On the Empirical Content of Cheap-Talk Signaling: An Application to Bargaining*

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Abstract

We outline an empirical framework to guide the analyses of signaling games and focus on three key features: sorting of senders, incentive compatibility of senders, and belief updating of receivers. We apply the framework to answer the following question: Can sellers credibly signal their private information to reduce frictions in negotiations? We argue that some sellers use round numbers to signal their willingness to cut prices in order to sell faster. Using millions of online bargaining interactions we show that items listed at multiples of $100 receive offers that are 8%-12% lower but are 15%-25% more likely to sell, demonstrating an incentive-compatibility trade-off. We then show evidence consistent with sorting and belief updating inherent to cheap-talk models. Patterns in real estate transactions suggest that round-number signaling plays a role in negotiations more generally. *JEL* classifications: C78, D82, D83, M21.

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1 Introduction

Since the seminal contributions of Spence (1973) and Crawford and Sobel (1982), costly and cheap-talk models of signaling have become the standard for understanding how economic agents communicate about payoff-relevant private information. Signaling models have been used to shed light on possible behaviors in a variety of domains, including educational attainment, bargaining, limit pricing, advertising, and political campaigning, to name a few. However the empirical counterpart to this literature — in particular the empirical validation of the signaling research agenda — is scarce at best.

The paucity of empirical work on this topic is reflected in the lack of guidance for how to undertake such an endeavor, however it is not for lack of significance or interest — by their nature, signaling equilibria are premised on private information and beliefs, neither of which is typically observed by the econometrician. The first broad contribution of this paper is methodological: we outline an empirical framework for the study of separating equilibria in signaling games. We then take this framework to the data, yielding our second broad contribution: to our knowledge, we demonstrate the first *complete* empirical confirmation of a separating equilibrium in the field. In particular, we introduce a large and novel dataset from eBay's Best Offer bargaining platform and show that sellers can use precise-number asking prices to credibly communicate a strong bargaining position, but often willingly use round-number asking prices to communicate a weak one.

For the applied econometrician seeking to document a separating equilibrium, our framework stresses the importance of three kinds of evidence: first, that senders sort, i.e. that the private type of senders is correlated with the signal they are observed sending; second, that receivers' beliefs about private types reflect that sorting, and third, that in equilibrium, sender sorting is incentive compatible. We apply our framework to data from online bargaining and offer empirical evidence on *each* of these points in this empirical setting. With respect to sender sorting, we demonstrate that sellers who use round-number asking prices are different than those who use precise numbers — the former are more likely to accept a given offer and, should they decline, make less aggressive counter-offers. On receiver beliefs, we show that buyers' beliefs about sellers' bargaining positions are reflected in their search behavior as well as their choices between bargaining and paying the asking price. Finally, and perhaps most convincingly, we offer evidence of incentive compatibility by documenting a trade-off: round number asking prices elicit lower offers, but more of them and sooner, and result in a higher probability of sale.

A concern with causal identification of the basic empirical findings may be that, for listings with round-number asking prices, there are unobservable differences in the seller attributes or in the products themselves, resulting in lower offers and lower prices. 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 have precise-number asking prices in the U.S. Assuming that U.S. buyers perceive the 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 signaling via roundness.

It is natural to wonder why sellers use roundness as a signal, rather than something more direct, or simply lowering their asking price. The answer to such a question necessarily lives outside of our cheap-talk signaling approach because by construction, there is no theoretical guidance about what kind of cheap-talk messages will be chosen. We do, however, endeavor to offer a few conjectures. First, the listing price is most likely an important signal of other characteristics of the item being sold, such as quality, consistent with the price-signaling literature (see Milgrom and Roberts (1986)). Perhaps a more satisfying answer, however, is that roundness is a signaling convention that is available in almost any market where bargaining occurs. The premise of this argument, that successful signaling conventions are likely to show up in many aspects of economic activity, suggests that our finding is much more general than the eBay environment. Indeed, we offer some evidence for this claim: we obtain data from the Illinois real estate market that has been used by Levitt and Syverson (2008) where we observe both the listing price and the final sale price. The data does not let us perform the vast number of tests we can for eBay's large dataset, but we are able to show that homes listed at round numbers sell for less than those listed at nearby precise numbers, consistent with the signaling approach we build on.

From a theoretical standpoint, the signaling equilibrium we document is closely related to the cheap-talk signaling models of bargaining in Farrell and Gibbons (1989), Cabral and Sákovics (1995), and Menzio (2007). We complement this literature by offering empirical validation, and we add to it in Appendix I with a stylized model of bargaining with sellers who differ in their level of patience.

A second related literature, though sparse, concerns the empirical documentation of aspects of signaling equilibria. The oldest thread 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. In our framework, this corresponds to partial evidence for incentive compatibility — the missing, and unobservable, piece being the differential costs of education that underlie Spence (1973). More recently, Kawai et al. (2013) document costly signaling in an online lending market by borrowers who seem to disclose their risk type by proposing higher interest rates. What is novel about their setting is that they are able to observe subsequent defaults of borrowers, a correlate of the private information of the borrowers in their setup. In our framework, this corresponds to evidence of sender sorting.

Our work also contributes to two separate strands of the literature that specifically shed light on bargaining and negotiation. The first of these is a growing literature in Industrial Organization on the empirics of bargaining and negotiation (Ambrus et al., 2014; Bagwell et al., 2014; Grennan, 2013, 2014; Larsen, 2014; Shelegia and Sherman, 2015). We contribute to this literature by documenting the important role of cheap-talk signaling as a framework for understanding the relationship between "negotiation", i.e. communication, and bargaining outcomes.

The second strand includes recent work in consumer psychology and marketing on "numerosity" and cognition, which had studied the use of round numbers in bargaining (Janiszewski and Uy, 2008; Loschelder et al., 2013; Mason et al., 2013). These papers argue that using round numbers in bargaining leads to an unequivocally worse outcome, i.e., lower prices. By way of explanations they offer an array of biases, from anchoring to linguistic norms, and come to the conclusion that round numbers are to be avoided by the skillful negotiator. This literature ignores the trade-off — that round numbers increase the frequency of offers and the likelihood of sale — and leaves unanswered the question of why, then, as we demonstrate below, round numbers are so pervasive in bargaining, even among experienced sellers, who go to great lengths to optimize the design, timing, and search visibility of their listings. We reconcile these facts with an alternative hypothesis: that the use of round numbers can be an informative signal — one we can study rigorously — that sellers use to credibly communicate with buyers.

2 Cheap-Talk Signaling in Negotiations

Will parties to a negotiation honestly reveal private information about their bargaining positions? From a naive perspective, this seems difficult to achieve in equilibrium: suppose that by sending a cheap and unverifiable signal of intransigence – "forty-two dollars and not a penny less" – I can achieve a better price, all else equal. If such a signal were effective then all sellers would have an incentive to employ it– even those who would happily settle for less. Knowing this, buyers ignore the message.

The problem with this assertion lies in its simplicity: if sellers only care about the price, it is impossible to describe an equilibrium that differentiates them. In other words, if we want to know how sellers credibly signal bargaining strength, we must first explain why anyone would willingly signal bargaining weakness. Fortunately the real world offers myriad examples of such behavior: rug stores are perennially "going out of business"– attracting buyers by advertising that they are compelled by circumstance to negotiate, and by a similar logic car dealerships advertise bargaining weakness when they announce the need to liquidate inventory.

The existing theoretical literature on negotiation has followed this intuition– parties to a negotiation use cheap talk to trade off between price and the probability of sale. Sellers with relatively low reserve prices then willingly signal their bargaining weakness in order to increase the likelihood of a transaction. Examples include Farrell and Gibbons (1989), Cabral and Sákovics (1995), Menzio (2007), and Kim (2012). In Appendix I we contribute another model in this spirit, wherein buyers and sellers arrive in continuous time and sellers use a cheap-talk signal to reveal whether they are patient or impatient.

These models depend on vastly different assumptions: seller heterogeneity may come from different valuations or different discount rates; market frictions may come from matching functions or assumptions about the arrival process of players, and there are many ways to formalize the bargaining procedure. Our goal is *not* to differentiate between them. We instead wish to keep the mechanisms as general as possible while drawing out the empirical implications of the broad assertion that a separating equilibrium of a signaling game is being played.

Consider a market with a seller who is privately endowed with a payoff-relevant type $\theta \in \{H, L\}$. Buyers in the market do not know the seller's type, but in the first stage the seller can send a cheap-talk signal $s \in \{strong, weak\}$ that may be informative in equilibrium. Let σ_θ denote the seller's signaling strategy that maps types into probability distributions over signals. Conditional on a signal s, the buyer has updated beliefs $\mu(s)$ over the seller's type. Finally, the seller and buyer engage in a second-stage bargaining game that maps buyer beliefs $\mu(s)$ into a probability of sale $q(s)$ and a negotiated price conditional on sale, $p(s)$. Sellers' payoffs depend on both of these outcomes as well as their type θ; we write this $\pi_\theta(p(s), q(s))$.[1]

Three empirical claims follow from the assertion that a separating equilibrium is being played and any complete empirical exposition of a signaling equilibrium requires demonstration of all three claims.

