Figure 2 represents, at that listing price, an average across all initial buyer offers for items in our sample of 2.8 million listings that received an offer.

What is remarkable about this scatterplot is that when the asking price is a multiple of \$100, the average ratio of the first offer to the listed price is at least five percentage points lower than the same average for nearby non-round listing prices. It suggests a non-monotonicity– that sellers who list at round numbers could improve their offers by either lowering or raising their price by a small amount. However, this is not borne out by seller behavior. We see many listings at these round numbers. Figure 3 presents a histogram of listing prices from our dataset, showing that round numbers are disproportionately more frequent. Moreover, as we document in Appendix H, choosing round-number listings is prevalent even among the most experienced sellers. This observation — that even experienced sellers seem to be selecting listing prices that elicit lower sale prices — motivates our theoretical framework.

3 Theoretical Framework

This section presents a stylized model in which round numbers are chosen strategically as a signal by impatient sellers who are willing to take a price cut in order to sell faster. The intuition is quite simple: if round numbers are a credible cheap-talk signal of eager (impatient) sellers, then by signaling weakness, a seller will attract buyers faster who rationally anticipate the better deal. In equilibrium, patient sellers prefer to hold out for a higher price, and hence have no incentive to signal weakness. In contrast, impatient sellers avoid behaving like patient sellers because this will delay the sale.

The model we have constructed is deliberately simple, and substantially less general than it could be. There are three essential components: the form of seller heterogeneity (here, in discount rates), the source of frictions (assumptions on the arrival and decision process), and the bargaining protocol (Nash). A very general treatment of the problem is beyond the scope of this paper, but we appeal to the fact that there are numerous models in the literature which share our intuition but differ in the above components.[6]

It is also important to note that we use a rather standard "non-behavioral" approach that imposes no limits on cognition or rationality. One may be tempted to connect roundness and precision with ideas about how limited cognition among sellers and buyers may impact outcomes. Perhaps, a round listing price reflects "cluelessness" or uncertainty about demand for the product listed. This idea is particularly compelling because it is intuitive that sellers use the Best Offer feature on eBay as a demand discovery mechanism. If, however, round-number sellers were more uncertain about demand then they should solicit more offers and take longer to sell; instead we find that they sell substantially sooner

[6] With respect to seller heterogeneity, the intuition requires heterogeneity in sellers' reserve prices. Farrell and Gibbons (1989) impose this directly, while Menzio (2007) takes as primitive heterogeneity in the joint surplus possible with each employer. Finally, Kim (2012) describes a market with lemons, so that sellers have heterogeneous unobserved quality. Another critical ingredient is explaining why sellers who offer buyers less surplus in equilibrium also have non-zero market share. In a frictionless world of Bertrand competition, this is impossible. To address this, frictions are an essential part of the model. In Farrell and Gibbons (1989) this is accomplished by endogenous bargaining breakdown probabilities. Recent work used matching functions to impose mechanical search frictions in order to smooth expected market shares. All that we require of the bargaining mechanism is that outcomes depend on sellers' private information. Farrell and Gibbons (1989) do the general case of bargaining mechanisms, while Menzio (2007) uses a limiting model of alternating offers bargaining from Gul and Sonnenschein (1988).

than precise-number sellers. It is for this reason that we build our model on heterogeneity in discounting rather than heterogeneity in seller informedness because the latter fails to fit the empirical facts. However, in general we acknowledge that alternative cheap-talk signaling models could be specified with similar predictions (e.g., with heterogeneity in seller costs)— our intention is not to sort between them, but rather to provide an illustrative example, to derive predictions, and to use them to prove the empirical relevance of cheap-talk signaling in bargaining.

3.1 A Simple Model of Negotiations

Consider a market in which time is continuous and buyers arrive randomly with a Poisson arrival rate of λ_b. Each buyer's willingness to pay for a good is 1, and their outside option is set at 0. Once a buyer appears in the marketplace he remains active for only an instant of time, as he makes a decision to buy a good or leave instantaneously.

There are two types of sellers: high types ($\theta = H$) and low types ($\theta = L$), where types are associated with the patience they have. In particular, the discount rates are $r_H = 0$ and $r_L = r > 0$ for the two types, and both have a reservation value (cost) of 0 for the good they can sell to a buyer. The utility of a seller of type θ from selling his good at a price of p after a period of time t from when he arrived in the market is $e^{-r_\theta t}p$.

We assume that at most one H and one L type sellers can be active at any given instant of time. If an H type seller sells his good then he is replaced immediately, so that there is always at least one active H type seller. Instead, if an L type seller sells his good then he is replaced randomly with a Poisson arrival rate of λ_s. Hence, the expected time between the departure of one L type seller and the arrival of another is $\frac{1}{\lambda_s}$. This captures the notion of a diverse group of sellers, where patient sellers are abundant and impatient sellers appear less frequently.

Buyers and sellers interact in the marketplace as follows. First, upon each buyer arrival to the marketplace, each active seller sends the buyer a cheap-talk signal "Weak" (W) or "Strong" (S). Being cheap-talk signals, these are costless and unverifiable, but they may affect the buyer's beliefs in equilibrium. Second, the buyer chooses a seller to match with. Third and finally, upon matching with a seller, the two parties split the surplus of trade between them given the buyer's *beliefs* about the seller's type.[7]

[7]For a similar continuous time matched-bargaining model see Ali et al. (2015). This split-the-surplus "Nash bargaining" solution is defined for situations of complete information, where the payoff functions are

When a buyer arrives at the marketplace she observes the state of the market, which is characterized by either one or two sellers. The assumptions on the arrival of seller types imply that if there is only one seller, then the buyer knows that he is an H type seller, while if there are two sellers, then the buyer knows that there is one of each type. A buyer chooses who to "negotiate" with given her belief that is associated with the sellers' signals. Nash bargaining captures the idea that bargaining power will depend on the buyers' beliefs about whether the seller is patient (S) or impatient (W).

We proceed to construct a separating Perfect Bayes Nash Equilibrium in which the L type chooses to reveal his weakness by selecting the signal W to negotiate a sale at a low price once a buyer arrives, while the H type chooses the signal S and only sells if he is alone for a high price. We verify that this is an equilibrium in the following steps.

1. **High type's price:** Let p_H denote the equilibrium price that a H type receives if he choose the signal S. The H type does not care about when he sells because his discount rate is $r_H = 0$, implying that his endogenous reservation value is p_H. Splitting the surplus, i.e. Nash bargaining in this setting, requires that p_H be halfway between that endogenous reservation value and 1, and therefore $p_H = 1$.

2. **Low type's price:** Let p_L denote the equilibrium price that a L type receives from a buyer if he chooses the signal W. If he waits instead of settling for p_L immediately, then in equilibrium he will receive p_L from the next buyer. The Poisson arrival rate of buyers implies that their inter-arrival time is distributed exponential with parameter λ_b, so the expected value of waiting is $p_L \mathbb{E}_t[e^{-rt}]$, where the discount can be solve analytically:

$$\begin{aligned} \mathbb{E}_t[e^{-rt}] &= \int_0^\infty e^{-rx} \lambda_b e^{-\lambda_b x} dx \\ &= \frac{\lambda_b}{r+\lambda_b} \underbrace{\int_0^\infty (r+\lambda_b) e^{-x(r+\lambda_b)} dx}_{=1} = \frac{\lambda_b}{r+\lambda_b}. \end{aligned} \tag{1}$$

common knowledge. We take the liberty of adopting the solution concept to a situation where one player has a belief over the payoff of the other player, and given that belief, the two players split the surplus.

The integral in the second line is equal to one by the definition of the exponential distribution. Nash bargaining therefore implies

$$p_L = \frac{1}{2} p_L \frac{\lambda_b}{r+\lambda_b} + \frac{1}{2} 1 \quad \Rightarrow \quad p_L = \frac{r+\lambda_b}{2r+\lambda_b}. \tag{2}$$

3. **Incentive compatibility:** It is obvious that incentive compatibility holds for H types. Imagine then that the L type chooses S instead of W. Because there is always an H type seller present, once a buyer arrives we assume that each seller gets to transact with the buyer with probability $\frac{1}{2}$. Hence, the deviating L type either sells at $p_H = 1$ or does not sell and waits for p_L, each with equal probability. Incentive compatibility holds if $p_L \geq \frac{1}{2} \frac{\lambda_b}{r+\lambda_b} p_L + \frac{1}{2} 1$, but this holds with equality from the Nash bargaining solution that determines the L type's equilibrium price.[8]

3.2 Equilibrium Properties and Empirical Predictions

In equilibrium, if both sellers are present in the market then any new buyer that arrives will select to negotiate with an L type in order to obtain the lower price of p_L. Furthermore, an H type will sell to a buyer if and only if there is no L type seller in parallel. Because L types are replaced with a Poisson rate of λ_s, the H type will be able to sometimes sell in the period of time after one L type sold and another L type arrives in the market. As a result, the equilibrium has the following properties: First, the L type sells at price $p_L < 1$ and the H type sells at price $p_H = 1$. Second, the L type sells with probability 1 to the first arriving buyer while the H type sells only when there is no L type. This implies a longer waiting time for a sale for H. In turn, this implies for any given period of time, the probability that an H type will sell is lower than that of an L type.

These equilibrium properties lend themselves immediately to several empirical predictions that we can take to our data. In light of the regularity identified in Figure 2, we take round numbers in multiples of \$100 to be signals of weakness, justified further in Section 4.1. As such, the testable hypotheses of the model are as follows:

[8] Because we use the Nash solution for the negotiation stage of the game, there is no deviation to consider there. One could consider an alternative game in which sellers commit to a single, public signal of their type which will be visible to all buyers. Then we should verify that the L type does not want to deviate and commit to choose the S signal forever until he makes a sale. If the L type commits to this strategy then his expected payoff can be written recursively as $v = \frac{1}{2}1 + \frac{1}{2} v \frac{\lambda_b}{r+\lambda_b}$. By analogy with (2) this implies $v = p_L$ and so we conclude that such a deviation is not profitable.

- H1: Round-number listings get discounted offers and sell for lower prices.
- H2: Round-number listings receive offers sooner and sell faster.
- H3: Round-number listings sell with a higher probability (Because listings expire, even L types may not sell).
- H4: In "thick" buyer markets (higher λ_b) discounts are lower.

We have chosen to model bargaining and negotiation using Nash Bargaining rather than specifying a non-cooperative bargaining game. As Binmore et al. (1986) show, the Nash solution can be obtained as a reduced form outcome of a non-cooperative strategic game, most notably as variants of the Rubinstein (1982) alternating offers game. Building such a model is beyond the scope of this paper, but analyses such as those in Admati and Perry (1987) suggest that patient bargainers will be tough and willing to suffer delay in order to obtain a better price. Hence, despite the fact that within-bargaining offers and counter-offers are not part of our formal model, the existing theoretical literature suggests the following hypotheses:

- H5: Conditional on receiving an offer, round-number sellers are more likely to accept rather than counter.
- H6: Conditional on countering, round-number sellers make less aggressive counter-offers.

In the above we have taken as given that round numbers are the chosen signal of bargaining weakness. A natural question would be, why don't impatient sellers just reduce their listing price rather than choose a round number? In practice, sellers may be trying to signal many dimensions of the item and their preferences simultaneously, and the level of the price is more likely to be useful for signaling item quality to buyers. As we show in Section 4.5 below, these signals are directing buyer search at an early stage, before buyers are exposed to— i.e. make the investment in examining— full item descriptions or multiple photographs. Therefore, if a seller has an item that he believes can sell for about \$70, but is willing to sell it faster at \$65, then by listing it at \$65 buyers may infer that it is of lower quality and not explore the item in more detail. Instead, the round number of \$100 signals to buyers "I'm ready to cut a deal."

4 Empirical Analysis

The goal of our empirical analysis is to test the six hypotheses using our data on Best Offer bargaining. Figure 2 is suggestive that, on average, listings at round-number prices receive lower offers than those at close-by precise-number prices. We proceed to develop an identification strategy based on local comparisons to estimate the magnitude of these discontinuities in expected bargaining outcomes conditional on the listing price. This strategy allows us to test hypotheses H1- H3.

A particular challenge is the presence of listing-level heterogeneity that may be observable to market participants but not to us. We address this problem in Section 4.3 using a sample of internationally visible listings from the ebay.co.uk website. Currency exchange rates obfuscate roundness of the listing price seen by U.K. buyers but not by those in the U.S., which lends itself to a difference-in-differences-style approach to show that unaccounted-for attributes correlated with roundness do not explain our results.

