Online Appendix: Communication, Learning, and Bargaining Breakdown: An Empirical Analysis

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1 A Straw Man: OLS Estimates

In the absence of a natural experiment, one might have been tempted to analyze the effect of communication by regressing a dummy for success on a dummy for the presence of a message. This will be misleading if bargainers are more likely to send messages when an interaction is, for reasons unobservable in our set of controls, less likely to succeed. In Table A-1 we present OLS estimates for such an analysis in a linear probability model approach.

Note that for these results we construct the message indicator a bit differently. $\mathbb{1}(\text{Message}^*)$ is actually $\mathbb{1}(\text{complier})$, the product of three dummy variables: one for whether any message was sent, one for whether the first offer in the interaction was made after May 23, 2016 (to rule out misclassified messages), and one for whether

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the buyer is a desktop user (to rule out cases where a message was sent by the seller but the buyer could not read it because they were on the mobile app). In models (1) through (4) we progressively add additional controls. The coefficient on $\mathbb{1}(\text{Message}^*)$ responds most significantly at the inclusion of ln(Asking Price), which is intuitive because messages are more common when bargaining over more expensive goods, recalling Table 2 However, the coefficient stabilizes at a relatively slight 1.5 percentage points, which is substantially lower than our estimated treatment-effect-on-the-treated of approximately 8. We take this to mean that the endogenous decision of whether to send a message is strongly negatively correlated with the error term in the OLS regressions. That is, bargainers are more likely to use messages when the chances of success are slight for reasons unobservable to the econometrician—evidence for this already appears in the difference between models (1) and (2), where the inclusion of the asking price removes some of the negative bias. Recall from Table **??** that messages are more frequently sent when the asking price is greater, which is also where the likelihood of breakdown is greater.

2 Alternative Outcomes

The bulk of our analysis has taken a dummy for bargaining success as the dependent variable. We might also be interested to know how other bargaining outcomes change with the introduction of communication. For instance, do buyers negotiate better deals? Is bargaining prolonged?

Our results for these questions are presented in Table A-2. Models (1) and (2) consider dependent variables for which we can use the entire sample: respectively, the number of offers in the bargaining interaction and the log of the first buyer offer. We find no statistically significant effect on either of these outcomes. In model (3) where we condition on bargaining success and measure the effect on negotiated prices. We find a strong negative effect. Note for models (2) and (3) that the controls include the sellers' asking price, so we can interpret this effect as a discount. One interpretation is that sellers have raised their asking prices, but we find such general equilibrium effects unlikely because of the low take-up rates of the messaging feature; also, we see no compositional changes in the prices bargained in the pre- and post periods. This leaves two additional hypotheses: first, that transactions that are new—that is, would not have happened but for messaging—are on average for lower-priced products than

Table A-1: OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Message)	-0.0076*	0.0208*	0.0152*	0.0151*		
	(0.0028)	(0.0027)	(0.0026)	(0.0026)		
ln(Ask Price)		-0.0827*	-0.0840*	-0.0840*	-0.0840*	-0.0840*
		(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Time Trend		0.0000	0.0001	0.0000	0.0000	
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	
$\mathbb{1}$(Monday)				0.0115*	0.0115*	0.0114*
				(0.0011)	(0.0011)	(0.0011)
$\mathbb{1}$(Tuesday)				0.0073*	0.0074*	0.0069*
				(0.0011)	(0.0011)	(0.0011)
$\mathbb{1}$(Wednesday)				0.0046*	0.0046*	0.0043*
				(0.0012)	(0.0012)	(0.0012)
$\mathbb{1}$(Thursday)				0.0022*	0.0023*	0.0022*
				(0.0011)	(0.0011)	(0.0011)
$\mathbb{1}$(Friday)				-0.0087*	-0.0086*	-0.0088*
				(0.0013)	(0.0013)	(0.0013)
$\mathbb{1}$(Saturday)				-0.0106*	-0.0106*	-0.0108*
				(0.0012)	(0.0012)	(0.0011)
$\mathbb{1}$(Precipitation)				-0.0014*	-0.0014*	-0.0008
				(0.0007)	(0.0007)	(0.0007)
$\mathbb{1}$(Holiday)				-0.0072*	-0.0072*	-0.0078*
				(0.0011)	(0.0011)	(0.0011)
Temperature				0.0006*	0.0006*	0.0006*
				(0.0001)	(0.0001)	(0.0001)
Category by Condition FE			✓	✓	✓	✓
N	3294362	3294362	3294362	3294362	3294362	3294362

Notes: This table reports OLS coefficients from a linear probability model in which each observation is a bargaining interaction and the dependent variable is a dummy for whether negotiations ended in a transaction. $\mathbb{1}$(Sunday) is excluded. Heteroskedacticity-robust standard errors, clustered by seller, are reported in parentheses, and * denotes statistical significance at $\alpha = 0.05$.

those that are not. This is consistent with the finding of Valley et al. (2002), as the new transactions are on the frontier where buyer and seller valuations are close, as well as our failure to find an effect on the buyer's initial offer. An alternative interpretation is that the composition of goods has not changed, but buyers are taking more of the surplus.

Next, in models (4), (5), and (6) we dive further into the question of the division of surplus. Here, we construct subsamples defined by the endogenous bargaining sequence. Model (4) uses the asking price for the subsample where the buyer's initial offer is accepted (recall that buyers always make the first offer). Model (5) takes the subsample in which the buyers initial offer was countered, and the seller's counter-offer was accepted. Finally, model (6) takes the subsample in which the buyer's initial offer was countered, then the buyer countered the seller's counter, and the seller accepted that counter-offer. In model (4) do we find an almost-significant effect. Moreover, the sign changes between the models are consistent with the hypothesis that bargainers are using messages to their own advantage. Note that the sample size shrinks fast when conditioning on these small subsets, so it is unsurprising that we lack the power to identify a significant effect.

3 Heterogeneous Effects

1 Effects by Price Range

Next, we present estimates of β^C_{iv} across different price categories in Table A-3. Our estimates range from 8.98 to 10.44 percentage points for interactions where the asking price is below \$150, and they are substantively smaller—statistically insignificant with point estimates ranging from 2.41 to 3.51 percentage points above \$150.

While it seems as if there is a substantially larger effect of communication for interactions that involve listings with lower asking prices, we note that this relationship flattens out when we consider the baseline success rates. Interactions in the lowest-price group (asking price less than \$50) are successful 52.94 percent of the time, while listings in highest-price group (asking prices above \$250) are successful 25.54 percent of the time. So the proportional effect is rather more similar—and not statistically distinguishable—and therefore we hesitate to draw conclusions.

2 Variation Across Categories

We next turn to category-specific estimates of β^C_{iv}. However, we note two words of caution: first, because the effects we are estimating are so small—from Table **??**, on the order of half a percent—splitting our sample quickly erodes power. In that spirit,

Table A-2: Estimates for Alternative Outcome Variables

	Full Sample			Conditional on Agreement		
	(1) No. Offers	(2) ln(First Offer)	(3) ln(Agreed Price)	(4) Buyer Offer	(5) Seller Counter	(6) Buyer Counter
β^C_{pp}	-0.0047	0.0130*	0.0087*	0.0108	0.0086*	0.0123*
	(0.0039)	(0.0031)	(0.0041)	(0.0058)	(0.0019)	(0.0047)
β^C_{dd}	-0.0040	0.0011	-0.0047*	-0.0068	0.0011	-0.0005
	(0.0028)	(0.0015)	(0.0024)	(0.0035)	(0.0012)	(0.0027)
β^C_{iv}	-0.0743	0.0206	-0.0959*	-0.2690	0.0119	-0.0042
	(0.0519)	(0.0276)	(0.0478)	(0.1384)	(0.0130)	(0.0229)
Controls	✓	✓	✓	✓	✓	✓
N_{pp}	1770261	1770261	832365	518199	128659	38829
$N_{dd,iv}$	3294362	3294362	1454658	861031	218678	85038

Notes: This table presents estimates for alternative left-hand-side variables. Note that all estimates of β^C_{pp} use the desktop sample only, and (3) is conditional on success. Model (4) uses interactions in which a buyer's initial offer was accepted by the seller; (5) uses interactions where the buyers offer was countered by the seller and the buyer accepted the counter-offer, and finally (6) uses the set of interactions where the buyer made an offer, the seller countered, the buyer countered the counter, and the seller accepted. Controls include a time trend; ln(ask price); category by condition fixed effects; day of week, precipitation, and holiday dummies and the temperature. Heteroskedacticity-robust standard errors, clustered by seller, are reported in parentheses, and * denotes statistical significance at $\alpha = 0.05$.