CLAIM 1: *(Sorting) By the definition of separation, sellers of different types choose different signaling strategies, i.e.,*

$$\sigma_H \neq \sigma_L. \tag{C1}$$

It is important to distinguish the claim that sellers *do* sort from the equilibrium claim, made below, that sellers rationally *should* sort. Therefore sorting is independent of seller optimization. It may be tested by demonstrating that covariates of sellers' types are correlated with sellers' signals.

CLAIM 2: *(Beliefs) By the definition of a perfect Bayesian equilibrium, buyers' beliefs are derived from Bayes' rule and therefore reflect separation of seller types, i.e.,*

$$\mu(strong) \neq \mu(weak). \tag{C2}$$

[1]For simplicity we have written this in the binary type, binary signal form, but the framework could be easily extended to allow for a continuum of types and an arbitrary signal space.

This claim is essential to separation but very difficult to test, as buyers' beliefs are not often directly elicited. However, in data-rich environments one might be able to offer indirect evidence. For instance, in e-commerce applications where the signal is mediated and behavioral data is available, one may be able to infer beliefs from the receiver's response to the receipt of the signal.

CLAIM 3: *(Incentive Compatibility) Finally, conditional on the beliefs induced by seller sorting, bargained quantities and prices rationalize the seller's signaling strategy. Suppose, without loss of generality, that type $\theta = H$ is more likely to send the signal "strong" than $\theta = L$ is. Seller optimization in a perfect Bayesian equilibrium implies two conditions:*

$$\pi_H(p(strong), q(strong)) \geq \pi_H(p(weak), q(weak)),$$

and

$$\pi_L(p(weak), q(weak)) \geq \pi_L(p(strong), q(strong)). \tag{C3}$$

Clearly, given a fixed probability of sale, all seller types prefer higher prices, and given an acceptable price, they all prefer a higher probability of sale, implying that π_θ is increasing in both of its arguments. It therefore follows that an implication of incentive compatibility is that there must be a tradeoff between price and quantity in the signal chosen.

We propose these three claims as a framework for empirical validation of signaling models.[2] Of course, they may not be testable in every application. To the extent that they are not, it may be difficult to rule out alternative hypotheses. For instance, in the context of the sheepskin literature, proving that there is a local treatment effect of passing the GED for students with similar unobservables (Tyler et al., 2000) is consistent with the signaling hypothesis of Spence (1973), but it is also consistent with a world in which employers find it costly to process information on applicants. In that world they may use the GED as a coarse proxy for unobservable attributes. This explanation is plausible, consistent with the evidence offered, and does not involve signaling.

Our particular application offers better leverage on the three empirical claims described above, thanks to our unique dataset that couples offer-level bargaining events with behavioral search data. We argue that, in bargaining, using a round asking price is a

[2] The way in which state these claims, especially Claim 3, is particular to the bargaining setting that we investigate. It is clear that as a matter of principle, these three claims apply to any signaling game.

signal of bargaining weakness, while using a precise number signals bargaining strength.[3] We do this by offering independent evidence on each of the three claims. With respect to sorting, we use offer-level bargaining data to show that sellers' subsequent bargaining behavior is correlated with the inferred bargaining type; with respect to beliefs, we employ behavioral data to show how roundness of the asking price guides buyer search on the eBay platform and election into bargaining rather than paying the asking price, and with respect to incentive compatibility, we demonstrate a trade-off: round numbers elicit lower offers but a higher likelihood of sale, while precise numbers yield the opposite.

Of course asking prices are payoff-relevant, so it is natural to wonder whether roundness is "cheap". We treat the use of round asking prices as a cheap-talk signal because, conditional on employing one, there is always a nearby precise-number price that could have been chosen. However, it is important to note that our model says nothing about the *level* of the price. In neither the theory nor the empirics do we build a demand system: we are solely concerned with the signaling content of roundness as compared with a nearby precise-number price.

Note also that we use a standard "non-behavioral" approach that imposes no limits on cognition or rationality. Prior work connected roundness and precision with ideas about how limited cognition among sellers and buyers may impact outcomes. In our setting, that approach raises more questions than it answers: first, if we can advantage ourselves by using precise numbers or adopting other cheap-talk signaling strategies, shouldn't everyone do it? Our evidence suggests that sellers do not; they are disproportionately likely to use round-number listing prices even though they yield lower negotiated transaction prices. Second, as we show in Appendix G, buyers who use round-numbers as their starting offer invite more aggressive behavior from sellers. This suggests that there is a strong understanding of what a player is signaling when using a round number on either side of the market, consistent with a high degree of sophistication. Third, it is hard to believe that our reactions to as abstract a concept as "roundness" are hard-wired; indeed, Thomas et al. (2010) demonstrates that perceptual biases concerning roundness in prices in the lab can be manipulated – even to the degree of changing sign – by "priming" experimental subjects. If this is true, then how should we think about the way that our real market experiences "prime" us to interpret roundness? We take the stance that Bayes' rule and rationality

[3]We are agnostic as to the primitive source of the variation in the "strength" of bargaining positions. It may come from impatience, cognitive or effort costs of bargaining, or variation in the outside option.

offer a simple way to think about market priming in equilibrium, while acknowledging that the mechanical truth of real-world decisions is more complicated.

3 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".

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.[4] 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.[5]

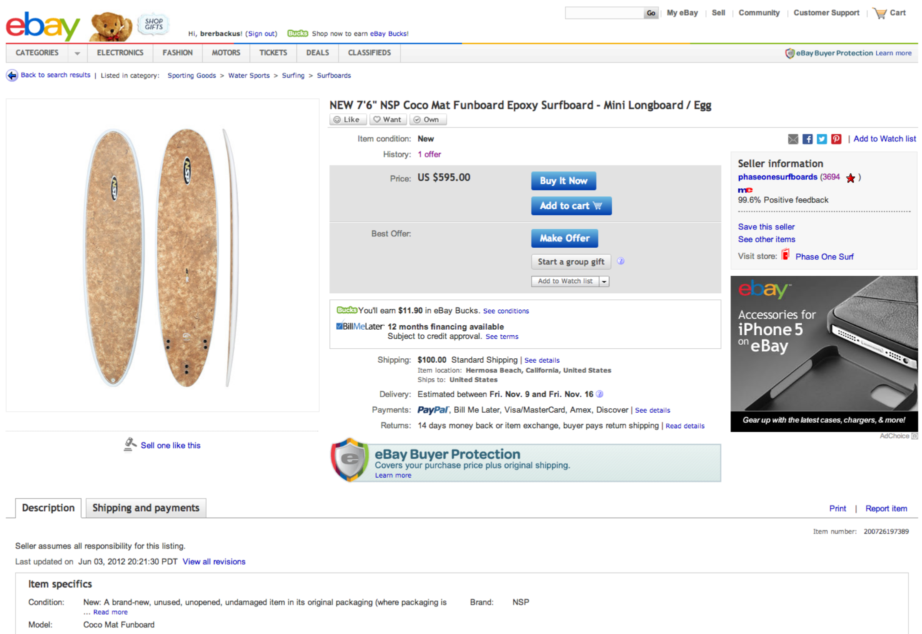
We restrict attention to items in eBay's Collectibles marketplace which includes coins, antiques, toys, memorabilia, stamps, art and other like goods. Our results generalize to other categories, but we believe that the signaling mechanism is naturally greatest in collectibles where there is greater heterogeneity 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 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, for which the benefit of bargaining is small, and the thin right tail of very expensive listings. We are left with 10.5 million listings, of which 2.8

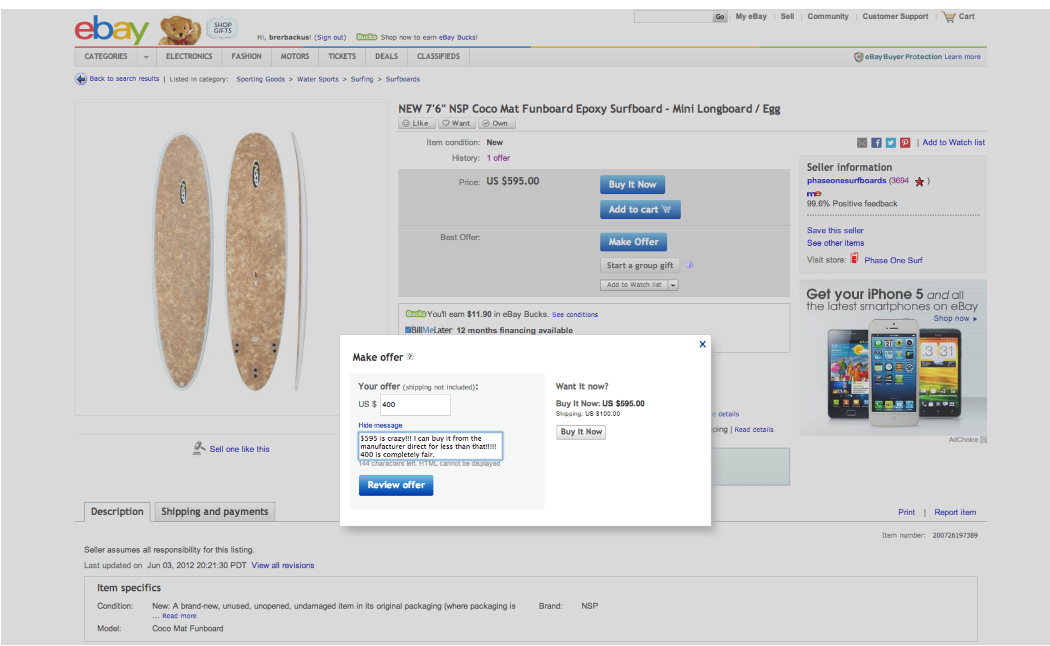
[4] The buyer can also send a message with their offer, as seen in frame (b) of Figure 1. We leave the analysis of those messages, which requires a different approach, for future work.

