Online Appendices

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

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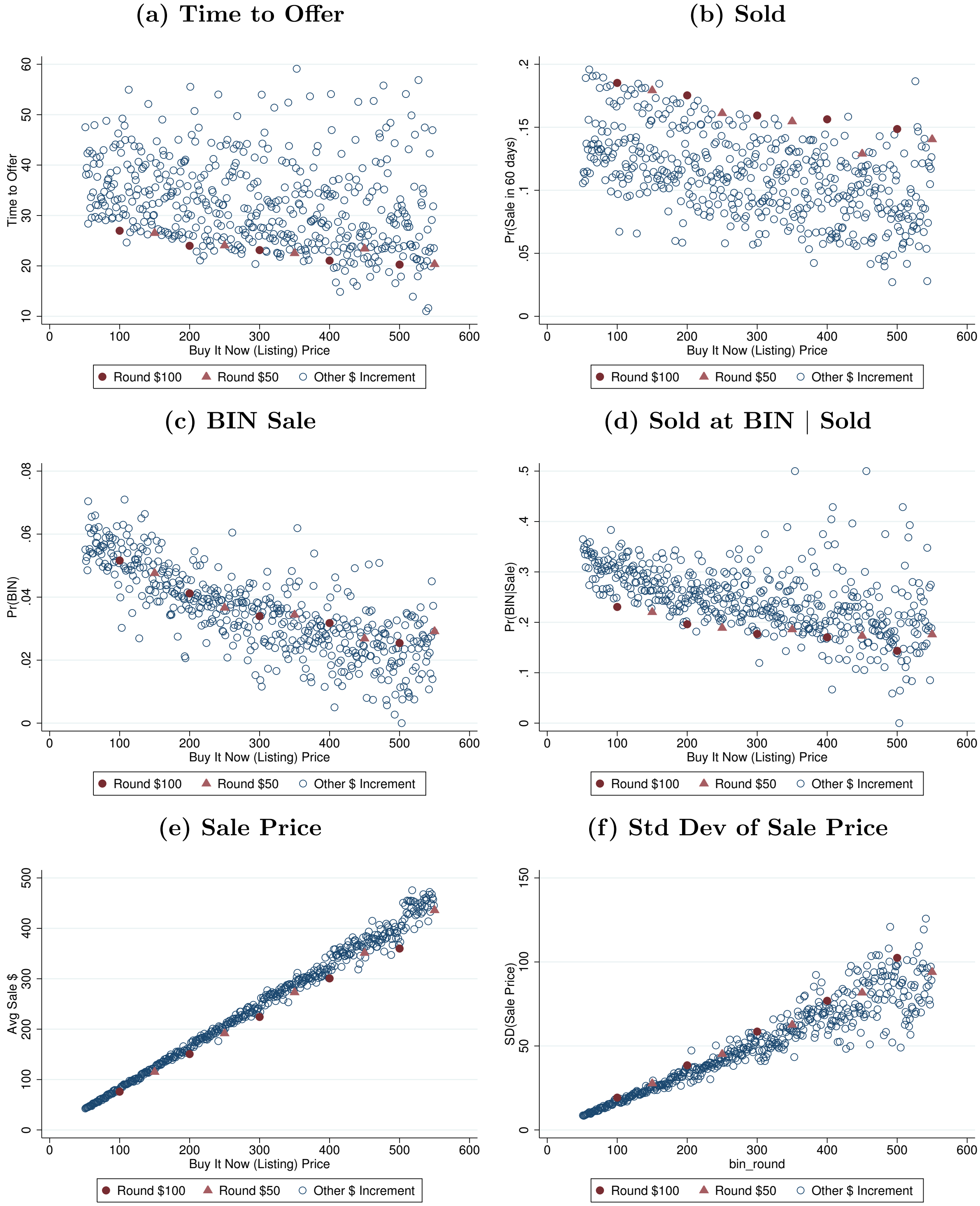
A Additional Outcomes

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.

Figure A-1c plots the probability of a Buy-it-Now sale (i.e. sale where the buyer accepted the listing price) by price BIN price. Figure A-1d shows the probability of a BIN sale conditional on sale decreases with BIN price, meaning that the probability of negotiating increases in the level of the BIN price. In this plot, we also see that round listings are less 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 of 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 Section 4.4.2, with results in Columns (5) and (6) of Table 5.

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.

Figure A-1: Additional Outcome Plots



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 belows. To this end we employ a cardinal basis spline approximation (De Boor, 1978; Dierckx, 1993), a semi-parametric tool for flexibly estimating continuous functions. Intuitively, a cardinal basis spline is a set of functions that form a linear basis for the full set of splines of some order p on a fixed set of knots. This is a convenient framework because the weights on the components of that linear basis can be estimated using OLS, which will identify the spline that best approximates the underlying function.

The approach requires that we pick a set of k equidistant "knots", indexed by t, which partition the domain of a continuous one-dimensional function of interest $f(\cdot)$ into segments of equal length.[1] 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:

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

[1] 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.

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

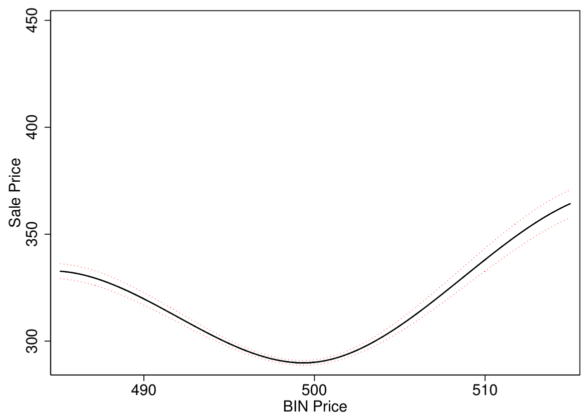
Here we present additional, albeit less formal evidence for our identification strategy. We begin with the premise – an intuitive assertion – that one would expect $\mathbb{E}[\text{sale price}|\text{BIN price}]$ to be monotonically increasing in the BIN price. This is testable insofar as we can estimate $g(\cdot)$ over large regions of the domain – we therefore employ the cardinal basis spline approach 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 $\mathbb{E}[\text{sale price}|\text{BIN price}]$ should allow for discontinuities at round numbers; that something other than the level of the price is being signaled at those points.

