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

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We outline a framework for the empirical analysis of signaling games based on three features: sorting, incentive compatibility, and beliefs. We apply it to document cheap-talk signaling in the use of round-number offers during negotiations. Using millions of online bargaining interactions, we show that items listed at multiples of $100 receive offers that are 8–12 percent lower but are 15–25 percent more likely to sell, demonstrating the trade-off requisite for incentive compatibility. Those same sellers are more likely to accept a similar offer, and buyers are more likely to investigate their listings, consistent with seller sorting and buyer belief updating.

I. Introduction

Since the seminal contributions of Spence (1973) and Crawford and Sobel (1982), costly and cheap-talk models of signaling have become

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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.[1]

The paucity of empirical work on this topic is reflected in the lack of guidance for how to undertake it. We believe that this reflects on the difficulty of the question rather than its significance: by their nature, signaling equilibria are premised on private information and beliefs, neither of which is typically observed by the econometrician. Therefore, 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: a careful documentation of a separating equilibrium in real market data. In particular, we introduce a large and novel data set 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, that is, 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. With respect to sender sorting, we demonstrate that sellers who use round-number asking prices are different from those who use precise numbers: the former are more likely to accept a given offer and, should they decline, make less aggressive counteroffers. On receiver beliefs, we show that buyers' beliefs about sellers' bargaining positions are reflected in their search behavior as well as their

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[1] This paper focuses on an example of cheap-talk signaling, but the analysis generalizes easily to costly signals. In his Nobel prize lecture in 2001, Michael Spence discusses the case of education signaling in which the costs go the "wrong" way and notes, "This case may or may not be interesting from an empirical point of view, but it does illustrate that *the more general formulation of the conditions for signaling are in terms of gross and net benefits and not just signaling costs*. I did not realize this when I first worked on signaling equilibria. I thought then that the absence of the intuitively plausible negative cost correlation condition would destroy a signaling equilibrium" (430; emphasis added).

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 may be that, for round-number listings, there are unobservable differences in the seller or product attributes 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 (http://ebay.co.uk) will sometimes appear in search results for user queries on the US site (http://ebay.com). A feature of the platform is that US buyers who see items listed by UK 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 United Kingdom while at the same time appear to have precise-number asking prices in the United States—an observable garbling of the purported signal. Assuming that US buyers perceive the same unobserved heterogeneity as their UK counterparts, we can compare their behavior to difference out the bias and demonstrate the existence of an effect of roundness on buyer behavior.

The theory of cheap talk offers no guidance on why sellers use roundness as a signal, rather than something more direct, or simply lowering their asking price, yet we endeavor to offer a few conjectures. First, the listing price is 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). Also, roundness is a signaling convention that is feasible in almost any market in which bargaining occurs. Indeed, we are able to offer some evidence that it is used elsewhere: we obtain data from the Illinois real estate market that have been used by Levitt and Syverson (2008) in which we observe both the listing price and the final sale price. The data do not let us perform the vast number of tests we can for eBay's large data set, 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 hypothesis.

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).[2] A second related literature, though sparse, documents aspects of signaling equilibria. The oldest concerns "sheepskin effects," or the effect of education credentials on employment outcomes (Layard and Psacharopoulos 1974; Hungerford and

[2] We offer another stylized model in this tradition in online app. I.

Solon 1987; Tyler, Murnane, and Willett 2000). 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's (1973) study. More recently, Kawai, Onishi, and Uetake (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 (Grennan 2013, 2014; Bagwell, Staiger, and Yurukoglu 2014; Larsen 2014; Shelegia and Sherman 2017; Ambrus, Chaney, and Salitskiy 2018). 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, Stuppi, and Trötschel 2013; Mason et al. 2013).[3] These papers argue that using round numbers in bargaining leads to an unequivocally worse outcome, that is, 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. The *Harvard Business Review* summarized this literature for practitioners: "The main takeaway is: **do not launch a negotiation with a round offer**" (Keloharju 2016; emphasis in original) 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. We reconcile these facts with an alternative hypothesis: that the use of round numbers can be an informative signal that sellers use to credibly communicate with buyers.

II. Cheap-Talk Signaling in Negotiations

Can cheap talk credibly signal a "strong" bargaining position? If so, it must be the case that some people will, seemingly counterintuitively, use cheap talk to signal that they are in a "weak" position. 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 dealer-

[3] Relatedly, Lacetera, Pope, and Sydnor (2012) find evidence of left-digit bias by identifying jump discontinuities in the expected auction price of a vehicle at round-number values of the odometer reading.

ships advertise bargaining weakness when they announce the need to liquidate inventory.

Existing theoretical literature showed that parties to a negotiation can use cheap talk to trade off between price and the probability of sale. Sellers with relatively low reserve prices willingly signal their weakness in order to increase the likelihood of a transaction. The models make 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 but to keep the mechanisms as general as possible while drawing out the empirical implications of the assertion that a separating equilibrium of a signaling game is being played.

Consider a market with a seller who has a private payoff-relevant type $\theta \in \{H, L\}$ that is unknown to buyers. In the first stage the seller can send a cheap-talk signal $s \in \{\text{strong, weak}\}$, and 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 $\pi_\theta(p(s), q(s))$.[4]

Three empirical claims follow from any separating equilibrium, and a thorough empirical exposition of a signaling equilibrium should aspire to demonstrate all three.

Claim 1 (Sorting). By the definition of separation, sellers of different types choose different signaling strategies, that is,

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

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's rule and therefore reflect separation of seller types, that is,

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

[4] For simplicity we use binary types and signals, but the framework could be easily extended to allow for a continuum of types and an arbitrary signal space. Alternatively, as in our empirical application, these binary signals may be thought of as partially informative with respect to a complex type space.

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

Claim 3 (Incentive compatibility). 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:

$$\pi_H(p(\text{strong}), q(\text{strong})) \geq \pi_H(p(\text{weak}), q(\text{weak}))$$

and

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

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 trade-off between price and quantity in the signal chosen.

We propose these three claims as a framework for empirical validation of signaling models.[5] To the extent that they are not testable in every application, it may be difficult to rule out alternative hypotheses. For example, in the context of education signaling, proving that there is a local treatment effect of passing the GED for students with similar unobservables (Tyler et al. 2000) is consistent with signaling (Spence 1973), but it is also consistent with employers finding 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 unique data set allows us to test our claims because it couples offer-level bargaining events with search behavior data. We argue that, in bargaining, a round asking price signals weakness, while a precise number signals strength. That is, sellers who use round asking prices are willing to trade off lower prices for a higher chance of selling their item.[6]

Because asking prices are payoff-relevant, it is natural to wonder whether roundness is "cheap." We treat round asking prices as a cheap-talk signal

[5] The formulation generalizes to costly signaling as well as games with more types and richer signals.