[5] 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 longer 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
Average First-Offer Ratio (Offer/Listing Price)	0.627	(0.188)	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	2.091	(4.985)	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	0.22	(0.414)	10472614
# 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 Best Offer-enabled collectibles listings created on eBay.com between June 2012 and May 2013 with BIN prices between $50 and $550.

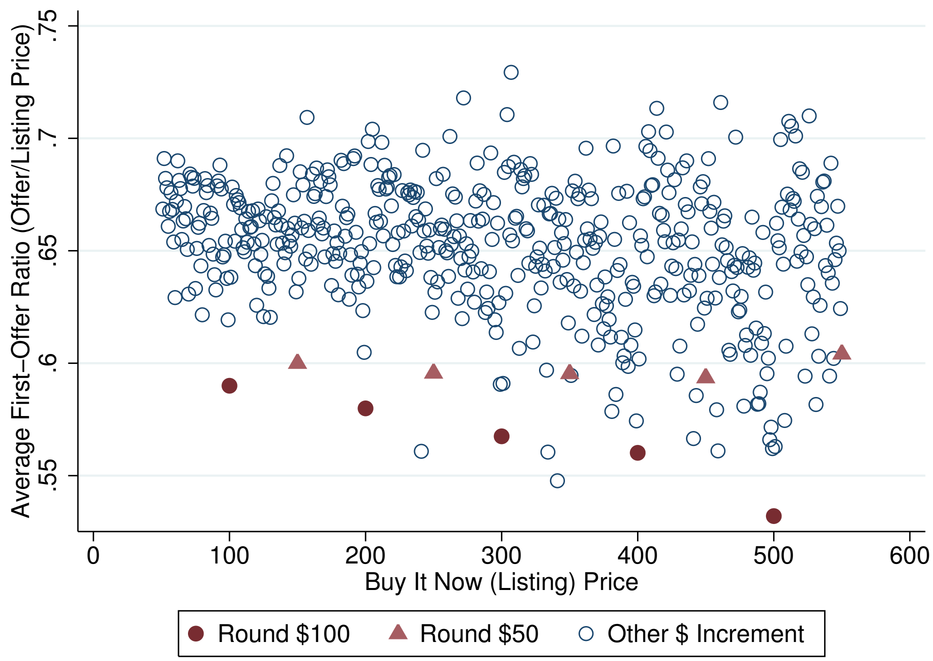
million received an offer and 2.1 million sold.[6] We construct several measures of bargaining outcomes, which are summarized in Table 1.

The average starting offer is 63 percent of the posting price and sale prices average near 79 percent of listed prices but vary substantially. 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. About 20 percent of items sell, of which 4.9 percent sell at the list price with no 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

[6]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

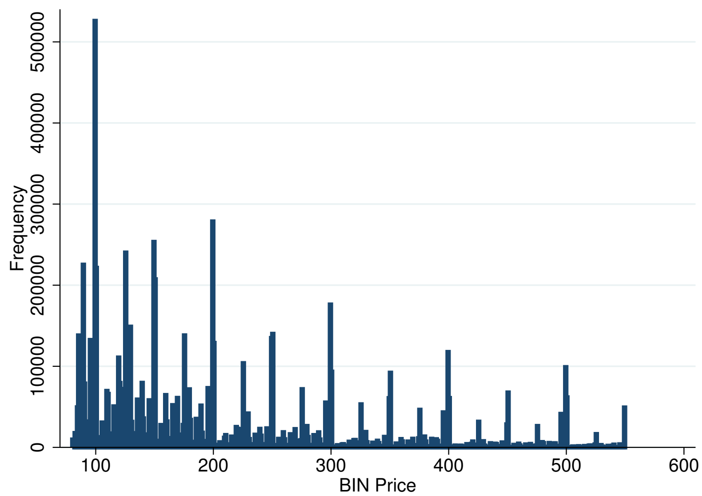


Notes: This scatterplot presents average first offers, normalized by the BIN price to be between zero and one, grouped by unit intervals of the BIN price, defined by $(z-1, z]$. When the BIN price is on an interval rounded to a number ending in "00", it is represented by a red circle; "50" numbers are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

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 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 grouped 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 more than five percentage

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.

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, 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 and receiving lower offers 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.

4 Empirical Analysis

The goal of our empirical analysis is to offer direct evidence on the three predictions of separating equilibrium from Section 2: sorting, beliefs, and incentive compatibility. In section 3 we offered some suggestive graphical evidence, but in order to rigorously study the use of round numbers we need to estimate the discontinuous effect of roundness vis-à-vis nearby precise asking 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. In addition, we exploit detailed offer-level bargaining data and behavioral data on buyer search that is unique to the study of electronic marketplaces. This richness is what allows us to offer evidence in support of seller sorting and the reflection of that sorting in buyers' beliefs.

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 4.2.2 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.S. buyers but not by those in the U.K., which lends itself to a difference-in-differences analysis to show that unaccounted-for attributes correlated with roundness do not explain our results.

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 signal discontinuities, $z \in \mathcal{Z}$, we can write:

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

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.:

$$\pi_z(\Delta) \equiv \mathbb{E}[y|z + \Delta] - \mathbb{E}[y|z] = g(z + \Delta) - g(z) - \beta_z. \tag{2}$$

For Δ large, this comparison is unhelpful for identifying β_z absent the imposition of an arbitrary parametric structure on $g(\cdot)$.[7] However, as $\Delta \to 0$, continuity implies $g(z+\Delta) - g(z) \to 0$, offering a nonparametric approach to identification of β_z:

$$\beta_z = -\lim_{\Delta \to 0} \pi_z(\Delta). \tag{3}$$

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 B2. 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 4.2.2.

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 B4 we employ a LASSO

[7] 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 D and Table A-3 in particular.

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 Bargaining Outcomes and Incentive Compatibility

This section implements the identification strategy outlined above to establish the tradeoff between price, and the time and likelihood of sale, which is a necessary for there to be an incentive compatibility tradeoff as described in Section 2. We use local linear regression in the neighborhood of $z \in \{100, 200, 300, 400, 500\}$ to estimate β_z, following the intuition of equation (3). 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).[8] 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 C 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:

$$y_j = a_z + b_z x_j + \beta_{z,00} \mathbb{1}\{x_j = z\} + \beta_{z,99} \mathbb{1}\{x_j \in [z-1, z)\} + \epsilon_j. \qquad (4)$$

[8] 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 include these dummy variables to account for potential differences of listing items just below the round numbers, as is common in many retail situations, and discuss this more in relation to left-digit inattention in Section 6. We estimate this model separately for each $z \in \{100, 200, 300, 400, 500\}$.

4.2.1 Offers and Prices

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 whether buyer beliefs differ for round versus nearby precise listing prices. 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 4.4.2.

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 proportional to 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. This translates to a 8%-12% effect on seller revenues. 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 separation of buyer beliefs.

Ancillary coefficients, i.e. the slope, and intercept of the linear approximation of $g(\cdot)$ as well as the bandwidth window are reported and discussed in Appendix D. Importantly, we find substantial variance in the slope parameters at different round numbers, which

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 (4) 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. Heteroskedactic-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

confirms the importance of treating $g(\cdot)$ flexibly. Our estimation bandwidth ranges from a narrow $6 (or 6 percent) near the $100 signal to a range of 16 percent near the $500 signal and this encompasses 25 percent of the total sample.

Coefficients on the indicator for the "99"s, i.e. $[z-1, z)$ intervals, are reported in Appendix E. 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 B we present estimates from a sieve estimator approach using orthogonal basis splines to 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 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 may be observable to buyers and sellers but is not 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 offer and price 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 (1), the expectation of y_j conditional on observables, as

$$\mathbb{E}[y_j|\text{BIN price}_j] = \int g(\text{BIN price}_j, \xi)dH(\xi|\text{BIN price}_j) + \sum_{z\in\mathcal{Z}} \mathbb{1}_z\{\text{BIN price}_j\}\beta_z. \quad (5)$$

From equation (5) 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 (3), which summarized the identification argument from Section 4.1:

$$\lim_{\Delta\to 0} \pi(\Delta) = \underbrace{\lim_{\Delta\to 0} \int g(z,\xi)[h(\xi|z+\Delta) - h(\xi|z)]d\xi}_{\equiv\gamma_z} - \beta_z. \quad (6)$$

The first term on the right-hand side of equation (6), 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— precisely, 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 defective items are more likely to use round prices. These are both plausible stories that raise concern over our identification strategy.