Table A-3: Estimates by Asking Price Range

	(1)	(2)
Ask Price in ($0,$50)	0.0945*	0.1044*
	(0.0366)	(0.0362)
Ask Price in [$50,$150)	0.0957*	0.0898*
	(0.0354)	(0.0351)
Ask Price in [$150,$250)	0.0387	0.0241
	(0.0490)	(0.0485)
Ask Price ≥ $250	0.0284	0.0351
	(0.0321)	(0.0318)
Controls		✓

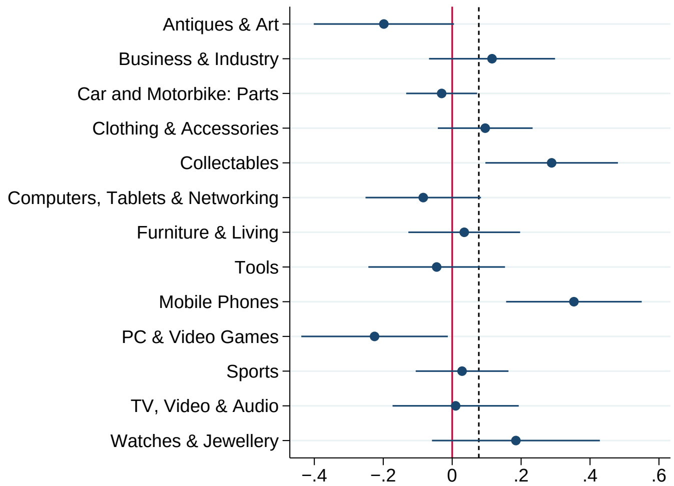
Notes: This table presents estimates of β_{iv}^{C} for four different price ranges. Note that price ranges are defined in USD. All parameters of the model are estimated independently for each coefficient estimate. In model (1), no controls are included, while in model (2), the full set of controls detailed in Table **??** are included. Heteroskedacticity-robust standard errors, clustered by seller, are reported in parentheses, and * denotes statistical significance at $\alpha = 0.05$.

the standard errors should be interpreted with caution because a table with many estimates implicitly suffers a multiple comparison problem. Similarly, the ordinal relationships of the point estimates should be interpreted with substantial caution.

Second, we remind the reader that selection into the Best Offer mechanism is endogenous. The composition of, for instance, CDs and DVDs conditional on enabling Best Offer may be very different than CDs and DVDs more generally. While we may think of the latter as being rather standardized, the former may be more likely to include box sets and out-of-print collectors editions.

Estimates are presented in Figure A-1. The dependent variable remains a dummy for whether the bargaining ended in a transaction. Standard errors are *not* adjusted for the multiple comparison problem. While we find intuition in some of the findings, e.g. the large effect in Collectibles, others remain a puzzle, e.g. the large effect in Mobile Phones or the negative one in Antiques and Arts. For the reasons above, we do not put much stock in these comparisons, ordinal or absolute.

Figure A-1: Category-Specific Effects



Notes: This figure presents category-specific estimates for all categories in our main sample with at least one hundred thousand interactions. The dependent variable is a dummy for whether the bargaining interaction ended in a transaction. All parameters of the model are estimated independently for each coefficient estimate. The solid vertical line is at zero, while the dashed vertical line is at our point estimate from Table **??** of 0.0773 for comparison.

4 Robustness

1 Sample Window

As a simple robustness test, we check the sensitivity of our estimates to the sample window. The main sample window is four weeks before and four weeks after the change on May 23, 2016, depicted graphically in Figure **??**. We also consider two, three, five, and six weeks in either direction, as well as the full dataset, seven weeks before and ten weeks after.

Table A-4 presents estimates varying the sample window. Consistent with the finding that the effect of introducing communication is not immediate, results are weaker for the shorter windows. This also reflects a loss of power as we lose observations. Extending the window for a longer time horizon, the estimates stabilize, however this may reflect other changes on the website.

2 Seller Fixed Effects

Next, we consider replicating the estimates from Table **??** with seller fixed effects. This is meant to address a number of concerns. Most importantly, the category fixed effects

Table A-4: Estimates by Sample Window

	(+/-2)	(+/-3)	(+/-4)	(+/-5)	(+/-6)	(+10/-7)
β^C_{pp}	-0.0008	0.0026	0.0023	0.0042*	0.0036*	0.0016
	(0.0030)	(0.0022)	(0.0019)	(0.0018)	(0.0017)	(0.0016)
β^C_{dd}	0.0017	0.0025	0.0042*	0.0047*	0.0040*	0.0034*
	(0.0017)	(0.0014)	(0.0012)	(0.0011)	(0.0010)	(0.0009)
β^C_{iv}	0.0344	0.0476	0.0773*	0.0865*	0.0731*	0.0597*
	(0.0337)	(0.0265)	(0.0226)	(0.0204)	(0.0190)	(0.0165)
Controls	✓	✓	✓	✓	✓	✓
N	1649026	2432528	3294362	4091076	4924926	6766228

Notes: This table presents estimation results mirroring Table **??** varying the sample inclusion window. Each cell is the result of an independent regression. Each row represents a different estimation strategy: respectively, pre-post, difference-in-differences, and instrumental variables. Each column represents a different sample, where the column header indicates the number of weeks before and the number of weeks after May 23, 2016. Heteroskedacticity-robust standard errors, clustered by seller, are reported in parentheses, and * denotes statistical significance at $\alpha = 0.05$.

that we include in our main specification are rather coarse, and so seller-level fixed effects might do a better job of controlling for product unobservables. In particular, we are concerned that the composition of listings on which interactions are occurring is different in unobservable ways for the treated group and the untreated group, which might lead us to find spurious effects.

Estimates are presented in Table A-5. We have limited ourselves to replicating only the models with the full set of controls. We see a slight attenuation of the estimates, but the $\hat{\beta}^C_{dd}$ and $\hat{\beta}^C_{iv}$ remain statistically significant and statistically indistinguishable from the estimates of Table **??**.

3 Additional Descriptives on Compliers

In Tables A-6, A-7, and A-8, we replicate the complier analysis of Table **??** using alternative variables that are part of our definition of a "complier" in the main analysis: whether an interaction involved a message, whether the buyer is a desktop user, and whether the interaction occurs after the policy change.

In Table A-9 we keep our original definition of compliers and extend Table **??** to include item categories and conditions.

Table A-5: Estimates with Seller Fixed Effects

	(1) Desktop	(2) Mobile	(3) Differences	(4) IV
$\mathbb{1}$(Post)	0.0024	0.0024	0.0008	0.0011
	(0.0016)	(0.0018)	(0.0013)	(0.0012)
$\mathbb{1}$(Desktop)			0.0355*	0.0355*
			(0.0008)	(0.0008)
$\mathbb{1}$(Post) · $\mathbb{1}$(Desktop)			0.0027*	
			(0.0011)	
$\mathbb{1}$(Message)				0.0561*
				(0.0222)
Controls	✓	✓	✓	✓
Seller FE	✓	✓	✓	✓
N	1770261	1524101	3294362	3294362

Notes: This table replicates models with the full set of controls from Table **??**, where we now also include seller fixed effects. Models (1) and (2) are pre-post estimates for the desktop and mobile samples, respectively, while models (3) and (4) are difference-in-differences and IV estimates, respectively. Standard errors are reported in parentheses, and * denotes statistical significance at $\alpha = 0.05$.

Table A-6: Complier Characteristics: Any Message

	$\mathbb{P}(x{=}1)$	$\mathbb{P}(x = 1 \mid \text{message})$	$\frac{\mathbb{P}(x=1\mid\text{message})}{\mathbb{P}(x=1)}$
Ask Price in (\$0,\$50)	0.52	0.41	0.78
Ask Price in [\$50,\$150)	0.27	0.29	1.08
Ask Price in [\$150,\$250)	0.09	0.11	1.31
Ask Price $\geq$ \$250	0.12	0.19	1.56
Friday, Saturday, or Sunday	0.42	0.42	1.01
Precipitation	0.46	0.64	1.41
Holiday	0.10	0.04	0.40
Post	0.50	0.94	1.89
Desktop	0.54	0.70	1.30

Notes: This table summarizes complier characteristics for the set of interactions that involve any message. Each row represents a dummy variable which is taken to be x in the column formulas above. The unit of observation is an interaction between a buyer and an item.