[6] 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. Moreover, if that variation is continuous, then roundness is a partially informative signal.

because, conditional on choosing one, there is 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.

Our cheap-talk approach is standard, that is, "nonbehavioral," and imposes no limits on cognition or rationality, unlike prior work on roundness. Indeed, the strong assumptions on rationality and beliefs imposed by perfect Bayesian equilibrium might seem extreme in the eBay environment, especially in light of extensive experimental evidence of behavioral biases. In private communications, a well-regarded economist made the point succinctly: "I sell on eBay sometimes—if this were a signaling equilibrium, wouldn't I know about it?" We make no claim that we are modeling the mechanical truth of individual decision making. We accept that the world is complicated and that as economic agents we engage with it using heuristics and rules of thumb. Indeed, experimental work on perceptions of roundness and precision have documented these heuristics (Thomas, Simon, and Kadiyali 2010). But where do heuristics come from? If they are informed by experience, as that same experimental work suggests, then experience that guides successful heuristic behavior can be a consequence of learned equilibrium behavior. Indeed, 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 either a high degree of sophistication or a well-established heuristic about bargaining.

An alternative behavioral hypothesis, however, can be made: perhaps uninformed or boundedly rational sellers use round numbers, and buyers believe that round numbers invite bargaining. We prefer our rational equilibrium–based explanation for several reasons. First, if buyers systematically target uninformed sellers, one would expect competitive pressure to diminish these rents, insofar as receiving offers allows for some demand discovery. Second, because bargaining is a price discovery mechanism, we expect rationally uninformed sellers to have stronger incentives to wait and collect information rather than, as our results suggest, accept lower offers sooner. One can imagine that ignorant sellers also have high bargaining costs or that they have priors about all offers being similar. But that implies that two independent assumptions need to be made about sellers who use round numbers: ignorance about prices, and little value from waiting for more offers. Third, it would be surprising if sellers on eBay systematically leave 8–12 percent of their revenue on the table. Fourth, and most compellingly, we find not only that the most experienced sellers 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. This fact is in contrast to behavioral biases, which are typically thought to diminish with market experience (List 2003).

III. Online Bargaining and Negotiations

The eBay marketplace became famous for its use of simple auctions to facilitate trade. In recent years, fixed-price listings have become more prevalent, and eBay's platform offers sellers using fixed-price listings the opportunity to sell their items using a bilateral bargaining procedure with a feature called "Best Offer."

The feature enables the "Make Offer" button that is shown below the "Buy It Now" button in figure 1. Upon clicking the Make Offer button, a prospective buyer is prompted for an offer in a stand-alone numerical field.[7] Submitting an offer triggers an email to the seller, who has 48 hours to accept, decline, or make a counteroffer. Once the seller responds, an email to the buyer prompts to accept and check out, make a counteroffer, or move on. This feature has grown in popularity, and bargained transactions now account for nearly 10 percent of total transaction value on eBay.[8]

Our data include offers, counteroffers, and transactions for all single-unit Best Offer listings in eBay's Collectibles Marketplace that started between June 2012 and May 2013. This subset of eBay includes coins, antiques, toys, memorabilia, stamps, art, and other like goods. 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 million received an offer and 2.1 million sold.[9]

Our data 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 28 days, on average, for the first

[7] Buyers can also send a message with their offer, as seen in fig. 1. See Backus, Blake, and Tadelis (2019) for the impact of messages on bargaining outcomes.

[8] See Backus et al. (2018) for more details on buyer and seller engagement on eBay's Best Offer sales mechanism. 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 their effectiveness.

[9] 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.

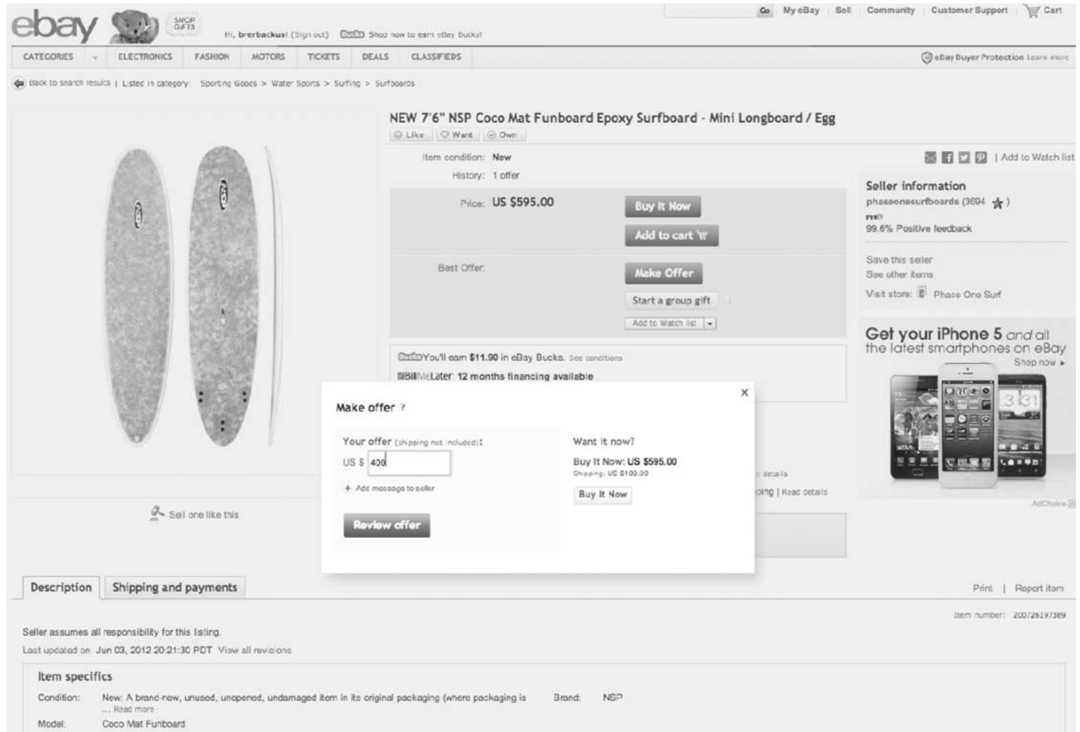

FIG. 1.—Best Offer on eBay. This figure depicts a listing with the Best Offer feature enabled, which is why the Make Offer button appears underneath the Buy-It-Now and Add to Cart buttons. When a user clicks the Make Offer button, a panel appears, prompting an offer, and, if desired, an accompanying message.