In addition, we exploit detailed offer-level and behavioral data to offer supplementary evidence for the signaling role of round numbers. This allows us to test hypotheses H4-H6, as well as to identify the role of round prices in guiding buyer search, by which we can shed some light on the signaling mechanism.

4.1 Framework and Identification

We are interested in identifying and estimating point discontinuities in $\mathbb{E}[y_j|\text{BIN price}_j]$, where y_j is a bargaining outcome for listing j, e.g., the average first offer or the time to the first offer. Assuming finitely many such discontinuities, $z \in \mathcal{Z}$, we can write:

$$\mathbb{E}[y_j|\text{BIN price}_j] = g(\text{BIN price}_j) + \sum_{z\in\mathcal{Z}} \mathbb{1}_z\{\text{BIN price}_j\}\beta_z, \tag{3}$$

where $g(\cdot)$ is a continuous function, $\mathbb{1}_z$ is an indicator function equal to 1 if the argument is equal to z and 0 otherwise, and $\mathcal{Z}$ is the set of points of interest. Therefore β is the vector of parameters we would like to estimate. Note that the set of continuous functions $g(\cdot)$ on $\mathbb{R}^+$ and the set of point discontinuities $(\mathbb{1}_z, z \in \mathcal{Z})$ are mutually orthonormal; this shape restriction, i.e. continuity of $g(\cdot)$, is critical to separately identify these two functions of the same variable. However, $g(\cdot)$ remains an unknown, potentially very complicated function of the BIN price, and so we remain agnostic about its form and exploit the assumption of continuity by focusing on local comparisons. Consider two points $z \in \mathcal{Z}$ and $(z + \Delta) \notin \mathcal{Z}$, and define the difference in their outcomes by $\pi_z(\Delta)$, i.e.:

$$\pi_z(\Delta) \equiv \mathbb{E}[y|z + \Delta] - \mathbb{E}[y|z] = g(z + \Delta) - g(z) - \beta_z. \tag{4}$$

For Δ large, this comparison is unhelpful for identifying β_z absent the imposition of an arbitrary parametric structure on $g(\cdot)$.[9] However, as $\Delta \to 0$, continuity implies $g(z + \Delta) - g(z) \to 0$, offering a nonparametric approach to identification of β_z:

$$\beta_z = - \lim_{\Delta \to 0} \pi_z(\Delta). \tag{5}$$

Estimation of this limit requires estimation of $g(\cdot)$, which can be accomplished semi-parametrically using sieve estimators or, more parsimoniously, by local linear regression in the neighborhood of z. In this sense our identification argument is fundamentally *local*. It is particularly important to be flexible in estimating $g(\cdot)$ because our theoretical framework offers no guidance as to its shape. Still, intuitively, one might suspect that it would be monotonically increasing, and this intuition motivates an informal specification test that we present in Appendix A2. There we show that failing to account for discontinuities at z creates non-montonicities in a smoothed estimate of $g(\cdot)$.

A few remarks comparing our approach to that in regression discontinuity (RD) studies are worthwhile. Though our identification of β_z is fundamentally local, there remain two basic differences: the first stems from studying point rather than jump discontinuities: where RD cannot identify treatment effects for interior points (i.e., when the forcing variable is strictly greater than the threshold), we have no such interior. Consistent with this, we avoid the "boundary problems" of nonparametric estimation because we have "untreated" observations on both sides of each point discontinuity. Second, RD relies on error in assignment to the treatment group so that, in a small neighborhood of the threshold, treatment is quasi-random. We cannot make such an argument because our model explicitly stipulates nonrandom selection on round numbers, that sellers deliberately and deterministically select into this group. It is therefore incumbent upon us to show that our results are not driven by differences in unaccounted-for attributes between round- and non-round listings, which we address in Section 4.3.

[9]For instance, if $g(x) = \alpha x$, then the model would be parametrically identified and estimable using linear regression on x and $\mathbb{1}_z$. Our results for the more flexible approach described next suggest that the globally linear fit of $g(\cdot)$ would be a poor approximation; see Appendix C and Table A-3 in particular.

For the construction of $\mathcal{Z}$ we have chosen to focus on round-number prices because they appear, from the histogram in Figure 3, to be focal points. A disproportionate number of sellers choose to use round numbers despite their apparent negative effect on bargaining outcomes. To further motivate this choice, in Appendix A4 we employ a LASSO model selection approach to detect salient discontinuities in the expected sale price. The LASSO model consistently and decisively selects a regression model that includes dummy variables for the interval $(z-1, z]$, where $z \in \{100, 200, 300, 400, 500\}$, and discards other precise-number dummy variables.

4.2 Round Numbers and Seller Outcomes

This section implements the identification strategy outlined above using local linear regression in the neighborhood of $z \in \{100, 200, 300, 400, 500\}$ to estimate β_z, following the intuition of Equation (5). Our primary interest is in identifying β_z, and therefore standard kernels and optimal bandwidth estimators, which are most often premised on minimizing mean-squared error over the entire support, would be inappropriate. In order to identify β_z we are interested in minimizing a mean-squared error *locally*, i.e. at those points $z \in \mathcal{Z}$, rather than over the entire support of $g(\cdot)$. This problem has been solved for local linear regression using a rectangular kernel by Fan and Gijbels (1992).[10] Therefore we use a rectangular kernel, which can be interpreted as a linear regression for an interval centered at z of width $2h_z$, where h_z is a bandwidth parameter that optimally depends on local features of the data and the data-generating process. See Appendix B for the details of the estimation of the optimal variable bandwidth.

We use separate indicators for when the BIN price is exactly a round number and when it is "on the nines", i.e., in the interval $[z-1, z)$ for each round number $z \in \mathcal{Z}$, to account for any "left-digit" effect. Therefore, conditional on our derived optimal bandwidth h_z and choice of rectangular kernel, we restrict attention to listings j with BIN prices $x_j \in [z - h_z, z + h_z]$, and use OLS to estimate:

$$y_j = a_z + b_z x_j + \beta_{z,00} \mathbb{1}\{x_j = z\} + \beta_{z,99} \mathbb{1}\{x_j \in [z-1, z)\} + \epsilon_j. \tag{6}$$

[10] Imbens and Kalyanaraman (2012) extend the optimal variable bandwidth approach to allow for discontinuities in slope as well as level. This is important in the RD setting when the researcher wants to allow for heterogeneous treatment effects which, if correlated with the forcing variable, will generate a discontinuity in slope at jump discontinuity. We do not face this problem because we study a point rather than a jump discontinuity, with untreated—and therefore comparable—observations on either side.

The nuisance parameters a_z and b_z capture the the local shape of $g(\cdot)$, $\beta_{z,00}$ captures the round-number effect, and $\beta_{z,99}$ captures any effect of being listed "on the nines." We estimate this model separately for each $z \in \{100, 200, 300, 400, 500\}$.

4.2.1 Offers and Prices: Testing H1

Our first set of results concerns cases where y_j is the average first buyer offer and the final sale price of an item if sold, which tests of H1, i.e., that round-number sellers receive lower offers and settle on a lower final sale price. Estimates for this specification are presented in Table 2. All results show estimates with and without eleven category-level fixed effects in order to address one source of possible heterogeneity between listings.

Each cell in the table reports results for a local linear fit in the neighborhood of the round number indicated (e.g., BIN=100), using the dependent variable assigned to that column. Table 2 reports the coefficient on the indicator for whether listings were *exactly* at the round number so that only $\beta_{z,00}$ is shown. Columns 1 and 2 report estimates for all items that receive offers while Columns 3 and 4 report estimates for all items that sell, including non-bargained sales. Results on sales are similar if the sample is restricted to only bargained items, and remain significant when standard errors are clustered at the category level. We discuss results of the buyers' choice to bargain in Appendix E.

The estimates show a strong and consistently negative relationship between the roundness of listed prices and both offers and sales. The effects are, remarkably, generally log-linear in the BIN price, a regularity that is not imposed by our estimation procedure. In particular, they suggest that for round BIN price listings, offers and final prices are lower by 5%-8% as a factor of the listing price compared to their precise-number neighbors. The estimates are slightly larger for the \$500 listing value. The statistically and economically meaningful differences in outcomes of Table 2 provide strong evidence for H1.

Ancillary coefficients, i.e. the slope, and intercept of the linear approximation of $g(\cdot)$ are reported and discussed in Appendix C. Importantly, we find substantial variance in the slope parameters at different round numbers, which confirms the importance of treating $g(\cdot)$ flexibly. Coefficients on the indicator for the "99"s, i.e. $[z-1, z)$ intervals, are reported in Appendix D. We find that, contrary to prior work on pricing "to the nines," in our bargaining environment these numbers yield outcomes that are remarkably similar to those of their round neighbors. This suggests that 99 listings also signal weakness. In Appendix A we present estimates from a sieve estimator approach using orthogonal basis splines to

Table 2: Offers and Sales for Round $100 Signals

	(1) Avg First Offer $	(2) Avg First Offer $	(3) Avg Sale $	(4) Avg Sale $
BIN=100	-5.372***	-4.283***	-5.579***	-5.002***
	(0.118)	(0.115)	(0.127)	(0.127)
BIN=200	-11.42***	-8.849***	-10.65***	-9.310***
	(0.376)	(0.369)	(0.401)	(0.393)
BIN=300	-18.74***	-14.78***	-17.04***	-15.94***
	(0.717)	(0.475)	(0.863)	(0.629)
BIN=400	-24.61***	-17.71***	-17.98***	-15.80***
	(0.913)	(0.894)	(1.270)	(1.186)
BIN=500	-39.43***	-28.58***	-35.76***	-30.55***
	(1.320)	(1.232)	(1.642)	(1.478)
Category FE		YES		YES

Notes: Each cell in the table reports the coefficient on the indicator for roundness from a separate local linear fit according to Equation (6) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column. Ancillary coefficients for each fit are reported in Table A-3. Heteroskedacticity-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

approximate $g(\cdot)$. Although this approach requires choosing tuning parameters (knots and power), it has an advantage in that pooling across wider ranges of BIN prices allows us to include seller fixed effects to control for seller attributes and to attempt several specification tests. Estimates from the cardinal basis spline approach are consistent with those from Table 2.

4.2.2 Offer Arrivals and Likelihood of Sale: Testing H2 and H3

Predictions H2 and H3 of the model are essential to demonstrate incentive compatibility in a separating equilibrium— in particular, that round-number listings are compensated for their lower sale price by a faster arrival of offers and a higher probability of sale. To test this in the data, we employ specification (6) for three additional cases: where y_j is the time to first offer, the time to sale, and the probability of sale for a listing in its first 60 days. Results for these tests are presented in Table 3. Columns 1 and 2 show that round-number listings receive their first offers between 6 and 11 days sooner, on an average of about 28 days as shown in Table 1. Columns 3 and 4 show that round-number listings also sell faster, between 10 and 14 days faster on a mean of 39 days. Hence, sellers can cut their time on the market by up to a third when listing at round numbers. Columns 5 and

Table 3: Throughput Effects of Round $100 Signals

	(1)	(2)	(3)	(4)	(5)	(6)
	Days to Offer	Days to Offer	Days to Sale	Days to Sale	Pr(Sale)	Pr(Sale)
BIN=100	-11.02***	-11.09***	-13.80***	-14.38***	0.0478***	0.0522***
	(0.333)	(0.331)	(0.434)	(0.432)	(0.00177)	(0.00176)
BIN=200	-11.53***	-11.52***	-15.15***	-15.64***	0.0550***	0.0590***
	(0.526)	(0.514)	(0.734)	(0.729)	(0.00254)	(0.00251)
BIN=300	-9.878***	-7.390***	-11.15***	-11.95***	0.0407***	0.0317***
	(0.655)	(0.384)	(0.784)	(0.673)	(0.00303)	(0.00217)
BIN=400	-7.908***	-6.125***	-10.73***	-10.87***	0.0329***	0.0319***
	(0.509)	(0.392)	(0.849)	(0.862)	(0.00245)	(0.00244)
BIN=500	-9.431***	-8.832***	-10.31***	-10.77***	0.0306***	0.0354***
	(0.637)	(0.619)	(1.004)	(1.009)	(0.00347)	(0.00348)
Category FE		YES		YES		YES

Notes: Each cell in the table reports the coefficient on the indicator for roundness from a separate local linear fit according to Equation (6) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column. Ancillary coefficients for each fit are reported in Table A-4. Heteroskedacticity-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

6 shows that round listings also have a consistently higher probability of selling, raising conversion by between 3 and 6 percent on a base conversion rate of 20 percent. Note that listings may be renewed beyond 60 days, however our estimates for the effect on the probability of sale are similar when we use alternative thresholds (30, 90, or 120 days).[11]

4.2.3 Effects of Market Thickness: Testing H4

Testing H4, that "thick" markets have lower price discounts, is more challenging than the previous three hypotheses because it requires a measure of market thickness. One could select products that are more standardized and for which markets are likely to be thick, compared to "long-tail" items for which markets are thin. Two drawbacks of this approach are first, that standardized items will have less scope for price discovery and bargaining,

[11] A thoughtful question we have received is whether we can calculate a discount rate consistent with our results that identifies the "indifferent" seller— indifferent between using a round- and a nearby precise-number listing price. In order to calculate this number we would need to make assumptions about sellers' costs as well as their outside option in the event of a failure to sell. We computed this estimate under a wide array of specifications, and the resulting discount rates ranged from arbitrarily large and negative to arbitrarily large and positive. We take from this exercise that it is impossible to learn about the discount rate itself absent more information on the seller?s problem, however we also take that our findings alone do not imply an unreasonably high or low discount rate.

and second, that any such selection would be ad hoc. Instead, we use behavioral data on Search Result Page (SRP) and View Item (VI) page visits to measure market thickness.