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.[9] 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. Instead, 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 (6), and β_z. Sellers who list on the U.K. eBay site (ebay.co.uk) enter a price in British Pounds, which 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.[10]

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

$$\pi_{z,C}(\Delta) \equiv g_C(z+\Delta) - g_C(z) - \mathbb{1}\{C = \text{UK}\}\beta_z. \tag{7}$$

The construction in equation (7) generalizes equation (2) to the two-country setting. Now, differencing $\pi_{z,UK}(\Delta)$ and $\pi_{z,US}(\Delta)$, we obtain:

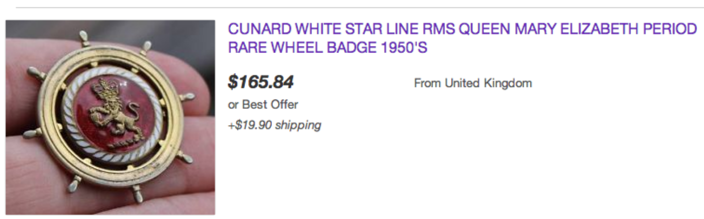
$$\pi_{z,UK}(\Delta) - \pi_{z,US}(\Delta) = [g_{UK}(z+\Delta) - g_{UK}(z)] - [g_{US}(z+\Delta) - g_{US}(z)] - \beta_z. \tag{8}$$

Following the logic of the identification argument in 4.1, we take the limit of equation (8) 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,

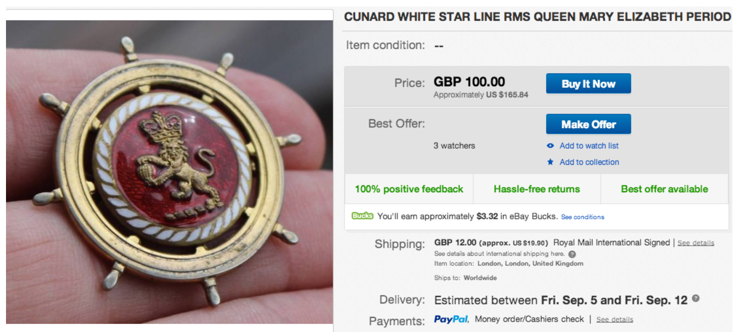
[9] In Appendix J, we explore the round-number listing effect in such "thick" markets, where we see less discounting associated with roundness.

[10] 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.

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.

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

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 C 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:

$$\begin{aligned} y_j =& (a_{z,UK} + b_{z,UK}(z - x_j))^{\mathbb{1}_{UK,j}} (a_{z,US} + b_{z,US}(z - x_j))^{\mathbb{1}_{US,j}} \\ &+ \gamma_{z,00}\mathbb{1}\{x_j = z\} + \beta_{z,00,UK}\mathbb{1}_{UK,j}\mathbb{1}\{x_j = z\} \\ &+ \gamma_{z,99}\mathbb{1}\{x_j \in (z-1, z)\} + \beta_{z,99}\mathbb{1}_{UK,j}\mathbb{1}\{x_j \in (z-1, z)\} + \varepsilon_j. \end{aligned} \tag{9}$$

In contrast with the estimator from equation (4), here the unit of observation is the buyer offer. The approach is similar in spirit to a difference-in-differences estimation

Table 3: **Effect of Roundness on Offers from the UK Specification**

	(1) Offer Amt (£)	(2) Offer Amt (£)
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 (9) 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. Heteroskedactic-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

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.

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. Our dependent variable is all initial offers made to

Table 4: **Throughput Effects of Round \$100 Signals**

	(1) Days to Offer	(2) Days to Offer	(3) Days to Sale	(4) Days to Sale	(5) Pr(Sale)	(6) 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 (4) 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. Heteroskedactic-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

these listings from a U.K. or U.S. buyer. This results in a total of 2.3 million offer-level observations over 600,000 listings. 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 (9) are presented in Table 3. 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 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 separation of buyer beliefs cannot be dismissed selection on unobservables.

4.2.3 Offer Arrivals and Likelihood of Sale

Following the evidence on lower offers and lower sale prices for round-number listings, the second essential component in demonstrating a tension of incentive compatibility is identifying a tradeoff—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 (4) 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.[11] Results for these tests are presented in Table 4. Columns 1 and 2 show that round-number listings receive their first offers between 6 and 11 days sooner, on an average of 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 an average 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 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).[12]

4.3 Seller Behavior and Evidence for Sorting

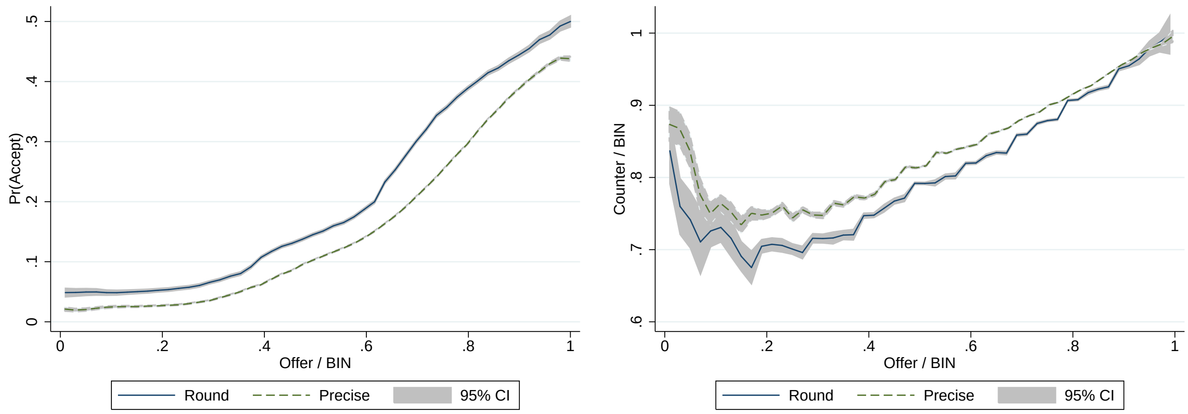
Figure 3 shows that some sellers use round list prices and some use precise list prices. But are these sellers sorting along a dimension indicative of differing preferences, or types? Buyer's beliefs and their corresponding lower offers suggest sellers who use precise listing prices should be eager to sell; formally, $\partial\pi_H(p(s), q(s))/\partial q > \partial\pi_L(p(s), q(s))/\partial q)$. If so, sellers who signal eagerness to sell would be *more* likely to accept a given offer, and also *less* aggressive in their counteroffers. 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 a seller accepting a first offer against the ratio of the buyers' first offer 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. The results show a clear and statistically significant difference:

[11]By default, listings are set to expire every 30 days but can be automatically extended in 30 day increments.

[12]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.

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.

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.[13]

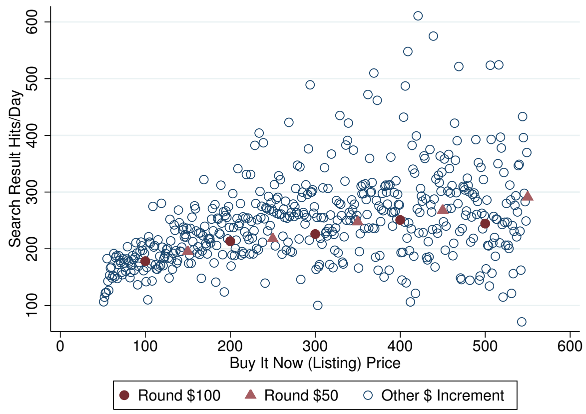
Panel 5b plots the level of the seller's counteroffer, conditional on making one, again normalized by the listing price, against the ratio of the buyer's offer to the listing price. Note that, unlike the results for the probability of acceptance, this sample of counteroffers is selected by the seller's 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.

4.4 Round Numbers and Buyer Beliefs

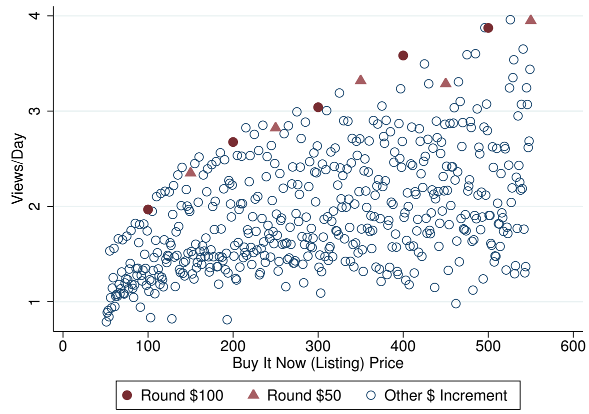
In this section we take advantage of our access to detailed data on eBay user behavior to isolate the effect of roundness as a signal on buyers' search behavior. Our model is, like other cheap-talk models, agnostic about the form of the signal itself. Why should sellers use roundness as a signal instead 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' behavior.

[13]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 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.

4.4.1 Buyer Search Behavior

We use eBay's data to tabulate the total number of searches that return each listing. A search result page (SRP) contains many entries similar to that shown in Figure 4a. We observe the total number of times users click on the view item (VI) button, which leads them to the VI 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. 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 list 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 they have a substantially higher view item rate.