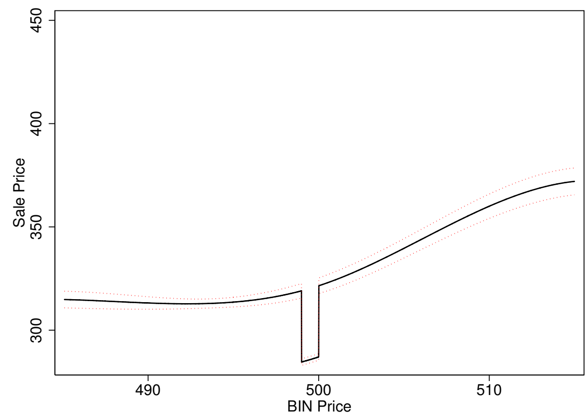
3 Basis Spline Robustness

An additional benefit of estimating $g(\cdot)$ globally, as the basis spline approach allows, is that we are able to employ the full dataset of listings and offers. This permits the estimation of seller-level fixed effects, which is important because they address any variation of a concern in which persistent seller-level heterogeneity drives our results. This is an extension of the local linear specification because it permits the use of all of listings simultaneously and not just those observations local to the threshold. That adds many observations per seller to each regression, some round and some non-round, identifying the effect within seller.

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.

Table A-1: Within Seller Variation of Roundness

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

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

Table A-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.[2]

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

2, which rules out most plausible stories of unobserved heterogeneity as an alternative explanation for our findings.

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

	(1) 1st Offer \$	(2) 1st Offer \$	(3) Sale Price \$	(4) Sale Price\$	(5) Days to Offer	(6) Days to Offer	(7) Days to Sale	(8) Days to Sale	(9) Sold	(10) Sold	(11) SRP	(12) SRP	(13) VI	(14) VI	(15) BIN|Sold	(16) BIN|Sold
BIN=100	-4.835***	-1.189***	-4.396***	-2.080***	-12.70***	-3.369***	-15.14***	-5.079***	0.0531***	0.0296***	-85.30***	-10.55	1.478***	0.488***	0.00328**	0.00290*
	(0.292)	(0.288)	(0.304)	(0.290)	(0.377)	(0.345)	(0.569)	(0.526)	(0.00336)	(0.00340)	(12.25)	(12.04)	(0.0739)	(0.0668)	(0.00157)	(0.00163)
BIN=200	-8.863***	-4.804***	-6.609***	-5.266***	-11.30***	-3.029***	-14.43***	-5.198***	0.0275***	0.0193***	-120.4***	-44.29**	1.922***	0.626***	0.00544**	0.00121
	(0.456)	(0.443)	(0.488)	(0.459)	(0.589)	(0.531)	(0.912)	(0.831)	(0.00524)	(0.00523)	(19.06)	(18.47)	(0.115)	(0.102)	(0.00244)	(0.00250)
BIN=300	-14.37***	-8.781***	-12.10***	-8.797***	-11.21***	-2.758***	-15.04***	-5.173***	0.0202***	0.00832	-114.7***	-5.687	2.045***	0.781***	0.00127	-0.00184
	(0.602)	(0.584)	(0.674)	(0.634)	(0.778)	(0.701)	(1.260)	(1.148)	(0.00693)	(0.00690)	(25.15)	(24.35)	(0.152)	(0.135)	(0.00323)	(0.00330)
BIN=400	-16.94***	-12.12***	-13.91***	-12.47***	-12.80***	-0.978	-14.20***	-1.654	0.00348	-0.0174**	-116.6***	44.96	2.322***	0.604***	0.00334	-0.00435
	(0.734)	(0.714)	(0.843)	(0.795)	(0.948)	(0.856)	(1.575)	(1.439)	(0.00844)	(0.00843)	(30.61)	(29.72)	(0.184)	(0.165)	(0.00393)	(0.00403)
BIN=500	-31.02***	-23.97***	-33.59***	-27.30***	-11.25***	-1.244	-12.92***	-1.950	0.0233**	0.0164	-124.0***	-10.16	2.114***	1.146***	0.000327	-0.00508
	(0.870)	(0.851)	(1.042)	(0.985)	(1.124)	(1.020)	(1.947)	(1.784)	(0.0100)	(0.0100)	(36.25)	(35.35)	(0.218)	(0.196)	(0.00466)	(0.00480)
Category FE		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes
Seller FE		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes
N	2804521	2804521	1775014	1775014	2804521	2804521	1775014	1775014	2804521	2804521	2649747	2649747	2668207	2668207	2804521	2804521

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.