In particular, more popular items with higher traffic, as measured by SRP and VI counts can be categorized as having more buyers interested in them, and hence, thicker markets than items with lower view counts. These items are different in myriad other characteristics, so we consider the results only suggestive.[12] The way in which traffic and item popularity are measured is explained in more detail in Appendix F.

Listings are divided into deciles in increasing order of SRP and VI visit frequency. We then replicate our local linear approach from equation (6) to estimate the effect of round listing prices on mean first offers within each decile. Figure A-3 in Appendix F plots the point estimates and confidence intervals of the discounts at round numbers. We find lower relative discounts for item deciles with higher view rates, which is consistent with H4. If we use search counts as a measure of popularity, we see a U-shaped pattern where both very low and very high search counts have lower discounts than the mid range of search counts. Nonetheless, this relationship is still positive as suggested by H4 — a linear fit of these coefficients has a significant positive slope.

4.3 Selection on Unobservable Listing Attributes

A natural concern with the results of Section 4.2 is that there may be unaccounted-for differences between round and non-round listings. There is substantial heterogeneity in the quality of listed goods that is observable to buyers and sellers but controlled for in our main specification. This includes information in the listing title, the listing description, as well as in the photographs. If round-number listings are of lower quality in an unobserved way, then this would offer an alternative explanation for the correlations we find. To formalize this idea, let the unobservable quality of a product be indexed by ξ with a conditional distribution $H(\xi|\text{BIN price})$ and a conditional density $h(\xi|\text{BIN price})$. In this light we rewrite equation (3), the expectation of y_j conditional on observables, as

$$\mathbb{E}[y_j|\text{BIN price}_j] = \int g(\text{BIN price}_j, \xi) dH(\xi|\text{BIN price}_j) + \sum_{z\in\mathcal{Z}} \mathbb{1}_z\{\text{BIN price}_j\}\beta_z. \quad (7)$$

[12] Our measure is an imperfect proxy for market thickness because traffic is only indirectly correlated with the arrival of buyers. Perhaps quirky yet undesired items receive traffic because they are interesting.

From equation (7) it is clear that the original shape restriction—continuity of $g(\cdot)$—is insufficient to identify β_z: we also require continuity of the conditional distribution of unobserved heterogeneity in the neighborhood of each element in $\mathcal{Z}$. Formally, consider the analogue of equation (5), which summarized the identification argument from Section 4.1:

$$\lim_{\Delta\to 0}\pi(\Delta) = \underbrace{\lim_{\Delta\to 0}\int g(z,\xi)[h(\xi|z+\Delta) - h(\xi|z)]d\xi}_{\equiv\gamma_z} - \beta_z. \tag{8}$$

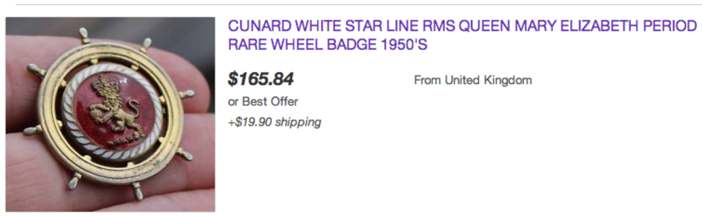
The first term on the right-hand side of equation (8), denoted γ_z, is a potential source of bias. Now, if we assume that the conditional distribution $h(\xi|\text{BIN price})$ is continuous in the BIN price, then that bias is equal to zero and therefore the estimates from Section 4.2 are robust to unobserved heterogeneity. This is important: unobserved heterogeneity alone does not threaten our identification argument— mathematically, the concern is *discontinuities* in the conditional distribution of unobserved heterogeneity. However, such discontinuities may exist: for example, if sellers are systematically more likely to round up than round down, then listings at round numbers will have a discontinuously lower expected unobserved quality (ξ) than nearby precise listings. Moreover, a similar outcome results if the propensity of sellers to round is correlated with ξ conditional on the BIN price, e.g. if sellers of used or defective items are more likely to round. These are both plausible stories that raise concern over the identification argument of Section 4.2.

The ideal experiment would be to somehow hold ξ fixed and observe the same product listed at both round and non-round BIN prices. With observational data this is possible if we restrict attention to well-defined products, but such products will also have a well-defined market price that leaves little room for bargaining.[13] A similar problem arises for field experiments: if one were to create multiple listings for the same product, experimentally varying roundness, they would generate their own competition. It wold be interesting, though outside of the ambition of this paper, to construct a field experiment with a diverse set of listings that is large enough to make the unobserved heterogeneity average out. Instead, here we adopt a strategy that takes advantage of the unique data already at our disposal.

We address the problem of unobserved heterogeneity by considering a special sample of listings that allows us to separate γ_z, the bias term defined in equation (8), and β_z. Sellers who list on the U.K. eBay site (ebay.co.uk) enter a price in British Pounds, which

[13] H4 suggests that in such "thick" markets, we should see little or no discount associated with roundness.

Figure 4: Example of Round UK Listing on US Site



(a) Search Results

(b) Listing Page

Notes: Frame (a) depicts a UK listing appearing in a US user's search results; the price has converted from British pounds into US dollars. The listing itself appears in frame (b), where the price is available in both British pounds and US dollars.

is displayed to U.K. buyers. The sellers can choose to make their listing visible on the U.S. site as well. U.S. buyers viewing those U.K. listings, however, observe a BIN price in U.S. dollars as converted at a daily exchange rate. Figure 4a gives an example of how a U.S. buyer sees an internationally cross-listed good. Because of the currency conversion, even if the original listing price is round, the U.S. buyer will observe a non-round price when these items appear in search results.[14]

This motivates a new identification strategy that is close in spirit to the "ideal" experiment described above: For listings that are round in British Pounds, we difference the offers of U.S. and U.K. buyers. This differencing removes the common effect of listing quality (γ_z), which is observed by both U.S. and U.K. buyers, leaving the causal effect of the round-number listing price (β_z). To formalize this, let $C \in \{UK, US\}$ denote the country in which the offers are made, and define

[14]We use daily exchange rates to confirm that extremely few US buyers observe a round price in U.S. dollars for U.K. listings. This sample is too small to identify a causal effect of coincidental roundness.

$$\pi_{z,C}(\Delta) \equiv g_C(z+\Delta) - g_C(z) - \mathbb{1}\{C = \text{UK}\}\beta_z. \tag{9}$$

The construction in Equation (9) generalizes Equation (4) to the two-country setting. Now, differencing $\pi_{z,UK}(\Delta)$ and $\pi_{z,US}(\Delta)$, we obtain:

$$\pi_{z,UK}(\Delta) - \pi_{z,US}(\Delta) = [g_{UK}(z+\Delta) - g_{UK}(z)] - [g_{US}(z+\Delta) - g_{US}(z)] - \beta_z. \tag{10}$$

Following the logic of the identification argument in 4.1, we take the limit of Equation (10) as $\Delta \to 0$ in order to construct an estimator for β_z based on local comparisons. Recall that as $\Delta \to 0$, $[g_C(z+\Delta) - g_C(z)] \to \gamma_z$ so that,

$$\beta_z = -\lim_{\Delta \to 0}[\pi_{z,UK}(\Delta) - \pi_{z,US}(\Delta)],$$

which extends the identification argument by differencing out the local structure of $g(\cdot)$, which is common to U.K. and U.S. buyers. As in Section 4.2, we employ the results from Fan and Gijbels (1992) and use a rectangular kernel with the optimal variable bandwidth; see Appendix B for details. Then, parameters are estimated with OLS using listings with BIN prices (denoted x_j, in £) in $[z-h, z+h]$ and offers y_j with the specification:

$$\begin{aligned} y_j =& (a_{z,UK} + b_{z,UK}(z - x_j))^{\mathbb{1}_{UK,j}} (a_{z,US} + b_{z,US}(z - x_j))^{\mathbb{1}_{US,j}} \\ &+ \gamma_{z,00}\mathbb{1}\{x_j = z\} + \beta_{z,00,UK}\mathbb{1}_{UK,j}\mathbb{1}\{x_j = z\} \\ &+ \gamma_{z,99}\mathbb{1}\{x_j \in (z-1, z)\} + \beta_{z,99}\mathbb{1}_{UK,j}\mathbb{1}\{x_j \in (z-1, z)\} + \varepsilon_j. \end{aligned} \tag{11}$$

In contrast with the estimator from Equation (6), here the unit of observation is the buyer offer. The approach is similar in spirit to a a difference-in-differences estimation across U.S. and U.K. buyers and round- and non-round listings. In the regression, γ_z captures the common, unobservable characteristics of the listing (observed to both U.S. and U.K. buyers), while β_z is the round-number effect, and is identified by the difference in the discontinuous response of U.K. and U.S. buyers to roundness of the listing price in British Pounds. Systematic differences between U.K. and U.S. buyers that are unrelated to roundness, e.g. shipping costs, are captured by allowing the nuisance constant and slope parameters to vary by the nationality of the buyer.

Table 4: Effect of Roundness on Offers from the UK Specification

	(1) Offer \$	(2) Offer \$
UK x Round £100	-2.213***	-2.048***
	(0.354)	(0.352)
UK x Round £200	-6.409***	-6.386***
	(1.000)	(0.964)
UK x Round £300	-9.418***	-6.764***
	(1.556)	(1.413)
UK x Round £400	-16.60***	-18.05***
	(2.500)	(2.426)
UK x Round £500	-15.33***	-19.06***
	(3.539)	(3.180)
Category FE		YES

Notes: Each cell in the table reports the coefficient on the interaction of an indicator for roundness with an indicator for a U.K. buyer from a separate local linear fit according to Equation (11) in the neighborhood of the round number indicated for the row, with the level of an offer, either from a U.K. buyer or a U.S. one, as the dependent variable. Heteroskedacticity-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

Note that on the listing page (depicted in Figure 4b), which appears *after* a buyer chooses to click on an item seen on the search results page (depicted in Figure 4a), the original U.K. price does appear along with the price in U.S. dollars. This means that buyers see the signal *after* selecting the item to place an offer. The late revelation of the signal will bias our results, but in the "right" direction because it will attenuate any difference between U.S. and U.K. offers which is a causal effect of round numbers. To the extent that we find *any* causal effect, we hypothesize that it survives due to the non-salience of the U.K. price in British Pounds during the search phase of activity, and we posit that it is a lower bound on the true causal effect of the round signal.

Our sample includes all U.K.-based listings created between June 2010 and June 2013 that are internationally visible. We then take as our dependent variable all initial offers made to these listings from a U.K. or U.S. buyer. This results in a total of 2.3 million offer-level observations over 600 thousand listings. In our sample we find that U.K. buyers tend to bid on slightly more expensive listings (£184 versus £163, on average) and correspondingly make somewhat higher offers (£113 versus £104, on average). Results from the estimation of Equation (11) are presented in Table 4. The estimated effects are smaller than in those in Section 4.2, which could be due to either selection on unobservable characteristics or attenuation from some U.S. buyers observing the roundness of the listing price in British Pounds after they select to view an item. Nonetheless, the fact that the differential response of U.S. versus U.K. bidders is systematically positive and statistically significant confirms that our evidence for H1 cannot be fully discounted by selection on unobservables.