This is strong evidence that buyers choose to further explore round-number listings when seeing only the search result page. The information listed in the search results page is limited to the title, an image thumbnail, and the (currency-converted) BIN price. Hence, buyers will form beliefs about the the items on the search result page, and then choose the more costly action of clicking to the VI page in order to investigate an item in more

Table 5: Buyer Beliefs: Search and BIN usage

	(1) SRP Hits Per Day	(2) SRP Hits Per Day	(3) VI Count Per Day	(4) VI Count Per Day	(5) Pr(BINN|Sale)	(6) Pr(BINN|Sale)
BIN=100	-40.18***	-23.25***	0.654***	0.703***	-0.0194***	-0.0172***
	(-62.81)	(-35.25)	(36.30)	(39.42)	(-6.99)	(-6.02)
BIN=200	-58.54***	-51.42***	1.005***	0.925***	-0.0154*	-0.0156*
	(-66.38)	(-49.35)	(26.61)	(25.31)	(-2.00)	(-2.03)
BIN=300	-66.59***	-50.42***	1.246***	0.944***	-0.0281*	-0.0228**
	(-51.58)	(-39.97)	(27.57)	(23.98)	(-2.40)	(-3.24)
BIN=400	-74.99***	-53.72***	1.469***	1.325***	0.000880	-0.00766
	(-41.16)	(-32.41)	(27.21)	(25.32)	(0.11)	(-0.93)
BIN=500	-95.67***	-82.99***	1.627***	1.384***	-0.000596	-0.00358
	(-45.57)	(-40.46)	(25.88)	(22.47)	(-0.05)	(-0.35)
Category FE		YES		YES		YES

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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

detail. That buyers are attracted disproportionately to round-number listings strongly suggests that they have different beliefs about those listings.

This helps to explain why sellers would use a price-based signal: it attracts buyers while they are looking at similar items on the search page. There are 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.

4.4.2 Deciding Whether to Bargain

We do not incorporate any bargaining costs or the option to pay the listed 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. We validate this premise in Appendix A, where one can see that the probability of negotiating increases in the level of the BIN price (and, therefore, the size of the expected negotiated discount from the BIN price).

Building on this intuition, we propose to study buyers beliefs about the expected discount using the likelihood that they engage in bargaining rather than take the BIN option. If round numbers are a signal of a sellers' willingness to take a price cut, then we should see relatively more negotiated outcomes for those listings than for nearby precise-number prices. In order to test this, we employ our local linear specification from equation (4) 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.

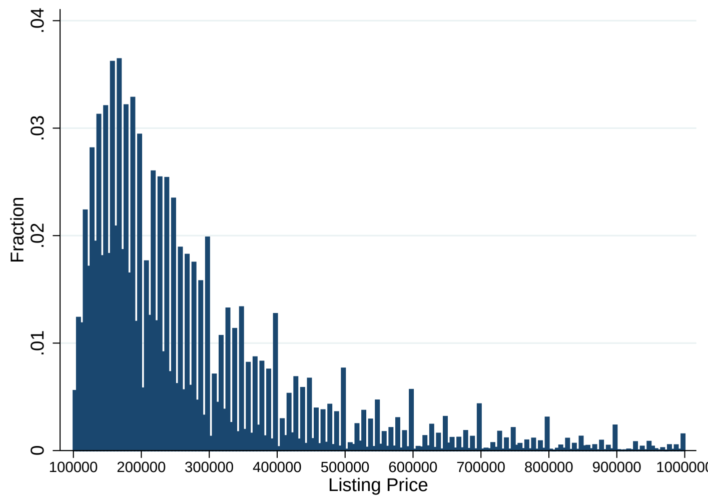
When we condition on sale and look at the effect of roundness on the probability paying the list price, as we do in Columns (5) and (6) of Table 5, for the elements of $\mathcal{Z}$ where we have the most observations we see a large and negative effect consistent with our prediction—that buyers are more 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.

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 more likely sales. We consider the real estate market as another illustration of the role of cheap-talk signaling in bargaining using round numbers. In contrast to eBay, real estate is a market with large and substantial transactions. Furthermore, participants 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 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

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., $\$80,000, \$90,000, \$100,000, \ldots$)

tens of thousands of dollars. Listings bunch at round numbers, particularly on more expensive listings, as shown in Figure 7.[14] 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 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.[15]

It is interesting to note that the magnitude and significance of this effect is stronger when real estate agent fixed effects are included, where the effect is estimated from within-

[14] 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.

[15] 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.

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 incentive compatibility 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.

Table 6: Real Estate Basis Spline Estimates

	(1) Sale $ / List $	(2) Sale $ / List $
Round $50k	-0.000879	-0.00150**
	(0.000747)	(0.000746)
Agent FE		YES
N	35808	35808

Standard errors, clustered on agent, in parantheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Here we report coefficients on a regression form of (1) 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

We have presented strong evidence of a cheap-talk signaling equilibrium being played in the field. On eBay's bargaining platform, 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. Importantly, we were able to show that subsequent seller behavior was consistent with the cheap-talk signaling interpretation — sellers who use precise-number asking prices continued to bargain more aggressively, while sellers who used round numbers were more likely to settle and made less aggressive counter-offers. Moreover, we have shown that buyers behave differently in how they respond to round versus precise-number listings, suggesting that they update their beliefs in ways that are consistent with the separating-equilibrium intent of the different signals.

This is a crucial, yet heretofore undemonstrated empirical identification of the complete set of components of a separating equilibrium. We argue that a complete picture of such an equilibrium requires proof of sorting, belief updating, and incentive compatibility. Our uniquely rich dataset on online bargaining allows us to identify all three, but this may be challenging more generally. Prior work in different settings has made compelling, if incomplete cases for the existence of separating equilibrium using only a subset of these tests.

It is also important to note that we break with existing research on the impact of round numbers on market outcomes by offering a fully rational model of their use as a cheap-talk signal. An alternative behavioral hypothesis, however, can be made: perhaps clueless or boundedly-rational sellers use round numbers, and opportunistic buyers take advantage of this with lower offers. We find this explanation unsatisfactory for several reasons. First, the effects we find are an order of magnitude larger than the effects of roundness when the behavioral story is well-identified. For instance, Lacetera et al. (2012) find a 1.2-1.6% discontinuous drop in revenues at wholesale auto auctions when a car passes a 10k mile threshold, compared with our 8-12% effect.[16] It is difficult to believe that sellers on eBay systematically leave 8-12% of their revenue on the table, given the care with which they optimize for listing design, listing timing, and search visibility. Second, if

[16]We do not believe left-digit inattention is salient in our setting for two additional reasons: first, because we find no evidence of asymmetry in the effect and second, we find in Appendix E that "pricing to the nines" is an equivalent signal to using around number; we take this to mean that the signal is in the use of *conventional* numbers, rather than any mathematical property of roundness.

buyers systematically target lazy sellers, one would expect competitive pressure to diminish these rents, insofar as receiving offers allows for some demand discovery. Third, because bargaining is a price discovery mechanism, one would expect rationally-clueless sellers to have stronger incentives to wait and collect information rather than, as our results suggest, accept lower offers *sooner*. Fourth, and most compellingly, we find that the most experienced sellers — sellers who cannot be fairly characterized as "clueless" — not only use these cheap-talk signals often, but that these signals predict an *even larger* discount for experienced sellers. In other words, it seems as if the signaling content of round numbers is *more* significant coming from an experienced bargainer, consistent with our interpretation of the signal as a rational market convention.

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.[17] 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.

[17]Experimental evidence in Thomas et al. (2010) demonstrates the plasticity of perceptual biases associated with roundness.

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Appendices

A Additional Outcomes

In Figure A-1, we present versions of Figure 2 with alternative dependent variables. Figure A-1a shows the decreased time to first offer associated with round-number listings. Figure A-1b shows that round listings are more likely to sell within 60 days. These plots permit a non-parametric visualization of the results captured in Table 4.

Figures A-1c and A-1d show that round listings are more likely to be purchased at the "Buy-It-Now" price. This is likely a result of the increased buyer arrival rate, as shown in Figure 6, because some fraction buyers will purchase without negotiation and a higher number of potential buyers will raise the number of such buyers. When we condition on the item selling, we find that the probability of selling at the BIN price is substantially lower for round listings. We test this relationship econometrically and explore this intuition further in Appendix 4.4.2

Figures A-1e and A-1f show the first and second moments of the distribution of sale prices for each listing price bucket. The sale price is, expectedly, increasing in the listing price. Although less salient on this scale, round-number listings are still well below the overall trend. The variance of sales is higher for round listings than non-round listings.