5 Text Analysis Details

1 Message Examples

Table A-10 shows a curated set of examples messages sent with offers in our data. Messages range from the simple declaration of an offer to signals of willingness-to-pay

Table A-7: Complier Characteristics: Desktop

	$\mathbb{P}(x{=}1)$	$\mathbb{P}(x = 1 \mid \text{desktop})$	$\frac{\mathbb{P}(x=1\mid\text{desktop})}{\mathbb{P}(x=1)}$
Ask Price in ($0,$50)	0.52	0.53	1.01
Ask Price in [$50,$150)	0.27	0.26	0.99
Ask Price in [$150,$250)	0.09	0.09	0.98
Ask Price $\geq$ $250	0.12	0.12	0.98
Friday, Saturday, or Sunday	0.42	0.41	0.97
Precipitation	0.46	0.45	0.99
Holiday	0.10	0.10	0.97
Post	0.50	0.50	0.99
Desktop	0.54	1.00	1.86

Notes: This table summarizes complier characteristics for the set of interactions that involve a desktop buyer. Each row represents a dummy variable which is taken to be x in the column formulas above. The unit of observation is an interaction between a buyer and an item.

Table A-8: Complier Characteristics: Post

	$\mathbb{P}(x{=}1)$	$\mathbb{P}(x = 1 \mid \text{post})$	$\frac{\mathbb{P}(x=1\mid\text{post})}{\mathbb{P}(x=1)}$
Ask Price in ($0,$50)	0.52	0.52	1.00
Ask Price in [$50,$150)	0.27	0.27	1.00
Ask Price in [$150,$250)	0.09	0.09	1.00
Ask Price $\geq$ $250	0.12	0.12	1.00
Friday, Saturday, or Sunday	0.42	0.42	1.02
Precipitation	0.46	0.66	1.46
Holiday	0.10	0.04	0.35
Post	0.50	1.00	2.00
Desktop	0.54	0.53	0.99

Notes: This table summarizes complier characteristics for the set of interactions that occur after the policy change. Each row represents a dummy variable which is taken to be x in the column formulas above. The unit of observation is an interaction between a buyer and an item.

or accept (e.g. "I do not go down").[1] Some messages are meant to entice better offers, such as offering bulk discounts. Some messages clarify aspects of the item (like missing a hard drive). Still others seem like endearment and politeness, perhaps an attempt to foster or appeal to other-regarding preferences. Therefore, messages seem to serve a multitude of functions: cheap talk, signaling about buyer and seller characteristics, resolving informational uncertainties about the product, endearment, and more.

2 Data Construction

The text analysis of Section **??** uses the dataset of 248,722 messages sent in the ten weeks following May 25, 2016. This reflects some preliminary cleaning: messages

[1] "MFG" is a common acronym translating to "with regards."

Table A-9: Complier Characteristics, Item Categories and Condition

	$\mathbb{P}(x=1)$	$\mathbb{P}(x = 1 \mid \text{complier})$	$\frac{\mathbb{P}(x=1 \mid \text{complier})}{\mathbb{P}(x=1)}$
Category, Clothing & Accessories	0.15	0.09	0.62
Category, Car & Motorbike: Parts	0.15	0.14	0.94
Category, Sports	0.06	0.06	1.05
Category, Computers, Tablets & Networking	0.05	0.07	1.29
Category, Mobile Phones	0.05	0.04	0.68
Category, Furniture & Living	0.05	0.05	1.10
Category, Collectables	0.04	0.05	1.07
Category, Handyman	0.04	0.04	1.18
Category, Business & Industry	0.04	0.05	1.43
Category, Antiques & Art	0.03	0.05	1.60
Category, Watches & Jewellery	0.03	0.03	0.87
Category, Tv, Video & Audio	0.03	0.04	1.23
Category, Pc & Videogames	0.03	0.02	0.72
Category, Beauty	0.03	0.02	0.74
Category, Modelling	0.03	0.04	1.19
Category, Garden & Terrace	0.02	0.03	1.17
Category, Toy	0.02	0.02	0.92
Category, Domestic Appliances	0.02	0.02	1.07
Category, Books	0.02	0.02	1.27
Category, Cameras & Camcorders	0.02	0.02	1.51
Category, Infant	0.01	0.01	0.52
Category, Movies & Dvds	0.01	0.01	0.58
Category, Music	0.01	0.01	1.08
Category, Coins	0.01	0.02	1.35
Category, Musical Instruments	0.01	0.01	2.18
Category, Pet Stores	0.01	0.01	0.91
Category, Office & Stationery	0.01	0.01	1.31
Category, Gourmet	0.01	0.01	1.23
Category, Stamps	0.01	0.01	1.50
Category, To Travel	0.00	0.00	1.14
Condition, New	0.50	0.43	0.86
Condition, Refurb	0.01	0.01	1.36
Condition, Used	0.43	0.48	1.12
Condition, Unknown	0.06	0.08	1.31

Notes: This table summarizes complier characteristics i.e. the characteristics of interactions in the treatment group that "comply" and involve a message between bargainers. Each row represents a dummy variable which is taken to be x in the column formulas above. The unit of observation is an interaction between a buyer and an item. The categories are ordered from the unconditional most common to least common.

consisting only of numbers or spaces are excluded. Also, messages such as "please enter your message here" (in a variety of languages), which we believe to be an artifact

Table A-10: Example messages

Censored Message Excerpts (from Google Translate)
This is unfortunately the best price we can offer you.
Hello, under it does not go unfortunately. MfG
Hello, would like to ask if you would sell the article also for 15, - Euro. LG S. [NAME]
I do not go down sry
Incl. Shipping.
Hello dear [PRODUCT]-interested. What would happen if we met in the middle? There are also figures outside of the electric carousel. Is that OK? Friendly Greetings [NAME]
Hello that would be my last price
let's meet in the middle?
This is definitely the minimum
And they have not sold the vest until today, beat them to 49.00 euros is a good price and they finally have their rest. . . Greetings
I would pay 105 euros if the [PRODUCT] was bought not more than 6 months ago and the original invoice with rest guarantee is available and included. To compare: New at Voelkner currently 119,04 with 2 years warranty! MfG
25 Euro since articles new & unused.
I intend not to issue any higher offer.
Since the hard disk is missing! it's alright?
With the purchase of several [PRODUCT], you save more - you pay postage only once.
not less....
... rarely laughed so much!
VERY SIMPLY
Would be glad if you accept this proposal.
Unfortunately, more I can not afford mfg
I'll buy the [PRODUCT]!
This is a super cheap price !!

Notes: Here we present a curated set of messages by both buyers and sellers, translated by Google Translate from the original German. We have censored any potentially identifying information, in particular individual and product names.

of third-party software for sellers to create listings and upload them via the API, have been manually detected and excluded.

Most of the analysis is conducted on the "processed" messaging dataset. The processing of the messaging takes place in four steps.

1. First, we use a Python implementation of Google's language detection algorithm to classify messages by language. After this, we keep only the messages that are detected to be in German.

2. Second, we remove all numbers, symbols, and extra spaces from each message.

3. Third, we remove stop words. This list of stop words comes from NLTK's set of German stop words. We remove "nicht" ("not") from this list as this token appears to be important in the context of bargaining.

4. Next, we stem the messages. To do this we use the NLTK's German Snowball Stemmer.

3 Heat Maps and their Corresponding Figures

Figure A-2 shows our heat map results and off-diagonal plots for different cuts of buyers based on the number of messages they sent throughout the ten week period following the introduction of messaging on eBay Germany Best Offer. As expected, these figures are filled with noise and present no obvious patterns. Figure A-3 depicts the same figures, but for sellers. Here, we find that our results strengthen as we restrict attention to experienced sellers. As a robustness check, Figure A-4 presents the heat map figures and off-diagonal plots for buyers and sellers who only sent one message during this time period. We find that sellers that send only one message have no patterns in messaging content, which further suggests that seller learning is driving our results among experienced sellers.

Figure A-5 includes the bottom gradient results for buyers and sellers without being scaled by the cosine distance between week 9 and week 10 messages. As seen in Panel (a), the cosine distance for buyer messages is close to being orthogonal (near one) for the group of buyers that sent six or more and five or more messages. One reason we are getting this result is because we have few buyers who've sent multiple messages, for instance, only 496 buyers sent five or more messages. This highlights one weakness of our cosine distance measure, namely that it's sensitive to the number of messages in each sample.