4.4 Further Evidence for a Separating Equilibrium: H5 and H6

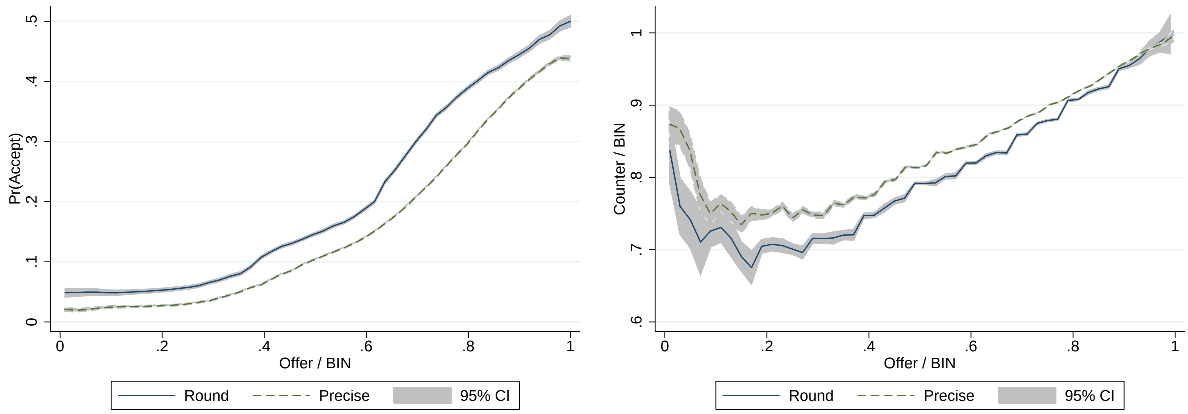
In addition to predictions for bargaining outcomes, i.e. H1-H4 from Section 3.2, our theoretical framework also offers predictions on the bargaining process based on the separation of patient versus impatient sellers. If sellers who use precise listing prices are in fact less patient, then we should also see that these sellers are *more* likely to accept a given offer (H5), and also *less* aggressive in their counteroffers (H6). To test these predictions we take advantage of our offer-level data to see whether, holding fixed the *level* of the offer, the sellers' type (as predicted by roundness/precision) is correlated with the probability of acceptance or the mean counteroffer. Results are presented in Figure 5.

In panel 5a we plot a smoothed estimate of the probability of acceptance against the ratio of the buyers' first offer in a bargaining interaction to the corresponding seller's listing price. Normalizing by the listing price allows us to compare disparate listings and hold constant the level of the offer. We plot this for sellers who use round and precise listing prices separately. The results show a clear and statistically significant difference: precise number sellers act as if they have a higher reservation price and are more likely to reject offers at any ratio of the listing price, consistent with H5.[15]

Panel 5b plots the level of the seller's counteroffer, conditional on making one, again normalized by the listing price, against the ratio of the buyer's offer to the listing price. Note that, unlike the results for the probability of acceptance, this sample of counteroffers is selected by the seller's decision to make a counteroffer at all. Again we see that precise sellers seem to behave as if they have a higher reservation price than round sellers; their counteroffers are systematically higher, consistent with H6.

[15]It may seem surprising that offers close to 100% of the list price are accepted only about half the time. We conjecture that many sellers do not respond to the email that alerts them of an offer.

Figure 5: Seller Responses to Lower Offers



(a) First Offer Acceptance **(b) Counter Offer Value**

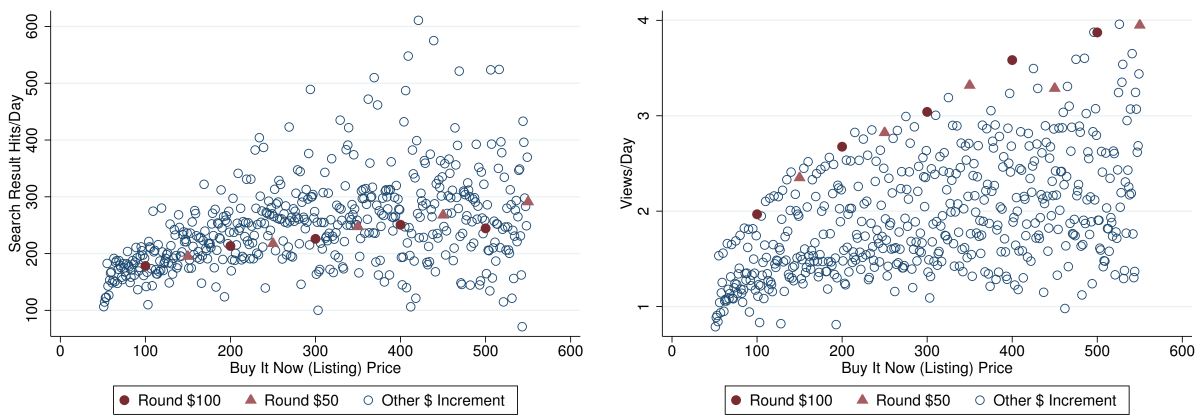
Notes: Frame (a) depicts the polynomial fit of the probability of acceptance for a given offer (normalized by the BIN) on items with listing prices between \$85 and \$115, plotted separately for \$100 'Round' listings and the remaining 'Precise' listings. Frame (b) depicts the polynomial fit of the counteroffer (normalized by the BIN) made by a seller, similarly constructed.

4.5 Signaling and Buyer Search Behavior

In this section we take advantage of our access to detailed data on eBay user behavior to isolate the effect of roundness as a signal on buyers' search behavior. Our model is, like other cheap talk models, agnostic about the form of the signal itself. Why should sellers use roundness as a signal instead of, for instance, language in the detailed description or a colored border on the photograph? We shed light on this by identifying the point at which this signal affects buyers' search behavior.

In order to do this we leverage eBay's data infrastructure to tabulate the total number of search events that returns each listing. A search result page (SRP) contains many entries similar to that shown in Figure 4a. We also collect the total number of times users view the item (VI) detail page, an example of which is shown in Figure 1a. We normalize these counts by the number of days that each listing was active to compute the exposure rate per day for each metric. Figure 6 replicates Figure 2 for these two normalized measures of exposure. Table 5 presents the results from a local linear estimation of the effect of a round BIN price on these two outcomes. Note that while the absolute magnitudes are smaller in Columns (3) and (4), they are quite a bit larger relative to the average levels that can be inferred from Figure 6. Round listings do not have a higher search exposure rate than non-round listings, but theys have a substantially higher view-item rate.

Figure 6: Search and View Item Detail Counts



(a) SRP Counts **(b) VI Count**

Notes: This plot presents average SRP and VI events per day by unit intervals of the BIN price, defined by $(z-1, z]$. On the x axis is the BIN price of the listing, and on the y axis is the average number of SRP arrivals per day, in panel (a), or the average number of VI arrivals per day, in panel (b). When the BIN price is on an interval rounded to a "00" number, it is represented by a red circle; "50" numbers are represented by a red triangle.

This is strong evidence that buyers select into round listings when seeing only information on the search result page. That information is limited to the item title, an image thumbnail, and the BIN price (or, currency-converted BIN price). This helps to explain why sellers would use a price-based signal: it attracts buyers at the moment they are looking at all similar items on the search page. There are of course, other potential signals on the search page, but these are not cheap: the photograph conveys important information, and Backus et al. (2014) observed that savvy sellers fill the title with descriptive words to generate SRP exposure. More importantly, however, the structure of the title and the photograph are eBay-specific; we conjecture that roundness of the asking price is used as a signal precisely because it is generic to bargaining marketplaces. Indeed, as we show in the next section, there is reason to believe that roundness may be a universal signal.

5 Further Evidence from Real Estate Listings

One might wonder whether the evidence presented thus far is particular to eBay's marketplace. Although that fact is interesting in itself, there is nothing specific to the Best Offer platform that would lead to the equilibrium we propose. There are many bargaining settings where buyers and sellers would want to signal weakness in exchange for faster and

Table 5: Roundness and Search and View Item Detail

	(1) SRP Hits Per Day	(2) SRP Hits Per Day	(3) VI Count Per Day	(4) VI Count Per Day
BIN=100	-40.18***	-23.25***	0.654***	0.703***
	(0.640)	(0.659)	(0.0180)	(0.0178)
BIN=200	-58.54***	-51.42***	1.005***	0.925***
	(0.882)	(1.042)	(0.0378)	(0.0365)
BIN=300	-66.59***	-50.42***	1.246***	0.944***
	(1.291)	(1.261)	(0.0452)	(0.0394)
BIN=400	-74.99***	-53.72***	1.469***	1.325***
	(1.822)	(1.657)	(0.0540)	(0.0524)
BIN=500	-95.67***	-82.99***	1.627***	1.384***
	(2.100)	(2.051)	(0.0629)	(0.0616)
Category FE		YES		YES

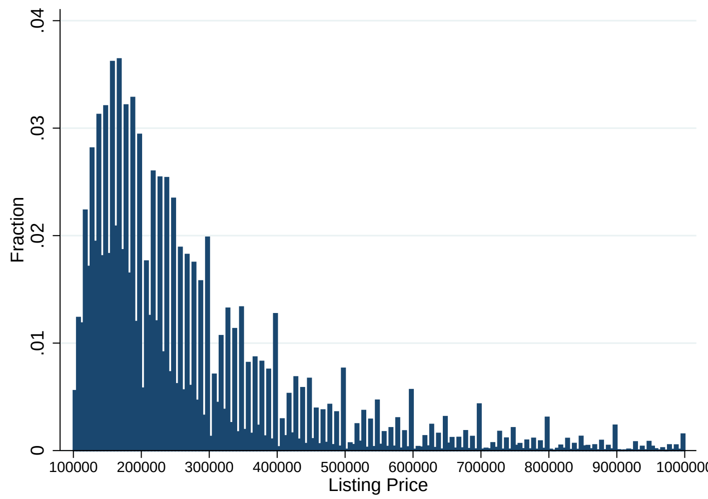
Notes: Each cell in the table reports the coefficient on the indicator for roundness from a separate local linear fit according to Equation (6) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column. Heteroskedacticity-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

more likely sales. We consider the real estate market as another illustration of the role of cheap-talk signaling in bargaining. In contrast to eBay, real estate is a market with large and substantial transactions. Sellers are often assisted by professional listing agents making unsophisticated behavior unlikely.

We make use of the Multiple Listing Service ("MLS") data from Levitt and Syverson (2008) that contains listing and sales data for Illinois in from 1992 through 2002. We consider round-number listings to be multiples of \$50,000 after being rounded to the nearest \$1,000, which counts listings such as \$699,950 as round. In this setting, conspicuous precision cannot be achieved by adding a few dollars but requires a few hundred or thousand dollars. This distinction is of little consequence since the average discount of 5% off list still reflect tens of thousands of dollars. Listings bunch at round numbers, particularly on more expensive listings, as shown in Figure 7.[16] Moreover, these higher value homes which are listed at round numbers sell for lower prices that non-round listings. Figure 8 mimics Figure 2 for the real estate data using sale prices. Listings at round \$50,000 sell

[16]Recent work by Pope et al. (2014) studies round numbers as focal points in negotiated real estate prices and argues that they must be useful in facilitating bargaining because they are disproportionately frequent. This is consistent with our finding, documented in Appendix G, that round-number buyer *offers* (as opposed to public seller listing prices) signal a high willingness to pay.

Figure 7: Real Estate Grouping at round-numbers



Notes: This is a histogram of seller's chosen listing prices for our dataset. The bandwidth is \$10,000 and intervals are generated by rounding up to the nearest round increment (e.g., $\$80,000, \$90,000, \$100,000, \ldots$)

for less on average, which is more pronounced at the higher end of the price distribution where there is greater clustering at round numbers.