4 LASSO Model Selection

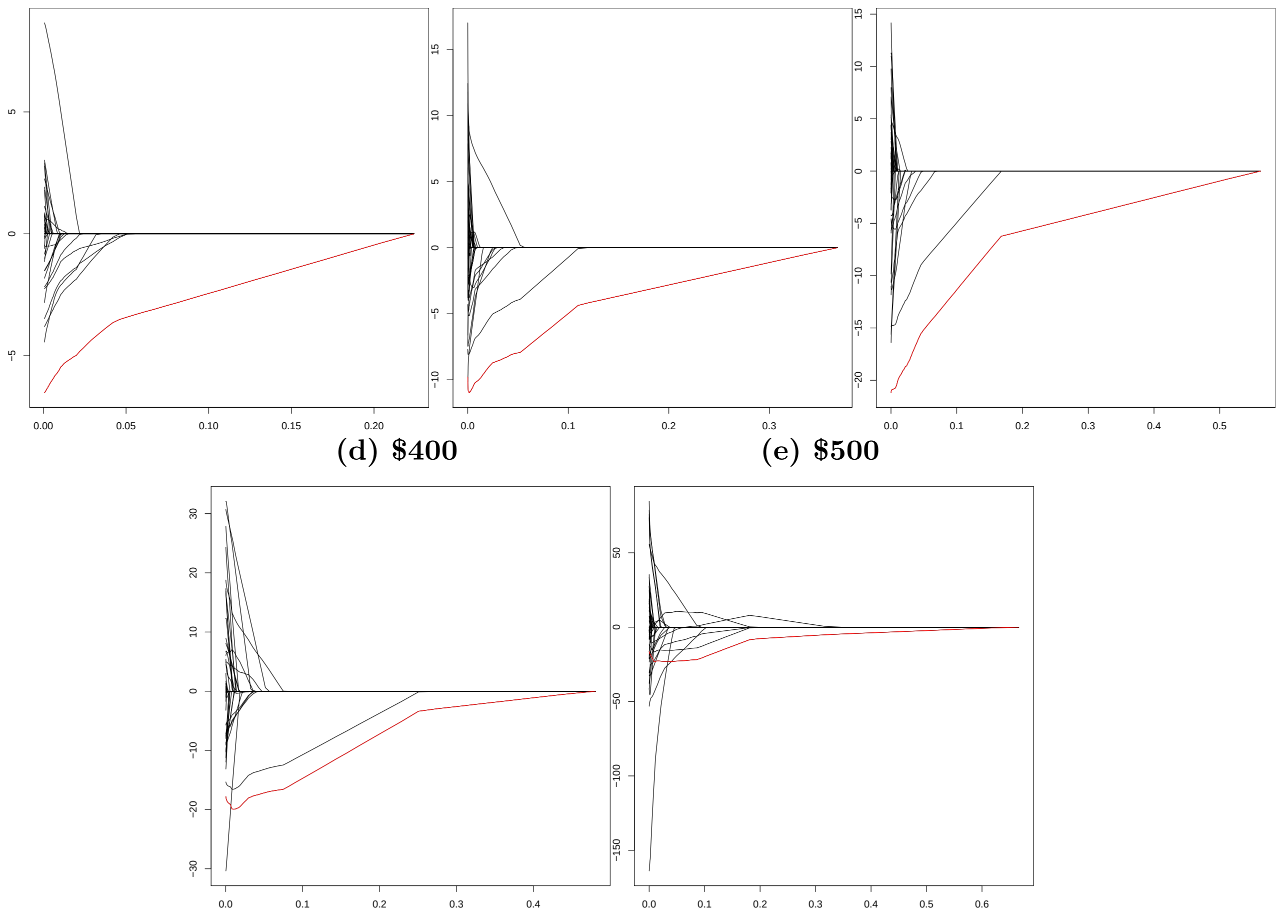
We employ the cardinal basis spline approach to offer supplementary motivation for our choice of the set of discontinuities $\mathcal{Z}$. Based on the size of our dataset it is tempting to suppose that approximation error in g would yield evidence of discontinuities at *any* point, and therefore it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

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

Note that we do not penalize the LASSO for using the cardinal basis spline series $b(x)$ to fit the underlying $g(\cdot)$. In this sense we are considering the minimal set of deviations from a continuous estimator. Figure A-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

Figure A-3: LASSO Model Selection

(a) $100 (b) $200 (c) $300 (d) $400 (e) $500



Notes: 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).

when the penalty term is large, and this pattern holds true for all five of the neighborhoods we study. Backus and Peng (2017) iterates on this procedure and shows how to select λ in order to control the false discovery rate of detected discontinuities.

C Bandwidth

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

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

	(1) Avg First Offer $	(2) Avg First Offer $	(3) Sale Price $	(4) Sale Price $
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

Notes: Here we report ancillary coefficients from separate local linear fits according to equation (4) in the neighborhood of the round number indicated, using the dependent variable shown for each column, corresponding to Table 2. Heteroskedacticy-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

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-4: Intercepts and Slopes for Local Linear Regressions - Sales

	(1) Days to Offer	(2) Days to Offer	(3) Days to Sale	(4) Days to Offer	(5) Sold	(6) Sold
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

Notes: Here we report ancillary coefficients from separate local linear fits according to equation (4) in the neighborhood of the round number indicated, using the dependent variable shown for each column, corresponding to Table 4. Heteroskedacticy-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) Sale Price $	(4) Sale Price $
BIN=099	-6.277***	-4.744***	-5.903***	-4.917***
	(0.0974)	(0.0955)	(0.104)	(0.106)
BIN=199	-14.21***	-9.742***	-11.75***	-9.035***
	(0.333)	(0.330)	(0.350)	(0.348)
BIN=299	-22.66***	-16.31***	-17.70***	-15.31***
	(0.640)	(0.398)	(0.767)	(0.543)
BIN=399	-32.99***	-22.00***	-22.61***	-17.89***
	(0.777)	(0.776)	(1.116)	(1.042)
BIN=499	-42.03***	-26.30***	-34.32***	-27.15***
	(1.193)	(1.123)	(1.451)	(1.302)
Category FE		YES		YES

Notes: Each cell in the table reports the coefficient on the indicator for BIN $\text{price}_j \in [z-1, z)$ from a separate local linear fit according to equation (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. Heteroskedacticy-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) Sale Price $	(4) Sale Price $
BIN=099 or 100	-4.793***	-3.944***	-4.615***	-4.101***
	(0.0519)	(0.0511)	(0.0709)	(0.0680)
BIN=199 or 200	-13.37***	-10.50***	-11.75***	-10.24***
	(0.164)	(0.164)	(0.183)	(0.183)
BIN=299 or 300	-20.90***	-15.30***	-19.04***	-16.52***
	(0.352)	(0.354)	(0.381)	(0.380)
BIN=399 or 400	-28.89***	-20.10***	-21.95***	-18.46***
	(0.606)	(0.611)	(0.690)	(0.674)
BIN=499 or 500	-40.48***	-26.66***	-34.77***	-28.58***
	(0.923)	(0.924)	(1.083)	(1.083)
Category FE		YES		YES