As a robustness check, Figure A-7 then includes the number of messages by group for buyers and sellers across weeks. We also include these figures scaled by the number of messages in week 10. In this figure, there is some noise in the number of messages by week, however, we don't see a significant rise in the number of messages sent by the set of sellers with multiple messages in later weeks—such a rise would cause concern for our main results in Section **??**.

6 An Exploration into Seller Messages

In Section ??, we presented results that suggest that sellers are learning across our ten-week sample period; furthermore, we found that this result is driven by experienced sellers. In this section, we implement a distributed multinomial regression model (DMR) from Taddy (2015) that explores the relationship between seller experience and the bigrams sent by sellers in our messaging dataset.

1 Data Reduction

For this analysis, we are using the same dataset as the one discussed in Section ??. Similar to Section ??, we construct a matrix $\mathbf{C}_s$ consisting of seller bigram counts; recall that element $c_{s,mj}$ of $\mathbf{C}_s$ corresponds to the number of counts for bigram j in message m. Now, in order to lower the computational costs of running a regression model, we went through of series of cleaning steps. These steps were aimed at reducing some of the high dimensionality of our messaging dataset without loss of significant information—as mentioned, we have more than 280,000 bigrams in our original sample of seller messages.

The processing steps are as follows: 1) we remove bigrams that contain less than 5 characters, 2) we remove bigrams where one of the tokens in the bigram contain only 1 character, 3) we drop all sellers that sent more than 21 messages, 4) we remove all bigrams that are used less than 10 times across seller messages, 5) we drop bigrams that are said by only one seller, and 6) we remove the empty rows that the previous two steps created in matrix $\mathbf{C}_s$.

For step 3, we drop sellers that are sending more than 21 messages as we expect that these sellers might be very different than sellers sending between 1 and 20 messages; for instance, these serial sellers are probably more likely to be active on different sites and, as a result, they might already have had experience sending messages to buyers prior to the introduction of messaging on eBay's Germany Best Offer platform. Second, as we are concerned about how sellers are changing messaging content from one message to another, it makes sense for us to set bounds on the message number. Dropping these sellers from our sample only removes 217 sellers out of our original $60,076$. In total, these steps reduce the dimension of matrix $\mathbf{C}_s$ to be 86,879-by-8,069; representing the 86,879 messages in our sample that contain 8,069 unique bigrams.

We construct our final dataset by then merging a number of controls to our matrix of bigram counts. In addition to the controls documented in Section **??**, we add dummies for the total number of messages sent by that seller, a variable representing the message length—which we measure by the number of tokens in the raw message—and the log of the offer price attached to the message. We then have 242 controls included in our analysis.

2 The DMR Model

Our main variable of interest is the message number sent by that seller. Here, we hope to further understand the bigrams that are correlated to seller experience. To do this, we implement a distributed multinomial model from Taddy (2015). This model was additionally used as the preferred specification in Gentzkow et al. (2019b); in this paper, the authors analyze congressional speeches from 1873 to 2016 in order to estimate the trends in partisanship.

In implementing this model, we are first assuming that our bigrams counts are being generated by the multinomial distribution.[2] Specifically, the counts in each message m are drawn by the multinomial distribution with parameters $n_m = \sum_j c_{mj}$, the total number of bigrams said in message m, and probability vector $\mathbf{p}_m$, indicating the probability of including each bigram conditional on the controls specified in the previous section. To compute these probability vectors, we we would then estimate

$$p_{mj} = \frac{exp(\zeta_{mj})}{\sum_{l=1} exp(\zeta_{ml})}, \text{ where } \zeta_{mj} = \alpha_j + \boldsymbol{\beta}_j \mathbf{v}_m + \rho_j x_m.$$

Here, the vector $\mathbf{v}_m$ represents our set of controls for message m; additionally, message number, our proxy for experience, is denoted by x_m.

Rather than running a computationally intensive multinomial logistic regression, Taddy (2015) notes that we can instead assume $c_{mj} \sim Pois(exp[\mu_m + \alpha_j + \boldsymbol{\beta}_j \mathbf{v}_m + \rho_j x_m])$ where we fix μ_m as $\hat{\mu}_m = log(n_m)$. This allows us to run separate Poisson regressions for each bigram.

[2] This assumes that each bigram in a message is independently generated. While this assumption is undoubtedly violated, assuming a multinomial distribution for text is common practice (see Taddy (2015), Gentzkow et al. (2019a)).

For each Poisson regression we then estimate the coefficient on message number for bigram j by minimizing

$$\sum_m [n_m exp(\zeta_{mj}) - c_{mj}(\zeta_{mj})] + \lambda[\frac{1}{\tau}\sum_k |\beta_{jk}| + |\rho_j|].^3$$

In this equation, we include L1 regularization through the penalizing term, λ, which reduces the number of features in our model by shrinking the coefficients $\boldsymbol{\beta}_j$ and ρ_j toward zero. For this exercise, we selected the λ that minimizes the mean out-of-sample deviance using 10-fold cross-validation (CV).[4] We chose to incorporate variable selection into our model in order to generate a more interpretable output and to avoid over-fitting our data. Importantly, we suspect that there are many bigrams in our dataset that have no or little relation to seller experience. This penalizing term then introduces sparsity into our model and will shrink the coefficients for message number to zero if they have little out-of-sample predictive power for those bigrams.

Next, we vary the level of τ. Setting $\tau = 0.1$, 0.5, 1, and 3 changes the extent of the penalty the model imposes on the set of controls. A smaller τ means that we will be incorporating a larger penalty on our controls rather than message number; while a larger τ will reduce the collinearity between our controls and variable of interest as we inflict a lower penalty on $\boldsymbol{\beta}_j$.

3 Experience Results

We present our results in three separate tables: First, Table A-11 includes the top and bottom 10 bigrams determined by the coefficients on message number for different levels of τ. Next, we generate an estimated experience score for each message. This is simply the summation of the bigram coefficients generated by our model for each message. We then present the top and bottom scoring messages in Tables A-12 and A-13.

In all three tables, we blocked out any potentially identifying information. This includes names, company names, addresses, and emails. We used Google Translate's API for the translations from German to English. In some of cases, we found that

[3]Note that the coefficients for our controls and message number are standardized so that they have a standard deviation of one.

[4]We ran the same model using 5-fold CV and found similar results. Results can be shown upon request.

using the web version of Google Translate produced a different result than the API; in these cases, we used the translation from the web if we found that it presented a more interpretable result. Finally, in Table A-11, note that these translations are generated on the stemmed bigrams; this will slightly change the translation from the translation of the words actually used in the message. See the next two tables for translations on the raw messages themselves.

The second column of these tables indicates the number of nonzero coefficients for message number. Here, we can see that as τ increases in size, our controls absorb a larger amount of the variation in ρ_j, effectively shrinking a growing number of these coefficients to zero. Additionally, we should note that the top and bottom bigrams and messages are fairly robust to the value we set for τ.

In Table A-11, within the top bigrams by message number, we see a lot of farewells and message sign-offs. For instance, "mfg" means "best regards" in German and is a common way to end communication in electronic messages—we see this in two separate bigrams in our $\tau = 3$ specification. Similarly, "lg" shows up for all values of τ and is another common farewell in German.

In our list of the bottom 10 bigrams, we don't see any farewells, but a few greetings do appear: "greeting [NAME]" and "dear interested person". The efficacy of greetings, farewells, and gratitude in successful bargaining and negotiations is unclear from the previous literature as some authors find that friendly communication will lead to more trust and reciprocity in bargaining and, as a result, better outcomes (Hine et al. (2009), Kopelman et al. (2006)); alternatively, others have found communicating in firm, and potentially more aggressive, tones are good strategies in negotiations (Jeong et al. (2019), Belkin et al. (2013)).

In Table A-12, the top scoring message for all versions besides $\tau = 3$, displays one interesting strategy that sellers may be adopting: Here, we see a seller justifying their cost through explaining that there is a "10% ebay commission, shipping, etc." In a similar fashion, we also see sellers justifying charging a higher price in the auction due to the "sales commission" and through the fact that the item is already discounted.

Alternatively, in Table A-13, sellers seem to be more often justifying the costs of the item through either the price they paid for the item or by providing details on the item: the "jacket [is] made of real leather," the "book was purchased completely new," the wardrobe is "very beautiful." Additionally, the sellers appear to be less assertive in their messaging through their usage of "would be happy," "I hope they can also make friends with my proposal," "if that's okay."