TABLE 1
Summary Statistics

Variable	Mean	Standard Deviation	Observations
Listing price (BIN)	166.478	118.177	10,472,614
Round $100	.053	.225	10,472,614
BIN in [99, 99.99]	.114	.318	10,472,614
Offers/views	.027	.09	10,395,821
Average first offer ($)	95.612	77.086	2,804,521
Sale price ($)	123.136	92.438	2,088,516
Search result page events/day	212.718	292.657	10,472,614
Views item events/day	2.091	4.985	10,472,614
Time to offer (days)	28.153	56.047	2,804,521
Time to sale (days)	39.213	67.230	2,088,516
Received an offer	.268	.443	10,472,614
Sold	.199	.4	10,472,614
Sold at BIN price	.049	.216	10,472,614
Listing price revised	.22	.414	10,472,614
# seller's prior Best Offer listings	69,974.77	322,691.987	10,472,614
# seller's prior listings	87,806.748	387,681.096	10,472,614
# seller's prior Best Offer threads	2,451.256	5,789.343	2,804,521

Note.—This table presents summary statistics for the main data set of Best Offer–enabled collectibles listings created on http://eBay.com between June 2012 and May 2013 with BIN prices between $50 and $550.

offer to arrive and do not sell for 39 days, with substantial variance. About 20 percent of items sell, and 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 seller's experience level.

To motivate the rest of the analysis, consider the scatter plot 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. Although listings can be made at the cent level, we group listings with BIN prices in the range $(z - 1, z]$ for all integers $z \in [50, 550]$. 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 scatter plot 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 5 percentage points lower than the same average for nearby nonround listing prices. It depicts a nonmonotonicity: that sellers who list at round numbers could improve their offers by either raising or lowering their list price by a small amount. However, figure 3 shows that round numbers are disproportionately more frequent. Moreover, as we document in appendix H, choosing round-number listings and receiving lower offers are prevalent even among the most experienced sell-

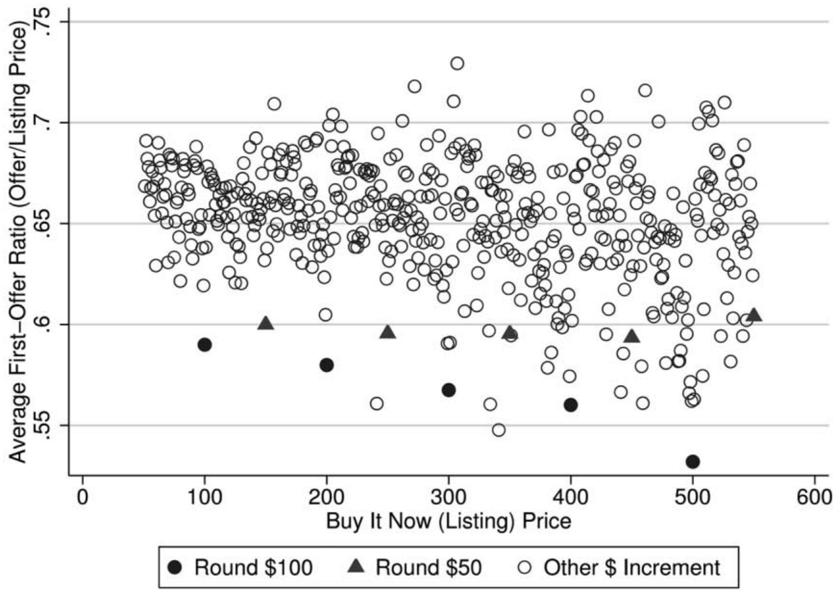

Fig. 2.—Average first offers by BIN price. This scatter plot presents average first offers, normalized by the BIN price to be between zero and one, grouped by unit intervals of the BIN price, defined by $(z-1,\ z]$. When the BIN price is on an interval rounded to a number ending in 00, it is represented by a circle; 50 numbers are represented by a triangle.

ers. This suggestive evidence motivates a more careful treatment of the claims of Section II, to which we now turn.

IV. Empirical Analysis

We now test the three predictions of separating equilibrium from Section II: sorting, beliefs, and incentive compatibility. Section III offers suggestive graphical evidence, but to rigorously study the use of round numbers we must estimate the discontinuous effect of roundness vis-à-vis nearby precise asking prices. We develop an identification strategy based on local comparisons to estimate the magnitude of these discontinuities in expected bargaining outcomes conditional on the asking price. We exploit detailed offer-level bargaining data and buyer search data to document seller sorting and buyers' updated beliefs.

A particular challenge is the presence of listing-level heterogeneity observable to market participants but not to us. We address this in Section IV.B.2 using a sample of internationally visible listings from eBay's UK site. Currency exchange rates cause US buyers to see precise prices when UK buyers see round ones. A difference-in-differences analysis

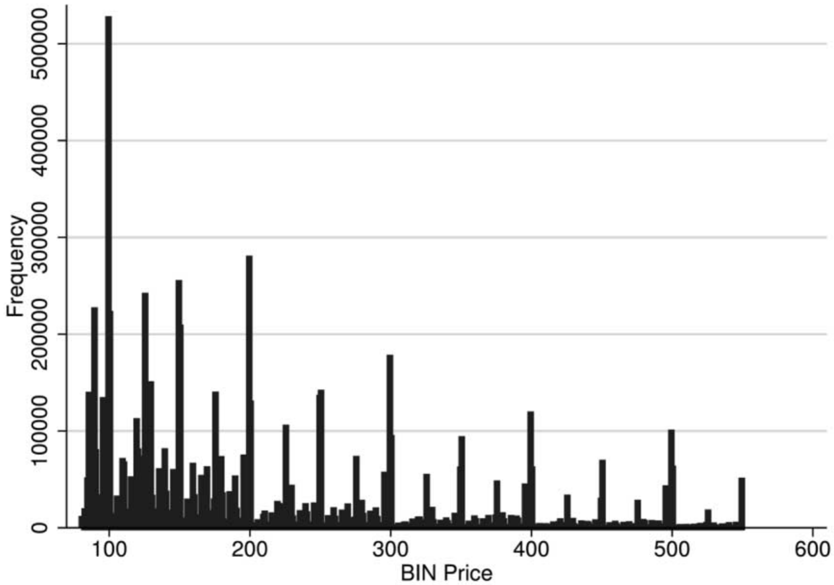

Fig. 3.—Buy-It-Now prices for Best Offer listings. This histogram depicts the frequency of sellers' chosen listing prices. The bandwidth is one, and unit intervals are generated by rounding up to the nearest integer.

shows that unaccounted-for attributes correlated with roundness do not explain our results.