Notes: Each cell in the table reports the coefficient on the indicator for BIN $\text{price}_j \in [z-1, z]$ from a separate local linear fit according to a modified version of equation (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. Heteroskedacticy-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
First Offer	110.1	99.96
	(85.50)	(82.11)
Listing BIN Price (£)	178.1	154.7
	(124.4)	(113.1)
Listing Round £100	0.0540	0.0453
	(0.226)	(0.208)
Listing 99 cents	0.0855	0.0759
	(0.280)	(0.265)
N	86930	409624

Notes: Here we report summary statistics corresponding to the sample for Table 3. Standard deviations are 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.[3]

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.

[3]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	-2.251***	-3.914***
	(0.553)	(0.256)
BIN=200	-6.505***	-9.227***
	(1.521)	(0.743)
BIN=300	-5.627**	-14.27***
	(2.566)	(1.395)
BIN=400	-4.134	-12.55***
	(3.908)	(2.373)
BIN=500	-0.890	-33.72***
	(5.205)	(3.338)
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. Heteroskedacticy-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

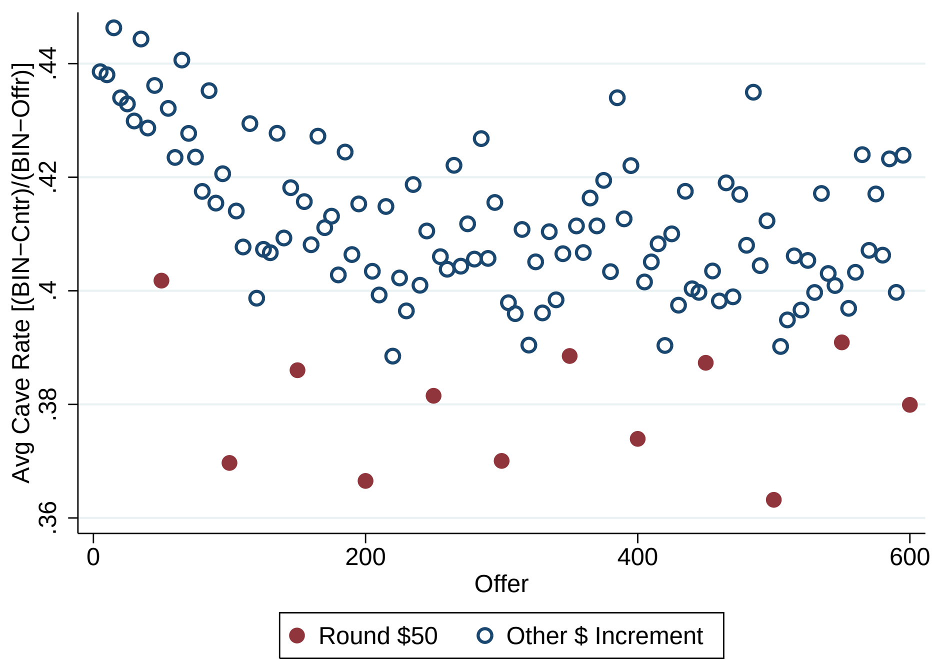
G Seller Response to Round Offers

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 for every listing in our data set. For tractability, we narrow the analysis to all listings with

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



Notes: 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	1.850***	0.0424	UK Offer=1	16.07***	5.356**
	(0.287)	(0.263)		(2.639)	(2.624)
BIN=100	-2.304***	-2.084***	BIN=400	-6.458*	-0.706
	(0.553)	(0.551)		(3.823)	(3.871)
BIN	0.681***	0.650***	BIN	0.969***	0.977***
	(0.0302)	(0.0283)		(0.186)	(0.184)
UK Offer =1 X BIN	0.246***	0.0964***	UK Offer =1 X BIN	-0.00867	-0.171
	(0.0410)	(0.0311)		(0.210)	(0.204)
Constant	65.35***	66.91***	Constant	246.9***	226.4***
	(0.243)	(0.347)		(2.315)	(4.329)
UK Bandwidth	9.81	10.16	UK Bandwidth	21.46	22.90
US Bandwidth	10.10	11.00	US Bandwidth	20.21	20.11
N	49887	67364	N	13786	13828
Near round $200:			**Near round $500:**		
UK Offer=1	4.952***	3.027***	UK Offer=1	31.03***	14.78***
	(1.007)	(0.989)		(3.441)	(3.384)
BIN=200	-7.853***	-6.145***	BIN=500	-4.369	2.415
	(1.512)	(1.505)		(5.201)	(5.203)
BIN	0.983***	0.885***	BIN	0.759***	0.771***
	(0.112)	(0.108)		(0.166)	(0.163)
UK Offer =1 X BIN	-0.140	-0.0980	UK Offer =1 X BIN	0.278	-0.0202
	(0.123)	(0.119)		(0.225)	(0.213)
Constant	129.2***	127.6***	Constant	297.6***	275.1***
	(0.911)	(1.276)		(2.799)	(5.934)
UK Bandwidth	12.37	12.65	UK Bandwidth	23.37	24.16
US Bandwidth	13.72	13.98	US Bandwidth	27.19	27.81
N	27708	27743	N	10474	10500
Near round $300:					
UK Offer=1	14.89***	8.591***			
	(1.951)	(1.496)			
BIN=300	-6.000**	-3.841			
	(2.728)	(2.524)			
BIN	1.050***	0.921***			
	(0.179)	(0.0979)			
UK Offer =1 X BIN	0.373*	-0.158			
	(0.221)	(0.109)			
Constant	185.5***	179.8***			
	(1.673)	(2.314)			
UK Bandwidth	14.92	21.36			
US Bandwidth	15.68	22.84			
N	16002	21131			
Category FE		YES			

Notes: Here we report ancillary coefficients from separate local linear fits according to equation (9) in the neighborhood of the round number indicated, using the dependent variable shown for each column, corresponding to Table 3. Heteroskedacticy-robust standard errors are in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$.