Table A-11: Seller Top and Bottom Bigrams Correlated with Message Number

τ	Nonzero	Bigrams
		Top 10
3	152	*thanks in advance mfg; award-understand; understand beg; without eba; low number of pieces; pray thanks; discount safeguarded; lg [NAME]; mfg sale; known does* dank vorausmfg; preis versteh; versteh bitt; ohn eba; gering stuckzahl; bitt dank; rabatt gewahrt; lg [NAME]; mfg verkauf; kund tut
1	1730	*so far; thanks in advance mfg; beg functional scope of supply; observe scope of delivery; Regular price insof; lg [NAME]; down selling price; shipping cost adjusted; award-understand; low number of pieces* insof schon; dank vorausmfg; bitt funktionslieferumfang; funktionslieferumfang beacht; verkaufspreis insof; lg [NAME]; runt verkaufspreis; versandkost angepasst; preis versteh; gering stuckzahl
0.5	3603	*beg functional scope of supply; observe scope of delivery; Regular price insof; thanks in advance mfg; so far; down selling price; lg [NAME]; award-understand; shipping cost adjusted; discount safeguarded* bitt funktionslieferumfang; funktionslieferumfang beacht; verkaufspreis insof; dank vorausmfg; insof schon; runt verkaufspreis; lg [NAME]; preis versteh; versandkost angepasst; rabatt gewahrt
0.1	6290	*Regular price insof; beg functional scope of supply; so far; observe scope of delivery; lg [NAME]; shipping cost adjusted; down selling price; rather tight; Newly listed; sale mfgruss* verkaufspreis insof; bitt funktionslieferumfang; insof schon; funktionslieferumfang beacht; lg [NAME]; versandkost angepasst; runt verkaufspreis; recht knapp; neu eingestellt; verkauf mfgruss
		Bottom 10
3	152	*counter already; gb memory card; miss it not; from august; for figure; sale however; greeting [NAME]; over-looking payment method; ready priced; far kart* entgeg schon; gb speicherkart; verpass nicht; ab august; fur figur; verkauf jedoch; gruss [NAME]; uberweis zahlungsmethod; bereit preislich; weit kart
1	1730	*counter already; is set; gb memory card; ready priced; greeting [NAME]; just give; extremely fair; suggest price proposal; not worn; month old* entgeg schon; eingestellt wurd; gb speicherkart; bereit preislich; gruss [NAME]; geb einfach; ausserst fair; preisvorschlag ordnung; nicht getrag; monat alt
0.5	3603	*woman has; is set; counter already; day would like; interess shipping; cm wide; extremely fair; natural possible; ready priced; just give* freu schon; eingestellt wurd; entgeg schon; tag mocht; interess versand; cm breit; ausserst fair; natur moglich; bereit preislich; geb einfach
0.1	6290	*woman has; cm wide; day would like; under asking price; new mature; extremely fair; dear interested person; is set; brand new unworn; rims tires* freu schon; cm breit; tag mocht; unt preisvorstell; neu reif; ausserst fair; lieb interessentin; eingestellt wurd; nagelneu ungetrag; felg reif

Notes: This table includes the top and bottom ten bigrams sent by sellers in both English and the original German ranked by our coefficients on message number for different levels of τ. The second column in the table indicates the amount of message number coefficients that are not penalized to zero for that value of τ.

4 Message Success Robustness

In this section, we replicate our analysis from Section **??** for the full set of sellers and for the set of sellers that sent fewer than 11 messages. Table A-14 presents the results from regressing message success on the cosine similarity of each message and the set of week 10 messages for our entire sample. Moreover, Table A-15 includes the same regression excluding sellers that sent 11 or more messages from the analysis. Our results are somewhat weaker when including the full set of sellers. Moreover, our coefficient on our similarity measure is negative and insignificant when including seller fixed effects. The results restricting to sellers with fewer than 11 messages largely align with our previous findings.

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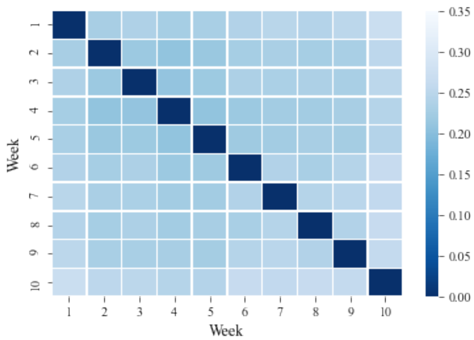
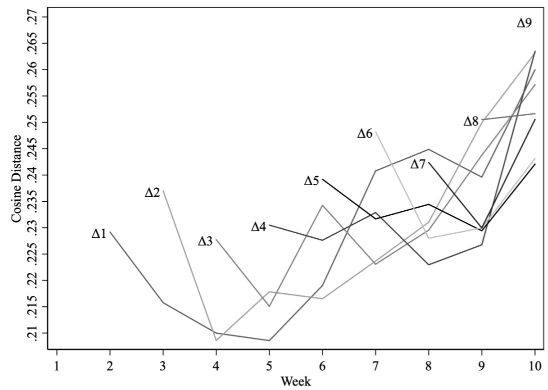
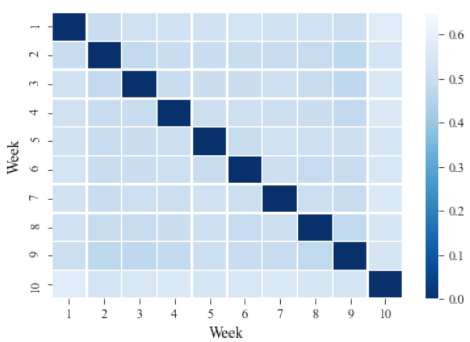
Figure A-2: Heat Maps and Off-Diagonal Figures for Repeat Buyers



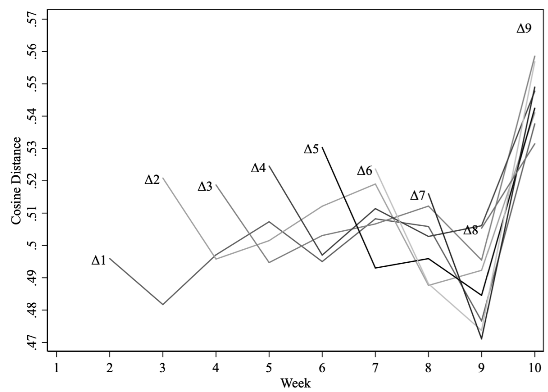
(a) 2+ Messages



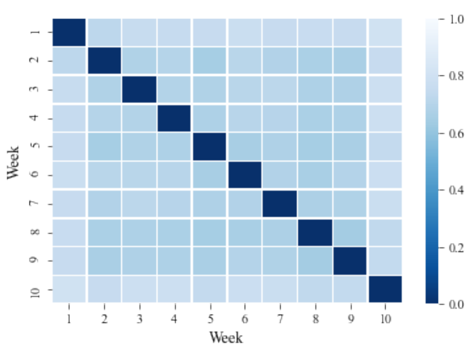
(b) 2+ Messages



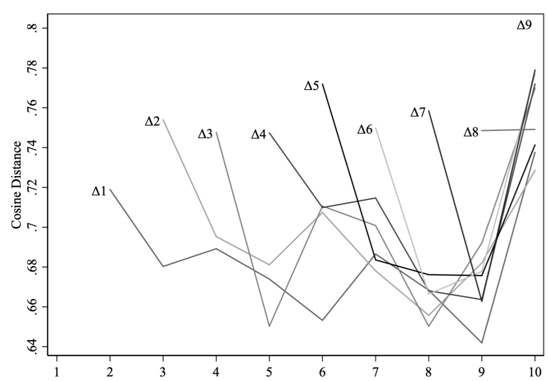
(c) 3+ Messages



(d) 3+ Messages



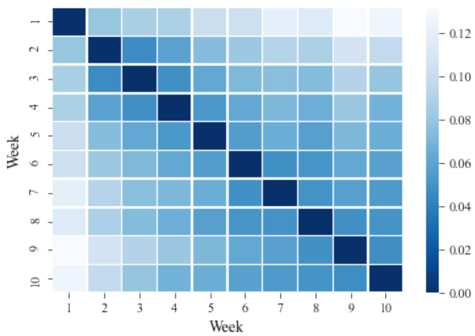
(e) 4+ Messages



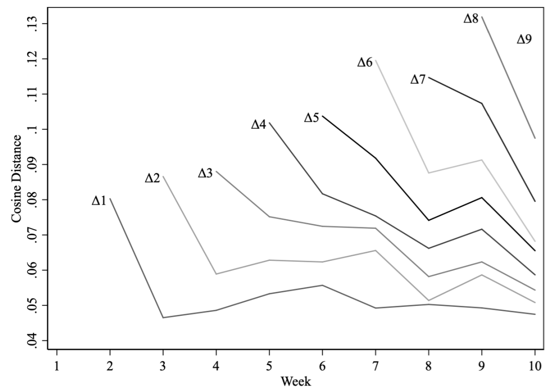
(f) 4+ Messages

Notes: This figure depicts heat map results and plots along the off-diagonals of those heat maps representing the cosine distance of message bigrams across the ten weeks following May 25, 2016 for different subgroups of buyers. Panels (a) and (b) shows the results for buyers that have sent two or more messages during our sample period, Panels (b) and (c) shows the same results for buyers that sent more than 3 messages, Panel (d) and (e) display the results for buyers that appear four or more times in our messaging dataset.