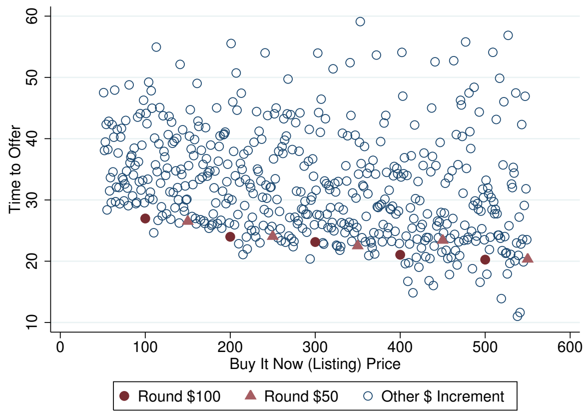
B Alternative Approach: Basis Splines

1 Basis Splines

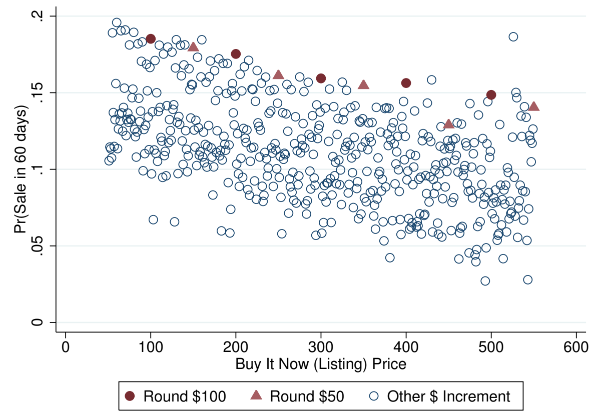
Our main results from Section 4.2 employ a local linear specification that identifies $g(\cdot)$ from equation (1) only in small neighborhoods of the discontinuities we study. There are a number of additional questions we could ask with a more global estimate of $g(\cdot)$: for instance, one might be 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 B3. 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

Figure A-1: Additional Outcome Plots

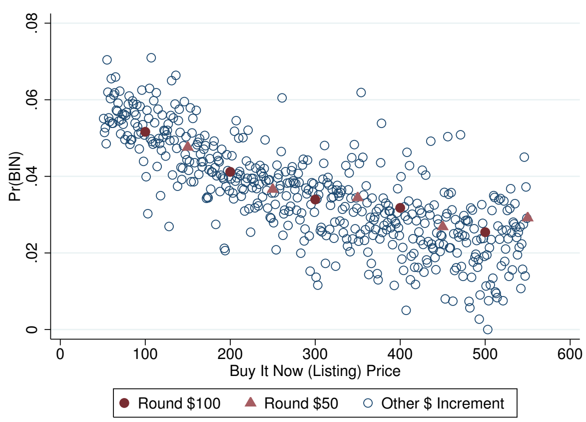
(a) Time to Offer



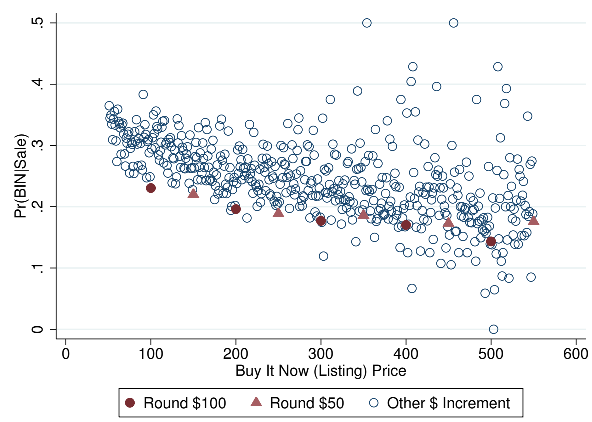
(b) Pr(Sale)



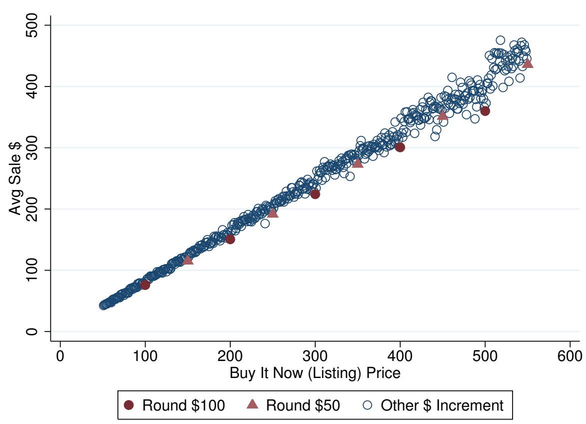
(c) Pr(BIN Txn)



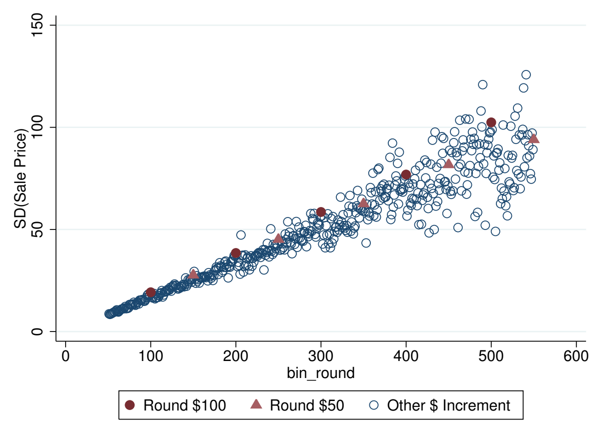
(d) Pr(BIN|Sale)



(e) Avg Sale Price



(f) Std Dev of Sale Price



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.[18] 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

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

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.

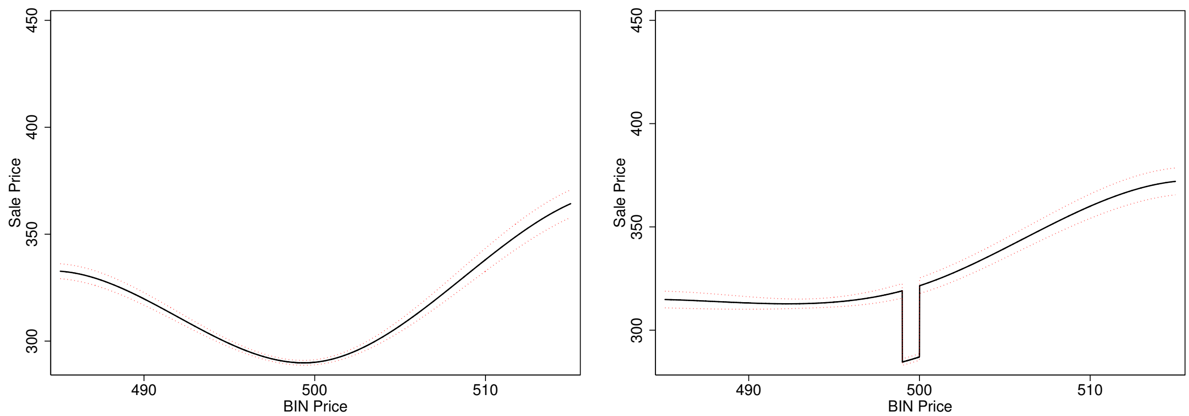
An advantage of the cardinal basis spline approach is that, for appropriately chosen α, any spline of order p on that same set of knots can be constructed as a linear combination of the elements of $\mathcal{B}_p$. Therefore we can appeal to standard approximation arguments for splines to think about 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 $\mathbb{E}[\text{sale price}|\text{BIN price}]$ 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

[18]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.

Figure A-2: 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.

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-2a. 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-2b, 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.

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

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.

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-10) 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.[19]

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.

4 LASSO Model Selection

We also employ the cardinal basis spline approach to offer supplementary motivation for our choice of the set of discontinuities $\mathcal{Z}$. 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 $k \in \{100, 200, 300, 400, 500\}$.

[19]Moreover, as shown in Table A-10, 22 percent of listings by the top decile of sellers are round.

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

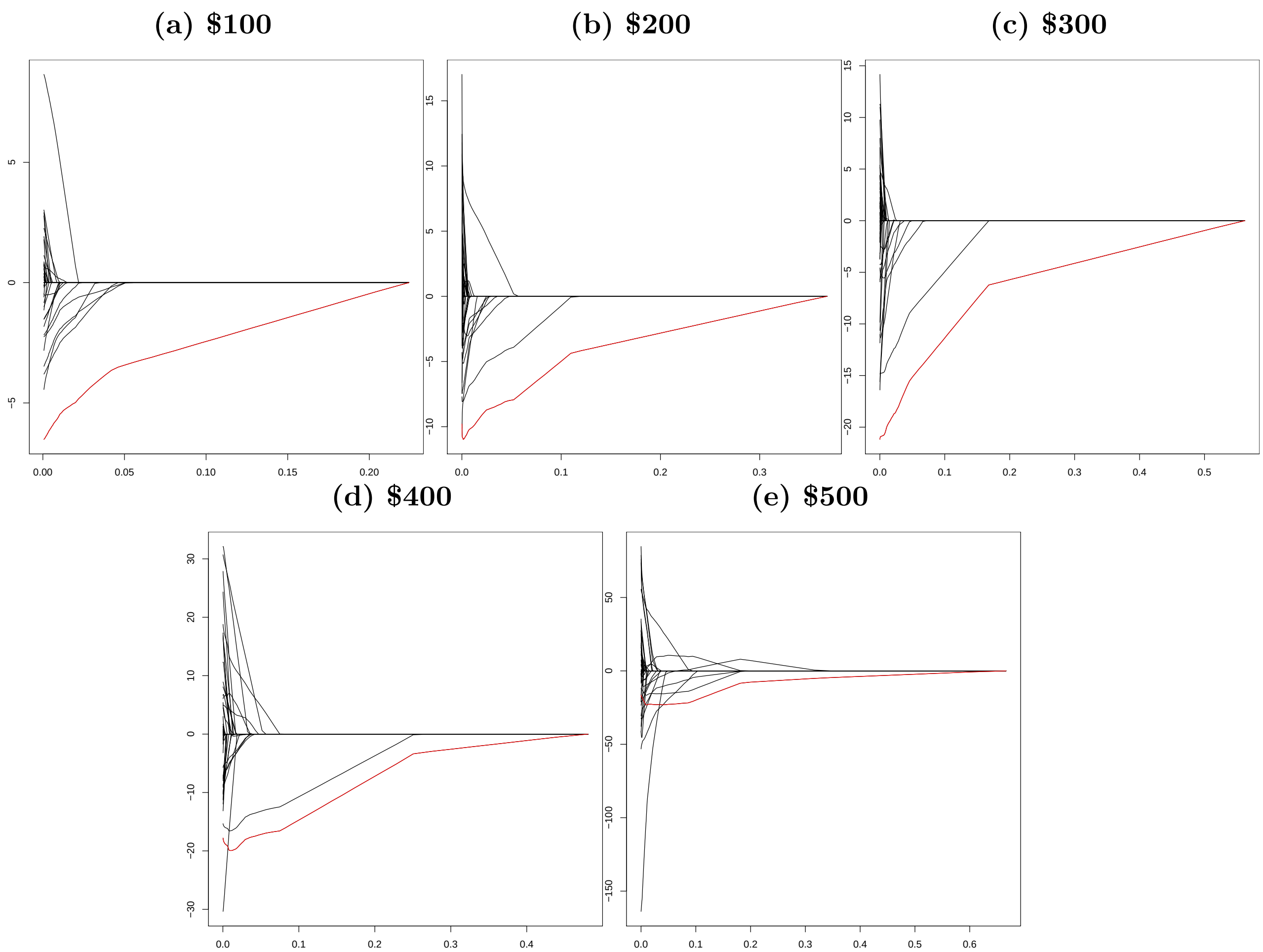
Notes: Here we report coefficients on a regression form of (1) where y_j is average first offers and sale prices and $g(\cdot)$ is approximated using a cardinal basis spline.