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 experienced 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.

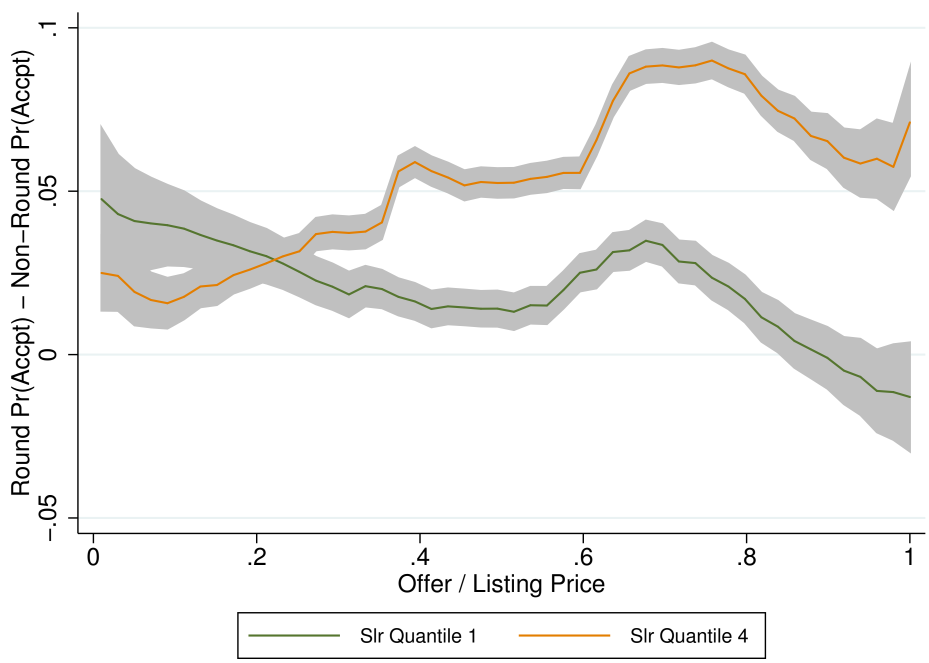
It would seem logical that such experienced sellers would only do this knowingly and so we check again for evidence of sorting across seller experience. Figure A-5 revisits the analysis of Figure 5a and shows the difference in the probability of accepting offers by offer fraction. We show the gap between 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.

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

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.

(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.[4]

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

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 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

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).

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.[5]

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

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

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

2. **Low type's price:** Let p_L denote the equilibrium price that a L type receives from a buyer if he chooses the signal W. If he waits instead of settling for p_L immediately, then in equilibrium he will receive p_L from the next buyer. The Poisson arrival rate of buyers implies that their inter-arrival time is distributed exponential with

[5] 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.

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

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

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.[6]

2 Equilibrium Properties and Empirical Predictions

In equilibrium, if both sellers are present in the market then any new buyer that arrives will select to negotiate with an L type in order to obtain the lower price of p_L. Furthermore, an H type will sell to a buyer if and only if there is no L type seller in parallel. Because L types are replaced with a Poisson rate of λ_s, the H type will be able to sometimes sell in the period of time after one L type sold and another L type arrives in the market. As a result, the equilibrium has the following properties: First, the L type sells at price $p_L < 1$

[6] 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.

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.[7] The way in which traffic and item popularity are measured is explained in more detail in Online 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 Online 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.

[7]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.[8]