A. *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, for example, the average first offer or the time to the first offer. Assuming finitely many signal discontinuities, $z \in \mathcal{Z}$, we can write

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

where $g(\cdot)$ is a continuous function, $\mathbf{1}_z$ is an indicator function equal to one if the argument is equal to z and zero 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 $(\mathbf{1}_z, z \in \mathcal{Z})$ are mutually orthonormal; this shape restriction, that is, continuity of $g(\cdot)$, is critical to separately identify these two functions of the same variable. However, $g(\cdot)$ remains an unknown, potentially 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 $\psi_z(\Delta)$, that is,

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

For Δ large, this comparison is unhelpful for identifying β_z without the imposition of an arbitrary parametric structure on $g(\cdot)$.[10] However, as $\Delta \to 0$, continuity implies $g(z+\Delta) - g(z) \to 0$, offering a nonparametric approach to identification of β_z:

$$\beta_z = -\lim_{\Delta \to 0} \psi_z(\Delta). \qquad (3)$$

Estimation of this limit requires estimation of $g(\cdot)$, which can be accomplished semiparametrically 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.[11]

Though our identification of β_z is fundamentally local, there remain two basic differences compared to regression discontinuity (RD) studies. 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. Instead, our model explicitly stipulates endogenous selection on round numbers by sellers deliberately selecting them. We must therefore show that our results are not driven by differences in unaccounted-for attributes between round and nonround listings, which we address in Section IV.B.2.

We construct $\mathcal{Z}$ by focusing on round-number prices because the histogram in figure 3 suggests them as focal points. A disproportionate number of sellers choose round numbers despite their apparent negative effect on bargaining outcomes. To further motivate this choice, in appendix B4 we employ a LASSO model selection approach to detect salient

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

[11] One might intuit that $g(\cdot)$ would be monotonically increasing, and this motivates an informal specification test that we present in app. B2. There we show that failing to account for discontinuities at z creates nonmonotonicities in a smoothed estimate of $g(\cdot)$.

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.

B. Bargaining Outcomes and Incentive Compatibility

Here, we document the trade-off between price and the time and likelihood of sale, which is essential to claim 3 (incentive compatibility). We use local linear regression in the neighborhood of $z \in \{100, 200, 300, 400, 500\}$ to estimate β_z. Our primary interest is in identifying β_z, and therefore, standard kernels and optimal bandwidth estimators, which are 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 at those points $z \in \mathcal{Z}$ rather than over the entire support of $g(\cdot)$. We follow the local linear regression approach of Fan and Gijbels (1992).[12] They employ a rectangular kernel, which can be interpreted as a linear regression for an interval centered at z of width $2h_z$, where the bandwidth parameter h_z depends on local features of the data and the data-generating process. See appendix C for details 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," that is, in the interval $[z-1, z)$ for each round number $z \in \mathcal{Z}$, to account for any asymmetric 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 ordinary least squares (OLS) to estimate

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

The nuisance parameters a_z and b_z capture the local shape of $g(\cdot)$, $\beta_{z,00}$ captures the round number effect, and $\beta_{z,99}$ captures the effect of pricing just below a round number. We estimate this model separately for each $z \in \{100, 200, 300, 400, 500\}$.

1. Offers and Prices

We start with y_j as the average first buyer offer and the final sale price of an item if sold, and estimates for these specifications are presented in table 2.

[12] 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.

TABLE 2
OFFERS AND SALES FOR ROUND $100 SIGNALS

	AVERAGE FIRST OFFER ($)		SALE PRICE ($)	
	(1)	(2)	(3)	(4)
BIN = 100	−5.372***	−4.283***	−5.579***	−5.002***
	(.118)	(.115)	(.127)	(.127)
BIN = 200	−11.42***	−8.849***	−10.65***	−9.310***
	(.376)	(.369)	(.401)	(.393)
BIN = 300	−18.74***	−14.78***	−17.04***	−15.94***
	(.717)	(.475)	(.863)	(.629)
BIN = 400	−24.61***	−17.71***	−17.98***	−15.80***
	(.913)	(.894)	(1.270)	(1.186)
BIN = 500	−39.43***	−28.58***	−35.76***	−30.55***
	(1.320)	(1.232)	(1.642)	(1.478)
Category fixed effects		Yes		Yes

NOTE.—Each cell in the table reports the coefficient on the indicator for roundness from a separate local linear fit according to eq. (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. Heteroskedasticity-robust standard errors are in parentheses.
* $p < .1$.
** $p < .05$.
*** $p < .01$.

All results show estimates with and without category fixed effects (of which there are 11). 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 nonbargained 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 Section IV.D.2.

The estimates show a strong and consistently negative relationship between round listed prices and both offers and sales. The effects are generally proportional to the BIN price, a regularity that is not imposed by our estimation procedure. In particular, for round BIN price listings, offers and final prices are lower by 5–8 percent as a factor of the listing price compared to their precise-number neighbors. This translates to a 8–12 percent effect on seller revenues. The estimates are slightly larger for the $500 listing value.

Ancillary coefficients, that is, 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 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 99s, that is, $[z-1, z)$ intervals, are reported in appendix E. We find that, contrary to prior work, in our bargaining environment these numbers yield outcomes that are similar to those of their round neighbors. 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), the advantage is that pooling across wider ranges of BIN prices allows us to include seller fixed effects to control for seller attributes.

Estimates from the cardinal basis spline approach are consistent with those from table 2.[13]

2. Selection on Unobservable Listing Attributes

There is substantial heterogeneity in the quality of listed goods that may be observable to buyers and sellers but not controlled for above, including information in the title, the description, or 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 $H(\xi|\text{BIN price})$. In this light we rewrite equation (1), the expectation of y_j conditional on observables, as

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

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 ξ in the neighborhood of each element in $\mathcal{Z}$. Formally, consider the analogue of equation (3), which summarizes the identification argument from Section IV.A:

$$\lim_{\Delta\to 0}\psi_z(\Delta) = \underbrace{\lim_{\Delta\to 0}\int g(z,\xi)\, dH(\xi|z+\Delta) - \int g(z,\xi)\, dH(\xi|z)}_{\equiv\gamma_z} - \beta_z. \tag{6}$$

[13] An alternative specification allowing for a jump and a kink discontinuity at z by interacting the slope and the constant coefficient with a dummy for being above or below z yielded similar results.