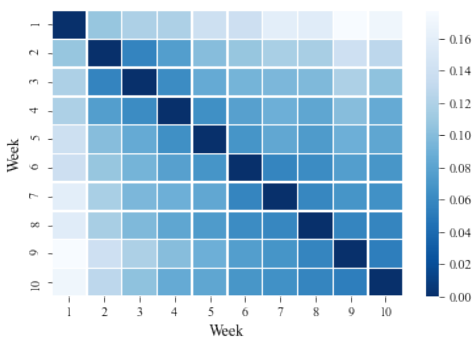
Figure A-3: Heat Maps and Off-Diagonal Figures for Repeat Sellers



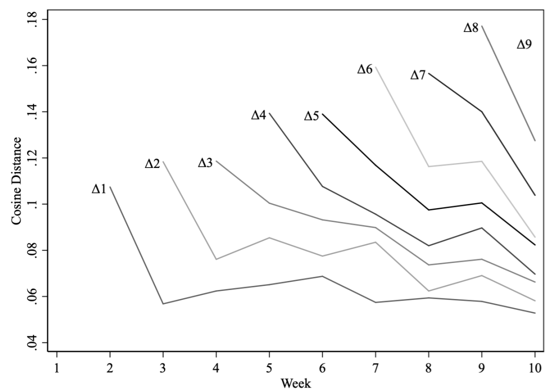
(a) 2+ Messages



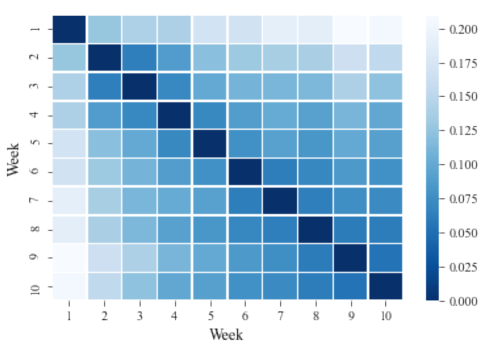
(b) 2+ Messages



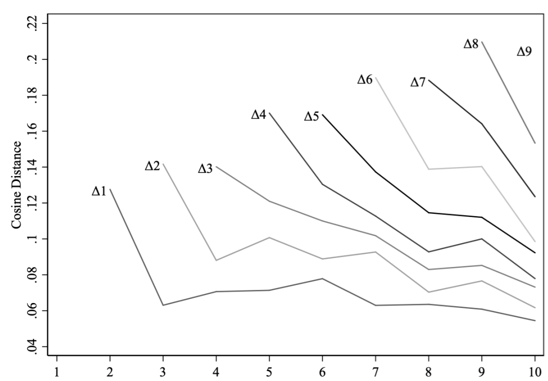
(c) 3+ Messages



(d) 3+ Messages



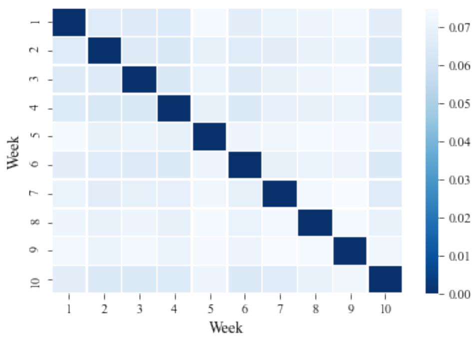
(e) 4+ Messages



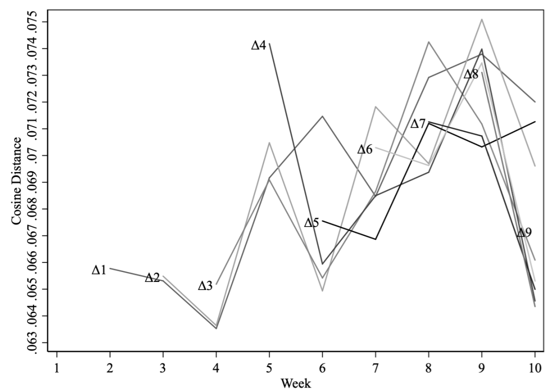
(f) 4+ Messages

Notes: This figure depicts heat map results and plots along the off-diagonals of those heat maps representing the cosine distance of message bigrams across the ten weeks following May 25, 2016 for different subgroups of sellers. Panels (a) and (b) shows the results for sellers that have sent two or more messages during our sample period, Panels (b) and (c) shows the same results for sellers that sent more than 3 messages, Panel (d) and (e) display the results for sellers that appear four or more times in our messaging dataset.

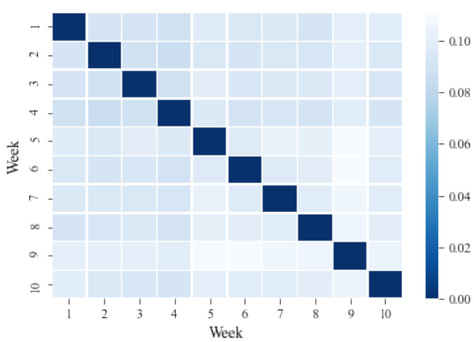
Figure A-4: Buyers and Sellers with No Experience



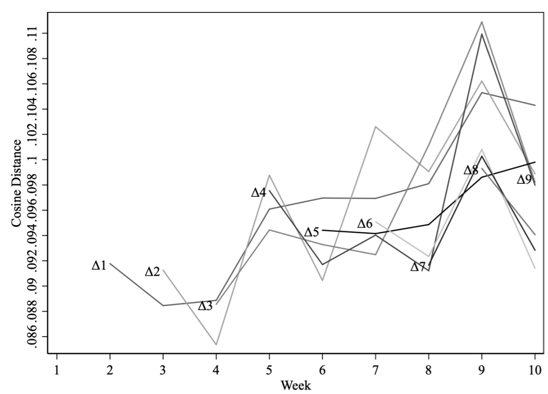
(a) Buyer Heat Map



(b) Buyer Convergence



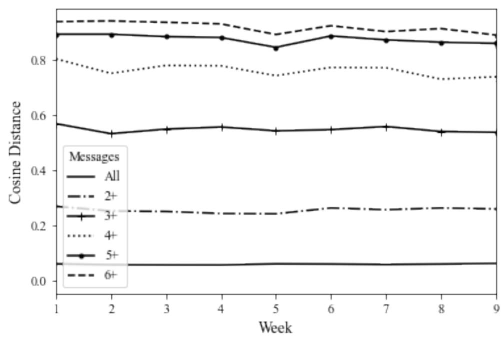
(c) Seller Heat Map



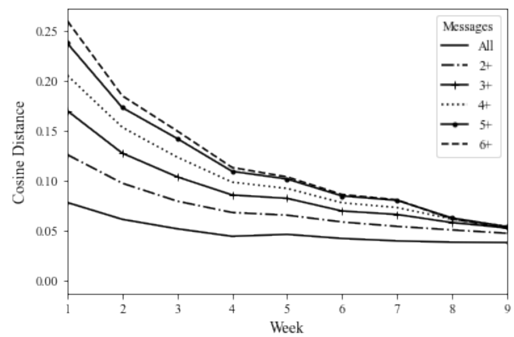
(d) Seller Convergence

Notes: This figure depicts heat map results and plots along the off-diagonals of those heat maps representing the cosine distance of message bigrams across the ten weeks following May 25, 2016 for buyers and sellers in our messaging dataset that only sent one message. Panels (a) and (b) shows the results for buyers who sent one message within our sample period and Panels (b) and (c) show the same results for sellers.