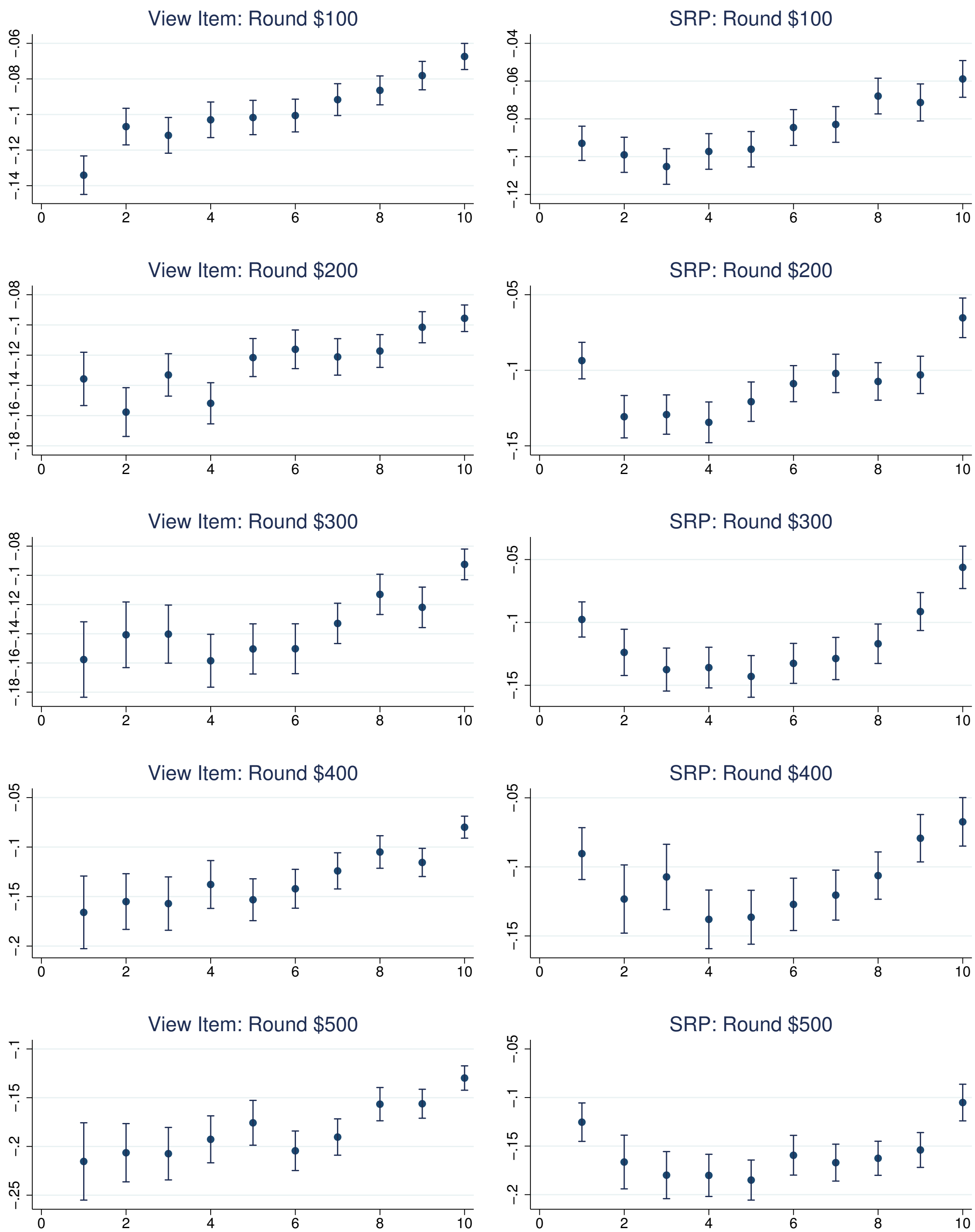
We proceed by grouping listings into deciles by view item counts. We first find that the baseline (non-round) mean offers vary across decile of exposure. This is an undesired byproduct of group by exposure: items in these groupings are different in ways other than pure buyer arrival rates (λ_b). We correct 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).

[8]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.

K Lesser Round Numbers

We present here estimates from the $10, $25, $50, and $75 round number thresholds for tables 2, 4, and 5. We find that effects continue to decrease and become and less precisely estimated as the salience of the round signal declines from multiples of $50 to $25 to $10.[9] That is especially true as we move to higher dollar amounts where the $25 multiple is a less salient signal.

This is consistent with the suggested effects of Figure 2, and the effects are generally consistent across all outcomes. The effects are indeed decreasing with the salience of the signal, but persist for the most part with the exception of the thinnest data at the $400 plus signals.

The large array of statistically significant coefficients results from the sheer size of the data. To ensure that these round numbers are not spurious requires some form variable selection. We use regularized regression in Online Appendix B4 and see that $100 are by far the most robust coefficient to regularization. We also note that the $10 multiples have results that are less than robust. This is likely because these local linear estimations include the nearest $100 round numbers which can tilt the linear approximation of running variable. Our primary estimates in the paper make use of optimal bandwidths which are small enough to exclude neighboring round numbers.[10]

Figure 2 draws our attention to the difference in proportional responses between $100 and $50 signals shown in Figure 2. That is, there is an increase in absolute effects for the $100 and not for the $50. This naturally appears in the regression results as well with effects that are similarly ‘flat’ for $25 and $75 signals. The roughly constant proportional effects only hold for the $100 signal which is the largest signal throughout the dollar values in our posting price range. If we had data that included larger prices, the $100 signal might also attenuate. We see some evidence of this in the last data point of Figure 8, where the $1 million signal has special significance. From this, we surmise that there is extra power from being the *most* round number for any given price.

We turn now to the offer-level effects. The Figure A-7 replicates Figures 5a and 5b for $75 (left), $110 (center), and $150 (right) round numbers. We see similar evidence of sorting at $75 and $150, but none at $110.

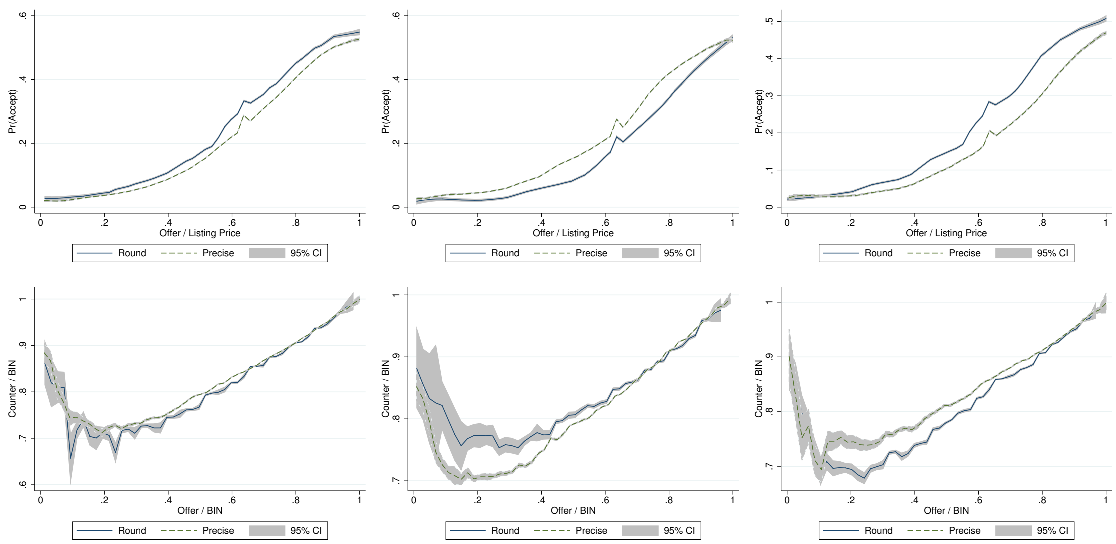
[9]To limit, somewhat, the size of this bewildering array of results, we show only the first multiples of $10.