The term denoted γ_z in equation (6) is a potential source of bias. Assuming that $H(\xi|\text{BIN price})$ is uniformly continuous in the BIN price, the bias is equal to zero and the estimates from Section IV.B are robust to unobserved heterogeneity. The concern is, therefore, discontinuities in the conditional distribution of unobserved heterogeneity. For example, if sellers systematically round up rather than round down, then listings at round numbers will have a discontinuously lower expected unobserved quality (ξ) than nearby precise listings. This can also happen if the propensity of sellers to round is correlated with ξ conditional on the BIN price, for example, if sellers of defective items are more likely to use round prices. These are both plausible stories that challenge our identification strategy.

The ideal experiment would hold ξ fixed and observe the same product listed at both round and nonround BIN prices. This is possible if we restrict attention to well-defined products, but these also have a well-defined market price that leaves little room for bargaining.[14] Field experiments also pose challenges: if we create multiple listings for the same product, randomly varying roundness, they would compete with each other.

We address the problem 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 UK eBay site (http://ebay.co.uk) enter a price in British pounds, which is displayed to UK buyers. The sellers can choose to make their listing visible on the US site as well. US buyers viewing those UK listings, however, observe a BIN price in US dollars as converted at a daily exchange rate. Figure 4*A* gives an example of how a US buyer sees an internationally cross-listed good. Because of the currency conversion, when the UK price is round, the US buyer observes a nonround price when these items appear in search results.[15]

This motivates a new identification strategy close in spirit to the "ideal" experiment: For listings that are round in British pounds, we difference the offers of US and UK buyers. This removes the common effect of listing quality (γ_z), which is observed by both US and UK buyers, leaving the causal effect of roundness (β_z). From a theoretical perspective, there are two key elements of the strategy: first, that the signal is garbled (some recipients do not observe the seller's signal) and, second, that the garbling device is observable to the econometrician.[16] To formalize the

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

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

[16] Ambrus et al. (2018) exploit the same idea to study the effects of delay in bargaining. There, unverifiable distances to a bargaining agent are taken as an instrument for delay, which is purportedly a (garbled) signal of one's bargaining position.

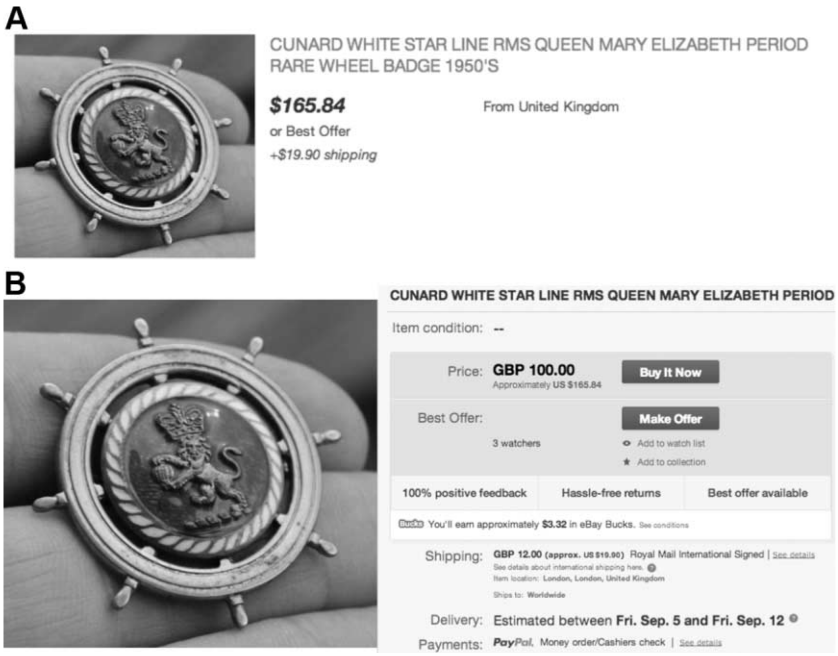

FIG. 4.—Example of round UK listing on US site. Panel A depicts a UK listing appearing in a US user's search results; the price has been converted from British pounds into US dollars. The listing itself appears in panel B, where the price is available in both British pounds and US dollars.

econometric argument, let $C \in \{\text{UK}, \text{US}\}$ denote the country in which the offers are made, and define

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

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

$$\begin{aligned}\psi_{z,\text{UK}}(\Delta) - \psi_{z,\text{US}}(\Delta) = {} & [g_{\text{UK}}(z + \Delta) - g_{\text{UK}}(z)] \\ & - [g_{\text{US}}(z + \Delta) - g_{\text{US}}(z)] - \beta_z.\end{aligned} \tag{8}$$

Following the logic of the identification argument in Section IV.A, 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

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

which extends the identification argument by differencing out the local structure of $g(\cdot)$, which is common to UK and US buyers. As in Section IV.B, we employ the results from Fan and Gijbels (1992) and use a rectangular kernel with the optimal variable bandwidth (see app. 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

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

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 across US and UK buyers and round and nonround listings. In the regression, γ_z captures the common, unobservable characteristics of the listing (observed by both US and UK buyers), while β_z is the round-number effect and is identified by the difference in the discontinuous response of UK and US buyers to roundness of the listing price in British pounds. Systematic differences between UK and US buyers that are unrelated to roundness, for example, shipping costs, are captured by allowing the nuisance constant and slope parameters to depend on the nationality of the buyer.

Note that on the listing page (depicted in fig. 4*B*), which appears after a buyer chooses to click on an item seen on the search results page (depicted in fig. 4*A*), the original UK price does appear along with the price in US 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; that is, it will attenuate the true effect. To the extent that we find any causal effect, we hypothesize that it survives because of the nonsalience of the UK price in British pounds during buyer search, and we interpret it as a lower bound on the effect of using a round-number listing price.