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:

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

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-3 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.

Figure A-3: 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 Bandwidth

We implement the optimal bandwidth selection proposed by Fan and Gij̀bels (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 the list price and analytically deriving $\tilde{g}'(\cdot)$ from the estimated coefficients.

D 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 4. Optimal bandwidth choices for both tables reflect the fact that there is more data available for lower BIN prices.

E 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.

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 (4) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column, corresponding to Table 2. Heteroskedactic-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

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

Heteroskedactic-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 (4) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column, corresponding to Table 4. Heteroskedactic-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 price$_j \in [z-1, z)$ from a separate local linear fit according to equation (4) 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. Heteroskedactic-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 price$_j \in [z-1, z]$ from a separate local linear fit according to a modified version of equation (4) 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. Heteroskedactic-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

F UK Ancillary Coefficients

The UK difference-in-difference estimation uses a different dataset than the primary specification. This sample uses *offer-level* data so that offers can be separately identified by country of origin. Table A-7 reports some basic summary statistics for this data. US offers are generally higher, but they are also on slightly more expensive items. A higher fraction of US offers are on round listings.

Table A-7: UK Data Summary Statistics

	US	UK
Offer Amt (£)	113.3	104.2
	(86.95)	(85.54)
Listing BIN Price (£)	184.7	163.2
	(125.7)	(117.4)
Listing Round £100	0.0528	0.0469
	(0.224)	(0.211)
Listing 99 cents	0.0984	0.0864
	(0.298)	(0.281)
N	404833	1999136

Notes: An observation is an offer. Means reported with standard deviations in parentheses.

Table A-8 shows the local linear estimation of the round number effect on offers made. There is a negative and statistically significant effect on US buyers, which suggest that there is either a selection bias or that the buyers react to the round price in pounds shown on the item detail page. The UK effect is substantially (and statistically) larger. The difference in these two measures is conceptually captured by the estimates in Table 3.[20]

Tabel A-9 presents the ancillary intercept and slope coefficients for the regression in Table 3. The base levels of UK and round are shown and the interaction of these two is coefficient presented in Table 3. Each country is allowed a separate intercept: the constant represents the US base level and the UK indicator is the difference in this intercept for the UK bidders. The BIN coefficient is the slope of the local linear fit and the interaction of the UK indicator and the BIN represents the difference in the slope for UK bidders.

[20]The difference is not exactly comparable due to different weighting in the pooled regression.

Table A-8: UK and US Separate Local Linear Estimation

	(1) US Buyers	(2) UK Buyers
BIN=100	-2.740***	-4.477***
	(0.325)	(0.141)
BIN=200	-2.772***	-8.409***
	(0.882)	(0.408)
BIN=300	-8.830***	-14.22***
	(1.272)	(0.650)
BIN=400	-5.680**	-18.07***
	(2.224)	(1.059)
BIN=500	-19.63***	-30.66***
	(2.909)	(1.519)
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 (4) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column. Each observation is an offer., dependent variable is offer made in GBP. Heteroskedactic-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

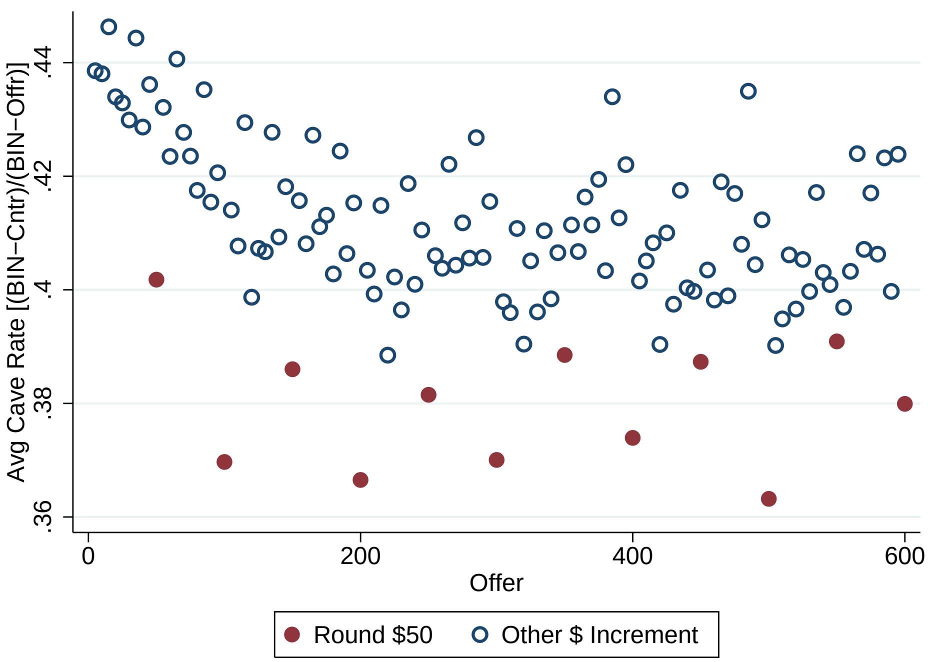
G Seller Response to Round Offers

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

Figure A-4: Seller Response to Buyer Offers by Value



Plot depicts the difference in the round and precise polynomial fit of the probability of acceptance for a given offer (normalized by the list price) on items with listing prices between $85 and $115. Separate differences are shown for the 1st and 4th quartile of sellers, by experience.

Table A-9: Intercepts and Slopes for UK Linear Regression

	(1) Avg First Offer $	(2) Avg First Offer $		(3) Avg First Offer $	(4) Avg First Offer $
Near round $100:			**Near round $400:**		
UK Offer=1	0.157	-0.564**	UK Offer=1	17.75***	8.596***
	(0.236)	(0.235)		(1.637)	(1.593)
BIN=100=1	-3.062***	-2.506***	BIN=400=1	-8.570***	-1.027
	(0.325)	(0.324)		(2.227)	(2.201)
BIN	0.706***	0.695***	BIN	0.944***	1.078***
	(0.0447)	(0.0444)		(0.164)	(0.161)
UK Offer=1 × BIN	0.194***	0.146***	UK Offer=1 × BIN	0.201	-0.0168
	(0.0487)	(0.0482)		(0.182)	(0.173)
Constant	65.76***	64.79***	Constant	242.9***	229.3***
	(0.216)	(0.280)		(1.480)	(2.333)
UK Bandwidth	7.782	7.837	UK Bandwidth	17.11	19.19
US Bandwidth	7.497	7.534	US Bandwidth	18.42	18.72
N	208343	208403	N	62597	63228
Near round $200:			**Near round $500:**		
UK Offer=1	5.984***	3.338***	UK Offer=1	15.12***	5.855***
	(0.769)	(0.728)		(2.401)	(1.957)
BIN=200=1	-3.580***	-2.254**	BIN=500=1	-26.12***	-13.34***
	(0.886)	(0.877)		(3.094)	(2.840)
BIN	0.977***	0.974***	BIN	0.752***	0.833***
	(0.131)	(0.129)		(0.252)	(0.150)
UK Offer=1 × BIN	0.135	-0.0898	UK Offer=1 × BIN	0.269	0.00434
	(0.150)	(0.140)		(0.289)	(0.166)
Constant	124.9***	121.5***	Constant	298.8***	271.7***
	(0.676)	(0.861)		(2.093)	(3.083)
UK Bandwidth	8.912	9.243	UK Bandwidth	19.21	21.05
US Bandwidth	9.073	9.225	US Bandwidth	19.54	20.74
N	104365	105911	N	47867	53340
Near round $300:					
UK Offer=1	14.62***	6.103***			
	(1.057)	(0.878)			
BIN=300=1	-10.31***	-7.896***			
	(1.384)	(1.264)			
BIN	1.377***	1.166***			
	(0.131)	(0.0853)			
UK Offer=1 × BIN	-0.0167	-0.358***			
	(0.144)	(0.0939)			
Constant	184.9***	175.1***			
	(0.954)	(1.283)			
UK Bandwidth	11.07	15.94			
US Bandwidth	12.04	15.89			
N	86755	94832			
Category FE		YES			

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Intercepts and Slopes for Each Local Linear Regression.