Table 6 presents estimates from the basis spline regressions of the sale fraction on a single dummy for whether or not the listing is round. Adding controls such as those found in Levitt and Syverson (2008) or, as shown here, listing agent fixed effects, absorbs contaminating variation in regions or home type. On average, round listings sell for 0.15% lower than non-round listings, which represents about \$600 or 3.4% of the the typical discount off of list price.[17] It is interesting that the magnitude and significance of this effect is stringer when real estate agent fixed effects are included, where the effect is estimated from within-agent variation. It is well known that the role of real estate agents is to help sellers and buyers meet their objectives. Hence, if an equilibrium is played, we would expect these expert players to play according to equilibrium. Unfortunately, we do not observe offers, unsold listings, or the time between listing and acceptance of an offer, so we are unable to test hypotheses H2-H6 in the real estate setting. Still, the fact that we are able to replicate our finding that round numbers are correlated with lower sale prices suggests that round-number signaling is more a general feature of real-world bargaining.

[17] The average sales prices is 94% of the list price so sales are negotiated down 6%. For comparison, on eBay the sales prices is 65% of list price so the effect at \$100 of 2% is 5.7% of the typical discount.

Figure 8: Real Estate Sales at Round Numbers

Notes: This scatterplot presents average real estate sale prices in Chicago, normalized by the listing price price to be between zero and one, grouped by $10,000 intervals of the listing price, When the listing price is on an interval rounded to the hundreds of thousands, it is represented by a red circle; numbers rounded to fifty thousands are represented by a red triangle.

Table 6: Real Estate Basis Spline Estimates

	(1) Sale $ / List $	(2) Sale $ / List $
Round $50k	-0.000956	-0.00145**
	(0.000652)	(0.000696)
Agent FE		YES
N	35808	35808

Notes: Here we report coefficients on a regression form of (3) where y_j is real estate sale prices in Chicago, $g(\cdot)$ is approximated using a cardinal basis spline, and the coefficient of interest is on a dummy for the listing price of a home being rounded up to a multiple of $50,000.

6 Discussion

This study began with an empirical observation that eBay sellers who list goods at round numbers with the Best Offer mechanism received substantially lower offers and final proceeds than sellers using more precise numbers in the same price range. We identified this effect nonparametrically and carefully demonstrated that it is not explained by unobserved differences in item or seller attributes. Our main contribution, however, is an explanation for the effect. We found strong evidence of behavior consistent with a cheap-talk signaling equilibrium where round-number listings elicit lower offers with a higher probability of a successful sale and less time on the market than similar precise-number listings. Moreover, we were able to show that subsequent seller behavior was consistent with that cheap-talk signaling interpretation– sellers who use precise-number listing prices went on to bargain more aggressively, while sellers who used round numbers were more likely to settle and made less aggressive counter-offers. The narrative behind our approach is one of sophisticated equilibrium behavior in which buyers and sellers are aware of the features and codes of an intricate separating equilibrium of a cheap-talk game. As we have demonstrated, the data are consistent with equilibrium behavior across many dimensions.

Other work on round numbers has focused on behavioral explanations, most notably Lacetera et al. (2012) who conjecture that the way buyers respond to round numbers is consistent with left-digit inattention, a form of bounded rationality. We don't believe that stories of bounded or partial rationality would easily explain the empirical findings of our study. In particular, as we show in Appendix D, there is no discontinuity of the left-digit bias type. In fact, the $99 signal (including anything from $99 to $99.99) seems to be equivalent to the $100 signal. Perhaps, there is no tension between our results and those of Lacetera et al. (2012) because their variable of interest is a vehicle's mileage, which is an exogenous characteristic of the item, while ours is the listing price, which is an endogenous signal chosen by the seller. We also note that we find price effects four to five times larger than theirs, which suggests that an alternative mechanism is at play.

One form of bounded rationality that seems appealing that sellers who are clueless about the item they are selling use round numbers because they are inattentive. Buyers thus target these clueless sellers with lower offers. If these clueless sellers are also more eager to sell, it would explain why round-number items would sell faster. There are several reasons that we find this story unappealing. First, why would the inattentive sellers systematically choose round numbers that are significantly higher than the final price? If their mistakes are equally likely to be both under- and over-estimates of the items they are selling, then competitive pressure would push under-estimated items to sell above the listed price. Second, if they are clueless, but rationally so, then they should try to collect more signals about the value of the item, thus waiting at least as long as others, if not longer, to sell their items. It seems therefore unlikely that clueless sellers would also be impatient. Finally, our data shows that even the most experienced sellers use round-number listings quite often, suggesting that this behavior is not likely to be a consistent mistake (see Appendix H). Though we acknowledge the intuitive appeal of the story, we conjecture that seller cluelessness is a correlate being in a weak bargaining position, rather than the primitive.

The fact that we find some supporting evidence from the real-estate market further strengthens our conclusion that round numbers play a signaling role in bargaining situations. People have used one form or another of bargaining for millennia. We don't believe that *all* people are literally playing a sophisticated Perfect-Bayesian equilibrium of a complex game; rather, we believe that they are playing *as if* they were. In other words, even if the mechanical truth is that there are cognitive heuristics or social norms behind our interpretation of the roundness and precision of numbers, the question then becomes why those heuristics or norms persist. We conjecture that they persist precisely because they are consistent with equilibrium play in a rational expectations model— that, in equilibrium, they are unbiased and create no incentive to deviate.[18] If this is indeed the case, it suggests that over time, players find rather sophisticated, if not always intuitive, ways to enhance the efficiency of bargaining outcomes in situations with incomplete information.

[18]Experimental evidence inThomas et al. (2010) demonstrates the plasticity of perceptual biases associated with roundness.

References

Admati, A. and Perry, M. (1987). Strategic delay in bargaining. *Review of Economic Studies*, 54(3):345–364.

Ali, S. N., Chen-Zion, A., and Lillethun, E. (2015). A networked market for information. Working Paper.

Ambrus, A., Chaney, E., and Salitskiy, I. (2014). Pirates of the mediterranean: An empirical investigation of bargaining with asymmetric information. Working Paper.

Backus, M., Podwol, J., and Schneider, H. (2014). Search costs and equilibrium price dispersion in auction markets. *European Economic Review*, 71:173–192.

Bagwell, K., Staiger, R., and Yurukoglu, A. (2014). Multilateral trade bargaining:A first peek at the GATT bargaining records. Working Paper.

Binmore, K., Rubinstein, A., and Wolinsky, A. (1986). The nash bargaining solution in economic modelling. *RAND Journal of Economics*, 17(2):176–188.

Cabral, L. and Sákovics, J. (1995). Must sell. *Journal of Econoomics and Management Strategy*, 4(1):55–68.

Coase, R. J. (1960). The problem of social cost. *Journal of Law and Economics*, 3:1–44.

De Boor, C. (1978). *A practical guide to splines. Number 27 in Applied Mathematical Sciences*, volume 27 of *Applied Mathematical Sciences*. Springer, New York.

DesJardins, S. L. and McCall, B. P. (2008). The impact of the gates millennium scholars program on the retention, college finance- and work-related choices, and future educational aspirations of low-income minority students. Working Paper.

Dierckx, P. (1993). *Curve and surface fitting with splines*. Oxford University Press, Inc.

Einav, L., Farronato, C., Levin, J. D., and Sundaresan, N. (2013). Sales mechanisms in online markets: What happened to internet auctions? NBER Working Paper.

Fan, J. and Gijbels, I. (1992). Variable bandwidth and local linear regression smoothers. *The Annals of Statistics*, 20(4):2008–2036.

Farrell, J. and Gibbons, R. (1989). Cheap talk can matter in bargaining. *Journal of Economic Theory*, 48(1):221–237.

Gedge, C., Roberts, J. W., and Sweeting, A. (2013). A model of dynamic limit pricing with an application to the airline industry. Working Paper.

Grennan, M. (2013). Price discrimination and bargaining: Empirical evidence from medical devices. *American Economic Review*, 103(1):145–177.

Grennan, M. (2014). Bargaining ability and competitive advantage: Empirical evidence from medical devices. *Management Science*, 60:3011–3025.

Gul, F. and Sonnenschein, H. (1988). On delay in bargaining with one-sided uncertainty. *Econometrica*, 56:601–611.

Hungerford, T. and Solon, G. (1987). Sheepskin effects in the return to education. *The Review of Economics and Statistics*, 69(1):175–178.

Imbens, G. and Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *Review of Economic Studies*, 79(3):933–959.

Janiszewski, C. and Uy, D. (2008). Precision of the anchor influences the amount of adjustment. *Psychological Science*, 19(2):121–127.

Kawai, K., Onishi, K., and Uetake, K. (2013). Signaling in online credit markets. Working Paper.

Kim, K. (2012). Endogenous market segmentation for lemons. *RAND Journal of Economics*, 43(3):562–576.

Kim, K. and Kircher, P. (2013). Efficient competition through cheap talk: Competing auctions and competitive search without ex ante price commitment. WorkingPaper.

Lacetera, N., Pope, D., and Sydnor, J. (2012). Heuristic thinking and limited attention in the car market. *American Economic Review*, 102(5):2206–2236.

Larsen, B. (2014). The efficiency of real-world bargaining: Evidence from wholesale used-auto auctions. NBER Working Paper No. 20431.

Layard, R. and Psacharopoulos, G. (1974). The screening hypothesis and the returns to education. *Journal of Political Economy*, 82:985–998.

Levitt, S. D. and Syverson, C. (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *The Review of Economics and Statistics*, 90(4):599–611.

Loschelder, D., Stuppi, J., and Trötschel, R. (2013). "€14,875?!": Precision boosts the anchoring potency of first offers. *Social Psychological and Personality Science*, pages 1–9.

Mason, M., Lee, A., Wiley, E., and Ames, D. (2013). Precise offers are potent anchors: Conciliatory counteroffers and attributions of knowledge in negotiations. *Journal of Experimental Social Psychology*, 49:759–763.

Menzio, G. (2007). A theory of partially directed search. *Journal of Political Economy*, 115(5):748–769.

Myerson, R. B. and Satterthwaite, M. A. (1983). Efficient mechanisms for bilateral trading. *Journal of economic theory*, 29(2):265–281.

Nelson, P. (1974). Advertising as information. *Journal of Political Economy*, 82(4):729–754.

NPR (2013). Next time you ask for a raise, you might want to round up.

Pope, D. G., Pope, J. C., and Sydnor, J. R. (2014). Focal points and bargaining in housing markets. Working Paper.

Rubinstein, A. (1982). Perfect equilibrium in a bargaining model. *Econometrica*, 50(1):97–110.

Shelegia, S. and Sherman, J. (2015). When the price you see is not the price you get: A field study. Working Paper.

Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics*, 87(3):355–374.

Thomas, M., Simon, D., and Kadiyali, V. (2010). The price precision effect: Evidence from laboratory and market data. *Marketing Science*, 29(1):175–190.

Tyler, J. H., Murnane, R. J., and Willett, J. B. (2000). Estimating the labor market signaling value of the ged. *Quarterly Journal of Economics*, 115(2):431–468.

Appendices

A Alternative Approach: Basis Splines

1 Basis Splines

Our main results from Section 4.2 employ a local linear specification that identifies $g(\cdot)$ from equation (3) only in small neighborhoods of the discontinuities we study. There are a number of additional questions we could ask with a more global estimate of $g(\cdot)$: for instance, one might be interested in the shape of $g(\cdot)$, or in using all of the data for the sake of estimating seller fixed effects as we do in Section A3. To this end we employ a cardinal basis spline approximation (De Boor, 1978; Dierckx, 1993), a semi-parametric tool for flexibly estimating continuous functions. Intuitively, a cardinal basis spline is a set of functions that form a linear basis for the full set of splines of some order p on a fixed set of knots. This is a convenient framework because the weights on the components of that linear basis can be estimated using OLS, which will identify the spline that best approximates the underlying function.

The approach requires that we pick a set of k equidistant "knots", indexed by t, which partition the domain of a continuous one-dimensional function of interest $f(\cdot)$ into segments of equal length.[19] We also select a power p, which represents the order of differentiability one hopes to approximate. So, for instance, if $p = 2$ then one implements a quadratic cardinal basis spline. Given a set of knots and p, cardinal basis spline functions $B_{j,p}(x)$ are constructed recursively by starting at power $p = 0$:

$$B_{j,0}(x) = \begin{cases} 1 \text{ if } t_j \leq x < t_{j+1} \\ 0 \text{ else} \end{cases}, \tag{1}$$

and

$$B_{j,p}(x) = \frac{x - t_j}{t_{j+p-1} - t_j} B_{j,p-1}(x) + \frac{t_{j+p} - x}{t_{j+p} - t_{j+1}} B_{j+1,p-1}(x). \tag{2}$$

[19] The fact that knots are equidistant is what makes this a *cardinal*, rather than an ordinary basis spline. In principle, one could pick the knots many different ways.