Our sample includes all UK-based listings created between January 1 and June 30, 2015, that are internationally visible. Our dependent variable is all initial offers made to these listings from a UK or US buyer. This results in a total of 2.9 million listings. We find that UK buyers tend to bid on slightly cheaper listings (£154 vs. £178, on average) and correspondingly make somewhat lower offers (£100 vs. £110, on average). Results from the estimation of equation (9) are presented in table 3. The estimated effects are somewhat smaller than those in Section IV.B, which could be due to either selection on unobservable characteristics or attenuation from US 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 US versus UK bidders is systematically

TABLE 3
Effect of Roundness on Offers from the UK Specification

	First Offer	
	(1)	(2)
UK × round £100	−3.561***	−1.902***
	(.618)	(.606)
UK × round £200	−4.176**	−3.329**
	(1.686)	(1.673)
UK × round £300	−15.25***	−11.07***
	(3.148)	(2.873)
UK × round £400	−15.90***	−13.07***
	(4.541)	(4.512)
UK × round £500	−48.40***	−38.70***
	(6.221)	(6.110)
Category fixed effects		Yes

Note.—Each cell in the table reports the coefficient on the interaction of an indicator for roundness with an indicator for a UK buyer from a separate local linear fit according to eq. (9) in the neighborhood of the round number indicated for the row, with the level of an offer, either from a UK buyer or a US one, as the dependent variable. Heteroskedasticity-robust standard errors are in parentheses.
* $p < .1$.
** $p < .05$.
*** $p < .01$.

positive and statistically significant confirms that our evidence for separation of buyer beliefs cannot be dismissed by selection on unobservables.

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 incentive compatibility is identifying a trade-off, 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.[17]

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 15 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

[17] By default, listings expire every 30 days but can be automatically extended in 30-day increments.

TABLE 4
SALE EFFECTS OF ROUND $100 SIGNALS

	Days to Offer		Days to Sale		Sold	
	(1)	(2)	(3)	(4)	(5)	(6)
BIN = 100	−11.02***	−11.09***	−13.80***	−14.38***	.0478***	.0522***
	(.333)	(.331)	(.434)	(.432)	(.00177)	(.00176)
BIN = 200	−11.53***	−11.52***	−15.15***	−15.64***	.0550***	.0590***
	(.526)	(.514)	(.734)	(.729)	(.00254)	(.00251)
BIN = 300	−9.878***	−7.390***	−11.15***	−11.95***	.0407***	.0317***
	(.655)	(.384)	(.784)	(.673)	(.00303)	(.00217)
BIN = 400	−7.908***	−6.125***	−10.73***	−10.87***	.0329***	.0319***
	(.509)	(.392)	(.849)	(.862)	(.00245)	(.00244)
BIN = 500	−9.431***	−8.832***	−10.31***	−10.77***	.0306***	.0354***
	(.637)	(.619)	(1.004)	(1.009)	(.00347)	(.00348)
Category fixed effects		Yes		Yes		Yes

NOTE.—Each cell in the table reports the coefficient on the indicator for roundness from a separate local linear fit according to eq. (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. Heteroskedasticity-robust standard errors are in parentheses.

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

6 shows that round listings also have a consistently higher probability of selling, raising conversion by between 3 and 6 percent on a base conversion rate of 20 percent. Note that listings may be renewed beyond 60 days; however, our estimates for the effect on the probability of sale are similar when we use alternative thresholds (30, 90, or 120 days).[18]

C. Seller Behavior and Evidence for Sorting

Claim 1 implies that sellers who use round-number listing prices prefer to trade quantity for price. If this is the case, then sellers who use round numbers will also be more likely to accept a given offer and 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

[18] While we have not modeled the underlying heterogeneity among sellers, it is natural to ask whether these results could be rationalized by reasonable variation. Consider the following example, calibrated by the results above: sellers who list at $100 can expect to sell for $65, with probability .25. Sellers who list at a nearby precise number can expect to sell for $70 with probability .20. Both sellers have an opportunity cost of selling (based on, e.g., the expected value of relisting or selling on another channel) of c, which is a function of their private type. Then, setting $.25 \cdot (65 - c) = .20 \cdot (70 - c)$, we find that the indifferent seller has an opportunity cost of 50. Sellers with a higher opportunity cost will prefer to use the precise number, while sellers with a lower opportunity cost will prefer the round number.

the probability of acceptance or the mean counteroffer. Results are presented in figure 5.

In panel A we plot a smoothed estimate of the probability of a seller accepting a first offer against the ratio of the buyer's 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: precise-number sellers are more likely to reject offers at any ratio of the listing price.[19]

Panel B 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.

D. *Round Numbers and Buyer Beliefs*

In this section we offer evidence for claim 2, that buyers' beliefs reflect sellers sorting across round and nonround listing prices. We take advantage of data on eBay user behavior to show that roundness guides buyers' search behavior and decisions to bargain.

These data also allow us to shed light on why roundness in particular is used as a signal. Theoretically, the form of a cheap-talk signal is arbitrary: 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 offer some insight on this point by identifying the moment, and the associated channels for signaling, at which the signal is received.

1. Buyer Search Behavior

We begin by tabulating the number of searches that return each listing. A search result page (SRP) contains many entries similar to that shown in figure 4*A*. We also 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 1. We normalize these counts (SRP and VI events) 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 measures of exposure. As panel A shows, round-number listings do not have a

[19] It may seem surprising that offers close to 100 percent 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.