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-10 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, but collectively still list round with more than 5 percent of their listings.

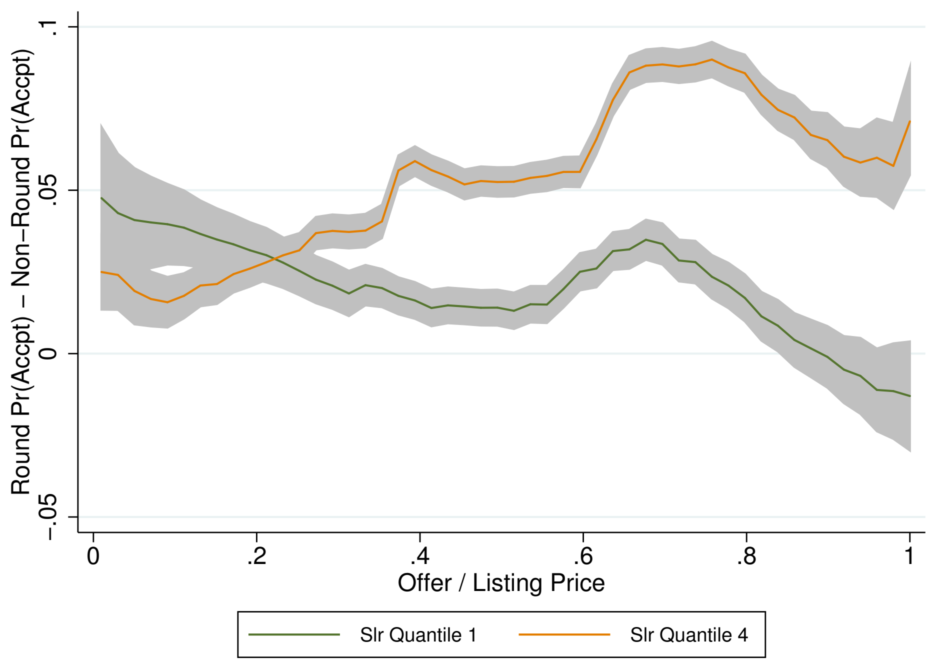
By interacting our measure of seller experience with a dummy for whether the listing is a round \$100, we can identify at different experience levels the round effect on received offers. The right pane of Table A-10 shows the estimates with and without seller fixed effects. Without seller fixed effects, 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 upper deciles. This means that the most experienced sellers use signal with the largest hit to price.

It would seem logical that such experienced sellers would only do this knowingly and so we check again for evidence of sorting across seller experience. Figure A-5 revisits the analysis of Figure 5a and shows the difference in the probability of accepting offers by offer fraction. We show the gap between responses on round and non-round listings for the least and most experienced sellers. We see that the most experienced sellers are even more likely to accept any offer when listing round. This increased sorting suggests that sellers learn to sort as they gain experience: and signal weakness only when most willing to accept any offer (e.g. when they are in a hurry to clear inventory).

I Model

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 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.

Figure A-5: Seller Response to Offers by Experience



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-10: 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 $\beta_1 00$ separately by decile of seller experience. Standard errors are in parenthesis.

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.[21]

[21]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

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 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.

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

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).

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.[22]

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

[22]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 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.

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:

$$\begin{aligned}\mathbb{E}_t[e^{-rt}] &= \int_0^\infty e^{-rx}\lambda_b e^{-\lambda_b x}dx \\ &= \frac{\lambda_b}{r+\lambda_b}\underbrace{\int_0^\infty (r+\lambda_b)e^{-x(r+\lambda_b)}dx}_{=1} = \frac{\lambda_b}{r+\lambda_b}.\end{aligned} \tag{5}$$

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

$$p_L = \frac{1}{2}p_L\frac{\lambda_b}{r+\lambda_b} + \frac{1}{2}1 \quad \Rightarrow \quad p_L = \frac{r+\lambda_b}{2r+\lambda_b}. \tag{6}$$

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.[23]

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

[23] 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 (6) this implies $v = p_L$ and so we conclude that such a deviation is not profitable.

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:

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 4.4.1 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."

2.1 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, 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.[24] The way in which traffic and item popularity are measured is explained in more detail in Appendix J.

Listings are divided into deciles in increasing order of SRP and VI visit frequency. We then replicate our local linear approach from equation (4) to estimate the effect of round listing prices on mean first offers within each decile. Figure A-6 in Appendix J 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.

[24]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.

J Separation in Thicker markets

An ancillary prediction of the model (Hypothesis H4) 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.[25]

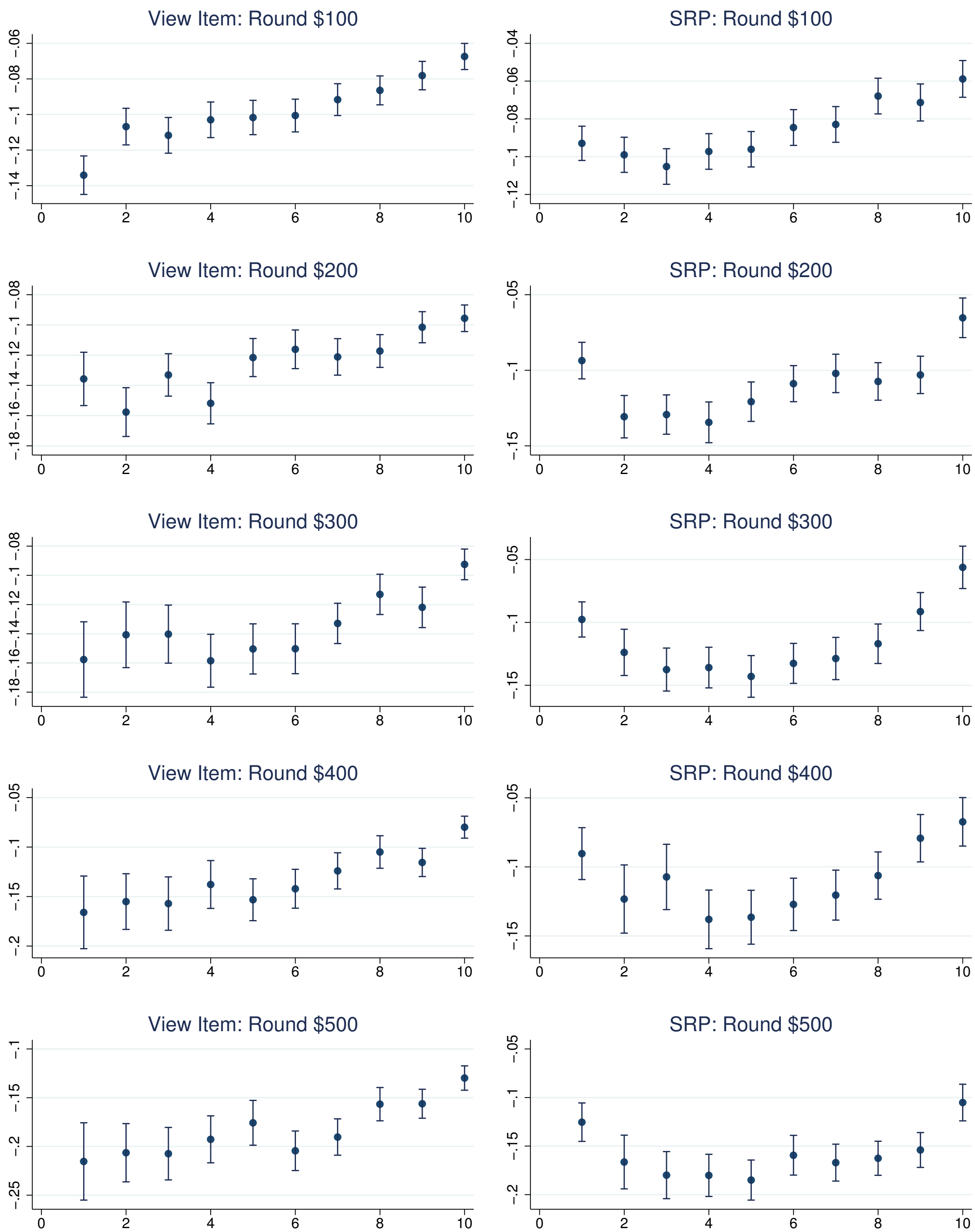
We proceed by grouping listings into deciles by view item counts. We first find that the baseline (non-round) mean offers vary across decile of exposure. This is an undesired byproduct of group by exposure: items in these groupings are different in ways other than pure buyer arrival rates (λ_b). We correct for this by normalizing estimates by the baseline mean offer. That is, we normalize β_z by the constant a_z in equation 4. Otherwise, estimation proceeds just as in equation 4, but separately for each decile of exposure.

Figure A-6 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 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).

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

Figure A-6: 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.