Given a set of cardinal basis spline functions $\mathcal{B}_p \equiv \{B_{j,p}\}_{j=1\ldots k+p}$, we construct the basis spline approximation as:

$$f(x) \simeq \sum_{j=1,\ldots,k} \alpha_j B_{j,p}(x), \tag{3}$$

where the vector α is chosen by OLS.

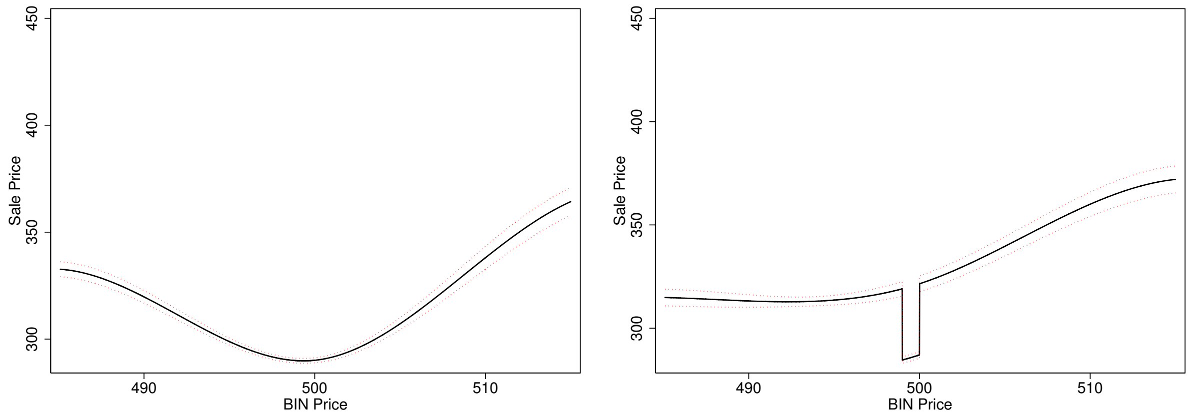
An advantage of the cardinal basis spline approach is that, for appropriately chosen α, any spline of order p on that same set of knots can be constructed as a linear combination of the elements of $\mathcal{B}_p$. Therefore we can appeal to standard approximation arguments for splines to think about the asymptotic approximation error as the number of knots goes to infinity.

2 Identification Argument with Basis Splines

Here we present additional, albeit less formal evidence for our identification strategy. We begin with the premise — an intuitive assertion — that one would expect $\mathbb{E}$[sale price|BIN price] to be monotonically increasing in the BIN price. This is testable insofar as we can estimate $g(\cdot)$ over large regions of the domain— we therefore employ the cardinal basis spline approach of Appendix 1 to estimate this expectation in the neighborhood of BIN prices near 500, *without* including dummies for round numbers. Predicted values from this regression are presented in Figure A-1a. One notes the counter-intuitive non-monotonicity in the neighborhood of 500; contrary to the premise with which we began, it appears that the derivative of $g(\cdot)$ is locally negative. This phenomenon can be documented near other round numbers as well.

To resolve this surprising outcome, it is sufficient to re-run the regression *with* dummies for $\mathcal{Z} = \{[499, 500), 500\}$. Predicted values from the regression with dummies are presented in Figure A-1b, which confirms that the source of the non-monotonicity was the behavior of listings at those points. We take this as informal evidence for the claim that a model of $\mathbb{E}$[sale price|BIN price] should allow for discontinuities at round numbers; that something other than the level of the price is being signaled at those points.

Figure A-1: Basis Spline Identification



(a) No Dummy **(b) With Dummy**

Notes: This figure depicts a cardinal basis spline approximation of $\mathbb{E}$[sale price|BIN price] without (a) and with (b) indicator functions $\mathbb{1}\{BIN \in [499, 500)\}$ and $\mathbb{1}\{BIN = 500\}$. Sample was drawn from collectibles listings that ended in a sale using the Best Offer functionality.

3 Basis Spline Robustness

An additional benefit of estimating $g(\cdot)$ globally, as the basis spline approach of Appendix 1 allows, is that we are able to employ the full dataset of listings and offers. This permits the estimation of seller-level fixed effects, which is important because they address any variation of a concern in which persistent seller-level heterogeneity drives our results. This is an extension of the local linear specification because it permits the use of all of listings simultaneously and not just those observations local to the threshold. That adds many observations per seller to each regression, some round and some non-round, identifying the effect within seller. Table A-1 shows the breakdown, by listing count, of the percentage of sellers that have a mix of both round and non-round listings. In general, we find that propensity to list round declines with experience (See Table A-8) and that first listings are more likely to be round than later listings. Yet even very large sellers use round numbers for some of their listings. For instance, 43 percent of sellers with 10 or more listings (19 percent of all sellers) have some mix of round and non-round listings, allowing for the identification of the sample.[20]

[20]Moreover, as shown in Table A-8, 22 percent of listings by the top decile of sellers are round.

Table A-1: Within Seller Variation of Roundness

	% Split	Count
1 Listing	0.00	99637
2-5 Listings	0.19	114609
6-9 Listings	0.32	35304
>=10 Listings	0.46	86445

Notes: Here we summarize the extent to which sellers, categorized by the number of listings they have generated, mix between round- and non-round listing prices, where roundness is defined by the use of an exact "00" number.

Table A-2 presents results with and without seller-level fixed effects for the average first offer as well as the sale price. These results are consistent with those from Table 2, which rules out most plausible stories of unobserved heterogeneity as an alternative explanation for our findings.

Table A-2: Basis Splines Estimation for Offers and Sales for Round \$100 Signals

	(1) Avg First Offer \$	(2) Avg First Offer \$	(3) Avg Sale \$	(4) Avg Sale \$
BIN=100	-4.835***	-1.189***	-4.396***	-2.080***
	(0.292)	(0.288)	(0.304)	(0.290)
BIN=200	-8.863***	-4.804***	-6.609***	-5.266***
	(0.456)	(0.443)	(0.488)	(0.459)
BIN=300	-14.37***	-8.781***	-12.10***	-8.797***
	(0.602)	(0.584)	(0.674)	(0.634)
BIN=400	-16.94***	-12.12***	-13.91***	-12.47***
	(0.734)	(0.714)	(0.843)	(0.795)
BIN=500	-31.02***	-23.97***	-33.59***	-27.30***
	(0.870)	(0.851)	(1.042)	(0.985)
Category FE		Yes		Yes
Seller FE		Yes		Yes
N	2804521	2804521	1775014	1775014

Notes: Here we report coefficients on a regression form of (3) where y_j is average first offers and sale prices and $g(\cdot)$ is approximated using a cardinal basis spline.

4 LASSO Model Selection

We also employ the cardinal basis spline approach to offer supplementary motivation for our choice of the set of discontinuties $\mathcal{Z}$. Based on the size of our dataset it is tempting to suppose that approximation error in g would yield evidence of discontinuities at *any* point, and therefore it is non-obvious that we should restrict attention to round numbers. To answer this concern we use LASSO model selection to construct $\mathcal{Z}$. We include dummies for $\lceil$BIN price$\rceil$ for all integers in the window $[k-25, k+25]$ for $k \in \{100, 200, 300, 400, 500\}$. These integers are constructed in similar fashion as the buckets used for Figure 2, where every listing is included and the dummy indicates whether the listing is in the range $(n-1, n]$ for all integers in the range $[k-25, k+25]$. We then include every dummy as well a continuous approximation to $g(\cdot)$ so that the LASSO optimization problem is as follows:

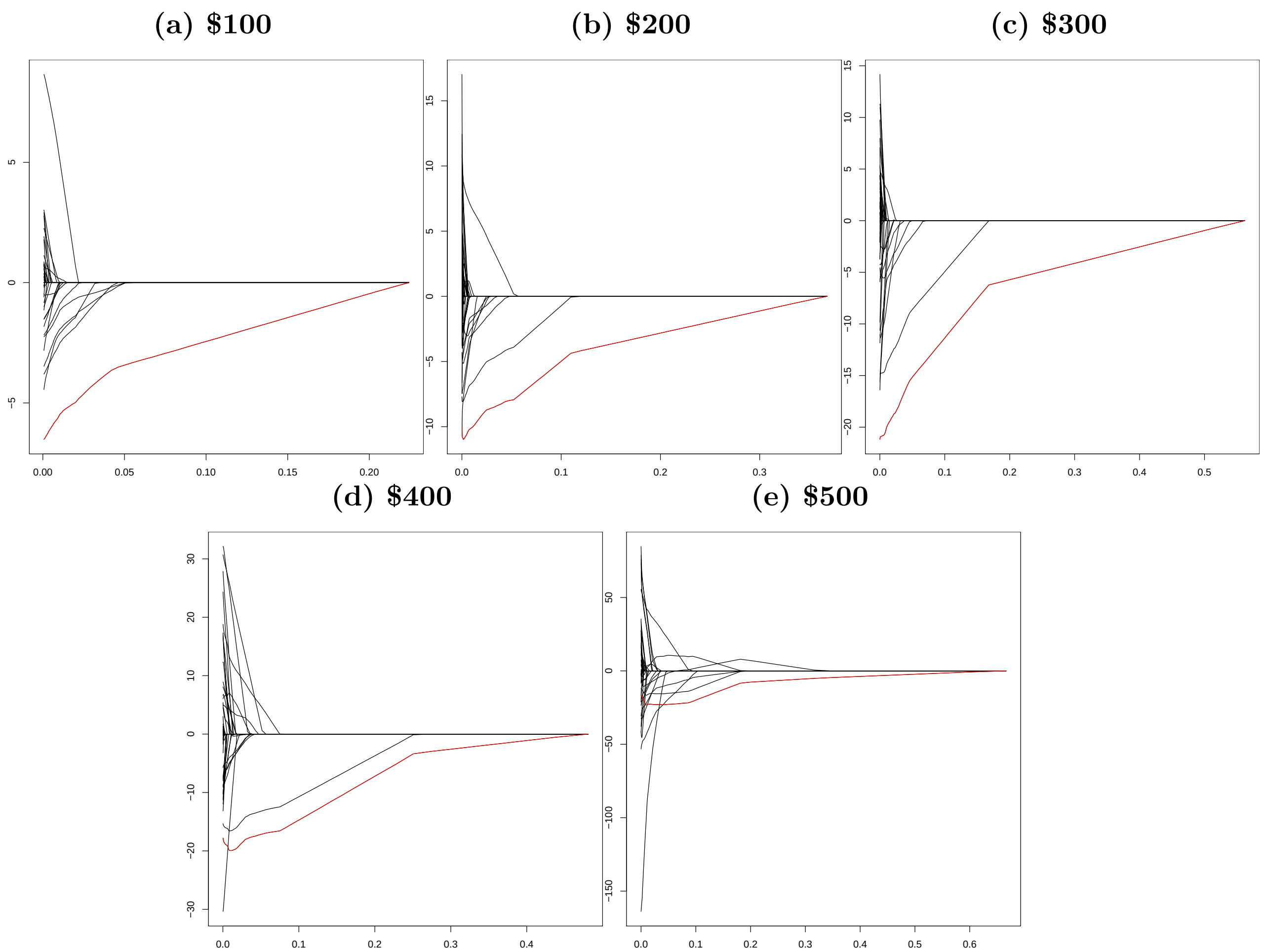
$$\min_{\beta} \frac{1}{N} \sum_{j=1,\dots,N} \left(y_j - \sum_{s \in \mathcal{S}} \gamma_z b_s(x) + \sum_{z \in \mathcal{Z}} \beta_z \mathbb{1}_z\{\text{BIN price}_j\} \right)^2 - \lambda \sum_{z \in \mathcal{Z}} |\beta_z| \tag{4}$$

Note that we do not penalize the LASSO for using the cardinal basis spline series $b(x)$ to fit the underlying $g(\cdot)$. In this sense we are considering the minimal set of deviations from a continuous estimator. Figure A-2 presents results. On the x axis is $log(\lambda/n)$, and on the y axis is the coefficient value subject to shrinkage. What is striking about these figures is that the coefficient β_{x00} (shown in red) is salient relative to other discontinuities, even when the penalty term is large, and this pattern holds true for all five of the neighborhoods we study.