[10]Bandwidths are shown in Table A3.

Table A-11: Estimates at $25, $50, and $75 'Round' Numbers

	(1) First Offer $	(2) First Offer $	(3) Sale Price $	(4) Sale Price $	(5) Days to Offer	(6) Days to Offer	(7) Days to Sale	(8) Days to Sale	(9) Sold	(10) Sold	(11) SRP	(12) SRP	(13) VI	(14) VI
Near round $25:														
BIN=125 or 124	-0.299***	-0.420***	-2.002***	-1.706***	-1.450***	-2.917***	-4.697***	-4.854***	0.0113***	0.0519***	-15.39***	-12.00***	0.256***	0.288***
	(0.113)	(0.111)	(0.166)	(0.149)	(0.241)	(0.252)	(0.337)	(0.319)	(0.000888)	(0.00146)	(0.669)	(0.646)	(0.0142)	(0.0139)
BIN=225 or 224	-2.591***	-1.832***	-4.706***	-3.579***	0.279	-1.607***	-2.740***	-4.042***	0.0209***	0.0535***	12.13***	-16.87***	0.489***	0.483***
	(0.349)	(0.346)	(0.370)	(0.369)	(0.380)	(0.380)	(0.567)	(0.565)	(0.00150)	(0.00234)	(0.998)	(1.148)	(0.0417)	(0.0431)
BIN=325 or 324	-1.276*	-1.042	-4.515***	-4.387***	-2.480***	-3.857***	-4.421***	-6.205***	0.0482***	0.0195***	-6.218***	-14.15***	0.805***	0.607***
	(0.725)	(0.634)	(0.691)	(0.620)	(0.536)	(0.533)	(0.858)	(0.848)	(0.00370)	(0.00212)	(1.863)	(1.770)	(0.0482)	(0.0444)
BIN=425 or 424	-6.231***	-1.697	-9.969***	-5.431***	-1.011	-2.321***	-1.269	-2.821**	0.0181***	0.0215***	20.63***	-20.30***	1.087***	1.087***
	(1.203)	(1.200)	(1.218)	(1.244)	(0.699)	(0.703)	(1.139)	(1.157)	(0.00279)	(0.00272)	(2.041)	(2.306)	(0.0605)	(0.0575)
BIN=525 or 524	-10.50***	-4.290**	-14.76***	-8.119***	-3.986***	-5.148***	-7.080***	-1.335	0.00730**	0.00825**	-7.114***	-9.732***	-0.316***	-0.258***
	(2.047)	(1.979)	(2.155)	(2.096)	(0.900)	(0.877)	(1.570)	(1.225)	(0.00366)	(0.00362)	(2.578)	(2.513)	(0.0694)	(0.0666)
Near round $50:														
BIN=150 or 149	-7.310***	-5.333***	-7.453***	-6.219***	-4.188***	-4.465***	-5.537***	-6.659***	0.0443***	0.0446***	-40.45***	-22.34***	0.244***	0.287***
	(0.121)	(0.124)	(0.170)	(0.171)	(0.332)	(0.336)	(0.455)	(0.459)	(0.00210)	(0.00209)	(0.684)	(0.621)	(0.0211)	(0.0210)
BIN=250 or 249	-13.07***	-9.338***	-12.31***	-10.58***	-3.950***	-4.326***	-6.039***	-7.246***	0.0591***	0.0628***	-50.06***	-35.70***	0.720***	0.724***
	(0.343)	(0.341)	(0.360)	(0.356)	(0.365)	(0.366)	(0.558)	(0.560)	(0.00241)	(0.00240)	(1.139)	(1.125)	(0.0311)	(0.0307)
BIN=350 or 349	-18.44***	-13.46***	-16.64***	-13.73***	-4.998***	-4.590***	-5.968***	-6.558***	0.0478***	0.0355***	-62.50***	-37.65***	1.115***	0.906***
	(0.696)	(0.633)	(1.258)	(1.047)	(0.521)	(0.460)	(0.788)	(0.725)	(0.00358)	(0.00194)	(1.666)	(1.090)	(0.0482)	(0.0390)
BIN=450 or 449	-19.97***	-11.99***	-14.67***	-14.52***	-0.272	-0.854	-2.490***	-3.922***	0.0196***	0.0213***	-36.35***	-31.22***	0.799***	0.741***
	(0.996)	(0.983)	(0.877)	(1.089)	(0.418)	(0.525)	(0.900)	(0.902)	(0.00280)	(0.00276)	(1.520)	(1.422)	(0.0451)	(0.0456)
Near round $75:														
BIN=75 or 74	0.351***	0.299***	-0.543***	-0.440***	-1.447***	-2.392***	-3.363***	-4.238***	0.0457***	0.0372***	-5.801***	-1.644***	0.102***	0.129***
	(0.0505)	(0.0496)	(0.0519)	(0.0513)	(0.203)	(0.201)	(0.257)	(0.256)	(0.00114)	(0.00114)	(0.476)	(0.462)	(0.00911)	(0.00895)
BIN=175 or 174	-1.438***	-1.318***	-3.567***	-3.101***	-2.936***	-3.508***	-4.671***	-4.599***	0.0441***	0.00605***	-20.28***	-15.60***	0.227***	0.386***
	(0.222)	(0.218)	(0.219)	(0.217)	(0.317)	(0.314)	(0.452)	(0.450)	(0.00209)	(0.00122)	(0.961)	(0.886)	(0.0217)	(0.0224)
BIN=275 or 274	-1.860***	-1.568***	-4.930***	-3.599***	-4.590***	-4.565***	-7.534***	-7.118***	0.0249***	0.0351***	-24.33***	-27.89***	0.830***	0.743***
	(0.531)	(0.478)	(0.491)	(0.481)	(0.450)	(0.416)	(0.688)	(0.640)	(0.00188)	(0.00171)	(1.458)	(1.359)	(0.0390)	(0.0358)
BIN=375 or 374	-6.610***	-1.812**	-7.936***	-4.681***	-1.128*	-2.577***	-4.417***	-5.570***	0.0169***	0.0175***	-27.14***	-25.71***	0.602***	0.657***
	(0.918)	(0.816)	(1.101)	(1.026)	(0.596)	(0.540)	(0.800)	(0.842)	(0.00243)	(0.00195)	(1.867)	(1.688)	(0.0502)	(0.0464)
BIN=475 or 474	1.831	5.482***	-2.052	2.430	-0.911	-0.494	-2.688***	-5.590***	0.0284***	0.0328***	33.65***	1.735	1.049***	0.898***
	(1.358)	(1.322)	(1.645)	(1.599)	(0.722)	(0.596)	(0.952)	(1.125)	(0.00252)	(0.00293)	(2.242)	(2.452)	(0.0769)	(0.0701)
Near round $110:														
BIN=110 or 109	-1.397***	-0.888***	-1.328***	-1.240***	-9.732***	-8.944***	-12.93***	-12.63***	0.0614***	0.0529***	25.57***	18.89***	0.417***	0.336***
	(0.152)	(0.150)	(0.152)	(0.152)	(0.404)	(0.402)	(0.558)	(0.557)	(0.00183)	(0.00186)	(0.944)	(0.932)	(0.0443)	(0.0512)
BIN=210 or 209	0.279	1.053*	-0.103	0.155	-9.043***	-8.352***	-11.58***	-10.95***	0.0516***	0.0422***	29.25***	8.796***	0.495***	0.292**
	(0.617)	(0.606)	(0.596)	(0.575)	(0.783)	(0.783)	(1.179)	(1.182)	(0.00369)	(0.00370)	(2.397)	(2.214)	(0.105)	(0.124)
BIN=310 or 309	4.391***	9.289***	3.030*	12.00***	-8.650***	-6.733***	-11.63***	-9.197***	0.0655***	0.0341***	43.09***	9.143**	1.066***	0.406***
	(1.580)	(1.408)	(1.569)	(1.311)	(1.315)	(1.186)	(2.190)	(1.918)	(0.00554)	(0.00475)	(4.613)	(4.307)	(0.116)	(0.104)
BIN=410 or 409	19.85***	15.16***	16.74***	10.46***	-7.064***	-5.251***	-13.96***	-12.33***	0.0444***	0.0363***	29.30***	31.92***	-0.0611	0.0450
	(2.809)	(2.722)	(3.060)	(2.956)	(1.479)	(1.476)	(2.204)	(2.221)	(0.00578)	(0.00574)	(6.374)	(6.039)	(0.116)	(0.113)
BIN=510 or 509	20.95***	14.50***	18.48***	8.986**	9.596***	10.63***	12.93***	14.91***	0.0369***	0.0216***	-63.42***	-48.16***	-0.525***	-0.651***
	(4.509)	(4.370)	(4.347)	(4.016)	(2.589)	(2.556)	(4.160)	(4.131)	(0.00716)	(0.00719)	(6.922)	(6.863)	(0.132)	(0.127)
Category FE		YES		YES		YES		YES		YES		YES		YES