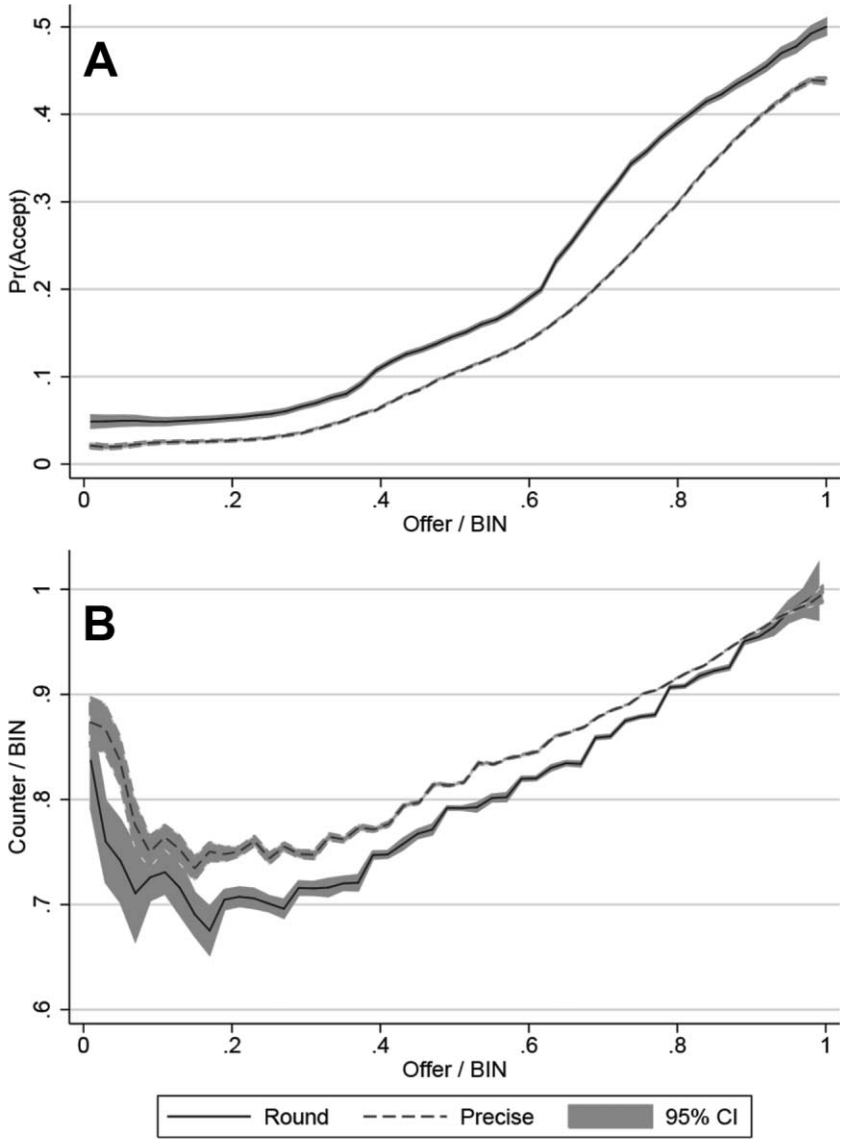

FIG. 5.—Seller responses to lower offers. Panel A depicts the polynomial fit of the probability of acceptance for a given offer (normalized by the BIN) on items with listing prices between $85 and $115, plotted separately for $100 "round" listings and the remaining "precise" listings. Panel B depicts the polynomial fit of the counteroffer (normalized by the BIN) made by a seller, similarly constructed.

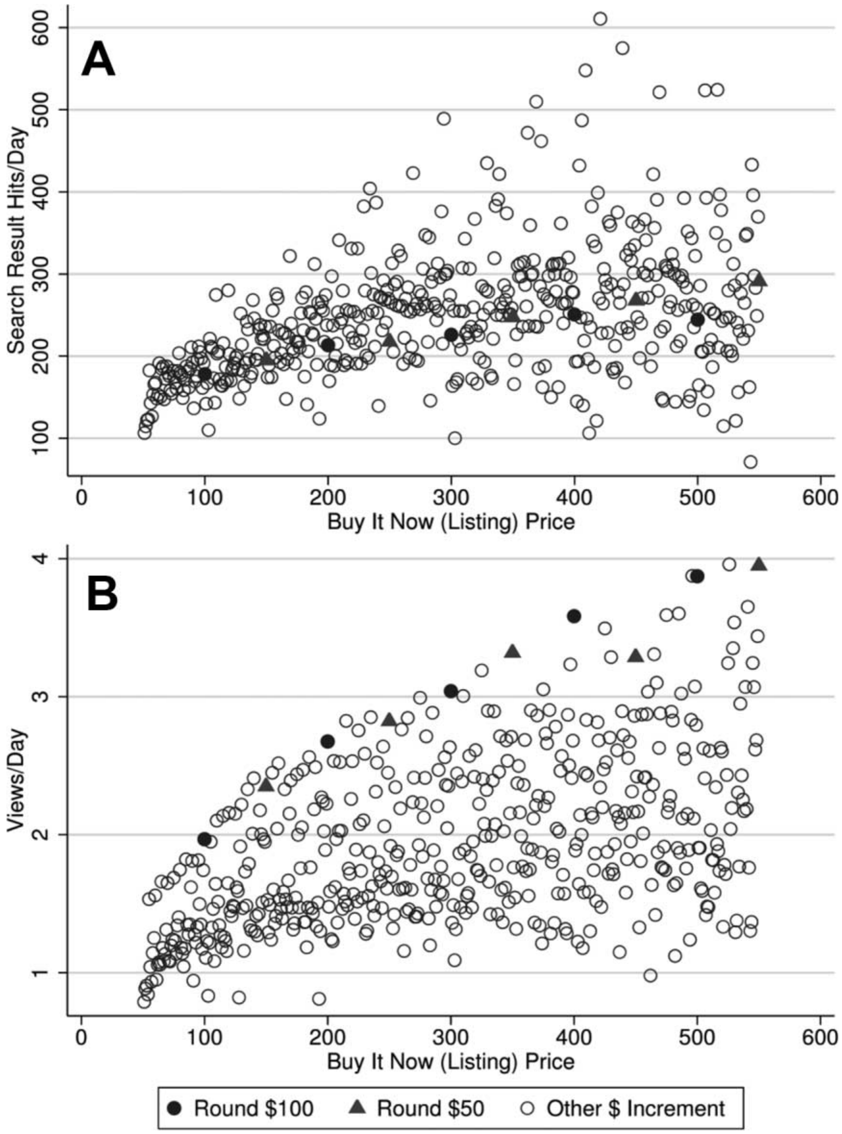

FIG. 6.—Search and view item detail counts. This plot presents average SRP and VI events per day by unit intervals of the BIN price, defined by $(z - 1,\ z]$. On the x-axis is the BIN price of the listing, and on the y-axis is the average number of SRP arrivals per day, in panel A, or the average number 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 circle; 50 numbers are represented by a triangle.

higher search exposure rate than nonround listings and seem to be less exposed. At the same time, however, they have a substantially higher VI rate as panel B demonstrates. This implies that when presented with a list of items on the SRP, buyers actively seek out and click on round-number listings, suggesting that they correctly infer these listings to be more attractive offerings.

Table 5 presents the results from a local linear estimation of the effect of a round list price on exposure. First note that columns 1 and 2 show that round-number listings do not appear more prominently in the SRP. If anything, they appear less frequently: the average number of an item's appearances in the SRP is 212, while round-number listings appear about 45–95 times less. Despite the fact that round-number listings appear less frequently, columns 3 and 4 show that round-number listings are viewed about one more time compared to the baseline of 2 in table 1. In summary, round listings do not have a higher search exposure rate than nonround listings, but they have a substantially higher view item rate, consistent with buyers updating their beliefs as stated in claim 2.