B Bandwidth

We implement the optimal bandwidth selection proposed by Fan and Gijbels (1992) and described in detail by DesJardins and McCall (2008) and Imbens and Kalyanaraman (2012). We estimate the curvature of $g(\cdot)$ and the variance in a broad neighborhood of each multiple of \$100, which we arbitrarily chose to be +/- \$25. We then compute the bandwidth to be $(\sigma^2)^{\frac{1}{5}} \times (\frac{N_l+N_r}{2} \times \mid \tilde{g}'(100*i) \mid)^{-\frac{1}{5}}$ where $i \in [1, 5]$. We estimate σ using the standard deviation of the data within the broad neighborhood of the discontinuity. We estimate $\tilde{g}(\cdot)$ by regressing the outcome on a 5th order polynomial approximation of and analytically deriving $\tilde{g}'(\cdot)$ from the estimated coefficients.

Figure A-2: LASSO Model Selection



Plots show coefficients (vertical axis) for varying levels of λ in the Lasso where the dependent variable of sale price and regressors are dummies for every dollar increment between -$25 and +$25 of each $100 threshold. The red lines represent each plots respective round $100 coefficient. The Lasso includes unpenalized basis spline coefficients (not shown).

C Local Linear Ancillary Coefficients

Table A-3 presents ancillary coefficients for the local linear regression results for Table 2. The BIN price variable is re-centered at the round number of interest, so that the constant coefficient can be interpreted as the value of $g(\cdot)$ locally at that point. The slope coefficients deviate substantially from what one might expect for a globally linear fit of the scatterplot in Figure 2 (i.e., roughly 0.65). In other words, it seems that the function $g(\cdot)$ exhibits substantial local curvature, which offers strong supplemental motivation for being as flexible and nonparametric as possible in its estimation. Similarly, Table A-4 presents ancillary coefficients corresponding to our local linear throughput results in Table 3. Optimal bandwidth choices for both tables reflect the fact that there is more data available for lower BIN prices.

D The 99 effect

The regressions of Section 4.2 included indicators $\mathbb{1}\{\text{BIN price}_j = z\}$ as well as indicators $\mathbb{1}\{\text{BIN price}_j \in [z-1, z)\}$ for $z \in \{100, 200, 300, 400, 500\}$. Table A-5 reports the coefficients on the latter indicators, which capture the effect of pricing "to the nines". Perhaps surprisingly, the results are very similar to those in Table 2; it seems that listing prices of \$99.99 and \$100 have the same effect relative to, for instance, \$100.24. We take this as evidence that the left-digit inattention hypothesis does not explain our findings. It suggests that what makes a "round" number round, for our purposes, is not any feature of the number itself but rather convention — a Schelling point — consistent with our interpretation of roundness as cheap talk.

This finding also suggests that we can pool the signals, letting $\mathcal{Z} = \{[99, 100], [199, 200], [299, 300], [399, 400], [499, 500]\}$. Results for that regression are reported in Table A-6. Consistent with our hypothesis, this does not substantively alter the results.

E Non-Bargained Transactions

Our model does not incorporate any costs of bargaining or the option to pay the advertised listing price. In reality buyers choose between paying full price and engaging in negotiation. On eBay, the former is done by clicking the "Buy-It-Now" button and immediately checking out. Though this is outside of our model, it is intuitive that when there is more surplus to be had from negotiation, i.e. when the seller uses a round listing price, buyers will be relatively less likely to exercise the Buy-it-Now option. In order to test this, we employ our local linear specification from Equation (6) to predict the likelihood that the a listing sells at the BIN price and, secondarily, the likelihood that a listing sells at the BIN price conditional on a sale.

Results are presented in Table A-7. Somewhat counter-intuitively, columns (1) and (2) suggest that round-number listings are more likely to sell at the BIN price than

Table A-3: Intercepts and Slopes for Each Local Linear Regression

	(1) Avg First Offer \$	(2) Avg First Offer \$	(3) Avg Sale \$	(4) Avg Sale \$
Near round \$100:				
Constant	60.17***	61.38***	82.26***	79.67***
	(0.0861)	(0.168)	(0.0902)	(0.178)
Slope	0.654***	0.687***	1.088***	1.074***
	(0.0184)	(0.0173)	(0.0181)	(0.0181)
Bandwidth	6.441	7.388	7.615	7.492
N	286606	289772	224868	224445
Near round \$200:				
Constant	119.2***	120.0***	162.8***	156.3***
	(0.314)	(0.467)	(0.322)	(0.503)
Slope	0.928***	1.006***	1.762***	1.592***
	(0.0639)	(0.0622)	(0.0674)	(0.0655)
Bandwidth	8.171	8.253	7.365	7.662
N	151004	151093	103690	103898
Near round \$300:				
Constant	175.5***	172.2***	242.9***	232.1***
	(0.609)	(0.586)	(0.735)	(0.756)
Slope	1.416***	0.737***	2.156***	1.408***
	(0.118)	(0.0210)	(0.149)	(0.0605)
Bandwidth	9.985	22.46	8.595	12.73
N	101690	137956	63270	70069
Near round \$400:				
Constant	231.6***	222.1***	322.4***	303.5***
	(0.660)	(1.058)	(1.020)	(1.335)
Slope	1.406***	1.234***	2.111***	1.763***
	(0.0742)	(0.0690)	(0.146)	(0.128)
Bandwidth	16.03	17.97	12.55	14.20
N	80967	81413	44154	44443
Near round \$500:				
Constant	279.7***	275.7***	396.8***	376.7***
	(1.065)	(1.432)	(1.276)	(1.641)
Slope	1.433***	1.457***	2.712***	1.748***
	(0.131)	(0.110)	(0.216)	(0.141)
Bandwidth	16.62	19.48	14.22	16.29
N	69129	69615	36003	37201
Category FE		YES		YES

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Here we report ancillary coefficients from separate local linear fits according to Equation (6) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column, corresponding to Table 2. Heteroskedacticity-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

precise-number listings. However, this derives from the fact that round-number listings enjoy heavier buyer traffic, as we have documented in Tables 3 and 5. When we condition on sale, as we do in columns (3) and (4), for the elements of $\mathcal{Z}$ where we have the most observations we see a large and negative effect consistent with our intuition— that buyers are more likely to engage in negotiation conditional on purchasing from a round- rather than a precise-number seller. In other words, buyers' decisions about when to engage in negotiation are consistent with beliefs implied by our model.

F Hypothesis H4

An ancillary prediction of the model is that "thick" markets will have lower discounts than thinner markets. Low type (inpatient) sellers do not have to wait as long for buyers in thicker markets so they do not have to offer as deep discounts to rationalize signaling weakness. We take this to the data by conjecturing that thicker markets will have more traffic (views and search events) for items in thicker markets. This is an imperfect proxy since traffic is only indirectly correlated with the arrival of actual buyers.[21]

We proceed by grouping listings into deciles by view item counts. We first find that the baseline (non-round) mean offers vary across decile of exposure. This is an undesired byproduct of group by exposure: items in these groupings are different in ways other than pure buyer arrival rates (λ_b). We correct for this by normalizing estimates by the baseline mean offer. That is, we normalize β_z by the constant a_z in Equation 6. Otherwise, estimation proceeds just as in Equation 6, but separately for each decile of exposure.

Figure A-3 shows the results. This figure plots the point estimates and confidence interval of the local linear estimation of the round-number BIN effect on mean first offers for each decile of view item detail counts and search result exposure counts. The x-axis shows the decile for each viewability metric, with 10 being have the highest search and item detail counts. The y-axis is interpretable as percentage effect of roundness because the coefficients are normalized by the baseline (precise) mean offers.

For the delineation across item detail views, we indeed see lower relative discounts for higher view rates, which bolsters H4. For the delineation across search counts, we see a peculiar u-shape pattern where both very low and very high search counts have lower

[21] For intuition on this, consider that quirky yet undesired items may still get a lot of traffic because they are interesting.

discounts than the mid range of search counts. On balance, this relationship is actually still positive (as a linear fit of these coefficients has a positive slope). We surmise that the selection effect of our imperfect proxy leads to a positive bias for the thinnest market items. Hence, we conclude only that this evidence is suggestive that thicker markets have lower discounts (H4).

G Seller Response to Round Offers

A natural extension of our analysis is to look at seller responses to round buyer offers. We limit our attention to the bargaining interactions where a seller makes at least one counter offer and compare the buyer's initial offer to level of that counter offer. We derive a metric of conciliation which indexes between 0 and 1 the distance between the buyer's offer and the BIN (the sellers prior offer). We show in Figure A-4 that round initial offers by buyers are met with less conciliatory counter offers by sellers. Roundness may be used as a signal to increase the probability of success at the expense seller revenue.

H Seller Experience

Next we ask whether or not seller experience explains this result. We might suspect that sophisticated sellers learn to list at precise values and novices default to round-numbers. There is some evidence for this, but any learning benefit is small and evident only in the most expert sellers. We define a seller's experience to be the number of prior Best Offer listings prior to the current listing. With this definition, we have a measure of experience for every listing in our data set. For tractability, we narrow the analysis to all listings with BIN prices between $85 and $115 and focus on a single round-number, $100. Table A-8 shows first the proportion of listings that are a round $100 broken down by the sellers experience at time of listing. The most experience 20 percent of sellers show markedly lower rounding rates.

By interacting our measure of seller experience with a dummy for whether the listing is a round $100, we can identify at different experience levels the round effect on received offers. The right pane of Table A-8 shows the estimates with and without seller fixed effects. Without seller fixed effects, we are comparing the effect across experienced and inexperienced sellers. As before, the only differential effect appears in the top two deciles of experience. Interestingly, when we include seller fixed effects, and are therefore comparing within sellers experiences, we see that the effect is largest in the middle deciles.

Table A-4: Intercepts and Slopes for Each Local Linear Regression - Throughput

	(1) Days to Offer	(2) Days to Offer	(3) Days to Sale	(4) Days to Offer	(5) Pr(Sale)	(6) Pr(Sale)
Near round \$100:						
Constant	35.34***	40.48***	46.67***	49.62***	0.133***	0.130***
	(0.274)	(0.543)	(0.355)	(0.651)	(0.00162)	(0.00240)
Slope	0.180***	0.263***	0.641***	0.686***	0.0100***	0.00781***
	(0.0582)	(0.0557)	(0.0742)	(0.0738)	(0.000735)	(0.000735)
Bandwidth	6.907	7.048	7.321	7.384	2.681	2.740
N	287366	289072	224354	224389	798842	799105
Near round \$200:						
Constant	32.70***	40.05***	45.37***	50.17***	0.128***	0.115***
	(0.482)	(0.711)	(0.671)	(0.936)	(0.00239)	(0.00304)
Slope	0.442***	0.648***	0.872***	1.021***	0.00663***	0.00325***
	(0.100)	(0.0945)	(0.137)	(0.136)	(0.000911)	(0.000911)
Bandwidth	7.841	8.106	8.308	8.564	3.493	3.722
N	150378	150989	104398	104430	425926	426091
Near round \$300:						
Constant	30.37***	36.52***	42.05***	47.09***	0.120***	0.103***
	(0.581)	(0.627)	(0.656)	(0.863)	(0.00285)	(0.00235)
Slope	-0.0746	0.0930***	0.144	0.204***	0.00562***	-0.00208***
	(0.112)	(0.0317)	(0.0965)	(0.0508)	(0.000904)	(0.000399)
Bandwidth	9.775	18.51	10.38	18.06	4.926	6.972
N	101507	120721	67702	75779	282623	344593
Near round \$400:						
Constant	26.37***	31.88***	39.25***	42.56***	0.119***	0.102***
	(0.402)	(0.504)	(0.528)	(1.019)	(0.00205)	(0.00245)
Slope	-0.0859**	-0.0439***	-0.0682	-0.0131	-0.00218***	-0.00267***
	(0.0425)	(0.0109)	(0.0429)	(0.0720)	(0.000428)	(0.000425)
Bandwidth	16.04	29.33	20.30	17.27	6.772	6.888
N	80967	117887	51208	46905	234627	234670
Near round \$500:						
Constant	28.24***	36.29***	41.62***	47.15***	0.119***	0.0998***
	(0.550)	(0.823)	(0.834)	(1.209)	(0.00325)	(0.00364)
Slope	0.260***	0.314***	0.340***	0.420***	0.00103	-0.00113*
	(0.0635)	(0.0602)	(0.0947)	(0.0944)	(0.000673)	(0.000673)
Bandwidth	16.26	18.45	19.96	19.98	5.605	5.378
N	69122	69342	37473	37477	208351	208293
Category FE		YES		YES		YES