Figure A-7: Acceptance and Counteroffers at \$75, \$110, and \$150



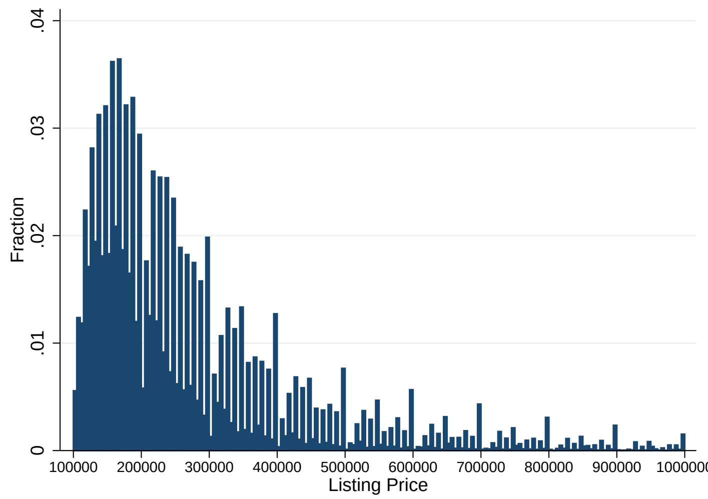
Notes: This figure replicates figures 5a and 5b for \$75 (left), \$110 (center), and \$150 (right) round numbers. The first row depicts the probability of acceptance, while the second row depicts counteroffers.

L Round Number Listings in Real Estate

We see 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 which allows us to partially replicate our analysis in the real estate market. 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. Listings bunch at round numbers, particularly on more expensive listings. In Figure A-8 we document the pattern of rounding in real estate listings. We observe the same tendency to round that we observed in Figure 3 where we documented listing prices for Best Offer listings, in

Figure A-8: Real Estate Grouping at round-numbers



Notes: This is a histogram of sellers' 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., $\$80,000, \$90,000, \$100,000, \ldots$)

particular, the tendency to round more at higher prices. Note that although the pattern is similar, the magnitudes are substantially higher suggesting that 'roundness' is context specific.

Figure A-9 mimics Figure 2 for the real estate data using sale prices and similarly shows that round listings sell for less. In addition to the graphical evidence, we estimate basis spline regressions of the sale fraction on a single dummy for whether the listing is round. Results are presented in Table A-12. Adding controls such as those found in Levitt and Syverson (2008) or, as shown here, listing agent fixed effects, absorbs variation in regions or home type. With controls, we found that 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.[11]

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-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

[11] 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 A-9: 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. 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.

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 A-12: 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

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

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