To confirm that buyers' responses are not the result of unobservables unique to round-number listings, we turn to the UK data. For each item we construct SRP and VI rates for UK and US buyers separately. Similarly to the exercise in Section IV.B.2, we look for a differential response to roundness (in British pounds) between UK and US buyers. In particular, we rerun regressions similar to columns 3 and 4 in table 5 but, in ad-

TABLE 5
Buyer Beliefs: Search and BIN Usage

	SRP Hits per Day		VI Count per Day		**1**{BIN|Sale}	
	(1)	(2)	(3)	(4)	(5)	(6)
BIN = 100	−40.18***	−23.25***	.654***	.703***	−.0194***	−.0172***
	(.640)	(.659)	(.0180)	(.0178)	(.00278)	(.00286)
BIN = 200	−58.54***	−51.42***	1.005***	.925***	−.0154**	−.0156**
	(.882)	(1.042)	(.0378)	(.0365)	(.00770)	(.00768)
BIN = 300	−66.59***	−50.42***	1.246***	.944***	−.0281**	−.0228***
	(1.291)	(1.261)	(.0452)	(.0394)	(.0117)	(.00705)
BIN = 400	−74.99***	−53.72***	1.469***	1.325***	.000880	−.00766
	(1.822)	(1.657)	(.0540)	(.0524)	(.00831)	(.00826)
BIN = 500	−95.67***	−82.99***	1.627***	1.384***	−.000596	−.00358
	(2.100)	(2.051)	(.0629)	(.0616)	(.0112)	(.0102)
Category fixed effects		Yes		Yes		Yes

Note.—Each cell in the table reports the coefficient on the indicator for roundness from a separate local linear fit according to eq. (4) in the neighborhood of the round number indicated for the row, using the dependent variable shown for each column. Heteroskedasticity-robust standard errors are in parentheses.

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

dition, interact the dummy variable for roundness with a dummy for whether the buyers are from the United Kingdom. If the response is driven by unobservables that are observable to UK and US buyers, then we should see no effect on the interaction. Table 6 presents regression estimates for this approach. We find that the effect of roundness on UK buyers' propensity to click through to the VI page is substantially larger than that for US buyers.

These results are consistent with our hypothesis. At the search page, buyers are forming beliefs about the anticipated surplus from particular listings and deciding whether to investigate further. The search page is also the first point at which buyers observe the listing price. If buyers who observe a round-number listing price anticipate more surplus at the negotiated price, consistent with our hypothesis, they should be more likely to continue to the VI page, as we see.

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, Podwol, and Schneider (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 conjec-

TABLE 6
UK Viewing Behavior Results

	VI Count per Day	
	(1)	(2)
UK × round £100	1.861***	1.915***
	(.104)	(.102)
UK × round £200	2.929***	2.745***
	(.165)	(.160)
UK × round £300	3.130***	3.158***
	(.261)	(.257)
UK × round £400	3.505***	3.478***
	(.709)	(.693)
UK × round £500	3.629***	3.772***
	(.436)	(.397)
Category fixed effects		Yes

Note.—Each cell in the table reports the coefficient on the interaction of an indicator for roundness with an indicator for UK buyers from a separate local linear fit according to eq. (9) in the neighborhood of the round number indicated for the row, with VI rate, from either UK buyers or US ones, as the dependent variable. Ancillary coefficients for each fit are reported in table A-9. Heteroskedasticity-robust standard errors are in parentheses.

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

ture 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.

2. Deciding Whether to Bargain

Our treatment of this marketplace has abstracted away from bargaining costs or the decision to bargain. 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, then buyers will be relatively less likely to exercise the BIN option. We validate this premise by showing in appendix A 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 seller's 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 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 of 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.

V. 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 close-by precise-number listings. Importantly, we showed that subsequent seller behavior was consistent with the sorting: 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 counteroffers. Moreover, we showed that buyers behave differently in how they respond to round- versus precise-number listings, suggesting that they update their beliefs in a consistent manner with a separating equilibrium.

One might wonder whether the evidence we presented is particular to eBay's marketplace or whether similar equilibria exist more generally in bargaining. There are many bargaining settings in which buyers and sellers would want to signal weakness in exchange for faster and more likely sales. To that end, we extend our analysis to the real estate market, which, in contrast to eBay, is a market with large and substantial transactions in which participants are often assisted by professional listing agents, making unsophisticated behavior unlikely.[20] We make use of data from the Multiple Listing Service from Levitt and Syverson (2008), which contains listing and sales data for Illinois from 1992 through 2002. We find that round listings 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. We document this finding in appendix L. 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 indeed a general feature of real-world bargaining.

The paucity of empirical work on signaling has persisted despite the extensive theoretical—even Nobel Prize–winning—research and its success as a modeling framework. We offered an empirical framework for documenting such equilibria, based on proof of sorting, belief updating, and incentive compatibility. Our uniquely rich data set on online bargaining allows us to identify all three, but this may be challenging more generally. As we explain in the introduction, prior work in different settings has made compelling, if incomplete, cases for the existence of separating equilibrium using only a subset of these tests.

We employed a "rational" rather than "behavioral" approach to explore the role of roundness. As described earlier, prior work on numerosity and cognition has taken the alternative path, concluding that savvy negotiators should exploit counterparties' biases and use precise numbers. This suggests that sellers who systematically choose round numbers are failing to serve their own interests. Our findings complicate this story. Sellers who use round numbers are significantly more likely to sell and tend to do so significantly sooner. In light of these large effects, it is not obvious which sellers, if any, are misoptimizing. Our results in appendix H show that restricting attention to experienced sellers tends to strengthen rather than weaken our results, in contrast with prior work on behavioral

[20] Pope, Pope, and Sydnor (2014) study round numbers as focal points in negotiated real estate prices and argue that their prevalence suggests that they must be useful to facilitate bargaining.

biases in market settings (List 2003; Backus et al. 2017). This is unsurprising given the magnitude of the effects, as experienced eBay sellers are characteristically careful optimizers. While we cannot rule out all alternative bias-driven hypotheses, we believe that the rational framework of perfect Bayesian equilibrium has generated compelling, testable, and empirically borne-out hypotheses in the data.

The supporting evidence from the real estate market further strengthens our conclusion that round numbers play a signaling role in bargaining situations more generally. We do not 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.[21] 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.

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

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