Heteroskedacticity-robust standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Here we report ancillary coefficients from separate local linear fits according to Equation (6) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column, corresponding to Table 3. Heteroskedacticity-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A-5: Offers and Sales for [$99,$100) Signals

	(1) Avg First Offer $	(2) Avg First Offer $	(3) Avg Sale $	(4) Avg Sale $
BIN=099	-6.277***	-4.744***	-5.903***	-4.917***
	(0.0974)	(0.0955)	(0.104)	(0.106)
BIN=199	-14.21***	-9.742***	-11.75***	-9.035***
	(0.333)	(0.330)	(0.350)	(0.348)
BIN=299	-22.66***	-16.31***	-17.70***	-15.31***
	(0.640)	(0.398)	(0.767)	(0.543)
BIN=399	-32.99***	-22.00***	-22.61***	-17.89***
	(0.777)	(0.776)	(1.116)	(1.042)
BIN=499	-42.03***	-26.30***	-34.32***	-27.15***
	(1.193)	(1.123)	(1.451)	(1.302)
Category FE		YES		YES

Notes: Each cell in the table reports the coefficient on the indicator for BIN $\text{price}_j \in [z-1, z)$ from a separate local linear fit according to equation (6) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column. Ancillary coefficients for each fit are reported in Table A-3. Heteroskedacticity-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A-6: Pooling 99 and 100

	(1) Avg First Offer $	(2) Avg First Offer $	(3) Avg Sale $	(4) Avg Sale $
BIN=099 or 100	-4.793***	-3.944***	-4.615***	-4.101***
	(0.0519)	(0.0511)	(0.0709)	(0.0680)
BIN=199 or 200	-13.37***	-10.50***	-11.75***	-10.24***
	(0.164)	(0.164)	(0.183)	(0.183)
BIN=299 or 300	-20.90***	-15.30***	-19.04***	-16.52***
	(0.352)	(0.354)	(0.381)	(0.380)
BIN=399 or 400	-28.89***	-20.10***	-21.95***	-18.46***
	(0.606)	(0.611)	(0.690)	(0.674)
BIN=499 or 500	-40.48***	-26.66***	-34.77***	-28.58***
	(0.923)	(0.924)	(1.083)	(1.083)
Category FE		YES		YES

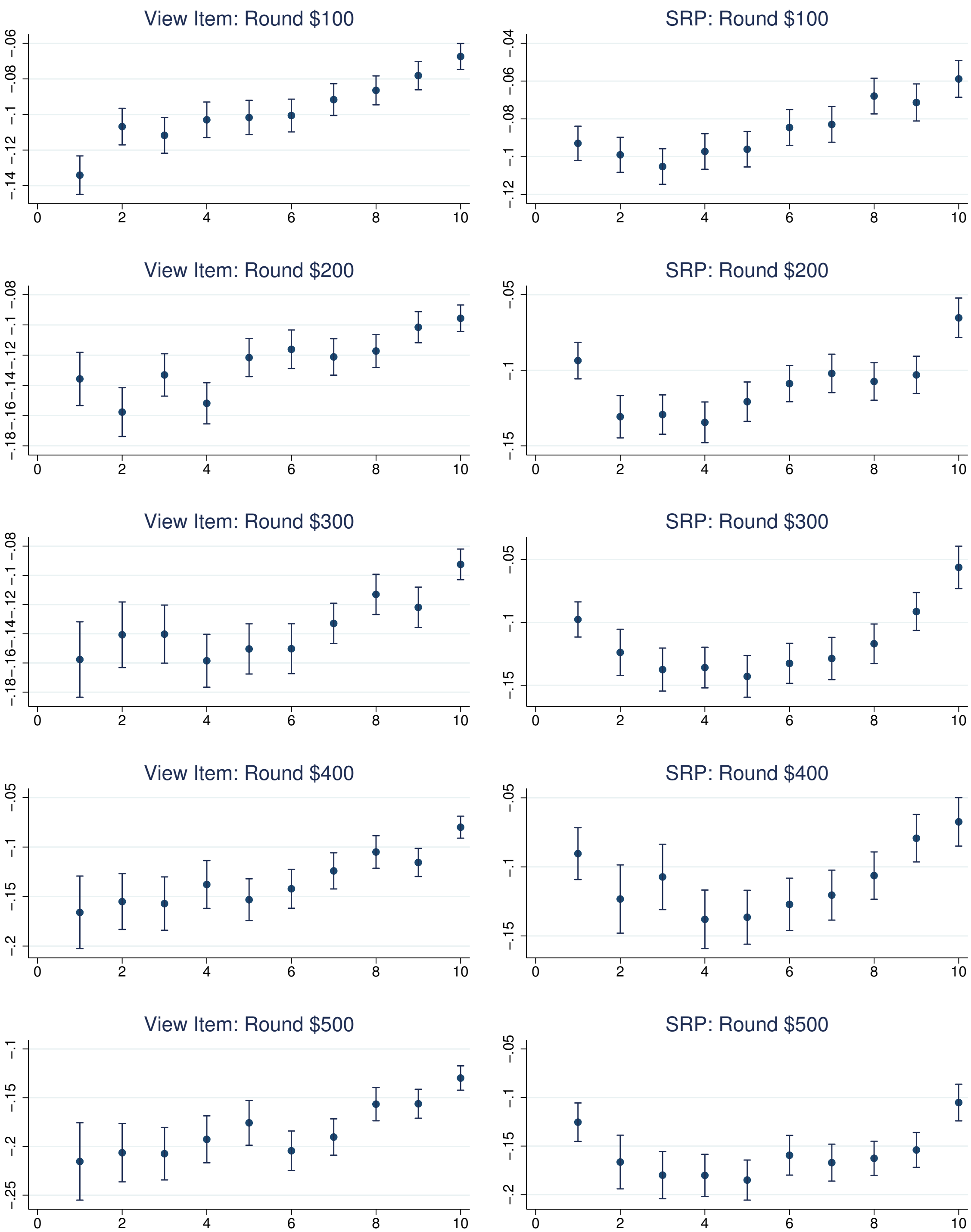
Notes: Each cell in the table reports the coefficient on the indicator for BIN $\text{price}_j \in [z-1, z]$ from a separate local linear fit according to a modified version of equation (6) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column. Ancillary coefficients for each fit are reported in Table A-3. Heteroskedacticity-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

Table A-7: Round Numbers and the Buy-it-Now Option

	(1) Pr(BIN)	(2) Pr(BIN)	(3) Pr(BIN|Sale)	(4) Pr(BIN|Sale)
BIN=100	0.00595***	0.00757***	-0.0194***	-0.0172***
	(0.00103)	(0.000893)	(0.00278)	(0.00286)
BIN=200	0.00556***	0.00611***	-0.0154**	-0.0156**
	(0.00138)	(0.00137)	(0.00770)	(0.00768)
BIN=300	0.000860	0.000959	-0.0281**	-0.0228***
	(0.00176)	(0.00111)	(0.0117)	(0.00705)
BIN=400	0.00395***	0.00397***	0.000880	-0.00766
	(0.00121)	(0.00118)	(0.00831)	(0.00826)
BIN=500	0.00315***	0.00463***	-0.000596	-0.00358
	(0.00100)	(0.00119)	(0.0112)	(0.0102)
Category FE		YES		YES

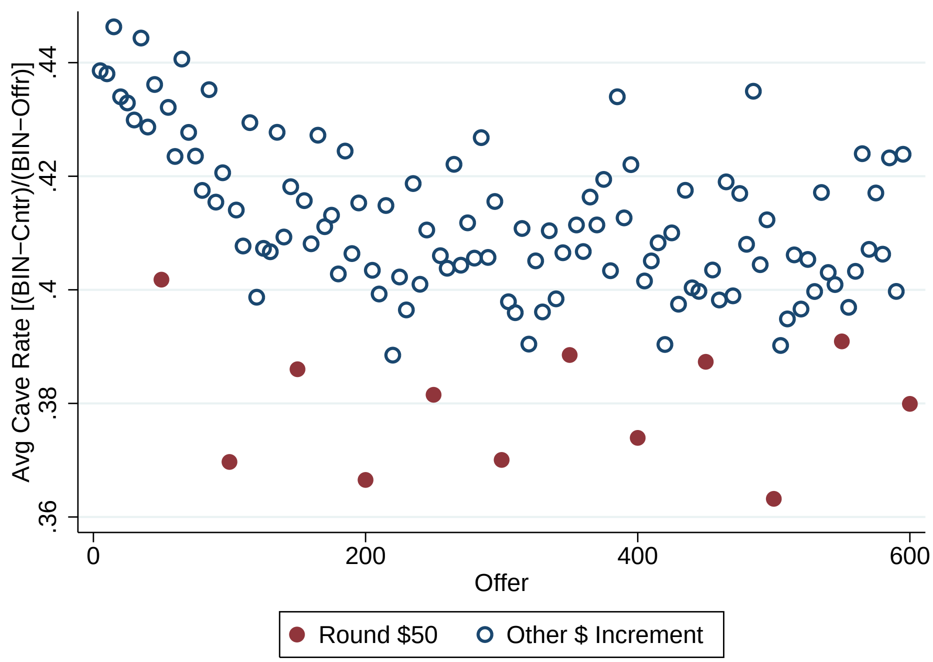
Notes: Each cell in the table reports the coefficient on the indicator for roundness from a separate local linear fit according to equation (6) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column. Ancillary coefficients for each fit are reported in Table A-3. Heteroskedacticity-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

Figure A-3: H4



Notes: This figure plots the point estimates and confidence interval of the local linear estimation of the round number BIN effect on mean first offers for each decile of view item detail counts and search result exposure counts.

Figure A-4: Seller Response to Buyer Offers



Notes: This scatterplot presents average seller counteroffers, normalized by the listing price price to be between zero and one, grouped by unit intervals of the buyer offer. When the buyer offer is round to the fifties, the average seller offer is represented by a filled red circle.

Table A-8: Seller Experience and Round Numbers

	Percent Round $100	Percent 99
1st Decile	0.164	0.0904
	(0.00224)	(0.00174)
2nd Decile	0.139	0.0982
	(0.00201)	(0.00172)
3rd Decile	0.127	0.0981
	(0.00197)	(0.00176)
4th Decile	0.118	0.105
	(0.00182)	(0.00174)
5th Decile	0.107	0.108
	(0.00165)	(0.00164)
6th Decile	0.102	0.118
	(0.00155)	(0.00163)
7th Decile	0.0927	0.122
	(0.00142)	(0.00159)
8th Decile	0.0822	0.124
	(0.00129)	(0.00151)
9th Decile	0.0683	0.129
	(0.00113)	(0.00146)
10th Decile	0.0507	0.126
	(0.000914)	(0.00131)
N	234635	234635

	Avg First Offer	Avg First Offer
Round $100 x 1st Decile	-8.257***	-1.386
	(0.700)	(2.168)
Round $100 x 2nd Decile	-8.377***	-3.314***
	(0.633)	(1.053)
Round $100 x 3rd Decile	-7.502***	-2.157**
	(0.614)	(0.848)
Round $100 x 4th Decile	-7.761***	-2.653***
	(0.560)	(0.705)
Round $100 x 5th Decile	-7.988***	-2.544***
	(0.513)	(0.607)
Round $100 x 6th Decile	-9.299***	-3.260***
	(0.461)	(0.519)
Round $100 x 7th Decile	-9.358***	-3.518***
	(0.422)	(0.455)
Round $100 x 8th Decile	-9.489***	-3.910***
	(0.373)	(0.391)
Round $100 x 9th Decile	-9.925***	-3.889***
	(0.326)	(0.333)
Round $100 x 10th Decile	-11.84***	-5.414***
	(0.250)	(0.248)
Category FE		YES
Seller FE		YES
N		

Notes: The left table documents prevalence of round-number listings by deciles of seller experience, where seller experience is measured by the number of past transactions. Standard deviations are presented in parenthesis. The right table replicates estimates of β_100 separately by decile of seller experience. Standard errors are in parenthesis.