Figure A-5: The Bottom Gradient for Buyers and Sellers with Different Experience Levels



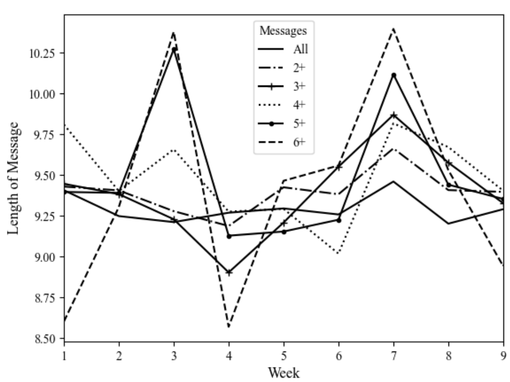
(a) Buyer



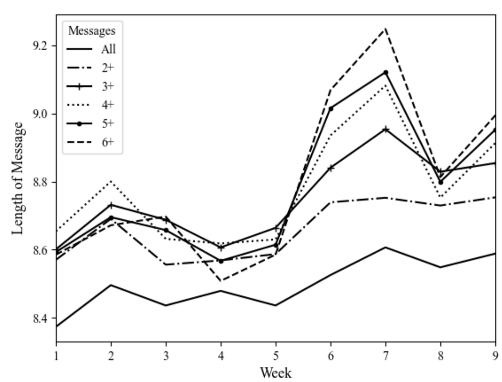
(b) Seller

Notes: This figure presents the cosine distance between the messages sent in weeks x and 10 for buyers, Panel (a), and sellers, Panel (b). Each panel is cut by groups, where All represents our results from buyer/seller messages for our entire sample of buyers/sellers, 2+ from our sample of messages sent by buyers/sellers who sent 2 or more messages, 3+ from our sample of messages sent by buyers/sellers who sent 3 or more messages, and so on.

Figure A-6: Message Length Over Time



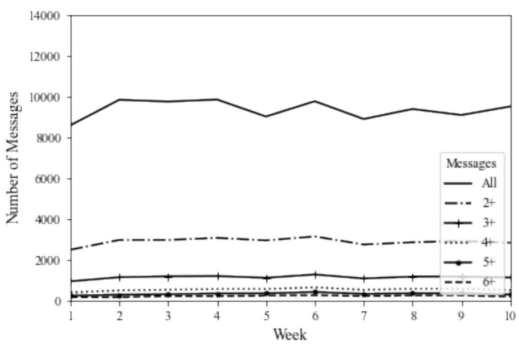
(a) Buyer



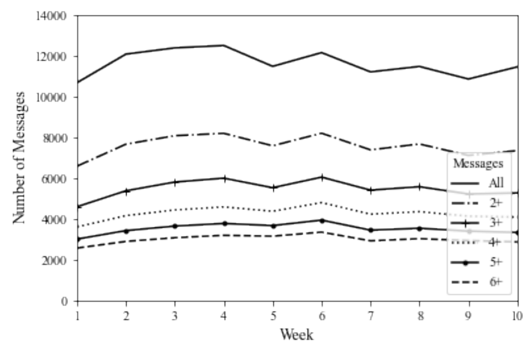
(b) Seller

Notes: This figure presents the average length of messages sent by buyers, Panel (a), and sellers, Panel (b), over our 10 week sample. Each panel is cut by groups, where All represents our results from buyer/seller messages for our entire sample of buyers/sellers, 2+ from our sample of messages sent by buyers/sellers who sent 2 or more messages, 3+ from our sample of messages sent by buyers/sellers who sent 3 or more messages, and so on. We measure message length by the number of words sent in the cleaned messages.

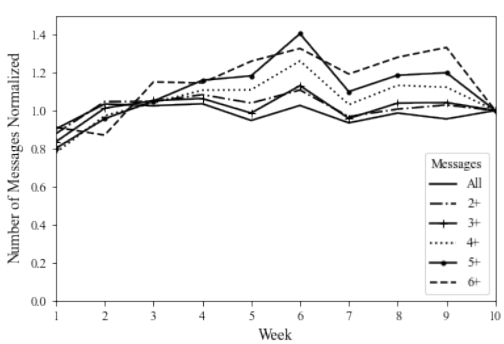
Figure A-7: Total Messages by Week for Buyers and Sellers



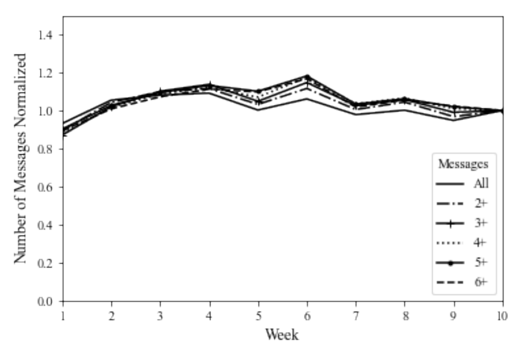
(a) Buyer



(b) Seller



(c) Buyer Normalized



(d) Seller Normalized

Notes: This figure presents the total number of messages sent by buyers, Panel (a), and sellers, Panel (b), by week. Panel (c) and Panel (d) are the buyer and seller number of messages scaled by the number of messages in week 10. Each panel is cut by groups, where All represents our results from buyer/seller messages for our entire sample of buyers/sellers, 2+ from our sample of messages sent by buyers/sellers who sent 2 or more messages, 3+ from our sample of messages sent by buyers/sellers who sent 3 or more messages, and so on.

Table A-12: Seller Top Messages

τ	Nonzero	Top Messages
3	152	1. *this is our lowest price, please understand, many thanks in advance ... mfg* (60) dies ist unser niedrigster preis, verstehen sie bitte, vielen dank im voraus...mfg
		2. *hello, this product we played 20 % discount, and the price is already miss you please understand, many thanks in advance ... mfg* (20) hallo, dieses produkt haben wir 20% rabatt gespielt, und der preis ist bereits mit verlust verstehen sie bitte, vielen dank im voraus...mfg
		3. *they have slight problems when assessing the price but I understand that!* (380) sie haben leichte probleme beim einschätzen des preises aber ich verstehe das!
1	1730	1. *thank you for your price suggestion, but unfortunately it is below my purchase price: 10% ebay commission, shipping, etc. are still going down and the selling price is calculated quite tightly. please also note the scope of functions / scope of delivery! kind regards* (40) danke für ihren preisvorschlag, liegt aber leider unter meinem einkaufspreis: 10% ebay-provision, versand usw. gehen ja auch noch runter und der verkaufspreis ist insofern schon recht knapp kalkuliert. bitte auch funktions- /lieferumfang beachten! mfg
		2. *this is our lowest price, please understand, many thanks in advance ... mfg* (60) dies ist unser niedrigster preis, verstehen sie bitte, vielen dank im voraus...mfg
		3. *hello, this product we played 20 % discount, and the price is already miss you please understand, many thanks in advance ... mfg* (20) hallo, dieses produkt haben wir 20% rabatt gespielt, und der preis ist bereits mit verlust verstehen sie bitte, vielen dank im voraus...mfg
0.5	3603	1. *thank you for your price suggestion, but unfortunately it is below my purchase price: 10% ebay commission, shipping, etc. are still going down and the selling price is calculated quite tightly. please also note the scope of functions / scope of delivery! kind regards* (40) danke für ihren preisvorschlag, liegt aber leider unter meinem einkaufspreis: 10% ebay-provision, versand usw. gehen ja auch noch runter und der verkaufspreis ist insofern schon recht knapp kalkuliert. bitte auch funktions- /lieferumfang beachten! mfg
		2. *this is our lowest price, please understand, many thanks in advance ... mfg* (60) dies ist unser niedrigster preis, verstehen sie bitte, vielen dank im voraus...mfg
		3. *hello, this product we played 20 % discount, and the price is already miss you please understand, many thanks in advance ... mfg* (20) hallo, dieses produkt haben wir 20% rabatt gespielt, und der preis ist bereits mit verlust verstehen sie bitte, vielen dank im voraus...mfg
0.1	6290	1. *thank you for your price suggestion, but unfortunately it is below my purchase price: 10% ebay commission, shipping, etc. are still going down and the selling price is calculated quite tightly. please also note the scope of functions / scope of delivery! kind regards* (40) danke für ihren preisvorschlag, liegt aber leider unter meinem einkaufspreis: 10% ebay-provision, versand usw. gehen ja auch noch runter und der verkaufspreis ist insofern schon recht knapp kalkuliert. bitte auch funktions- /lieferumfang beachten! mfg
		2. *to get big discount, please send inquiry to delivery address directly to our e-mail. thank you and friendly greetings, [NAME] [NAME] [company] [address] celle phone: xxxxx xxxxxxx email: email@email.de* (100) um großer rabatt zu bekommen, bitte senden sie anfrage mit lieferadresse direkt auf unsere e-mail. danke und freundliche grüße, [NAME] [NAME] [company] [address] celle telefon: xxxxx-xxxxxxx email: email@email.de
		3. *hello, thank you very much for your interest! I can offer you the lock for 80+ postage if we do not go to the auction. I pass the sales commission on to you. just send me a message! best regards* (90) hallo, vielen dank für ihr interesse! ich kann ihnen das schloß für 80 + porto anbieten, wenn wir auf die auktion verzichten. die gesparte verkaufsprovision gebe ich so an sie weiter. senden sie mir hierzu einfach eine nachricht! beste grüße

Notes: This table presents the top three messages sent by sellers based on the summation of the coefficients on message number for each bigram in the message for different levels of τ. The second column in the table indicates the amount of message number coefficients that are not penalized to zero. We include the listing price in euros rounded to the nearest tens place in parenthesis next to each message. Finally, the German version of the message is included below each English translation.

Table A-13: Seller Bottom Messages

τ	Nonzero	Bottom Messages
3	152	1. *good morning, thank you for your best offer. like I get to meet them on my original award, 50 I can still give so. so we would be able to meet in the middle us virtually. with the request for your understanding! m* (400)
		guten morgen, herzlichen dank für ihren preisvorschlag. gerne komme ich ihnen auf meinen ursprünglichen preis entgegen, 50 kann ich schon noch nachgeben. so würden wir uns quasi in der mitte treffen können. mit der bitte um verständnis! m
		2. *I just discovered a very small hole on the back, so the price is a little bit more accommodating .... best regards!* (20)
		auf der rückseite habe ich gerade ein ganz kleines löchlein entdeckt, daher komme ich im preis etwas entgegen ... . schönen gruß!
		3. *good day, many thanks for your interest in the wardrobe stand of classicon. it is a very beautiful piece of furniture in excellent condition. like I get to meet them in the award. beautiful greetings to jump!* (1350)
		guten tag, vielen dank für ihr interesse an dem garderobenständer von classicon. es handelt sich um ein sehr schönen möbelstück in hervorragendem zustand. gerne komme ich ihnen im preis entgegen. schöne grüße nach springe!
1	1730	1. *love potential customer, I like to go even at 55 down, but since that is not further jacket made of real leather and as well as not being worn. I ask for understanding and would be happy about their purchase still very! nice greetings, [NAME] [NAME]* (60)
		liebe interessentin, ich gehe gerne noch auf 55 runter, weiter jedoch nicht, da die jacke aus echtleder und so gut wie nicht getragen ist. ich bitte um verständnis und würde mich über ihren kauf trotzdem sehr freuen! schöne grüße, [NAME] [NAME]
		2. *Suggest Price is ok, but please note notebook holidays. Shipping only possible again from 19:08. if that's okay, please buy.* (10)
		preisvorschlag ist in ordnung, bitte aber urlaubsnotiz beachten. versand erst wieder ab dem 19.08 möglich. wenn das okay ist, bitte kaufen.
		3. *since the book was purchased completely new and is not available in the book trade, I ask for understanding that I no longer priced under these above-mentioned Suggest Price can go. I hope they can also make friends with my proposal against.* (10)
		da das buch völlig neu gekauft wurde und im buchhandel nicht erhältlich ist, bitte ich um verständnis, das ich preislich nicht mehr unter diesen o.g. preisvorschlag gehen kann. ich hoffe, sie können sich mit meinem gegenvorschlag auch anfreunden.
0.5	3603	1. *love potential customer, I like to go even at 55 down, but since that is not further jacket made of real leather and as well as not being worn. I ask for understanding and would be happy about their purchase still very! nice greetings, [NAME] [NAME]* (60)
		liebe interessentin, ich gehe gerne noch auf 55 runter, weiter jedoch nicht, da die jacke aus echtleder und so gut wie nicht getragen ist. ich bitte um verständnis und würde mich über ihren kauf trotzdem sehr freuen! schöne grüße, [NAME] [NAME]
		2. *I myself had EUR 80.00 plus shipping paid now for it: shipping included insured EUR 70.00. I would be happy if the beautiful part is in good hands! kind regards!* (80)
		ich selbst hatte euro 80,00 plus versand bezahlt, für sie nun: euro 70,00 inklusive versicherter versand. ich würde mich freuen, wenn das schöne teil in gute hände kommt! herzliche grüße!
		3. *since the book was purchased completely new and is not available in the book trade, I ask for understanding that I no longer priced under these above-mentioned Suggest Price can go. I hope they can also make friends with my proposal against.* (10)
		da das buch völlig neu gekauft wurde und im buchhandel nicht erhältlich ist, bitte ich um verständnis, das ich preislich nicht mehr unter diesen o.g. preisvorschlag gehen kann. ich hoffe, sie können sich mit meinem gegenvorschlag auch anfreunden.
0.1	6290	1. *love potential customer, I like to go even at 55 down, but since that is not further jacket made of real leather and as well as not being worn. I ask for understanding and would be happy about their purchase still very! nice greetings, [NAME] [NAME]* (60)
		liebe interessentin, ich gehe gerne noch auf 55 runter, weiter jedoch nicht, da die jacke aus echtleder und so gut wie nicht getragen ist. ich bitte um verständnis und würde mich über ihren kauf trotzdem sehr freuen! schöne grüße, [NAME] [NAME]
		2. *I myself had EUR 80.00 plus shipping paid now for it: shipping included insured EUR 70.00. I would be happy if the beautiful part is in good hands! kind regards!* (80)
		ich selbst hatte euro 80,00 plus versand bezahlt, für sie nun: euro 70,00 inklusive versicherter versand. ich würde mich freuen, wenn das schöne teil in gute hände kommt! herzliche grüße!
		3. *sorry, but there is my lowest painful limit because the shoes have well over EUR 150 cost. I would be happy if the beautiful shoes treat anyway. me they are unfortunately too small.* (60)
		sorry, aber da ist meine unterste schmerzgrenze, da die schuhe weit über eur 150 gekostet haben. würde mich freuen, wenn sie sich die schönen schuhe trotzdem gönnen. mir sind sie leider zu klein.

Notes: This table presents the bottom three messages sent by sellers based on the summation of the coefficients on message number for each bigram in the message for different levels of τ. The second column in the table indicates the amount of message number coefficients that are not penalized to zero. We include the listing price in euros rounded to the nearest tens place in parenthesis next to each message. Finally, the German version of the message is included below each English translation.

Table A-14: Message Success (All Sellers)

	(1)	(2)	(3)
Sim(m, week 10)	0.0456*	0.0345*	-0.0277
	(0.0168)	(0.0170)	(0.0352)
Message Length		0.0009*	0.0002
		(0.0002)	(0.0004)
N	113600	113600	73839
Controls	✓	✓	✓
Seller FE			✓

Notes: This table presents our results from regressing message success onto a measure of seller experience. Sim(m, week 10) is the cosine similarity between a message and the set of week 10 messages. All models include our main set of controls: time trend; ln(ask price); category by condition fixed effects; day of week, precipitation, holiday dummies, and the temperature. Model (3) includes seller fixed effects. Robust standard errors are reported in parentheses and * denotes statistical significance at $\alpha = 0.05$.

Table A-15: Message Success (Sellers with Fewer than 11 Messages)

	(1)	(2)	(3)
Sim(m, week 10)	0.0589*	0.0485*	0.0671
	(0.0235)	(0.0236)	(0.0457)
Message Length		0.0014*	0.0003
		(0.0002)	(0.0005)
N	95617	95617	55903
Controls	✓	✓	✓
Seller FE			✓

Notes: This table presents our results from regressing message success onto a measure of seller experience. Sim(m, week 10) is the cosine similarity between a message and the set of week 10 messages excluding sellers who sent more than 11 messages. All models include our main set of controls: time trend; ln(ask price); category by condition fixed effects; day of week, precipitation, holiday dummies, and the temperature. Likewise, all models drop sellers sending more than 10 messages. Model (3) includes seller fixed effects. Robust standard errors are reported in parentheses and * denotes statistical significance at $\alpha = 0.05$.